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High-resolution synthetic residential multi-energy load profiles under electrification scenarios in New Zealand and Germany

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Abstract

Understanding current and future residential energy demand is crucial for energy system planning and demand-side management (DSM). In this database, we generate high-resolution (1 min) residential multi-energy load profiles for Auckland and Christchurch (New Zealand) and Oldenburg and Karlsruhe (Germany). We use residential load simulator, a stochastic bottom-up tool, to simulate household electricity and heating demand by aggregating individual appliance consumption based on occupant behaviour and statistical data. Based on projected electrification trends, we simulate future energy demand scenarios, by integrating electric vehicle adoption and electrification of space heating. The resulting dataset provides valuable insights into how residential load profiles may evolve. The data can be used by researchers and urban planners as inputs into energy capacity expansion planning models, grid stability analyses, and DSM strategies.

1. Introduction

The transition away from fossil fuels requires a diversified energy mix with a significant share of intermittent renewable sources such as solar and wind. Electrification across various sectors and the emergence of increasingly decentralised energy systems introduce major shifts in electricity grids, posing significant challenges for urban energy system modelling [1, 2]. Demand-side management (DSM) offers a crucial flexibility mechanism to support the increasing integration of renewable energy resources [3, 4]. However, demand-side data is often proprietary [5], and future demand profiles are difficult to project. To bypass lengthy data acquisition processes (often ranging over multiple years) and to account for evolving consumption patterns, simulating future load profiles becomes imperative [1]. The shortage of models capable of simulating multi-energy load profiles based on interview-based data—often characterised by high uncertainty—poses a significant barrier to effective energy system assessment [6]. The temporal resolution of demand data may significantly affect energy system modelling outcomes, especially for systems with high levels of renewable generation [7]. For residential systems, [8] showed that hourly aggregation can lead to an underestimation of system costs and inaccurate sizing of PV, inverter, and battery capacities. To effectively evaluate DSM strategies and electrification impact, highly time-resolved, multi-energy load profiles are essential [9] found that smaller time steps (e.g. 5 min) improve the management of daily demand evolution in DSM applications, while noting that time resolutions of at least 30 min are required to identify relevant control dynamics. Similarly, [10] emphasises the importance of capturing high-resolution temporal variability to compare Demand Response (DR) strategies under realistic conditions. Although most DR methods currently use 15 to 30 min resolutions, they recommend time steps as short as 1 min. Coarser temporal resolutions have also been shown to significantly distort estimates of electric vehicle (EV) charging loads [11]. In addition to their direct use in DSM, DR, and micro-grid research, sub-hourly data can enhance the representation of load dynamics in energy system models such as Homer Pro [12, 13] and Homer Grid [14] (1 min to hourly resolution), PLEXOS [15] (supports sub-hourly input time steps for dispatch and market simulation), and distribution-system simulators like OpenDSS [16] (5 min).

The lack of highly resolved demand-side data is a recognised issue worldwide [17, 18] and has been highlighted for countries like the United States [5] and several European countries [18]. In this work, we begin to address this gap by developing high-resolution residential demand data for four cities in New Zealand and Germany.

In 2023, the residential sector became the largest sector of electricity demand in New Zealand, surpassing the demand from the industrial sector for the first time [19], with growing electrification trends further reshaping consumption patterns [20]. While the residential sector in New Zealand is already largely electrified, with approximately 88% of electricity or grid electricity generated from renewables [19], the increasing adoption of EVs is set to shift energy demand traditionally classified under the transport sector to the electricity demand of households [21].

Despite the sector's significance, data on residential load profiles for New Zealand are lacking. Existing studies based on data collection efforts, such as the household energy end-use project (HEEP1) [22], provide foundational insights into residential energy end-use. However, the dataset is outdated, with data collection completed in 2005. Efforts to update this dataset with the ongoing project HEEP2 [23], involving 750 households across the country, are underway, but the data collection phase will not be completed until May 2025. The release timeline for the new data will depend on subsequent processing and validation phases following the end of data collection. Other sources, such as the EECA energy end use database [24] and Rewiring Aotearoa's technical report [21], continue to rely on the HEEP1 report. While initiatives like the GREEN Grid project have monitored residential electricity use at a 1 min resolution [25], they remain limited in scale, covering only 42 houses in the North Island. Current residential electricity demand data, provided by the Electricity Authority [26], offers monthly aggregated residential consumption trends for New Zealand's main centres. However, it lacks device-level granularity and time resolution and does not extend to non-electric loads such as water heating or cooking.

A similar situation is observed in Germany. Although residential load profiles are available to some extent, they exhibit low temporal resolution and are based on outdated models that do not account for future electricity consumption with highly electrified loads [27]. City-specific data seems to be fully absent, often due to strict data protection policies [27]. Previous studies have attempted to address these gaps, such as cross-country residential electricity load profiling in Europe, but they are often limited to hourly resolution and lack integration of end-use specificity, weather dependencies, and open-source accessibility [28].

To overcome these limitations, we apply the tool *residential load simulator* (resLoadSIM) [29], while demonstrating its application across cities in two different continents. Unlike previous studies, where resLoadSIM was used to model current electricity load [30] and to investigate future energy community scenarios in sub-urban Latvia [31], the tool is applied to examine future trends in space heating (SH) and the widespread adoption of EVs at a city-level. The presented datasets provide future residential electricity demand based on different electrification scenarios and address the question of how electricity demand changes under different electrification scenarios, for different cities, and for different countries (here, selected New Zealand and German cities).

This work contains time series data of electrical and energy demand for the residential sector of selected cities in New Zealand (Auckland and Christchurch) and Germany (Oldenburg and Karlsruhe). Using the tool resLoadSIM (developed by the European Commission), we produced one reference scenario, reflecting the current energy mix and four future scenarios for each city accommodating different stages of electrification, specifically targeting SH devices and EV adoption. The dataset is aggregated at the city-level and has a 1 min time resolution across one year (i.e. 525 600 time steps) based on 2022 weather data. However, this approach can be applied to any weather year, provided the necessary data is available, ensuring flexibility and transferability.

Alongside the data, we publish an updated version of the resLoadSIM tool with comprehensive documentation, advancing transparency, reproducibility, and practical reuse by other researchers. Although resLoadSIM is an established modelling framework, no formal description of the model workflow has previously been published. This paper, therefore, provides a concise overview of its structure and workflow to ensure reproducibility and transparency of the generated datasets.

The dataset is helpful for:

- o Researchers, as input into energy capacity expansion planning models,
- o Urban city planners, to give insights on how changing heating devices and transitioning to EVs affect residential load,
- o The energy sector, to assess demand site management options and infrastructure management strategies,
- o Any other user and application that needs current and future residential demand profiles at a high temporal resolution.

2. Method summary

To generate the residential multi-energy load profiles presented in this study, we used resLoadSIM, a bottom-up, stochastic tool developed by the European Commission's Joint Research Centre (JRC). resLoadSIM simulates 1 min electricity demand profiles for various household appliances, using probability and statistical data, occupant activity profiles and behaviour, device ownership statistics, and appliance operation. To generate household load profiles, the tool aggregates appliance-level consumption. While primarily focused on electricity demand, resLoadSIM also accounts for heat-related appliances such as SH and domestic hot water (DHW) heating, depending on the modelling configuration.

Future residential load profiles were generated under scenarios accounting for increasing adoption of EVs and electrification of SH devices. For the present work, two minor extensions of the tool were implemented: (1) the inclusion of electric resistive heaters as a distinct heating-technology category, and (2) a standalone Python activation script that interfaces with the C++ simulation machine to automate execution of the model workflow. This section provides an overview of resLoadSIM's key components, configuration and parametrisation, and the data sources used to map city-specific conditions and trends. All data processing steps are detailed below, and the full source code, documentation, additional scripts, input datasets, and output files are publicly available in the corresponding Zenodo database [32] and GitHub repository [29].

