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# Optimisation of Integrated Heat Pump and Thermal Energy Storage Systems in Active Buildings for Community Heat Decarbonisation

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**Abstract:** The electrification of residential heating systems, crucial for achieving net-zero emissions, poses significant challenges for low-voltage distribution networks. This study develops a simulation model to explore the integration of heat pumps within active building systems for community heating decarbonisation. The model optimises heat pump operations in conjunction with thermal energy storage units to reduce peak demand on low-voltage networks by using real-time measured electricity demand data and modelled heat demand data for 76 houses. The study employs an algorithm that adjusts thermal storage charging and discharging cycles to align with off-peak periods. Three scenarios were simulated: a baseline with unoptimised heat pumps, a fixed threshold model, and an active building model with daily optimised thresholds. The results demonstrate that the active building model achieves a 21% reduction in peak demand on the low-voltage substation compared to the baseline scenario; it also reduces the total electrical energy consumption by 12% and carbon emissions by 17%. The fixed threshold scenario shows a 16% improvement in peak demand reduction, but it also shows an increase in energy consumption and emissions. These findings highlight the potential of active buildings to enhance the efficiency and sustainability of residential energy systems, marking a significant step toward decarbonising residential heating while maintaining grid stability.

**Keywords:** heat decarbonisation; active buildings; community energy; heat pump optimisation; electrification challenges

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## 1. Introduction

The reduction in greenhouse gas emissions remains a crucial global issue, with residential heating systems recognised as major sources of carbon emissions [1]. Many countries, including the United Kingdom (UK), have set targets to produce electricity from Renewable Energy Systems and achieve net-zero carbon emissions by 2050 [2]. This transition to carbon-neutral residential heating has become a fundamental element of international energy policies [3], with the Climate Change Committee emphasising that space heating and domestic hot water contribute approximately 18% of overall UK carbon emissions [4].

Decarbonising the heating sector fully to meet governmental targets presents significant challenges [5], with electricity emerging as the most promising substitute for fossil-fuel-based heating due to its growing utilisation of renewable and low-carbon sources [6]. Among the technologies facilitating this transition, Heat Pumps (HPs) are particularly notable for their energy efficiency [7,8]. HPs demonstrate a higher energy output compared to the input, with a Coefficient of Performance (COP) typically ranging from three to four, compared to less than one for resistive electric heaters [9,10]. Research conducted in Germany has emphasised that HPs are poised to play a pivotal role in the electrification of heating systems in buildings [11], with air-source heat pumps projected to be the dominant technology in the field of heat electrification [3].

However, the widespread implementation of these heat pumps faces technical obstacles, primarily the production of relatively low-temperature water (40 °C to 50 °C) compared to traditional gas boilers (70 °C) [10,12]. This necessitates either substantial retrofitting of existing buildings [13] or the use of high-temperature HPs capable of producing water at 65 °C to 70 °C [14,15]. While high-temperature HPs offer a viable alternative, they typically exhibit lower COPs at elevated temperatures, impacting overall energy efficiency and cost-effectiveness. Integrating HPs with thermal energy storage (TES) systems, which require water temperatures over 50 °C and ideally over 60 °C, could play a crucial role in balancing load demands on the grid by storing excess heat during off-peak times and releasing it when needed.

The transition towards electrification in heating and transportation, while environmentally advantageous, presents challenges for the Low-Voltage (LV) grid [16–18]. Increased demand for heating and electric vehicles can overload local electricity networks, especially during peak times [19]. This predicament is further compounded by the increasing demand for electric vehicles, necessitating significant investments in low-carbon electricity production and conducive policies [5,20,21]. Managing this demand surge is essential to maintain power delivery stability and efficiency, requiring innovative grid management and infrastructure upgrades.

Active buildings offer a potential solution, with their capacity to control and produce their own energy, incorporating technologies like solar panels, battery storage, and heat pumps [22,23]. These structures not only reduce the carbon footprint related to residential heating but also aid in stabilising demand on the LV grid by generating surplus energy during peak load periods [23]. The integration of HPs within active buildings, particularly when combined with TES and smart control systems, represents a promising avenue for exploring how to effectively minimise stress on the LV network amid increased electrification.

