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Data-based, high spatiotemporal resolution heat pump demand for power system planning

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ABSTRACT

Decarbonizing the residential building sector by replacing gas boilers with electric heat pumps will dramatically increase electricity demand. Existing models of future heat pump demand either use daily heating demand profiles that do not capture heat pump use or do not represent sub-national heating demand variation. This work presents a novel method to generate high spatiotemporal resolution residential heat pump demand profiles based on heat pump field trial data. These spatially varied demand profiles are integrated into a generation, storage, and transmission expansion planning model to assess the impact of spatiotemporal variations in heat pump demand. This method is demonstrated and validated using the British power system in the United Kingdom (UK), and the results are compared with those obtained using spatially uniform demand profiles. The results show that while spatially uniform heating demand can be used to estimate peak and total annual heating demand and grid-wide systems cost, high spatiotemporal resolution heating demand data is crucial for spatial power system planning. Using spatially uniform heating demand profiles leads to 15.1 GW of misplaced generation and storage capacity for a 90% carbon emission reduction from 2019. For a 99% reduction in carbon emissions, the misallocated capacity increases to 16.9-23.9 GW. Meeting spatially varied heating load with the system planned for uniform national heating demand leads to 5% higher operational costs for a 90% carbon emission reduction. These results suggest that high spatiotemporal resolution heating demand data is especially important for planning bulk power systems with high shares of renewable generation.

1. Introduction

This paper addresses the research question: *What are the implications of spatiotemporal differences in residential heat pump demand for power system planning?* A data-based, high spatiotemporal resolution model of heating electrification is compared to a spatially uniform model of heat pump demand.

Decarbonizing residential heating is crucial to reduce greenhouse gas emissions in many countries: for instance, 17% of emissions in the UK came from heating homes in 2019 [1]. In countries like the UK, where gas is the dominant fuel for residential heating, switching to electric heat pumps is expected to be the dominant strategy for heating decarbonization [2]. Based on the 2018 and 2019 British generation mix, switching from a gas boiler to a heat pump can reduce greenhouse gas emissions from heating a household by at least 65% [3], and this reduction will only grow as the UK Government has committed to decarbonize the electricity supply by 2035.

The electrification of residential heat is expected to be a major driver of the electricity demand increase in the coming decade. The UK Climate Change Committee projects 12 million residential heat pumps by 2035 in their central scenario, which could add 20 GW of peak demand to a 50 GW peak system by 2035 [2,4]. Lizana et al. [3] demonstrated that just 10% of British households switching to heat pumps could increase peak electricity demand by 4.5%. Accounting for such a large growth in load is crucial for bulk power system planning. However, detailed heat pump demand data to support a cost-effective capacity expansion planning is limited in countries transitioning from a gas-dominated to a heat pump-dominated residential heating sector. In particular, a lack of data can make it challenging to capture the spatiotemporal variations in heat pump load that are crucial for planning where to build new weather-driven renewable capacity.

Several methods have been proposed to models heat pump demand for power system planning. The most common approaches can be divided into physics-based modeling, degree-day models, and statistical models [5]. Each of these approaches projects heating electricity load at different spatial and temporal resolutions; however, they all have

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important limitations for cost-optimal, high spatial resolution power system planning.

Physics-based building models use detailed building parameters, historical weather data, and energy balance equations to calculate building energy consumption. This approach has been used to project spatial variation in heating demand in Italy [6] and Texas [7]. However, physics-based modeling requires a large amount of data about different regional building archetypes and is computationally intensive. Moreover, calibrating these models using historical energy demand requires a large amount of data, as demonstrated in the ResStock project in the United States [8]. For these reasons, spatiotemporally granular heat demand profiles from physics-based modeling have not been incorporated into bulk power system planning. Heinen et al. [9] use a physics-based model in an investment planning problem for Ireland. However, they only use a single heat demand profile from a dwelling model and weather data from Dublin, where one-third of the Irish population lives. For a wider variety of housing stock and weather conditions, the data requirements for physics-based modeling of heat pump demand with high spatial granularity quickly become prohibitive for power system planning.

Degree-day models use regressions of historical heating demand against heating degree days to model daily heating demand at high spatial resolution, but their hourly heating profiles do not reflect geographically-specific heat pump demand patterns. Many degree-day models use standard German gas profiles from BDEW, a German energy industry association [10], to generate hourly heat pump demand profiles for capacity expansion studies. For instance, the BDEW model is used to develop the When2Heat model [11], which only provides one profile for each European country. Similarly, the sector-coupled PyPSA-Eur model [12] uses hourly gas demand profiles from BDEW. These gas-based profiles tend to overestimate peak heat pump demand because gas boilers typically have higher thermal capacities than heat pumps: in the UK, gas boilers typically have a capacity of 20 to 30 kW, but the median heat pump capacity in a British trial was just 8 kW [13]. This capacity difference leads to peakier gas demand profiles compared to more continuous heat pump demand profiles, and Watson et al. [13] found that using gas demand overestimates peak heat pump demand by 8% compared to using empirical data from British heat pump trials. Eggimann et al. [14] use population and heating degree days to spatially and temporally disaggregate heating demand and use half-hourly heat pump profiles from Love et al. [4] based on field trials. However, this set of profiles is limited to just 4 day types: a medium winter weekday, medium winter weekend, cold winter weekday, and cold winter weekend. Recently, Staffell et al. [5], introduced a global model for hourly heating and cooling demand at regional resolution. Because they use globally representative heating demand profiles for temporal upscaling of heating demand, this approach is likely to lead to less accurate daily heating profiles than models based on geographically-specific heat pump trials that reflect national heating patterns.

Statistical models based on heat pump field trial data have also been developed recently to predict hourly heat pump demand but do not account for spatiotemporal demand variation. Watson et al. [13,15] develop temperature-based statistical models of hourly heat pump demand based on heat pump field trials; however, they do not spatially disaggregate demand below the national level. Similarly, Ruhnau et al. [16] develop statistical models of hourly heating demand and coefficient of performance (COP) based on temperature and other weather variables in Britain at the national level. While Canet et al. [17] provide annual heating demand for 35,000 local areas in England and Wales to downscale their statistical model of half-hourly heat pump demand, they only provide a single heating pattern for air-source and ground-source heat pumps for the entire region. While these studies accurately represent hourly variation in heating demand, none of them capture sub-national differences in temporal heating demand.

Despite challenges in modeling spatial and temporal variation in heat pump demand, several studies suggest that these regional differences will affect power systems planning for the heating transition. Previous studies have demonstrated spatial variation in demand growth from residential heating electrification in the UK [14], Italy [6], and Texas [7]. However, these studies did not investigate the impact of these spatiotemporal variations on bulk power system planning.

Spatiotemporal variation in heat pump demand seems likely to impact energy systems planning models given the implications of spatial and temporal resolution highlighted in other studies. Several studies on the energy transition have demonstrated the importance of high spatial and temporal resolution for energy system planning models. For power systems with high shares of renewable generation, Frysztacki et al. [18] have demonstrated that capacity expansion models with low spatial resolution that ignore network congestion can underestimate costs by up to 23%. Similarly, Heuberger et al. [19] find that using a high spatial resolution network model to plan investments to meet electric vehicle (EV) loads reduces the need for dispatchable power capacity and increases the value of energy storage. Crozier et al. [20] explored spatiotemporal variation in electric vehicle use and electricity demand in analyzing how EV charging will impact the transmission and distribution systems. Jalil-Vega and Hawkes [21] have demonstrated the importance of using high spatial resolution demand and network topology in an investment model considering different heat supply technologies and gas, electricity, and heat network infrastructure.

These recent studies have demonstrated that accounting for spatial and spatiotemporal variation is crucial in energy systems planning models. Although several publications have modeled heat pump load, existing models either do not accurately capture hourly heat pump usage patterns or do not represent sub-national heating demand variation (*research gap 1*). Moreover, no previous study has analyzed the implications of these spatiotemporal variations for bulk power systems planning for an entire grid region (*research gap 2*).