2.1. Tool configuration and parametrisation

resLoadSIM is a tool written in C++, designed for residential multi-energy load generation at scales ranging from individual households to neighbourhoods and entire cities. The tool consists of four main configuration files—*location, tech, households*, and *resLoadSIM* settings—along with a newly added Python wrapper script (*resLoadSIM.py*) that facilitates running the C++ model and streamlines the overall execution process. Figure 1 illustrates the structure of the main configuration files with their individual requirements and key outputs of the simulation.

The data processing pipeline, including the data sources used to parameterise resLoadSIM and the data flow, is illustrated in figure 2. The primary data sources for the parametrisation included national census datasets, complemented by information from official websites and relevant research studies. Where data gaps remained, default values and assumptions provided by the software developers were applied.

The model setup involves four main configuration files, each defining specific input parameters that enable both location-specific and scenario-based simulations.

The *resLoadSIM.py* script initiates the simulation using the configuration files stored in the input folder. Once a simulation is complete, an output folder is generated, containing detailed consumption data, including electric load profiles for each type of household appliance, heat demand by technology and hot water demand, and a summary report with total electricity and heat consumption per device.

The following sections describe the configuration, data sources, and parameters utilised to reflect location-specific conditions for the selected cities.

2.1.1. Simulation requirements and settings

Simulation parameters—the number of days and households to be modelled—are defined in the executable file *resLoadSIM.py*. This script was developed and configured as part of this study to run resLoadSIM. The number of households used for each city was based on 2022 population data, and all simulations were carried out over a full year (365 d).

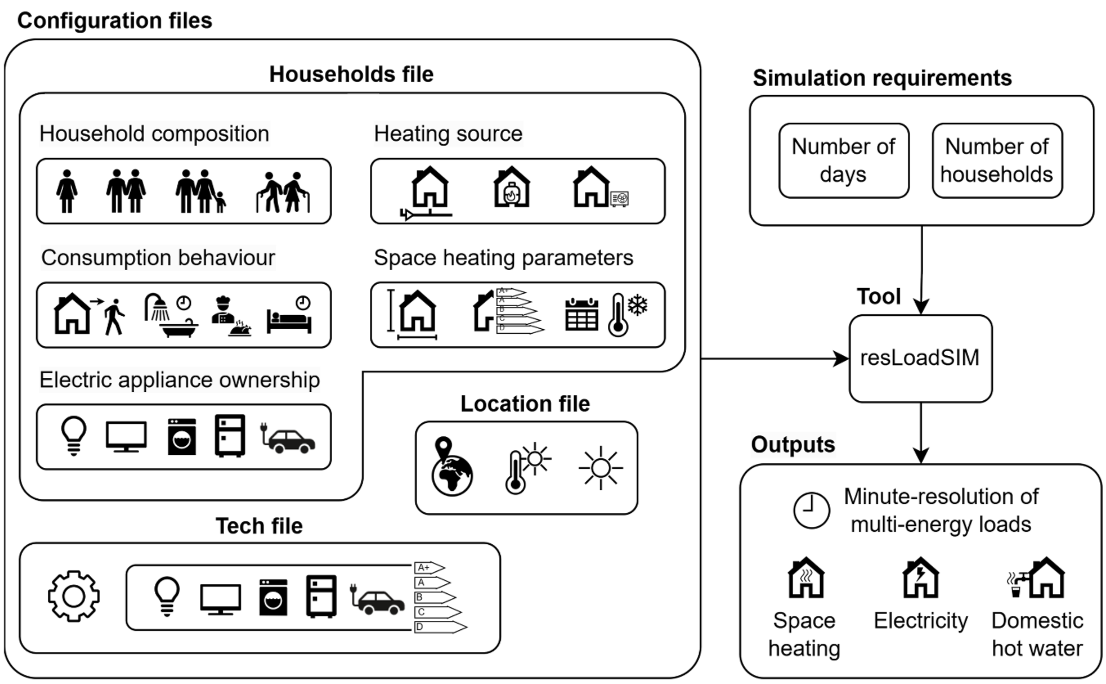

Figure 1. Input configuration framework for resLoadSIM version 6.2.0: main configuration files, simulation requirements, workflow, and key outputs.

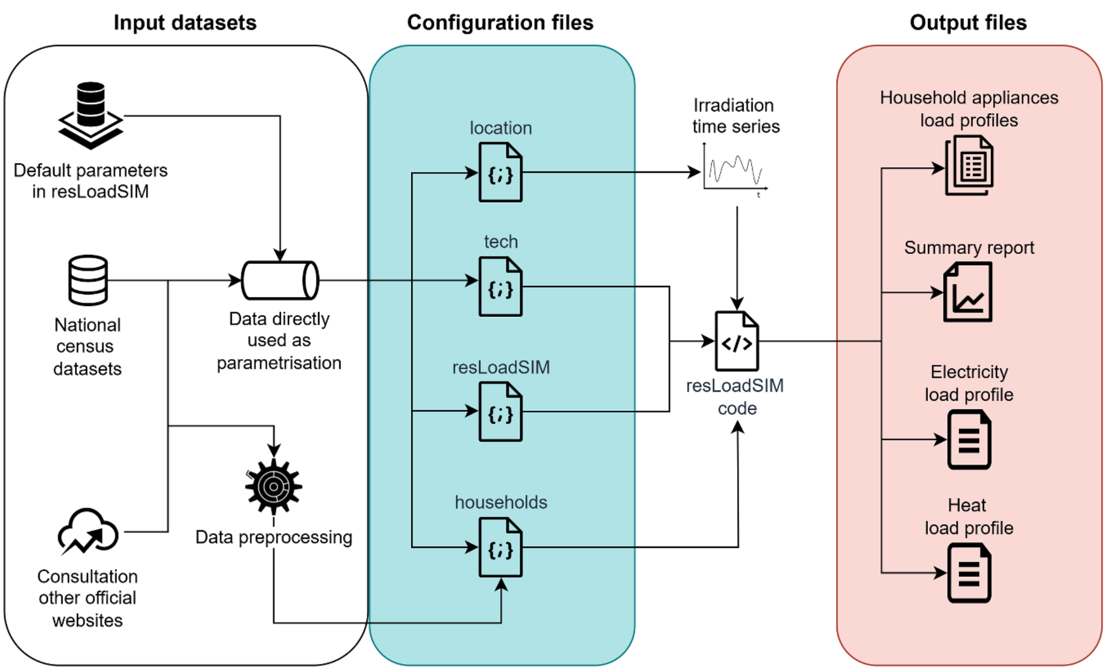

Figure 2. resLoadSIM data processing pipeline and data flow including input datasets (data sources and processing steps), configuration files, and output files.

Additionally, the tool includes an optional configuration file (also named resLoadSIM) that allows users to activate specific modes or settings, such as peak shaving or grid interaction scenarios. However, to generate the load profiles presented in this study, these advanced settings were not enabled.

2.1.2. Location and technical parameters

The location file specifies whether the simulation represents an urban or rural setting and provides the geographic coordinates (latitude and longitude) of the study area. These coordinates are used to access an API that retrieves localised hourly meteorological data (global solar irradiation and 2 m air temperature) from the Photovoltaic Geographic Information System (PVGIS) service [33] for the simulated period (year 2022 in this study). PVGIS, maintained and distributed by the JRC of the European Commission, provides access to several meteorological datasets through a web user interface and API. For Europe, PVGIS draws solar radiation and temperature data from the SARAH-3 satellite dataset [34], whereas for most other global regions it relies on the ERA5 reanalysis dataset [35]. Accordingly, PVGIS-SARAH3 data were used for the German cities, and PVGIS-ERA5 data for New Zealand cities. Currently, the integrated data retrieval workflow in resLoadSIM is implemented only for European regions. For the cities in New Zealand, PVGIS-ERA5 irradiation and temperature data were manually downloaded from the PVGIS webpage.