This study is set against the backdrop of the Trent Basin project, a development of up to 500 energy-efficient residential homes in the waterside regeneration zone of Nottingham, UK [24]. The unique community-based setup of Trent Basin allows for a detailed examination of heat decarbonisation strategies within an integrated urban planning framework. Despite the acknowledged benefits of HPs, optimal methods for their implementation, particularly in diverse residential settings, remain underexplored. Therefore, this study investigates the potential of these technologies to manage the energy load dynamically, analysing the interplay between HP operations, TES cycling, and usage patterns of electricity and heat in residential settings. This approach seeks to reduce peak demand pressures on the grid, offering a proactive solution to the challenges posed by rising electricity demands. Furthermore, the research explores how smart controls can enhance the efficiency of these interactions by adjusting to both user needs and grid capacity in real-time, thus potentially easing the burden on existing infrastructure without compromising household energy needs.

The aim of this research is to develop a model that optimises the installation and operational strategies of HPs with TES, informed by real-time domestic energy demand data. By focusing on the Trent Basin project, this model provides a replicable framework for similar urban decarbonisation initiatives, utilising hourly data on electricity and heat demand to maximise efficiency. By examining the potential of HPs and TES systems within the Trent Basin project, this study provides valuable insights into optimising residential heating practices and energy management. It contributes to the ongoing efforts of heat decarbonisation and smart heating solutions, offering an understanding of how such systems can be effectively implemented in community-scale projects.

## 2. Method

This research employs a comprehensive modelling approach to explore and optimise heat decarbonisation strategies within the Trent Basin project's Phases 1 and 2, which comprise 76 houses. The methodology centres around the development and application of a dynamic simulation active building model constructed in MATLAB version R2023a, which integrates real-time and empirically modelled data to assess the performance and energy management potential of HPs and TES solutions. This model has been constructed to replicate real-world conditions with high fidelity by integrating hourly data on electricity and heat demand, ambient temperatures, and substation capacities. Its primary objective is to pinpoint the most effective operational tactics that reduce energy usage and peak load effects on the electricity distribution substation, all the while ensuring thermal satisfaction throughout the community. The following sections detail the specific data collection procedures, model development, and the optimisation techniques employed to achieve these goals.

### *2.1. Data Collection and Demand Modelling*

Many properties within Phases 1 and 2 of the Trent Basin development are outfitted with devices and sensors that capture a wealth of information, including indoor environmental conditions and electricity consumption [25]. A publicly accessible Application Programming Interface (API) was employed, facilitating the retrieval of real-time and historical data that are available at varying granularities from hourly to yearly intervals. This resource was instrumental not only in data collection but also in validating the data used in our simulations, ensuring that our model's inputs were accurate and reflective of actual conditions [24].

To capture the electricity demand with sufficient granularity, sensors within each home were set to record the maximum power usage for each hour, focusing on peak usage instances rather than average consumption. This approach ensures that the model considers potential stress on the electrical infrastructure by operating under a worst-case scenario assumption, wherein each house reaches its maximum demand simultaneously.

Directly measured heat demand data were not fully available for Trent Basin properties. Consequently, an alternative strategy employing the Integrated Environmental Solution's (IES, Glasgow, UK) Digital Twin Toolset was adopted. Through the Integrated Community Design (iCD) tool version 2023 [26], simulated heat demand data were generated, utilising detailed 3D models of the residences. These models incorporated extensive specifications, such as building dimensions and thermal properties of construction materials, to yield an accurate representation of the heat demand.

The iCD tool uses a physics-based simulation engine, similar to that which underpins the Virtual Environment tool but allows for scalability with a simplified version for large-scale projects. This setup restricts the number of modelled parameters to provide results suitable for community-level analysis. Each building's specific characteristics—type, floor area, number of bedrooms, number of storeys, storey height, and roof type—were input into the model.

Additionally, the settings for hours of use were based on typical occupancy profiles (6 a.m. to 10 a.m. and 4 p.m. to 11 p.m.), simulating a worst-case scenario to assess potential impacts on energy demand. The U-values for walls, windows, and roofs were aligned with UK building standards for the respective construction years of the phases, enhancing the models' realism and applicability.

The simulation data from the iCD tool, detailed at an hourly resolution, complemented by peak electricity demand data from monitored properties, provided a comprehensive analysis of energy consumption patterns. This dataset was essential for exploring effective heat decarbonisation strategies within the Trent Basin project. A detailed description of this modelling process and its validation can be found in our previous work [27].

Further enriching the dataset, hourly external ambient temperature readings recorded by the Trent Basin weather station were also retrieved using the API. This data source was a critical parameter in assessing and adjusting the performance of the heat pumps. The model accounted for the dynamic nature of HP's COP, which was calibrated against varying outdoor temperatures using the manufacturers' performance tables [28,29]. This specific local data integration ensures that the simulation reflects realistic environmental conditions affecting HP operations within the community. Table 1 shows a sample of the

COP/Performance table for an 8 kW high-temperature HP at a Leaving Water Temperature (LWT) of 55 °C.