This paper presents a novel method for generating heat pump demand profiles at high spatiotemporal resolution to support power system planning. This method balances low data requirements with data from heat pump field trials that more accurately reflects heat pump demand patterns (*addressing research gap 1*). Field trial data are scaled for multi-regional spatial analysis using weather reanalysis data that is widely available at high spatial and temporal resolution. The resulting spatially varied demand profiles are integrated into the electricity-only PyPSA-Eur generation, storage, and transmission expansion planning model [22] to understand power system implications and compare different planning scenarios (*addressing research gap 2*). The method is applied to a case study in Britain, and the results are compared to a uniform national-level profile under different policy scenarios to understand the implications of spatiotemporal variations in heat pump demand for power systems planning. This study builds on a previous work that investigates the implications of spatiotemporal differences in heating demand for just three urban areas within Britain [23]. This work expands the methods by improving model accuracy, incorporating transmission expansion, and including the entire grid area with interconnected countries.

This study has two main research contributions:

- Introducing a high spatiotemporal resolution model of residential heat pump demand that combines a statistical model based on field trial data with high spatiotemporal resolution weather data. This method represents heat pump demand profiles more accurately than existing degree-day models at higher spatial resolution than existing statistical models (*addressing research gap 1*). The data requirements are limited to heat pump trial data and widely available ERA5 reanalysis weather data.
- Assessing the implications of spatiotemporal differences in heat pump demand on bulk power systems planning (*addressing research gap 2*) through an open-source model available on GitHub as GeoHeat-GB.

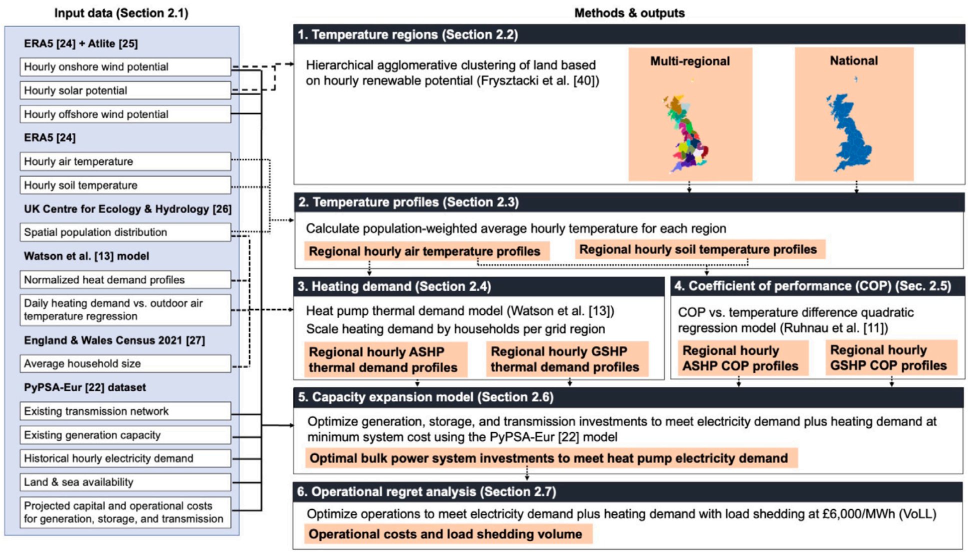

Fig. 1. Summary of data sources, methods, and outputs for this study. Outputs for each step are highlighted in orange.

This paper is structured as follows. First, the methods and data are described in Section 2. In Section 3, results are discussed, starting with the projected heat pump demand in Section 3.1, then the power systems planning results for the central policy scenario and additional scenarios are discussed in Sections 3.2 and 3.3. Finally, conclusions are presented in Section 4.

2. Methods and data

The methods and data used in this paper are summarized in Fig. 1. The input data are obtained from five sources: the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5), the UK Centre for Ecology and Hydrology, the Watson et al. [13] model, the England and Wales Census 2021, and the PyPSA-Eur dataset. The method is divided into five steps: (1) temperature regions, (2) temperature profiles, (3) heating demand, (4) coefficient of performance (COP) and (5) capacity expansion model. This last step is built on the electricity-only version of the capacity expansion model PyPSA-Eur to incorporate exogenous heating demand into power systems planning. This modified version of the model and additional documentation are available on GitHub as GeoHeat-GB.

The input data are further described in Section 2.1, and the methods are detailed in Sections 2.2 through 2.8.

2.1. Input data

This section describes the input data used in this analysis, as summarized in Fig. 1.

The European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5) provides hourly estimates of climate variables at 0.3 degree (approximately 30 km) spatial resolution from January 1940 to present [24]. In this work, the 2 m air temperature and the soil temperature level 4 variables are used to calculate heating demand and heat pump coefficient of performance (COP) as described in Section 2.5. These parameters represent the air temperature 2 m above the surface and the temperature of the soil between 1 and 3 m below the surface, respectively. Weather data from the ERA5 dataset is processed into hourly renewable onshore wind, offshore wind, solar photovoltaic, and hydropower generation potential at 0.3 degree spatial resolution using the Atlite toolkit [25].

High-resolution spatial UK population data is used from the UK Centre for Ecology and Hydrology to determine the layout of households within the British Grid [26]. This 1 km × 1 km population data is based on the 2011 Census and Land Cover Map 2015.

A constant occupation of 2.4 people per household is assumed across the whole of Britain, thus neglecting regional differences in household size. This assumption is based a population-weighted average of the average household size in England and Wales in both the 2011 and 2021 Census, which was 2.4 people per household [27], and the average Scottish household size of 2.14 people in 2020 [28]. This assumption is validated by comparing modeled annual heating demand with historical heating demand in Section 2.9.

The model from Watson et al. [13,29] is used to generate half-hourly heat pump thermal demand profiles for British households based on average daily outdoor air temperature from ERA5. This model has two components shown in Fig. 2: (a) normalized half-hourly heating demand profiles for different temperature ranges and (b) a piecewise linear regression of outdoor air temperature and total heating demand. The hourly thermal heating demand profiles shown in Fig. 2(a) are based on data from the UK Renewable Heat Payment Plan (RHPP), which monitored 700 homes with heat pumps across Britain that were not connected to the gas grid from August 2011 to March 2014. The daily temperature and heating demand regression shown in Fig. 2(b) is based on the RHPP electric heat pump demand data and additional data from the Energy Demand Research Project (EDRP), which includes half-hourly thermal demand between May 2009 and July 2010 from over 6600 single-family homes with gas boilers. Watson et al. [13] weight EDRP data to be socio-economically representative. This regression is based on a heating pattern breakdown consistent with 25% ground-source heat pumps (GSHPs) and 75% air-source heat pumps (ASHPs), as observed in the RHPP trials.

The PyPSA-Eur model dataset was used as part of the electricity-only PyPSA-Eur capacity expansion model [22]. PyPSA-Eur uses Corine Land Cover data to calculate land availability for renewable expansion and excludes natural protection areas based on Natura 2000 [30,31]. Offshore wind locations for each country are limited to their exclusive economic zones [32], and bathymetric data from GEBCO 2014 is used to limit development where the seabed is too deep [33]. Information on the European power grid was obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E) interactive

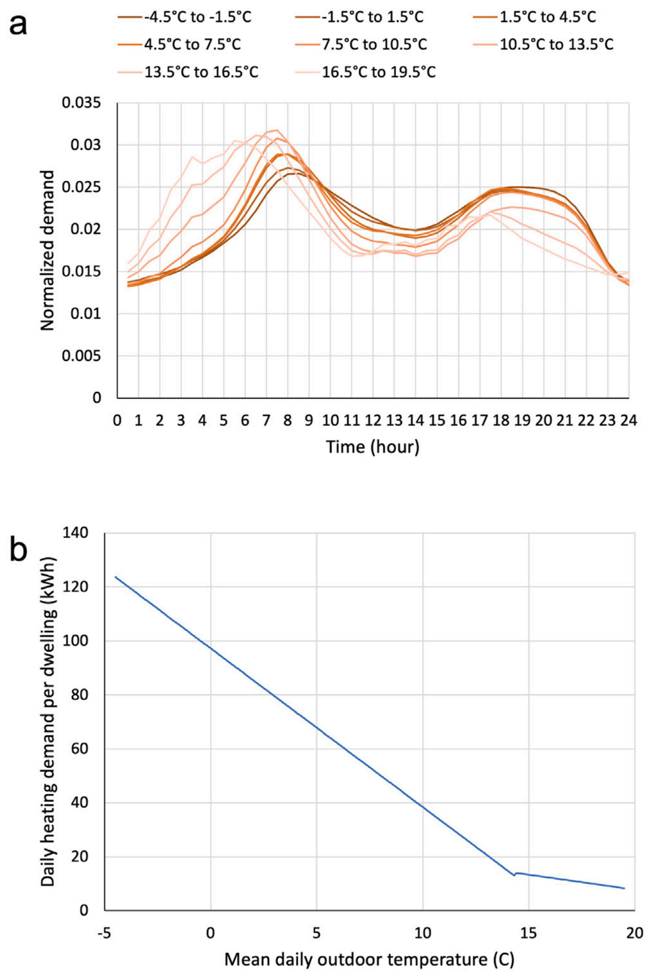

Fig. 2. (a) Half-hourly thermal heating demand profiles normalized to integrate to 1 unit-day and (b) daily heating demand per dwelling and daily mean temperature piecewise linear regression model recreated from Watson et al. [13,29] data based on British heat pump trials and gas boiler operation data. Data used under a CCBY4.0 license.