The tech file defines the technical specifications and operational characteristics of individual household appliances, such as stoves, dishwashers, heat pumps (HPs), and e-vehicles. The corresponding parameter descriptions and values are detailed in the Zenodo [32] and the GitHub [29] repository, respectively. Technical parameters for batteries and solar modules were not defined, as rooftop solar installations were excluded from our modelling.

2.1.3. Household characteristics and energy consumption

The household file enables the parametrisation of detailed household composition information, behaviour, and device ownership. This file was parameterised distinctively across the different cities, mostly based on recent census data. The following subsections present several parameters of the household file and how they have been adjusted to represent city-specific conditions. A full list of parameters, along with their definitions and sources, is provided in the supporting Excel file on Zenodo [32].

2.1.3.1. Household composition and occupancy behaviour

In the household file, resLoadSIM categorises households into six different types based on the number of residents: 1-person, 2-person, 3-person, 4-person, 5-person, and 6-or-more person households. Several parameters are structured as vectors, varying according to the number of residents. These include household area range [m^2], the amount of laundry [kg], and appliance ownership rates [%].

The household composition is further specified by the percentage of single-person and two-person households comprising retirees. For Germany, household composition data for 2022 was obtained [36] and filtered for Karlsruhe and Oldenburg. For New Zealand, data was sourced from the 2018 census [37], assuming individuals aged 65 and older are retirees. Retired individuals were assigned to either single-person or two-person households based on their recorded relationship status.

To capture consumption patterns and daily household behaviour, the tool includes parameters defining time periods when residents are typically at home, awake, or engaged in activities outside the household. resLoadSIM simulates these behaviours by adjusting wake-up and bedtime periods, distinguishing between weekdays and weekends, and accounting for different routines of retired individuals. These behaviours are represented as vectors containing an average value, standard deviation, and minimum and maximum activity times. Using the parameters listed in the supplementary Excel file [32], we calibrated the tool to present the composition and occupancy behaviour of households in both German and New Zealand cities.

2.1.3.2. Space heating (SH) and domestic hot water (DHW)

The tool defines the distribution of heating technologies used for SH and DHW. resLoadSIM considers various heating systems, including oil, gas, district heating, HPs (with electric backup), solar collectors, and electric heating.

For Germany, heating source distributions based on the 2022 census were obtained from the Research Data Centre of the Federal Statistical Office and the Statistical Offices of the Federal States of Germany [38], and filtered for the respective city. Due to software constraints, heating sources such as heating oil, wood, wood pellets, and coal were grouped under the category oil. For Auckland and Christchurch, heating device ownership data was sourced from the 2023 census [39], which required extensive preprocessing. While the 2023 data reports the distinct number of households with specific heating devices for Auckland and Christchurch, they do not capture combinations of devices often used in New Zealand (e.g. HPs with electric heaters). To address this, we used 2018 census data, which includes detailed information on multi-device ownership [40]. Assuming the distribution of combinations has remained stable, we used the 2018 proportions to estimate combined device ownership for 2023. These estimates allowed us to calculate the share of SH demand covered by each technology, which in turn informed the parametrisation used in our tool.

The tool defines a *heating period* during which heating devices are enabled to meet SH requirements. This period varies based on local climate conditions:

- Germany: 15 September 1 of June
- New Zealand: 1 April to 1 October

The simulated heating demand depends on outdoor temperatures during the modelled time period, and the household area. The household area is defined based on the number of residents. Additionally, a desired indoor temperature is set for both heating and cooling requirements.

SH demand per household [kWh m^{-2}] is expressed through *energy classes*. This vector categorises households into energy efficiency classes (A+, A, B, C, D, E, F, and H), each corresponding to a specific range of annual heating demand per unit area [41]. In Germany, this data is publicly available at the city level [42]. For New Zealand, where such classification was unavailable, we assumed an average heating requirement [43] of 120 kWh m^{-2} and assigned 100% of households to the energy efficiency class D, which is a limitation.

To model hot water consumption, parameters define both the temperature and volume of water used for activities such as handwashing, showers, and baths. To reflect cultural differences of water usage, we derived the share of DHW in total household energy consumption using national energy statistics (24% for New Zealand [24] and 16% for Germany [44]).

2.1.3.3. Electric household appliances and e-vehicles

In resLoadSIM, various parameters define the appliance ownership, operation, and household routines that influence electricity and heat consumption. While most input variables we parametrised based on literature values, due to data limitations, appliance ownership was either assigned default values or manually/iteratively adjusted in small steps to reproduce realistic city-wide annual energy consumption. The model outputs were compared against reported city-level totals for 2022, and appliance parameters were refined until the simulated demand closely matched the reported values. A detailed list of the parameters, including their adjustment method and reference is provided in the supplementary parametrisation Excel file [32]. The tool includes the following household technologies: air conditioners, boilers, circulation pumps, computers, stoves, gas stoves, dishwashers, freezers, fridges, general heating, lighting, solar modules, tumble dryers, TVs, vacuum cleaners, washing machines and EVs.

For Germany, parameters related to additional TVs, fridges, computers, vacuum usage intervals, and lighting factors were adjusted iteratively based on recent country-specific electricity consumption data [44] to ensure that modelled household electricity consumption remains proportional to real-world energy use distributions. For New Zealand, these values were manually adjusted to ensure that the annual electricity consumption aligns with the typical distribution of electricity use across household appliances [24].

2.1.3.3.1. E-vehicles

In resLoadSIM, each EV is represented as an autonomous object linked to a household. Its daily travel, energy consumption, and charging behaviour are simulated individually based on probabilistic rules and local conditions (e.g. air temperature, occupation of household members). resLoadSIM distinguishes between urban and rural transport modes, which define the speeds at which the EV can travel (40–50 km h^{-1} for urban, 50–80 km h^{-1} for rural). Since only city-wide load profiles were modelled, 100% of vehicles were operated in urban transport mode.

In the model, each household can own a maximum of one EV, and daily driving behaviour is generated probabilistically based on the household's occupation type (working, retired). Stochastic distributions and day-type schedules determine departure times, destinations (home, work, shopping, recreation), trip distances, and durations. The model currently considers only roundtrips originating from home, to either work, shop, or recreation and back. Recreational travel distances are randomly drawn between 5 and 50 km, while the distances for work and shopping trips are based on a household-specific 4×4 distance-matrix. For urban transport modes, these distances range from 5–15 km (10–50 km for rural) between home and work, and from 1–5 km (5–10 km for rural) for travels between the home and shops. The energy consumption of each EV is calculated from the vehicle-specific efficiency (in kWh per 100 km) and the modelled travel distance, adjusted for ambient temperature to account for heating or air-conditioning use (for more details on the methodology, please refer to [45]).

Charging is available to all EVs at home, while 5% of the EVs can charge at the workplace and 5% at shopping locations. For all case studies and scenarios, charging was uncontrolled; thus, no smart-charging control was enabled. The charging begins randomly upon arrival at a destination, based

Table 1. Summary of simulated scenarios combining different levels of space heating electrification and EV adoption for New Zealand (NZ) and for German (DE) cities.