**Table 1.** Performance/COP table for 8 kW high-temperature HP [28].

| | **LWT = 55 (°C)** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Ambient Temperature (°C) | −15 | −10 | −7 | −2 | 2 | 7 | 12 | 15 | 20 | 25 |
| COP | 1.65 | 1.94 | 2.33 | 2.74 | 2.96 | 3.40 | 3.57 | 3.82 | 4.29 | 4.76 |

Although the overall capacity of the LV substation, as provided by the National Grid, is known to be 800 Kilowatts (kW) [30], the lack of hourly load data necessitated an assumption that the collective load of the 76 houses represents the total demand on the substation. It is important to acknowledge that other houses and businesses may also be connected to this substation, potentially increasing its total load. However, for the purposes of this study, this assumption allows the model to simulate the electrical demand against the substation's known capacity, ensuring that the community's energy usage remains within the infrastructural limits.

The hourly grid carbon intensity was obtained from National Grid ESO—Electricity System Operator—Data Portal [31], which further enriched the dataset, allowing for a nuanced evaluation of the carbon footprint associated with the community's energy consumption.

This comprehensive suite of data not only fed into the development of the simulation model but also provided a foundation for the subsequent stages of analysis, laying the groundwork for the robust optimisation processes that form the foundation of this research.

### *2.2. Model Development*

The model, designed in MATLAB, reflects the operational dynamics of HPs and TES systems, as well as their interaction with the electrical grid infrastructure. It is also underpinned by several key assumptions. Firstly, the collective load of the 76 houses is considered to represent the total demand on the substation, simplifying the grid interaction model. Secondly, in the active building model scenario, historical data serve as a proxy for forecasts, allowing for the simulation of predictive control strategies. Finally, it is assumed that thermal comfort is maintained whenever the heat demand is met, linking system performance directly to occupant satisfaction.

The model incorporates three distinct scenarios to evaluate and compare different control strategies:

#### 2.2.1. Baseline Scenario

This scenario simulates the operation of heat pumps without thermal storage or demand-side management. It serves as a reference point to assess the effectiveness of more advanced control strategies.

In the baseline scenario, each building's heat pump operates independently to meet its heating demand without any consideration of grid conditions or energy storage. The heat pumps turn on whenever there is a heating demand and turn off when the demand is met. This represents a traditional, non-optimised approach to building heating. The electricity consumption in this scenario is directly tied to the heating demand and the heat pump's COP based on the outdoor temperature. This scenario helps quantify the potential benefits of more sophisticated control strategies by providing a comparison point.

#### 2.2.2. Fixed Threshold Scenario

In this scenario, fixed LV demand thresholds are set for the entire year to control HP operation and TES charging. Two key thresholds are established:

- 140 kW for direct HP activation to meet heating demand.
- 180 kW for using HP to charge TES.

These thresholds were determined through an iterative process, analysing historical electricity and heat demand data to optimise system efficiency without overloading the substation. The process involved testing various threshold combinations over the entire year's data to find the set that minimised peak demand while ensuring heat demand was met; in addition, it was found that using a combination of 2 thresholds helped reduce the peak electrical demand on the grid. This scenario uses the same control logic as the active building model but with fixed thresholds that do not change throughout the year.

The fixed threshold scenario represents a middle ground between the baseline and the fully optimised active building model. It introduces smart control based on grid conditions but does not adapt to daily variations in demand patterns or weather conditions. This approach offers improved grid integration compared to the baseline while being simpler to implement than daily optimisation.

#### 2.2.3. Active Building Model Scenario

This advanced scenario implements the daily optimisation of thresholds for each building. The model determines optimal thresholds for each day based on forecasted demand profiles, allowing for more adaptive and efficient system operation.

The active building model dynamically manages the operation of HPs and TES based on projected demands, optimising energy usage and managing the load on the local electricity grid effectively. While the model is designed to use forecasted data, the current implementation uses historical data as a proxy for forecasts, simulating the decision-making process that would occur with real-time predictive capabilities.

The optimisation algorithm for the active building model works as follows:

- For each day and each building, the model tests a range of threshold combinations (30–200 kW for both thresholds).
- For each threshold combination, it simulates the building's operation for the day, calculating the resulting peak electricity demand.
- The threshold combination that minimises the building's peak electricity demand is selected for that day.