map [34] using GridKit [35]. This dataset includes existing buses, lines, links, generators, transformers, and converters. Hydroelectricity generation and storage capacities from Kies et al. [36],Pfluger et al. [37] are used along with hydroelectricity generation per country and year from the US Energy Information Administration for 2000–2014 [38]. Hourly demand data for each European country is compiled from a variety of electricity system operators [39]. Demand data for 2019 is used since it was the most recent representative period before COVID-19, which significantly altered demand patterns. This demand is spatially allocated across NUTS3 regions from Eurostat [40] within each country based on population and gross domestic product.

2.2. Temperature regions

To assess the impact of heating demand spatiotemporal resolution on power system planning, two approaches are considered for analysis: (1) a novel multi-regional approach based on 30 temperature zones within Britain; and (2) a single, countrywide approach. The latter approach results in a single heating demand profile for all of Britain, similar to the data provided in Ruhnau et al. [11]. The analysis performed using the 30 temperature zones is referred to as “multi-regional”, and the analysis using the single, national temperature region is referred to as “national”. The boundaries of these two sets of regions are shown in the regional boundaries box of Fig. 1.

For the multi-regional approach, the borders are derived by using the hierarchical agglomerative clustering (HAC) of the high-voltage transmission network. The approach developed by Frysztacki et al. [41], which groups buses in areas with similar hourly onshore wind and solar capacity factors, is used because it improves the accuracy of capacity siting and power flows in models with high shares of renewable energy compared to other methods. The minimum number of regions that capture the transmission constraints of the British system, per the 2022 National Grid Electricity Ten Year Statement [42], is found to be 30.

2.3. Temperature profiles

For each temperature region in the national and multi-regional approaches, weighted hourly air and ground temperatures are calculated. Specifically, assuming that more populated areas will have a larger impact on heating demand, a population-weighted average of the soil and air temperatures from ERA5 [24] is taken using 1 km by 1 km population data based on Census 2011 and Land Cover Map 2015 [26].

2.4. Heating demand

The Watson et al. [13] model is used to calculate hourly thermal heating demand for each region using its mean daily air temperature. Thermal heating demand and coefficient of performance (COP) are modeled separately rather than modeling electric heating demand directly; this enables updating the COP model to reflect heat pump efficiency improvements and analyzing different sink temperature assumptions such as the effect of high-temperature radiators or underfloor heating. For the national heating demand approach, demand is distributed to each region proportionally to its population. To establish the maximum possible impact of heat pump use on the power system, it was assumed that all households in Britain use heat pumps for space and water heating, with 75% of households in each region using ASHPs and 25% using GSHPs.

Changes in electric heating demand in countries with high voltage direct current (HVDC) connections to Britain are beyond the scope of this work. Because every country is constrained to produce 95% of its own demand on average over a year, as discussed in Section 2.6, ignoring potential electricity demand changes due to heat pump adoption in other countries should have little effect on planning the British grid in this model.

While the Watson et al. [13] model is based on a limited heat pump demand dataset, as discussed in Section 2.1, high spatial granularity weather reanalysis data from ERA5 Copernicus European Centre for Medium-Range Weather Forecasts [24] for each region is leveraged as the input to the model to attain high spatiotemporal granularity heating demand data. Watson et al. [13] suggest that their model can be used for either national or regional projections of heat pump demand within Britain by using the appropriate population-weighted temperature. Furthermore, Anderson et al. [43] have already demonstrated good agreement between a temperature-based model trained on the RHPP trial data and local heat pump demand profiles from a small trial in London.

This spatial interpolation of demand profiles based on local temperature is subject to several assumptions. There must be sufficient households within each region for load diversification to occur. The least populous region used in the multi-regional analysis has 10,880 households, which is well above the threshold for heat pump load diversification of 275 households identified by Love et al. [4]. It is assumed that all temperature regions have enough households to include nationally representative diversity in housing stock and heating demand patterns. Due to a lack of spatially granular heat pump trial data, similar heating response to outdoor temperature is assumed among all regions.

2.5. Coefficient of performance

ASHP and GSHP COP are calculated based on quadratic regressions of the temperature difference ΔT between the heat source and sink [11]:

$$COP = \begin{cases} 6.08 - 0.09 \cdot \Delta T + 0.0005 \cdot \Delta T^2 & \text{ASHP} \\ 10.29 - 0.21 \cdot \Delta T + 0.0012 \cdot \Delta T^2 & \text{GSHP} \end{cases} \tag{1}$$

All sinks are assumed to be radiators, and their outlet temperature is calculated based on the outdoor air temperature, following Ruhnau et al. [11]:

$$T^{sink} = 40\ ^\circ\text{C} - 1.0 \cdot T^{out} \tag{2}$$

As in Ruhnau et al. [11], a minimum temperature difference of 15 °C is imposed to avoid unrealistically small temperature differences at warm outdoor temperatures.

$$\Delta T = \begin{cases} 15\ ^\circ\text{C} & T^{sink} - T^{source} < 15^\circ\text{C} \\ T^{sink} - T^{source} & otherwise \end{cases} \tag{3}$$

This process produces hourly COP profiles for ASHPs and GSHPs in each temperature region using hourly air and soil temperatures, respectively, as the source temperature.

Note that these COP values do not account for auxiliary systems such as defrosters for ASHPs or potential backup heaters. It is also assumed that ground thermal energy is restored on an annual basis for GSHPs. Any energy that may be used in a reverse cycle to replenish thermal energy in the ground over the course of the year is neglected. The COP sensitivity analysis performed in Appendix demonstrates that neither the extra electricity consumed by auxiliary systems nor potential future improvements in heat pump efficiency significantly alter the key results of this work.

2.6. Capacity expansion model

The PyPSA-Eur electricity-only capacity expansion model v.0.6.1 [22,44] is expanded to include exogenous heat pump demand. This model optimizes investment in and operation of generation, storage, and transmission to minimize cost while meeting inelastic electricity demand. Because power systems planners have little control over individual households' choice of heating system, heat pump adoption is determined exogenously. This approach contrasts with the sector-coupled PyPSA-Eur v.0.8.0 [45,46] and higher, which endogenously determines the share of heat pumps by co-optimizing power systems planning and heating decarbonization. Despite this difference, the scripts in GeoHeat-GB that model additional demand from heat pumps are inspired by their analogues in PyPSA-Eur 0.8.0.

As mentioned in Section 2.2, the British transmission system is modeled using 30 nodes and their corresponding regions. Countries and regions with existing and planned HVDC connections with Britain are modeled with a single node per synchronous region in each country to approximate future electricity trade. Thus 9 additional nodes are included for France, Ireland, Northern Ireland, East and West Denmark, Germany, Belgium, Norway, and the Netherlands. Each of these additional nodes are characterized by their own demand, generation, and renewable potential data. This approach differs from that of Heuberger et al. [19], who modeled interconnectors as generators or storage units demanding on historical trade patterns, because new connections have unknown trade behavior, and historical trade patterns across existing interconnections may change during the transition to low-carbon power systems across Europe.

To avoid distorting the optimization by excluding any demand changes from transitioning to heat pumps outside of Britain, each country is constrained to meet 95% of their own electricity demand on average over the year. This figure was selected because about 5% of British electricity consumption was met by net electricity imports

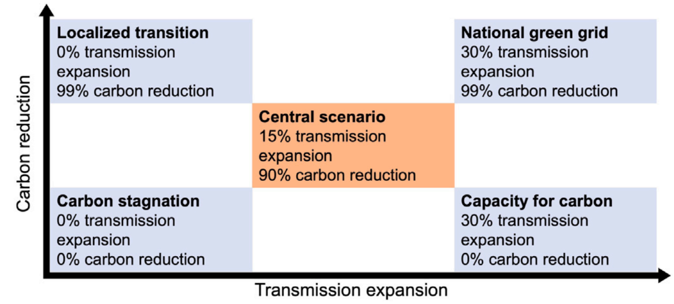

Fig. 3. Matrix of policy scenarios developed in this study.

from 2015 to 2021 [47]. Notably, this represents an absolute increase in British electricity imports due to increased electricity demand from heat pumps. This constraint on electricity trade also limits the distorting effect of assuming there is a single grid planner for all countries interconnected with Britain.