Scenario	Heating configuration	EV adoption	Description
Reference	2022 shares of heating technologies	2022 shares of EVs	Baseline reflecting 2022 energy mix of respective city
Hybrid heating—38% EV	• Heat pumps supplemented by existing electric heating (NZ) • Heat pumps + projected share of district heating (DE)	38%	Future scenario with mixed heating technologies (heat pump, electric heating, district heating) and mid-level EV uptake
High HP—38% EV	• 100% heat pumps (NZ) • Heat pumps + existing share of district heating (DE)	38%	Future scenario with high heat pump adoption and mid-level uptake of EV
Hybrid heating—100% EV	• Heat pumps supplemented by existing electric heating (NZ) • Heat pumps + projected share of district heating (DE)	100%	Future scenario with mixed heating technologies (heat pump, electric heating, district heating) and fully electrified transport
High HP—100% EV	• 100% heat pumps (NZ) • Heat pumps + existing share of district heating (DE)	100%	Future scenario with high heat pump adoption and fully electrified transport

on a sigmoid probability function of the battery's state of charge. Until the battery reaches its maximum capacity, charging power follows a piecewise, vehicle-specific charging curve.

Vehicle parameters were chosen to reflect the most registered EV model in each region in 2022: for Germany, a Tesla Model 3 Long Range (75 kWh battery, 16 kWh/100 km consumption, 11 kW AC max power), and for New Zealand, a Nissan Leaf (59 kWh battery, 17.8 kWh/100 km consumption, 6.6 kW AC max power). Charging curves were parametrised according to typical curves for the respective EV model. No DC fast-charging was enabled in this study.

A key challenge in modelling EV adoption is that resLoadSIM assigns a maximum of one EV per household, whereas real-world data indicates that the total number of internal combustion engine vehicles exceeds the number of households in New Zealand [46]. For current load profiles, this assumption has a minimal impact due to low EV penetration rates [47, 48]. However, for future electrification scenarios, this simplification would underestimate total EV demand. To address this, a two-step approach was applied. First, the tool was run assuming 100% of households owned one EV to generate an aggregated EV demand profile based on the number of households. Second, the resulting EV loads were scaled proportionally based on the total number of vehicles in each city to match the projected EV penetration rates for each scenario.

2.2. Scenario definitions to generate current and future load profiles

To simulate future energy demand, resLoadSIM was used to model various electrification scenarios, focusing on (a) EV adoption rates and (b) shifts to electrified SH technologies.

For each city, we first simulated a reference scenario, using current (as of 2022) shares of EVs and SH technology. The sources and data-processing steps used to determine the shares of heating technology for each city are descripted in the section SH. The EV market penetrations for the reference scenario were obtained from the New Zealand transport agency [47] and the Kraftfahrt Bundesamt [48] for Germany, both referring to the year 2022 and filtered for the respective city. A detailed list of all input parameters, including their definitions, values, and sources, is provided in the supporting Excel file available on Zenodo [32]. To assess future trends, we then created four future scenarios, combining two levels of EV adoption with two levels of SH electrification. All simulations use 2022 as the reference year for weather, population, and household composition data. Future scenarios modify only the shares of heating technologies and EV market penetration to represent increasing degrees of electrification. A summary of the scenarios, including their heating configuration, EV adoption, and brief descriptions is provided in table 1. The specific shares of each technology per scenario are presented in table 2.

Table 2. Technology shares for heating and EV adoption scenarios across selected cities. The table compares the reference case with four future scenarios: Hybrid heating and high heat pump (HP) at 38% and 100% EV adoption.

City	Technology	Reference	Hybrid heating −38% EV	High HP −38% EV	Hybrid heating −100% EV	High HP −100% EV
Auckland	Heat pumps	30%	58%	100%	58%	100%
	Electric heating	42%	42%	—	42%	—
	District heating	—	—	—	—	—
	Oil	12%	—	—	—	—
	Gas	16%	—	—	—	—
	Electric vehicles	2.02%	38%	38%	100%	100%
Christchurch	Heat pumps	30.7%	65%	100%	65%	100%
	Electric heating	35%	35%	—	35%	—
	District heating	—	—	—	—	—
	Oil	8.6%	—	—	—	—
	Gas	25.7%	—	—	—	—
	Electric vehicles	1.85%	38%	38%	100%	100%
Oldenburg	Heat pumps	0.4%	92.3%	94.9%	92.3%	94.9%
	Electric heating	—	—	—	—	—
	District heating	3.4%	6%	3.4%	6%	3.4%
	Oil	1.4%	—	—	—	—
	Gas	93.1%	—	—	—	—
	Electric vehicles	1.4%	38%	38%	100%	100%
Karlsruhe	Heat pumps	1.9%	49.0%	70.7%	49.0%	70.7%
	Electric heating	—	—	—	—	—
	District heating	28.1%	49.8%	28.1%	49.8%	28.1%
	Oil	13.9%	—	—	—	—
	Gas	54.9%	—	—	—	—
	Electric vehicles	1.8%	38%	38%	100%	100%

2.2.1. EV adoption

For EV adoption, we used a projected share of 38% for EVs in New Zealand for the year 2035 [49]. For comparability, we applied the same percentage to the German cities. To model a fully electric scenario, we used a 100% penetration of EVs in all cities.

2.2.2. SH electrification

New Zealand shows a clear trend of adopting HPs [50]. Traditionally, HPs are installed in the main living area but are supplemented with electric resistance heaters (electric heating) to achieve comfortable temperatures throughout the entire house. Even though we assume a very high share of HPs in the future, we did not want to neglect the fact that houses will most likely continue using supplementary electric heaters in the future. For Germany, data on projected future shares of district heating is available [51]. We combine those trends with the remaining heat demand met via HPs. To compare our results, for Germany, we also simulated a scenario with high HP penetration accommodating for the district heating share to remain the same as in the reference scenario.

As a result, we differentiate between:

- **Hybrid heating (New Zealand)**: Heating demand is met by HPs supplemented by existing shares of electric resistance heating.
- **Hybrid heating (Germany)**: Projected shares of district heating + remaining demand via HPs.

- **High HP heating**: In Auckland and Christchurch, 100% of the heating demand is met by HPs. In Karlsruhe and Oldenburg, heating demand is met by the reference share of district heating, with the remaining demand covered by HPs.

3. Resource description

All data and methods described in this work are available in the (Zenodo repository [32]). The datasets for each city are provided (.csv format), containing time series data for electricity and heat consumption (in kW) at one-minute resolution over a full year (525600 time steps).

The Zenodo repository is organised as follows:

- **Visualisation-scripts**: Python scripts used to generate the visual figures of sample outputs.
- **Model-inputs**:
  - o An Excel worksheet listing all parameters of each configuration file, including their definitions and sources.
- **Data (simulation outputs)**: Each city-specific folder includes:
  - o. **Summary**: Overview of total electrical load per scenario.
  - p. **Total-electrical-loads**: One-minute resolution data for total electricity consumption per scenario.
  - q. **Space-Heating**: Scenario-specific heating load profiles, including total and, where applicable, disaggregated profiles by heating technology (e.g. HPs, electric heating, oil, gas).
  - r. **Electric-Vehicles**: Electricity demand of EVs at one-minute resolution for the reference, 38%, and 100% EV scenarios.
  - s. **Other-appliances:** electricity consumption of total electrical appliances, total hot water consumption, washing machine, and tumble dryer, all at 1 min resolution.

Additional README files are included in several folders, providing further details on file contents and structure.

4. Technical validation

We validated the aggregated monthly electricity data for New Zealand's main centres (filtered for Auckland and Christchurch) against publicly available records for 2022 from the Electricity Authority [52]. The comparison showed good agreement, with mean absolute percentage errors (MAPE) of 9.6% for both Auckland and Christchurch. Seasonal deviations were slightly larger during winter months, particularly for Christchurch, which showed a winter MAPE of 15.1% compared to 8.8% in summer. This is consistent with a modest underestimation of peak winter loads and a slight overestimation of summer load for both cities. Despite these differences, the model captures key seasonal and monthly patterns well and provides a robust basis for comparative and scenario-based analyses. A detailed breakdown of MAPE across temporal aggregations is provided in table 3.