This daily optimisation allows the system to adapt to changing weather conditions, occupancy patterns, and grid dynamics, potentially leading to more efficient operation compared to fixed thresholds.

The control logic for fixed threshold and active building scenarios operates as follows:

- When the projected peak electrical power on the substation remains below Threshold 1 (T1), HPs are activated to satisfy immediate heating needs, optimising responsiveness and efficiency.
- If the peak is anticipated to stay below Threshold 2 (T2) and immediate heating demand is low, energy is diverted to thermal storage, leveraging off-peak electricity periods to build up thermal energy reserves for use during high electricity demand times.
- When the load exceeds T2, the system prioritises using stored thermal energy to meet heating demands, minimising the electrical load on the grid during peak periods.

This algorithm continuously analyses input data, including current load conditions and ambient temperatures, to align operational decisions with the overarching goal of reducing peak electricity demand and enhancing system efficiency. This proactive management approach ensures optimal system operations across varying environmental and demand scenarios.

The model's development constitutes a rigorous process that synthesises real-time and historical data to accurately represent and optimise the performance of the active building model within the Trent Basin project. By comparing the three scenarios (baseline, fixed thresholds, and active building), the study provides valuable insights into the potential benefits of more sophisticated control strategies in active building systems. A schematic diagram for the system's inputs, outputs, and control algorithm is presented in Figure 1.

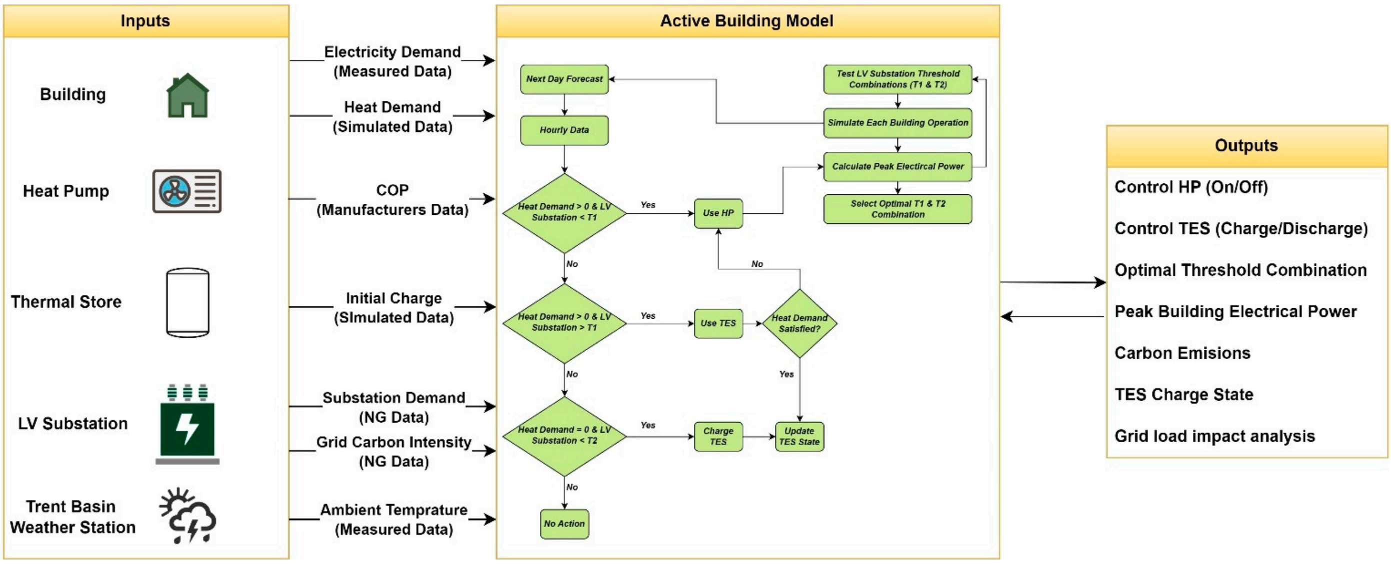


**Figure 1.** Active building model schematic.

### 2.3. System Configuration

The system configuration of the model is illustrated in Figure 2, showcasing the community infrastructure and the individual building system. At the community level, it shows the Trent Basin project with 76 houses connected to the LV substation via the electrical network. The figure also shows the communication between the buildings and the LV substation, highlighting the data exchange that provides the buildings with the necessary information about substation capacity to make decisions regarding optimising the thresholds, as described in the model development section.