In this capacity expansion model, thermal heating demand is added to a ground-source and air-source heating bus for each temperature region. Hourly thermal heating loads from the Watson et al. [13] model for GSHPs and ASHPs are added to these respective buses based on regional temperature. Heat pumps are added as links between their respective thermal buses and the electricity bus for each region. The hourly efficiency of these links is set as the COP based on the hourly temperature in that region. A cost for heat pump capacity is not included because they are likely to be household expenses, rather than power system expenses.

2.7. Operational regret analysis

To assess the practical consequences of planning a power system with national heating demand data, an operational optimization with multi-regional heating demand is performed on the systems planned in the capacity expansion model. The uniform national heating demand profiles and COP values are replaced with their multi-regional equivalents. Then, the hourly operation of the planned power system is optimized for the same weather-year for which it was planned. To maintain problem feasibility, load shedding is allowed at a cost of €6900 per MWh, in line with the value of lost load established in the UK of £6000 per MWh [48]. The requirement for each country to produce 95% of their own electricity demand on average over the year is also removed to maintain problem feasibility.

2.8. Transmission and carbon budget scenarios

To explore the impact of high spatiotemporal resolution heating demand on power system planning under a variety of future policies, different scenarios are analyzed. These scenarios were defined by the maximum allowable transmission expansion and the power sector carbon budget, as shown in Fig. 3.

These two axes are chosen for their high impact on power systems planning and high uncertainty. Transmission expansion has faced policy and permitting hurdles and currently requires nearly a decade of permitting. Different carbon budgets in the power sector reflect the uncertainty about the availability of firm generation compared to the availability of gas generation today [49]. High-carbon scenarios represent a future in which the heating sector switches to electricity as its primary fuel, but the power system undergoes a less dramatic transition. In these scenarios, existing fossil fired capacity remains operational, but all new electricity demand from heat pumps is met with zero-carbon generation. Alternatively, policy could push the power sector to be more reliant on weather-dependent renewable generation and other zero-carbon generation sources, as reflected in the low-carbon scenarios.

Transmission expansion is limited based on the proportional increase in GW-km from the existing system. A maximum of 30% transmission expansion is estimated from National Grid Electricity Ten Year Statement 2022 power flow diagrams [42]. This figure represents a liberal expansion of transmission infrastructure. Conversely, low transmission expansion scenarios are considered in which no additional capacity is added. The central scenario includes 15% transmission expansion.

A range of carbon reductions relative to 2019 power sector emissions are also considered. For all modeled countries, 2019 carbon dioxide equivalent emissions from the public electricity and heat production sector [50] are used as the baseline. The central scenario value of a 90% carbon reduction is chosen in line with the UK CCC central scenario emissions for the power sector for 2035 [2]. For the low-carbon and high-carbon scenarios, 99% and 0% reductions are chosen, respectively. Notably, the 0% carbon reduction still represents a reduction in per-MWh emissions because of increased electricity demand from heat pumps compared to 2019 while the carbon budget remains constant.

2.9. Model validation

To validate the use of national and multi-regional temperature profiles in the Watson et al. [13] model, the total annual heating demand and peak electrical heating demand are compared with other sources. The historical annual heating demand is only available in thermal terms because the majority of heating in Britain currently uses thermal fuels. However, the peak electrical heating demand is a key quantity for planning the power system and has been estimated in several papers.

The total annual heating demand for all of Britain is compared with the historical demand for space and water heating. The Energy Consumption in the UK dataset [51] gives the total annual final energy consumption for domestic space and water heating for different fuels. This final energy consumption is converted to thermal demand using typical efficiencies of different heating technologies from the IEA [52]. The prevalence of different boiler types in England from the English Housing Survey Headline Report [53] is used to calculate a weighted average efficiency for boilers. The average efficiency of 95% is applied to natural gas and oil final energy consumption. The solid fuel and bioenergy and waste categories are assumed to be burned in pellet stoves with 85% efficiency, and both electricity- and heat-based heating systems (such as district heating) are assumed to have 100% efficiency. This method gives a historical thermal energy demand of 337.9 TWh for domestic space and water heating in 2019. The total annual thermal demand calculated from the national approach (335.5 TWh) and multi-regional approach (340.3 TWh) only deviate by −0.7% and +0.7%, respectively.

To further validate the use of different temperature profiles in the model, the peak electricity demands for both approaches are compared to previous projections. Using national temperature profiles leads to a peak electric heating demand of 41.4 GW and using multi-regional temperature profiles leads to 42.3 GW. These peak values agree with those of the When2Heat model [11] for 2019 with a COP weighted as 75% ASHP with radiators and 25% GSHP with radiators for space heating and a COP weighted as 75% ASHP to water and 25% GSHP to water for hot water. Using this approach gives a peak heating demand of 40.4 GW, which is just 1.0 GW lower than the peak obtained using the national approach and 1.9 GW lower than that obtained using the multi-regional approach. These figures are much lower than the peak demand projections from Watson et al. [15] of 62 GW for a cold year in the 2020s with very good heat pump performance (seasonal performance factor (SPF)> 3). This difference arises from the use of different weather-years and different heat pump performance assumptions. Both winter 2018–19 and winter 2019–2020 were milder than average [54,55], so it is expected that the 2019 peak demand to be less than that of a cold year in the 2020s. Moreover, the SPF for both GSHPs and ASHPs is above 4 in every region, so heat pump performance is much better than that considered in Watson et al. [15] based on the RHPP trials. Overall, the peak electricity demand used in this work is in line with recent estimates for a mild winter with high performance heat pumps.

2.10. Study limitations

The scope of this work is limited to the residential sector space heating and hot water demand. This paper focuses on a high-penetration end state for residential heat pumps to understand the maximum possible effect on power system planning, so spatial differences during the heating electrification transition are not considered. Only a single weather-year of heating demand and renewable generation data is analyzed to demonstrate the impact of high-resolution heating demand data, but robust power system planning should consider multiple weather years of data. The impact of climate change on heating demand is not considered. Other growing electricity loads, such as EV charging, are outside the scope of this analysis, but should be considered in power systems planning.

3. Results and discussion

In this section, the results and their implications for bulk power systems planning with residential heat pump demand are discussed. First, projected heat pump demand is discussed in Section 3.1. Next, the results of the capacity expansion model are discussed for the central scenario in Section 3.2 and for the additional scenarios in Section 3.3.

3.1. Projected heat pump demand

This section explores projected heat pump demand. Section 3.1.1 connects spatial differences in temperature and heating demand differences between the national and multi-regional approach. Section 3.1.2 discusses the change in national peak electricity demand based on both models. Finally, Section 3.1.3 analyzes spatiotemporal differences in heating demand between the two approaches.

3.1.1. Spatial differences in temperature and heating demand

The spatial differences in temperature and heating demand between the national and multi-regional approaches are illustrated in Fig. 4.

Fig. 4(a) and (b) shows the spatial differences in mean temperature and temperature standard deviation used in the multi-regional analysis. Although both approaches provide good reliability in comparison with total historical thermal heating demand, temperature differences across regions are notable.

Using the national approach, the hourly temperature profile for 2019 showed a population-weighted mean temperature of 10.5 °C and a standard deviation of 5.3 °C. With the multi-regional approach, the mean annual temperature by region, shown in (a), ranges from 8.0 °C in the north of Britain to 11.4 °C in the south. Generally, the mean temperature increases from the northwest to the southeast. Fig. 4(b) shows the standard deviation in hourly temperature, which ranges from 3.9 °C on the northeast coast to 5.9 °C inland in the south. The hourly temperature standard deviation is generally lower in coastal areas and the north and higher inland and south. This result is explained by the high thermal capacity of oceans and seas, which keeps coastal temperatures steady when the temperature varies inland.