Additionally, we compared the proportional contributions of electricity and SH to total annual residential energy consumption for both New Zealand and Germany. For Germany, this was done at the city-level (Oldenburg [53] and Karlsruhe [54]), whereas for New Zealand, only national-level data were available [24].

The simulated household electricity load profiles were validated using a two-step validation process applied to German cities. The first validation step compares the model's average daily electricity and heat demand per household with the corresponding values reported for Karlsruhe [54] and Oldenburg [53]. Tables 4 and 5 summarise these comparisons. While heat demand shows relatively small deviations (within $\pm 11\%$), electricity demand shows a modest underestimation in Karlsruhe (-18%) and slight overestimation in Oldenburg ($+3.5\%$). These deviations, when considered alongside the strong seasonal correlation patterns, support the model's overall capability to reproduce realistic residential energy demand patterns at both household and city scales.

In the second validation step, simulated electricity loads for Oldenburg were compared with the DLR dataset which was for example used in the project NOVAREF [55]. The selected dataset comprises 2-second interval consumption data from twelve single-family households in Oldenburg and surrounding area, collected between 2013 and 2016 for a duration of one year. The data was collected using specially

Table 3. Mean Absolute Percentage Error (MAPE) between simulated and measured monthly electricity demand for Auckland and Christchurch across different temporal aggregations and seasons in 2022.

Aggregation period	Auckland MAPE (%)	Christchurch MAPE (%)
Annual	8.5	6.1
Monthly	9.6	9.6
Spring	7.9	7.4
Summer	9.9	8.8
Autumn	8.6	3.7
Winter	11.6	15.1

Table 4. Comparison of simulated (resLoadSIM) and real residential energy consumption for Karlsruhe and Oldenburg. The table includes annual electricity and heat consumption, and average daily per-household values. All values are rounded to two significant digits for clarity.

	Karlsruhe		Oldenburg	
Metric	Simulated with resLoadSIM	Real	Simulated with resLoadSIM	Real
Numbers of households	160 000	160 000	93 000	93 000
Annual electricity consumption [MWh/year]	320	390	200	200
Annual heat consumption [MWh/year]	1800	2000	990	1000
Average daily electricity consumption per household [kWh/day]	5.6	6.8	6.0	5.8
Average daily heat consumption per household [kWh/day]	31	35	29	30

Table 5. Deviation of resLoadSIM simulated results from measured data in Karlsruhe and Oldenburg. Deviations are expressed in absolute values (kWh/day) and as percentages relative to real consumption. All values are rounded to two significant digits for consistency.

Deviation metric	Karlsruhe	Oldenburg
Electricity deviation [kWh/day]	−1.2	+0.2
Electricity deviation [% of real]	−18%	+3.5%
Heat deviation [kWh/day]	−3.8	−1.1
Heat deviation [% of real]	−11%	−3.6%

developed measurement technology. The measurement data covers seven existing buildings and five low-energy houses. For compatibility with the simulation output, the DLR data were resampled to a 1 min resolution, normalised by annual energy consumption, and compared with the normalised simulation outputs from resLoadSIM. The DLR dataset represents gross residential electricity demand and therefore excludes rooftop PV self-generation, ensuring consistency with the simulated electricity loads, which also represent gross demand.

Additionally, the simulated profiles for Oldenburg and Karlsruhe were compared with measured reference data from Ulm (145 households, May 2009 to May 2010, collected at a 15 min time resolution). The measured loads originate from smart meter data collected within the Intelliekon project, funded by the German Federal Ministry of Education and Research (BMBF), in which around 150 households in the Ulm area were equipped with smart meters [56]. Before validation, the Ulm dataset underwent a brief data quality assessment.

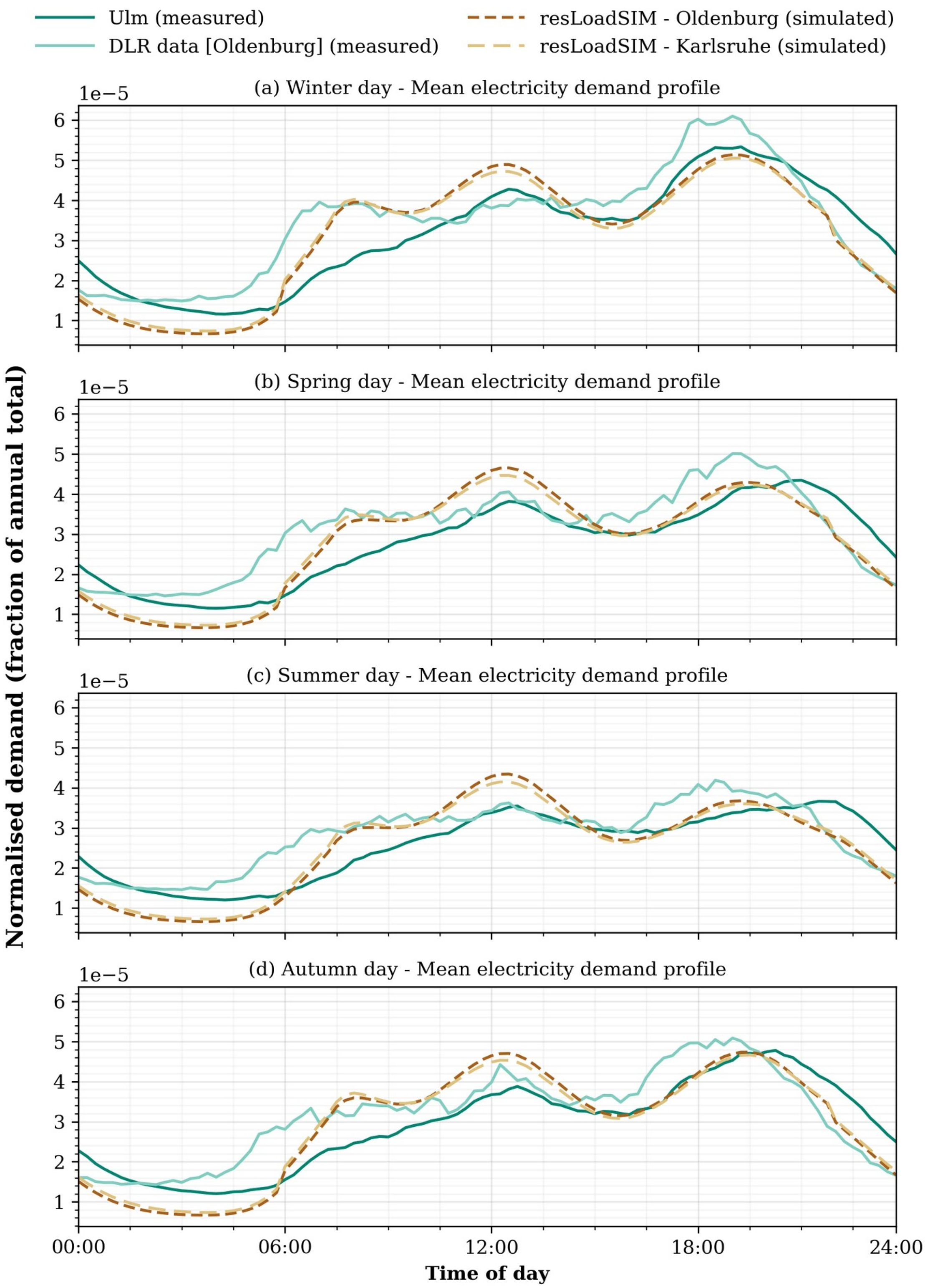

Figure 3. Comparison of mean daily electricity demand profiles between simulated data (resLoadSIM) for Oldenburg and Karlsruhe against measured data (Ulm and DLR data) for each season. Each panel shows the average normalised electricity demand (as a fraction of total annual demand) at 15 min resolution for: (a) winter, (b) spring, (c) summer, and (d) autumn days.