Figs. 4(c) and (d) compare the heat pump load differences in total heating demand (c) and peak heating demand (d) when using the national approach. This analysis highlights the significant spatial differences in the heat pump demand.

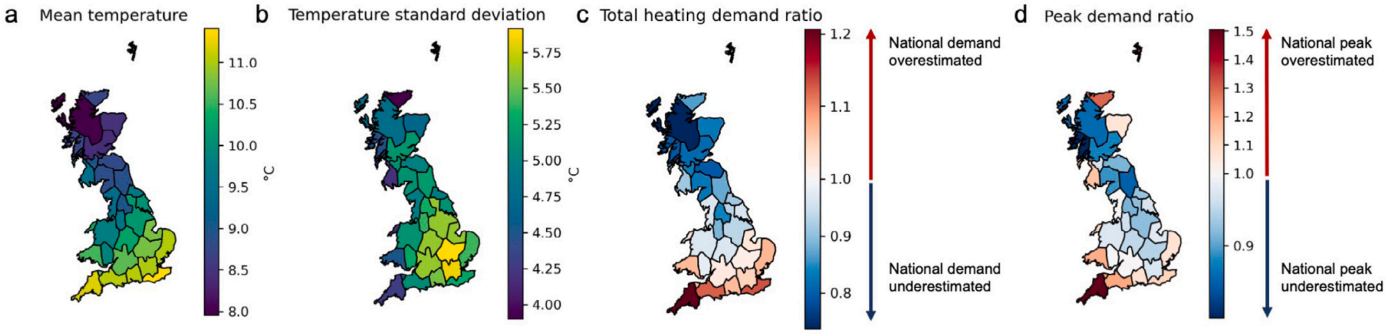

Fig. 4. Maps summarizing spatial differences in temperature data and comparing homogeneous and heterogeneous heating demand profiles in each region. Maps of (a) the mean and (b) standard deviation of hourly temperature in 2019. Map (c) displays the ratio of total heating demand using the national approach compared to the multi-regional approach. Map (d) shows the peak demand ratio comparing the regional heating demand at the peak system demand time when using the national approach compared to the multi-regional approach.

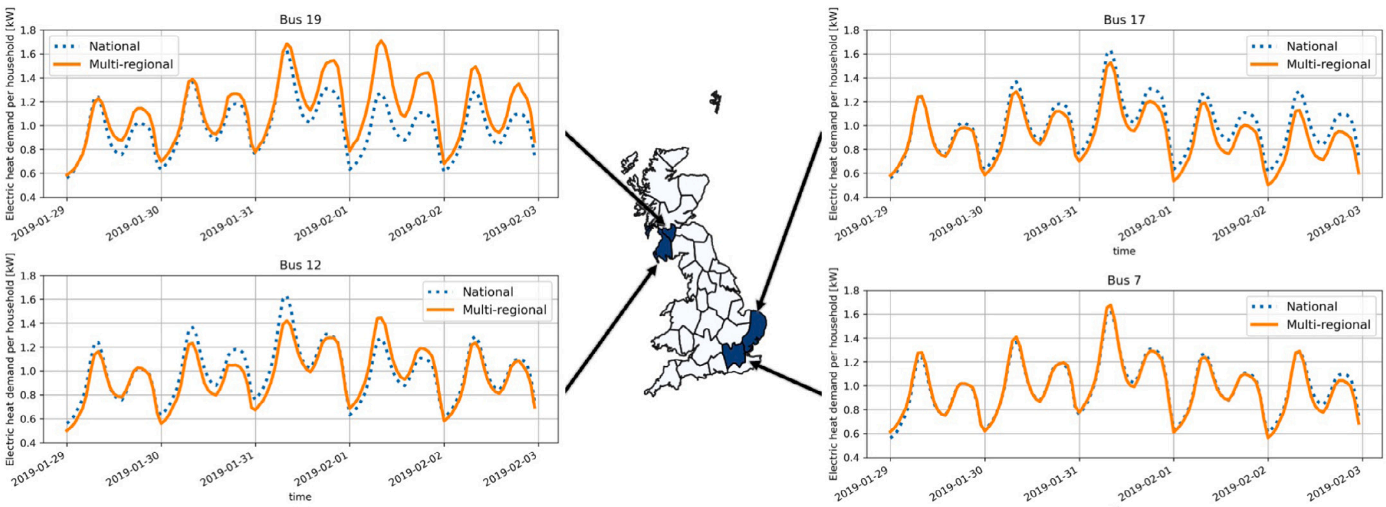

Fig. 5. Map illustrating the spatiotemporal inconsistencies between uniform heating demand per household based on national temperature (shown with dotted blue lines) and spatially varied heating demand based on multi-regional temperature (shown with solid orange lines) in four regions. Hourly electrical heating demand is shown for five days, including the peak heating demand day.

The results in Fig. 4(c) demonstrate that using a national temperature region overestimates annual electrical heating demand by up to 26% in the south of Britain and underestimates by up to 21% in the north compared to the multi-regional approach. These errors are closely correlated with mean temperature: regions with lower mean temperatures have their demand overestimated when using a homogeneous heating demand profile. Temperature standard deviation has a secondary effect on the total heating demand estimate ratio: coastal regions in the south with low standard deviation in temperature have consistently higher temperatures, so they have some of the highest overestimates in homogeneous heating demand.

The results in Fig. 4(d) displays the ratio of the regional heating demand at the peak system demand time. It was found that using national temperature to model heating demand overestimates the peak consumption in coastal regions, particularly in the south, by up to 51% and underestimates peak consumption inland by up to 20%. This result is explained by the lower temperature standard deviation in coastal areas, which suggests that the temperature in those regions will drop less than the temperature inland on cold days.

3.1.2. National peak electricity demand

Whether a spatially homogeneous or heterogeneous heating demand profile is used, switching all current British households to heat pumps nearly doubles the 2019 total peak demand of 51.4 GW. Using a spatially homogeneous heating demand profile leads to little difference in the total peak demand: peak demand is 91.0 GW with a homogeneous heating profile and 91.4 GW with the heterogeneous heating profile. No matter the spatial resolution of the heating demand used, the heating demand peaks at 8 am on 31 January 2019. This peak time is one hour earlier than the historical electric peak demand, which occurred at 9 am on 31 January 2019. At the new peak time, there is 49.6 GW of historical electrical demand as well as 41.4 GW of heating demand when using homogeneous heating demand profiles and 42.3 GW of heating demand when using heterogeneous heating demand.

3.1.3. Spatiotemporal differences in heating demand

Using a spatially homogeneous heat demand profile leads to spatiotemporal inconsistencies with local temperature-based heating demand in different regions throughout the year, as illustrated in Fig. 5. This figure shows hourly electric heating demand per household in 4 sample regions from 28 January to 2 February 2019, which includes the peak heating demand at 8 am on 31 January. Regions are labeled based on their clustered electrical bus number, as described in Section 2.2.

The shape of the heating demand profiles are similar in all regions for the days shown in Fig. 4 because occupancy patterns determine hourly heating patterns during the heating season. However, there are important daily differences in the magnitude of heating demand based on the regional temperature. At Bus 19, an inland region in northern Britain, both morning and evening heating peaks and total heating

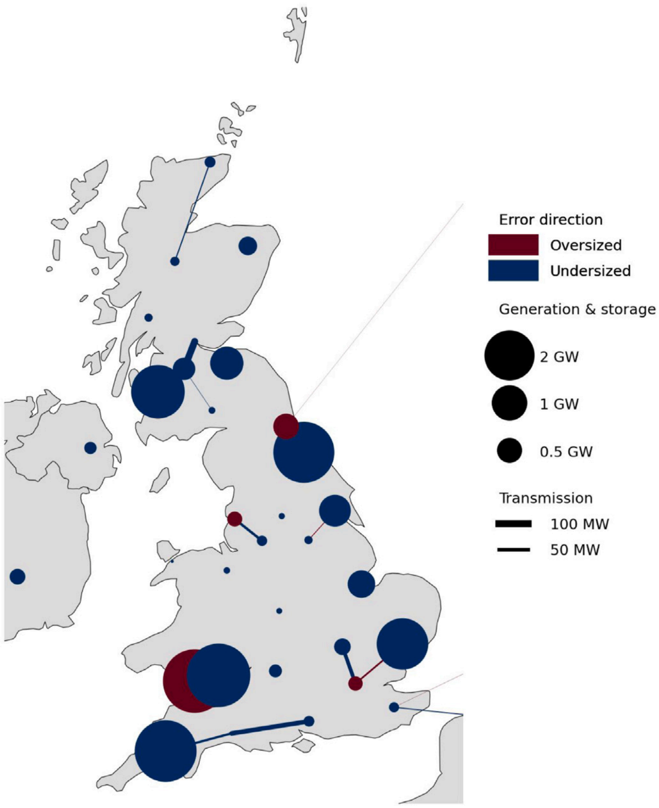

Fig. 6. Generation and transmission planned capacity differences when using heating demand based on national temperature vs. multi-regional temperatures for the central scenario. Infrastructure with an oversized capacity when using uniform, national temperature-based heating demand is shown in red, and infrastructure with an undersized capacity is shown in blue. The legend displays transmission and generation and storage capacities for scale.

demand are underestimated when using the national approach. In contrast, using a national temperature-based approach at Bus 12, a coastal region in northern Britain, tends to overestimate morning and evening peaks but underestimates total heating demand. Bus 7 is an inland region in southern Britain where using the national approach heating demand underestimates morning and evening peaks and overestimates the annual total heating. Because Bus 7 has the highest population of any region in Britain, it has the smallest inconsistencies between multi-regional temperature-based heating demand and heating demand based on a national, population-weighted temperature profile. For Bus 17, a coastal region in southern Britain, it was found that using a homogeneous heating profile overestimated both morning and evening peaks and total heating demand.

3.2. Central scenario capacity expansion results

This section discusses the results of capacity expansion for the central policy scenario (described in Section 2.8) using the national and multi-regional approaches.

Using spatially varied heating demand profiles leads to a 1.0% higher total system cost than using spatially uniform heating demand profiles, resulting in a net present system cost of €60.6 billion per year compared to €59.7 billion.

Despite similarities in total system costs, using spatially varied and uniform heating demand profiles leads to different spatial allocations of power system infrastructure. Fig. 6 displays the differences in generation, battery storage, and transmission capacity when planning with the national approach compared to multi-regional approach for modeling heating demand. Infrastructure with an oversized capacity when using a national temperature-based approach is shown in red, and infrastructure with an undersized capacity is shown in blue.

Compared to using multi-regional temperatures, using heating demand based on the national temperature for capacity siting leads to widespread undersizing of generation and battery storage. The total absolute error for generation and storage, which represents the amount of spatially misallocated capacity with respect to the multi-regional approach, is 15.1 GW, which corresponds to 1.3% of planned capacity in Britain. In the each region, the misplacement ranges from 2.25 GW of oversizing at Bus 11 to 2.25 GW of undersizing at Bus 28.

Using spatially uniform heating demand leads to smaller spatial misallocation of transmission infrastructure: the total absolute error for transmission is just 600 MW, and the total absolute percent error is 0.18%. The largest portion of errors are concentrated at just a few lines, with line-specific errors ranging from 190 MW of oversizing to 10 MW of undersizing.

There is no clear relationship between spatial differences in heating demand, shown in Fig. 4, and power system infrastructure misplacement because of the complex interactions between heating demand, renewable availability, and transmission network topology. As Fig. 6 shows, undersizing of generation and storage capacity is widespread across Britain, with significant undersizing in coastal areas. Oversizing of generation and storage capacity occurs across central and northern Britain, with smaller oversizing in the south. The lack of a clear heuristic for predicting the impact of spatiotemporal differences in heating demand underlines the importance of using high resolution demand for spatial planning of power system infrastructure.

Fig. 7 shows the breakdown of generation and storage capacity differences between capacity expansion planning using the national and multi-regional approach for modeling heating demand at each bus by technology type. Technologies with higher capacity when using the multi-regional approach are positive, and technologies with lower capacity when using the multi-regional approach are negative.

The most pronounced difference when using the multi-regional heating demand model is higher battery storage capacity. The largest increase in battery storage capacity is at Bus 28, a coastal region in the southwest of Britain where peak demand is slightly higher under the multi-regional approach. This extra battery storage capacity may be used to meet increased peaks in heating demand locally and in neighboring inland regions. The largest decrease in battery capacity is at neighboring Bus 11, where peak demand decreases under the multi-regional approach, reducing the need for local capacity. In several regions in coastal Britain, including Buses 15, 17, 18, and 29, using uniform heating undersizes both onshore wind and battery capacity. This finding is consistent with the work of Heuberger et al. [19], who find that spatially granular modeling increases the value of energy storage when planning for EV adoption. This increased battery capacity may be used to store extra onshore wind generation to meet inland local demand peaks when coastal demand peaks are lower than under the national approach. Battery capacity decreases and solar capacity increases at Bus 21, possibly to complement the increased onshore wind and battery capacity at adjacent Bus 15. Battery capacity also increases significantly at Bus 12, a coastal region with HVDC connections to Northern Ireland where peak temperature decreases, enabling storage of imported electricity to meet increased peak demand at neighboring buses.

3.3. Capacity expansion results for additional scenarios

This section discusses the results of capacity expansion planning for the remaining policy scenarios (described in Section 2.8) using the national and multi-region approaches, including the costs and siting errors.

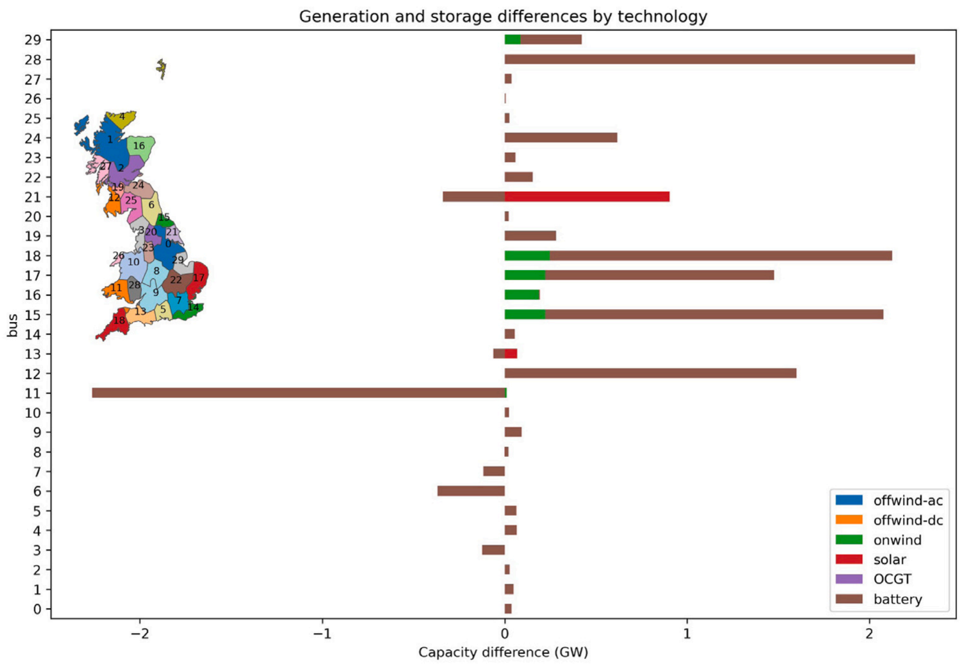

Fig. 7. Breakdown of generation and storage differences at each bus between the national heating demand and multi-regional heating demand capacity expansion plans by technology. Undersized capacity in the national case is shown as positive, and oversized capacity is shown as negative. Regional map inset for reference.

Table 1
National vs. multi-regional heating demand net present value system costs.

Scenario	National cost [B€]	Multi-regional cost [B€]	National error [%]
Central	59.7	60.6	−1.5
Localized transition	78.1	79.1	−1.2
National green grid	69.4	70.3	−1.3
Capacity for carbon	54.7	55.6	−1.6
Carbon stagnation	55.0	55.9	−1.6

3.3.1. System costs

Table 1 compares the annualized system costs for the two approaches in each scenario.

In all of the scenarios considered, using the national model of homogeneous heating demand underestimates total annualized systems costs by 1%–2% with respect to the multi-regional model, as shown in Table 1. This result suggests that using high spatiotemporal resolution heating demand data is not necessary to estimate total systems costs within the range of policy scenarios considered.

The scenario systems costs shown in Table 1 also highlight the value of transmission expansion in low carbon budget scenarios. Increasing transmission expansion from 0% to 30% leads to approximately €9 billion of net present value savings for 99% carbon reduction but less than €1 billion in savings for 0% carbon reduction. Note that these costs are for the entire modeled system, including interconnected countries.