Households with more than 5% missing records were excluded, leaving 134 valid homes for analysis. To correct for physically implausible zero-load values, we applied a base night-time load of 0.04 kW per household for the period between midnight and 6 a.m., and linearly interpolated daytime zero values using adjacent valid data points. To ensure further comparability, the EV component was removed from the simulated electricity totals for Oldenburg and Karlsruhe, as the measured Ulm dataset does not include EV charging loads. Figure 3 shows the normalised mean daily electricity demand profiles for an average day in each season for each of the datasets, as a fraction of annual total electricity.

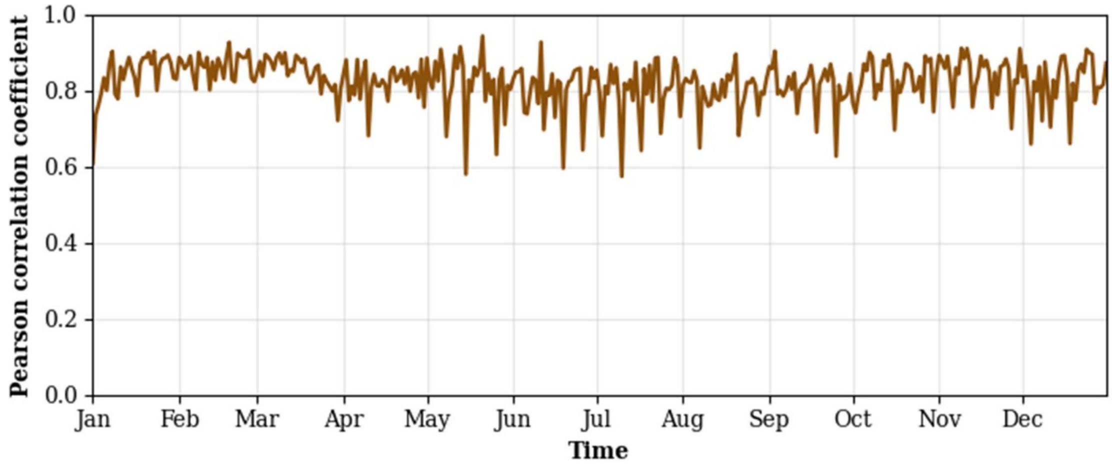

Figure 4. Pearson correlation coefficient between simulated (Oldenburg, resLoadSIM) and measured (Ulm) electricity demand.

Table 6. Seasonal median evening peak timing, peak magnitude error, and peak-to-mean ratio comparing simulated (resLoadSIM) electricity loads for Oldenburg and Karlsruhe against measured Ulm data.

	Median evening timing error (minutes)		Evening peak magnitude error (%)		Evening peak-to-mean ratio (%)	
Season	Oldenburg	Karlsruhe	Oldenburg	Karlsruhe	Oldenburg	Karlsruhe
Spring	60	45	−25	−26	−17	−19
Summer	90	90	−11	−14	−38	−40
Autumn	30	30	−25	−26	−23	−25
Winter	45	45	−17	−19	−31	−32

Table 7. Seasonal median evening peak timing, peak magnitude error, and peak-to-mean ratio comparing simulated (resLoadSIM) electricity loads for Oldenburg against measured DRL data.

Season	Median evening timing error (minutes)	Evening peak magnitude error (%)	Evening peak-to-mean ratio (%)
Spring	65	−54	−150
Summer	70	−74	−350
Autumn	80	−55	−170
Winter	60	−58	−160

The figure reveals that the simulated and measured loads follow similar diurnal patterns across all four seasons. The simulated profiles generally capture the overall daily trends but diverge in timing and magnitude during peak morning and evening periods.

The evening peaks are well reproduced, while resLoadSIM tends to overestimate morning and midday peaks and slightly underestimate nighttime demand (approximately 8:30 pm –6 am). The Pearson correlation coefficient (Oldenburg against Ulm data, figure 4) confirms a strong agreement in daily load curve shape, with a mean daily correlation of 0.81 for both cities. This indicates that the intra-day temporal pattern is reproduced consistently across seasons.

Beyond correlation, we assessed magnitude- and timing-based metrics to evaluate operational realism (table 6 against Ulm data, table 7 against DLR dataset). For each season, we computed the median evening peak timing error (difference in minutes between simulated and measured peaks within the 16:00–22:00 window) and the evening peak magnitude error (percentage difference in peak height).

Simulated evening peaks typically occurred 30–90 min earlier than the measured peaks in the Ulm data. The alignment was best in autumn (≈30 min shift), while summer showed the largest offset (≈ 90 min). The median daily peak timing error over the whole year is approximately 75 min (45 min in the evening), and the overall peak timing error (comparing seasonal mean days) is around 15 min for both cities, indicating that seasonal averages smooth out part of the daily variability.

When comparing simulated Oldenburg loads with the higher-frequency DLR dataset, timing deviations are more pronounced: the median daily peak timing error over the year is approximately 240 min (≈70 min in the evening), and the overall peak timing error across seasonal mean days is about 320 min. These larger offsets reflect the higher temporal sensitivity of minute-resolution data, where even small differences in appliance operation or occupant behaviour lead to visible timing shifts.

The peak-to-mean ratio quantifies how pronounced the peaks are compared to average demand. A global peak-to-mean error of −0.3 (Oldenburg) and −0.4 (Karlsruhe) implies that simulated peaks are flatter and less pronounced than in the measured Ulm data. Focusing on the evening period, the median daily evening peak-to-mean difference is −0.08 (Oldenburg) and −0.09 (Karlsruhe), showing that the model reproduces the relative evening peak intensity well.

Compared with the Ulm validation, the DLR comparison reveals stronger differences in peak magnitude and shape. Evening peak magnitudes are systematically underestimated by 54%–74%, and the corresponding peak-to-mean ratios are between −150% and −350%, indicating that simulated peaks are considerably flatter than those captured in the high-frequency DLR measurements. On a global scale, the peak-to-mean error of −2.0 and a median daily evening peak-to-mean difference of −0.95 further confirm that short-term variability and sharp individual load spikes in measured household data are not fully reproduced by the aggregated stochastic simulation.

When comparing the globally normalised total load profiles, the MAPE yields 28% for Oldenburg and 27% for Karlsruhe, relative to the annual mean normalised profile against the Ulm data. This indicates that, on average, the simulated load fractions deviate by around 28% from the measured temporal distribution across 15 min intervals. While this value appears high, it primarily reflects systematic underestimation of night-time demand shares in the simulated profiles, which inflate percentage errors where absolute loads are low. Since both datasets were normalised to the same annual total, the MAPE here quantifies temporal shape mismatch rather than per-household magnitude error. Against the DLR dataset, the MAPE increases to 42%, consistent with the higher temporal resolution and smaller household sample, both of which amplify apparent deviations.

The observed differences between the DLR- and Ulm-based validation results are consistent with expectations given the scale and resolution of the datasets. The DLR dataset comprises high-frequency (2 s, resampled to 1 min) measurements from only twelve single-family homes, where stochastic effects from individual occupant behaviour and appliance coincidence dominate the load shape. In contrast, the Ulm dataset aggregates 145 households at a 15 min resolution, averaging out random fluctuations and yielding smoother and more representative aggregate demand patterns. With increasing household count, stochastic variations cancel out statistically, and the aggregated load converges toward a stable mean profile. This explains why the Ulm-based validation shows lower magnitude and timing errors. These findings align with recent studies showing that errors decrease significantly with increasing level of aggregation [57, 58].