3.3.2. Generation and storage locations

Fig. 8 illustrates the generation, storage, and transmission planned capacity differences between the national and multi-regional models. Table 2 compares error metrics for the spatial misallocation of storage and generation capacity using the national heating demand approach with respect to the multi-regional heating demand approach in each scenario for the regions within Britain.

Using spatially uniform heating demand leads to non-optimal siting of generation and storage capacity within Britain for meeting multi-regional heating demand in all scenarios, with larger differences in non-central scenarios. The largest total absolute errors (TAE) shown in Table 2 are 25.6 GW for the carbon stagnation scenario and 23.9 GW for the localized transition scenario, which suggests that high spatiotemporal resolution heating demand is key when planning systems with limited transmission expansion no matter the carbon budget. The total absolute percent error (TAPE) values for placement within Britain are greater than or equal to the central scenario TAPE value, which indicates that these higher total misplacement values are not solely due to differences in total capacity in Britain. These results suggest that high spatiotemporal resolution heating demand is crucial for spatial power system planning under a wide variety of policy futures.

The range of errors in generation and storage capacity with respect to the multi-regional approach shown in Table 2 demonstrates that spatial misallocation of storage and generation is highly concentrated at a few buses. This pattern can be observed in Fig. 8 as well. Capacity misplacement is concentrated in a few regions for the high-carbon scenarios, carbon stagnation and capacity for carbon. In both high-carbon scenarios, nearly identical magnitude over- and undersizing is seen at adjacent buses, which could indicate that using spatially uniform heating demand leads to misplacement of high-capacity fossil fuel plants within an area of Britain. In low-carbon scenarios, localized transition and national green grid, the spatial mis-sizing of generation and storage capacity is more evenly distributed among the buses. This difference arises due to the weather dependence of renewable generation: a high-renewable system relies on overcapacity and storage to meet demand, so planning with the incorrect demand profiles has a widespread impact on the spatial distribution of generation and storage.

As in the central scenario, no clear heuristic emerges in the additional scenarios for the differences in storage and generation capacity siting when using national heating demand in power system planning compared to multi-regional heating demand. As Fig. 8 shows, the location of over- and undersized assets changes depending on the carbon

Table 2
Generation and storage capacity errors.

Scenario	TAE [GW]	Max. bus error [GW]	Min. bus error [GW]	TAPE [%]
Central	15.1	2.25	−2.25	1.3
Localized transition	23.9	3.06	−5.91	1.5
National green grid	16.9	1.12	−3.02	1.3
Capacity for carbon	23.2	4.09	−3.83	2.3
Carbon stagnation	25.6	3.83	−8.27	2.6

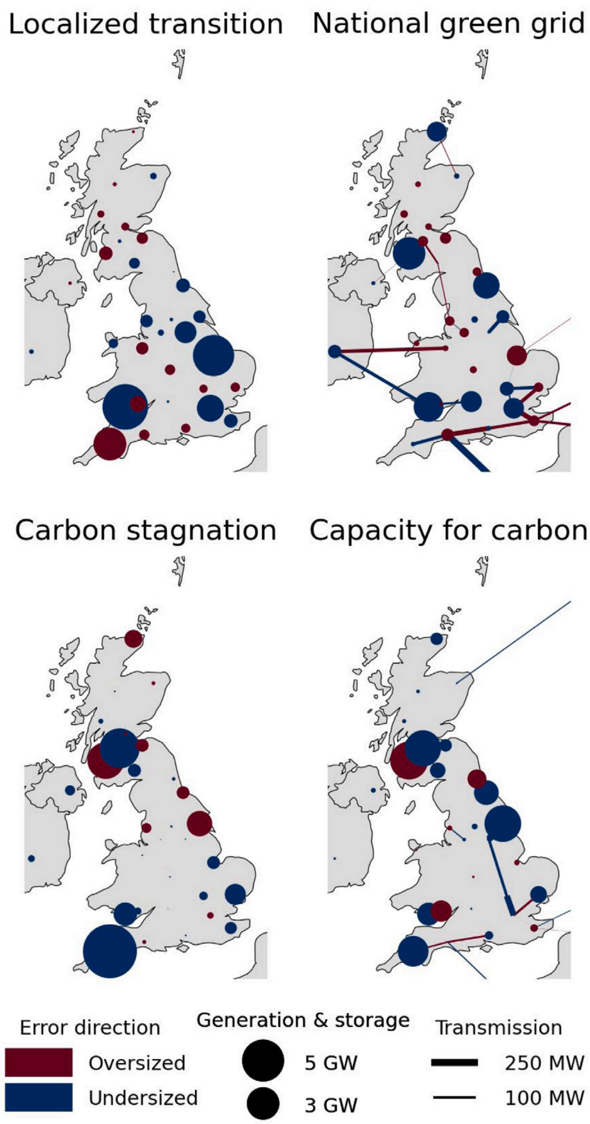

Fig. 8. Generation and transmission planned capacity differences using heating demand based on national temperature vs. local temperature for four different transmission expansion and carbon budget scenarios. Infrastructure with an oversized capacity when using uniform, national temperature-based heating demand is shown in red, and infrastructure with an undersized capacity is shown in blue. The legend displays transmission and generation and storage capacities for scale.

budget, which reflects the influence of firm generation availability on storage and generation capacity needs. In the high-carbon scenarios, the largest differences are in coastal Britain. In the low-carbon scenarios, the capacity differences are spread across Britain with large differences near the coasts and significant differences inland. These results demonstrate that using high spatiotemporal resolution heating demand data changes the optimal generation and storage placement under a wide variety of transmission expansion and carbon budget constraints.

3.3.3. Transmission expansion locations

Table 3 shows the error metrics with respect to the multi-regional heating demand approach for the spatial allocation of transmission capacity when using spatially uniform heating demand in each of the scenarios considering transmission expansion.

Under all scenarios, planning with spatially uniform heating demand profiles leads to sub-optimal placement of transmission system upgrades to meet spatially varied heating demand. The TAE and TAPE for transmission capacity are slightly higher in the capacity for carbon scenario than in the central scenario. Both of these errors are much higher in the national green grid scenario: the TAE and TAPE are about 3 times higher than under the central scenario at 2.2 GW and 0.63%. While the magnitude of capacity misallocation is smaller for transmission than for storage and generation, the long timeline for transmission expansion makes these differences crucial.

This analysis of generation, storage, and transmission capacity differences underlines the importance of using high spatiotemporal resolution heating demand data in bulk power systems planning. In all carbon budget and transmission expansion scenarios, using the multi-regional model of heating demand leads to different spatial distributions of infrastructure than using the national model. Moreover, using spatially varied heating demand leads to higher differences in infrastructure placement under low carbon budget scenarios compared to the central scenario, which demonstrates that high spatiotemporal resolution heating demand is crucial for spatial planning to achieve power sector decarbonization goals.

3.4. Operational regret analysis

Operating a power system planned based on a uniform national heating demand to meet multi-regional heating demand is more expensive than operating a system planned to meet multi-regional heating demand. Table 4 compares the operational costs to meet multi-regional heating demand for a power system planned based on national heating demand and a multi-regional heating demand. Under the central scenario, planning with uniform national demand increases operational costs by €500 million per year, which is 5% higher than the system planned with multi-regional demand. These additional costs primarily come from increased use of biomass, combined-cycle gas, and nuclear generators. The difference in operational costs is much higher under the low-carbon scenarios: the localized transition national system operational costs are 323% higher and the national green grid costs are 25% higher due to increased load shedding in both scenarios.

Low-carbon power systems planned with uniform national heating demand experience more load shedding under multi-regional heating load than the systems planned to meet multi-regional heating demand. While no significant load shedding occurs in the central and low-carbon scenarios, large amounts of load shedding occur in both of the low-carbon scenarios, as shown in Table 5. The vast majority of this load shedding occurs outside of Britain, which reflects the limitations of planning a high-renewable system without including the entire European grid. Enforcing a 99% carbon reduction for countries outside Britain without considering connections to other regions causes marginal power prices to exceed €6900 per MWh and triggers load shedding even for the system planned with multi-regional heating demand under the national green grid scenario. However, increased load shedding outside of Britain for the national system indicates that British electricity exports have higher costs.

Table 3
Transmission capacity errors.

Scenario	TAE [GW]	Max line error [GW]	Max line error [GW]	TAPE [%]
Central	0.6	0.19	−0.10	0.18
National green grid	2.2	0.17	−0.23	0.63
Capacity for carbon	1.0	0.08	−0.24	0.31

Table 4
Operational costs for meeting multi-regional heating demand.

Scenario	National system (€B)	Multi-regional system (€B)	National additional cost [%]
Central	8.6	8.1	5
Localized transition	10.9	2.6	323
National green grid	91.0	73.0	25
Capacity for carbon	10.7	10.4	3
Carbon stagnation	11.5	11.1	3

Table 5
Load shedding to meet multi-regional heating demand.

Scenario	National system load shed [TWh]	Multi-regional system load shed [TWh]
Cental	0	0
Localized transition	1.20	0
National green grid	12.58	9.99
Capacity for carbon	0	0
Carbon stagnation	0	0

The majority of the load shedding in Britain affects inland population centers. For the national system under the localized transition scenario, 245 GWh of load shedding occurs at Bus 7, the most populous bus in the country that includes London. For both the national and multi-regional systems under the national green grid scenario, 18 GWh of load shedding occurs in Britain, primarily inland in central Britain at Buses 8 and 23, which include the Manchester and Birmingham urban areas. Even in the multi-regional system, the lack of renewable generation overcapacity compared to the localized transition scenario leads to marginal prices exceeding €6900 that trigger load shedding. This result suggests the need to increase the value of lost load in high-renewable systems with high shares of electrified heating.

4. Conclusions

This paper analyzes the implications of spatiotemporal differences in residential heat pump load for bulk power system planning. This question is addressed using the novel approach of modeling residential heat pump demand by scaling data from field trials with high spatiotemporal resolution temperature data to generate spatially varied heat demand profiles. The results of capacity expansion planning using these multi-regional profiles are compared with those based on a single national heating profile for a case study in Britain. Large regional differences in total and peak heat demand are identified between the two approaches. These differences lead to significant differences in the spatial planning of generation and storage capacity, especially in low-carbon scenarios.

Comparing the multi-regional model with the national model reveals regional differences in peak demand and total annual heating demand. While both the national and multi-regional approaches only deviate by −0.7% and +0.7% from the historical annual heating demand on the national level, respectively, the multi-regional model accounts for spatial differences in heating demand. In comparison, the national temperature-based model overestimates total heating demand in southern regions by up to 26% and underestimates demand in northern regions by up to 21%. In the hour when peak system-wide heating demand occurs, using national temperature overestimates the electric heating demand in coastal areas by up to 51% and underestimates it inland by up to 20% compared to the multi-regional approach. Using multi-regional temperatures to model heating demand reveals significant regional differences in Britain, a medium-sized country with a temperate climate, and could have an even more substantial impact in larger countries with more variable climates.

High spatiotemporal resolution heating demand is necessary to correctly site generation and storage capacity in bulk power system planning. Under a central scenario for carbon reduction and transmission capacity expansion in the British power system in 2035, using a spatially uniform heating demand profile leads to a total absolute error in the spatial allocation of generation and storage of 15.1 GW (1.3%) compared to a high-resolution demand pattern based on local temperatures. These capacity differences are spatially concentrated in a few locations and primarily reflect the need for more battery storage capacity to meet regional heating peaks when using high spatiotemporal resolution heating demand. For low carbon budget scenarios, the total absolute error increases to 16.9 GW (1.3%) with 30% transmission expansion and 23.9 GW (1.5%) with no transmission expansion. This trend suggests that high spatiotemporal resolution heating demand data is even more important for spatial planning of bulk power systems with very high shares of renewable generation. As countries transition from gas boilers to heat pumps for residential heating, high spatiotemporal resolution data about residential heat pump demand is crucial for power system planners striving for ambitious decarbonization targets.

Spatial misplacement of power system infrastructure due to low spatial resolution heating demand projections increases operational costs and leads to load shedding under the low-carbon scenarios. Under the central scenario, operational costs increase 5% when operating a system planned with national heating demand to meet multi-regional heating demand. Under the low-carbon scenario with 30% transmission expansion, increased load-shedding outside of Britain indicates higher-cost British electricity exports for a system planned with national demand. For the low carbon scenario with no transmission expansion, operating a system planned with uniform national demand leads to 245 GWh of load shedding in the most populous region.

This study reveals several areas for future research. Incorporating residential building renovations into the heating demand model may provide options for reducing the power system impact of widespread heat pump adoption. Including the heating demand time series in the network clustering algorithm can identify the necessary level of heating demand spatial resolution for power systems planning. Finally, using high spatial resolution demand data reveals an increased need for battery storage capacity in many locations, and heat pump flexibility has the potential to replace some of this storage. Future work will explore the regional availability of heating flexibility and its role in power systems planning.

CRediT authorship contribution statement

Claire Halloran: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Jesus Lizana:** Writing – review & editing. **Filiberto Fele:** Writing – review & editing, Conceptualization. **Malcolm McCulloch:** Supervision.

Declaration of competing 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.

Data availability

Data will be made available on request.

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Appendix. COP sensitivity analysis

A sensitivity analysis of COP values is performed to understand the impact of this parameter on the results for the central scenario. The lower sensitivity is set to 85% of the time-varying COP values calculated in Section 2.5 based on the correction factor of 0.85 used in Ruhnau et al. [11] to account for the electricity consumption of auxiliary systems including defrosters. The upper sensitivity is set to 115% of the baseline COP values to reflect potential future improvements in heat pump efficiency.

The key results for this sensitivity analysis are shown in Table A.1. As expected, the national and multi-regional peak demand decrease as COP values increase. Despite the change in peak demand, the spatial misplacement metrics are within the same order of magnitude. The relative changes in key indicators are shown in Fig. A.1. At 115% of the baseline COP values, spatial misplacement metrics increase significantly: generation and storage TAE increase by 23% and transmission TAE increases by 217%. These results suggest that using high spatiotemporal resolution heat pump demand is crucial for spatial power systems planning even as heat pump efficiency improves.

Table A.1
Key indicators for COP sensitivity analysis.

	85% COP	100% COP	115% COP
Multi-regional peak demand [GW]	49.7	42.3	36.8
National peak demand [GW]	48.7	41.4	36
Generation TAE [GW]	11.3	15.1	18.5
Generation TAPE [%]	0.99	1.3	1.6
Transmission TAE [GW]	0.6	0.6	1.9
Transmission TAPE [%]	0.2	0.18	0.6

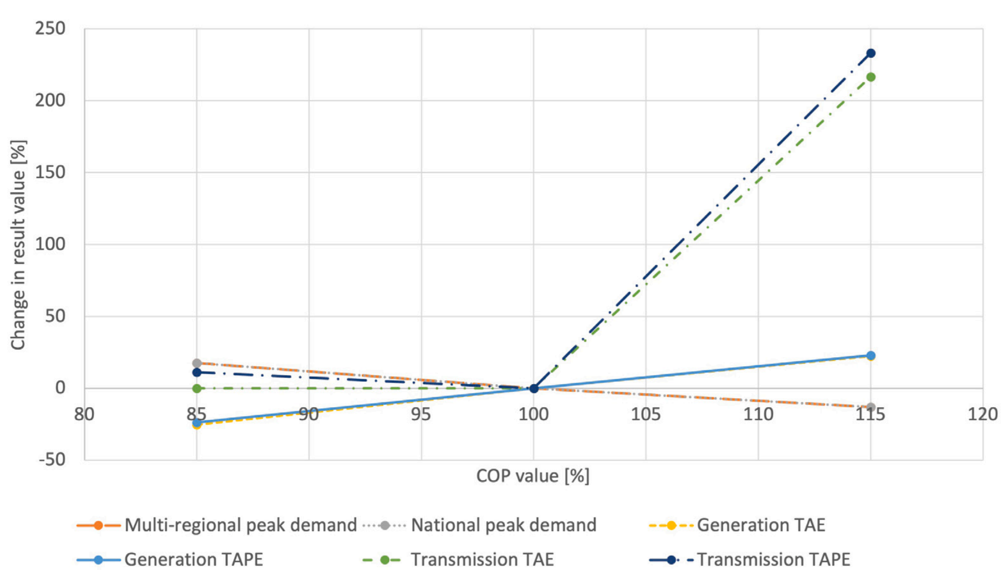

Fig. A.1. Relative change in key indicators for COP sensitivity analysis.

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