Overall, these metrics confirm that resLoadSIM captures the seasonal and diurnal shape of residential load well, while absolute magnitudes and timing exhibit modest biases. For DSM applications, these biases should be considered; users may apply a calibration factor (e.g. scaling by the ratio of annual or daily peaks) to restore realistic magnitudes, if more up-to-date empirical data becomes available.

It is important to note that the simulated data reflects the socio-technical conditions of 2022–2023, while the measured datasets represent household consumption trends from 2009–2010 (Ulm data) and 2013–2016 (DLR data). Germany had significant changes in domestic power use between these periods, such as the widespread use of LEDs and more energy-efficient appliances, which lowers the baseload overall, but also causes a general increase throughout the day due to increasing home office activities.

Therefore, the observed flatter simulated evening peaks and minor timing offsets are not unexpected. They reflect both model uncertainty and structural changes in consumption behaviour over the past 10–15 yr. The discrepancies in this case are consistent with the short-term timing variability seen across measured household datasets.

The validation is applied only to the reference scenario, which reflects current patterns of residential energy use. As empirical data for future, highly electrified households are not available, the modelled future load profiles cannot be directly validated. Instead, the validation shows that resLoadSIM replicates important demand patterns under known conditions, supporting confidence in the model's structure and its suitability for exploring projected technology adoption scenarios. Additional validation opportunities are expected to emerge as empirical data from more electrified households become available.

5. Usage notes, limitations & future work

This dataset supports research in energy system analysis, electrification scenarios, and grid planning by providing high-resolution residential energy-load data. It includes profiles relevant for evaluating electrification adoption rates, grid operation strategies, variable renewable energy integration, and DSM measures. While the datasets are generated at a one-minute resolution, users can easily sample the data to coarser temporal resolutions (e.g. 5 min, 15 min, or hourly) according to their modelling needs.

The data is based on a single weather year, which affects heating and cooling demand patterns across locations. While this approach ensures consistency between locations and scenarios, it does not capture inter-annual variability in temperature that can affect heating and cooling demand. Future work could include multi-year variability analyses or projected typical meteorological years for each city to better quantify uncertainty and long-term variability in future residential load patterns. Electric vehicle charging behaviour is based on one representative vehicle model per country, which simplifies the diversity of vehicle types and battery capacities. Demand patterns are sensitive to assumptions about daily travel distances, battery size, and the availability of workplace or public charging. Broader adoption of smart-charging control could substantially alter the magnitude and timing of EV loads. Future work could extend the datasets to include smart-charging strategies. The share of EVs enabled to charge at work or at public places, as well as the distances travelled, are currently represented through fixed values or ranges hidden inside the code and not accessible via input file parameterisation. Future work could improve the model's accessibility by making those values easier to adjust. These enhancements would enable sensitivity analyses of EV charging behaviour and its impact on aggregated residential demand.

Rooftop photovoltaic self-generation is not included in this dataset, as we focused on residential gross demand. When comparing the datasets with emerging empirical datasets or city-level statistics, users may need to apply a PV back-calculation or correction, particularly in regions with high rooftop PV penetration, such as Germany. Heating sources such as heating oil, wood, pellets, and coal are grouped under a general 'oil' category as a modelling simplification. The reference scenarios include solar collector shares for Karlsruhe (1.2%) and Oldenburg (1.7%), though these systems do not affect electric loads and were not included for New Zealand cases, given their even lower market penetration. In the current model configuration, the shares of heating and cooling technologies are defined independently, so the proportion of households with HPs for heating does not imply an equivalent share using them for cooling. As a proxy, model users could adjust the share of air conditioners to approximate future cooling from reversible HPs. In future scenarios, widespread adoption of reversible HPs may increase summer electricity demand. Therefore, users who intend to use the datasets for long-term system or DSM studies should consider additional cooling loads, as the share of cooling devices has been kept constant across the modelled scenarios in this study.

While the datasets generated in this study are most representative of the specific climatic and technological conditions of Germany and New Zealand, the modelling approach using resLoadSIM is fully transferable to other regions. The model structure and input configurations can be adapted to reflect local climate data, housing characteristics, and energy-use behaviours, given suitable available input statistics. The datasets may also serve as a reference for cities with similar climate conditions and technology adoption and standards. Future work could extend this framework by conducting regional sensitivity analyses to quantify the influence of weather, household composition, and behavioural factors on residential energy loads.

Python scripts are provided in the Zenodo repository [32] to support data visualisation and exploration. These include tools for plotting seasonal profiles, scenario comparisons, and daily load patterns (see figures 5–7). The repository also contains metadata and parameter files that describe the dataset structure and modelling assumptions in detail.

While the simulation model (resLoadSIM) generates load profiles at 1 min resolution for a wide array of household appliances, this dataset focuses on the largest drivers for demand: SH, hot water, EVs, and other key appliances relevant to demand-side analysis. A total household electricity load profile is included, aggregating all appliance-level consumption, including devices not published individually.

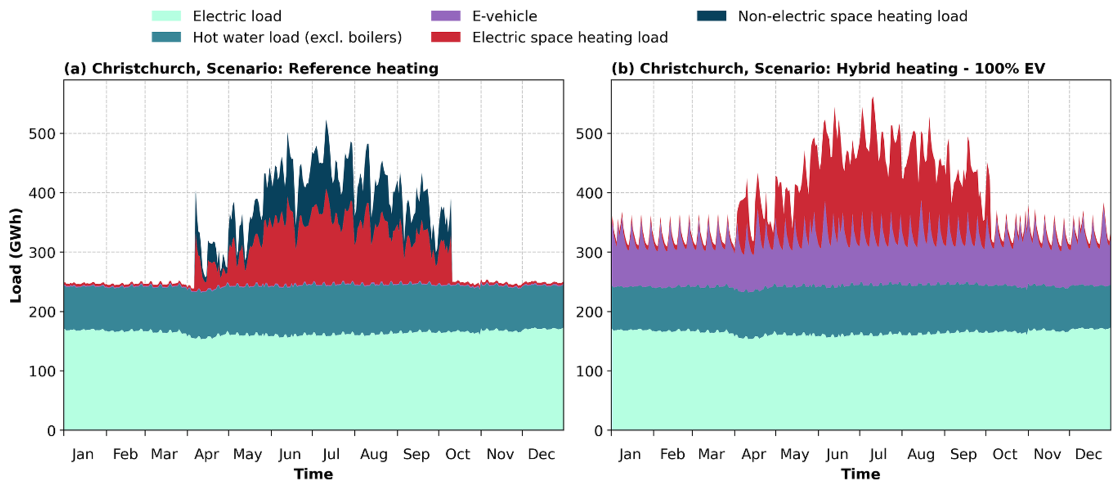

Figure 5. Full year of energy loads under reference scenario (a) and electrification scenario (b) with hybrid heating and 100% EVs in Christchurch.

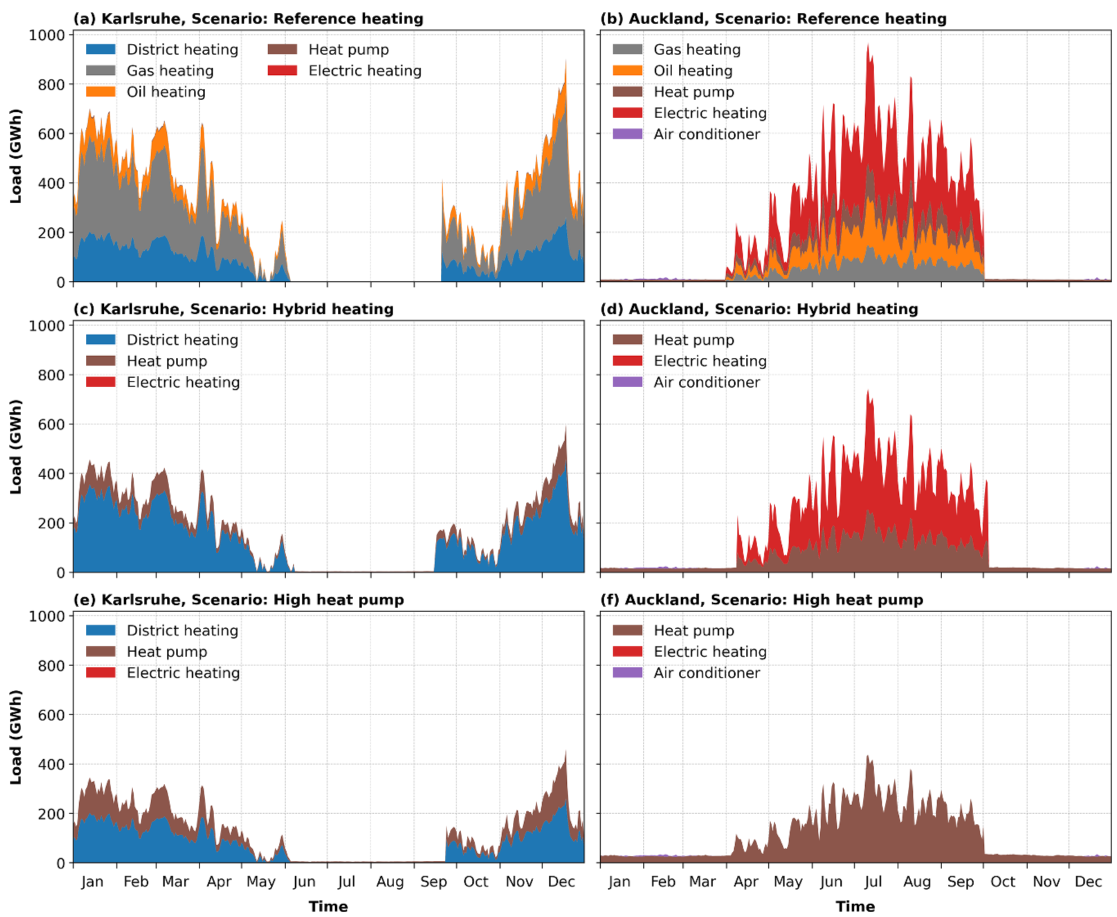

Figure 6. Comparison of space heating load across different electrification scenarios for Karlsruhe and Auckland.

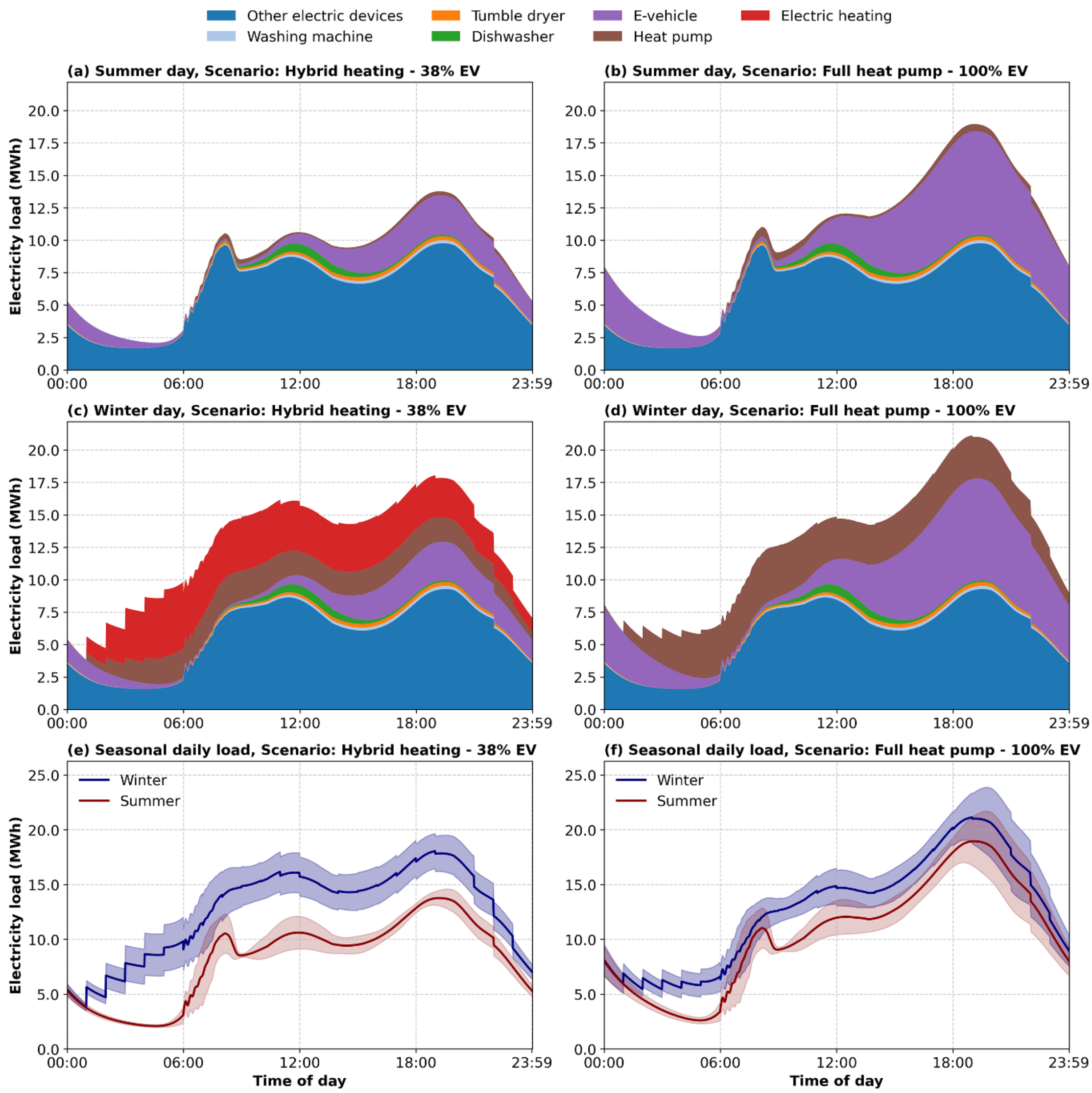

Figure 7. Mean daily electricity load patterns for hybrid and full heat pump scenarios in Auckland. The left panels represent the hybrid heating scenario with 38% adoption, while the right panels correspond to the full heat pump scenario with 100% electric vehicle (EV) uptake. Panels (a) and (b) show the mean daily electricity loads for a summer day (December–February), and (c) and (d) depict the same for a winter day (June–August) across different electricity devices. Panels (e) and (f) illustrate the seasonal progression of total electricity loads over a day.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.15362255 [32].

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Code availability

The resLoadSIM version 6.2.0 code, its activation code, and the configuration files used to run resLoadSIM for each presented scenario are available in the GitHub repository [29]. A readme file within the repository provides a step-by-step installation guide.

Installation Requirements.

- **C++ Compiler**: A C++ compiler is required to run resLoadSIM. The presented dataset was generated using C++ compiler version 9.4.0.
- **CMake** (Optional): While not strictly required, CMake is needed if you wish to use the provided makefiles from the GitHub repository. CMake version 3.5 was used for this dataset.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Rights and permissions

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