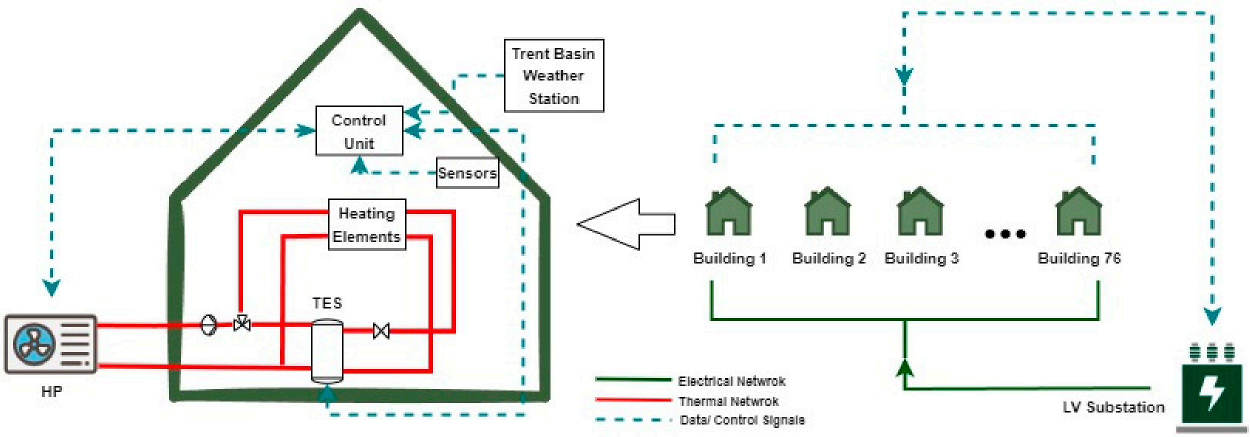


**Figure 2.** System configuration of the model on both community and building levels.

At the individual building level, each building is equipped with an individual heating system consisting of a high-temperature HP, capable of producing water at temperatures up to 65 °C, suitable for space heating and domestic hot water, and coupled with TES units for each house. The HP and TES units are connected to the heating elements, which, in the model, represent the heat consumers, such as the space heating system (radiators or underfloor heating) and domestic hot water system. While the control unit manages the operation of the HP and TES units based on the heating demand, grid conditions, and the real-time data from the sensors utilise the algorithm mentioned in the model development section.

*2.4. Sizing HP and TES Units*

The sizing strategy adopted in this research is simplified, aiming to ensure each element is adequately dimensioned to meet energy demands while facilitating the optimisation process. Also, it is only specific to the Trent Basin project and may not be directly applicable to other scenarios without adaptation.

While community-scale district heating could potentially offer greater efficiency, this study focuses on individual high-temperature HPs and TES units. This choice reflects a more realistic solution for the existing UK building stock, requiring lower infrastructure and cost investment compared to community-scale systems. Cost considerations were not factored into the sizing methodology at this stage, although efforts were made to maintain realistic sizes for both HPs and TES units.

HP capacity is determined based on the average heat demand observed during the coldest days, providing a buffer for colder-than-average periods. TES units are sized to independently meet the heat demand for a 3 h duration, based on the average demand during cold days. Table 2 summarises the capacities of the HPs and TES units, categorising houses into TES/HP capacity groups. These capacities underpin the optimisation algorithm, which tests various threshold combinations to minimise peak electricity demand while meeting heating needs efficiently.

**Table 2.** Summary of the HP and TES units used in the model.

| Category Number | HP Size (kW) | TES Size (kWh) | Number of Houses |
|---|---|---|---|
| 1 | 5 | 10 | 6 |
| 2 | 6 | 15 | 31 |
| 3 | 8 | 20 | 16 |
| 4 | 16 | 30 | 23 |

This simplified approach allows the model to implement the control logic and adapt to changing conditions daily. While not optimised for cost, it provides a foundation for exploring system behaviour and optimisation strategies.

*2.5. Model Outputs and Analysis*

Upon processing the inputs and applying the operational strategies based on the predefined scenarios, the model generated a series of outputs that provided detailed insights into the energy management of the Trent Basin project. These outputs included the operational status of HPs and TES units, the satisfaction of heat demand, hourly electricity consumption, and overall system efficiency. The following subsections describe the equations used to calculate the model output, which was derived from fundamental principles of thermodynamics and electrical engineering.

2.5.1. Electricity Consumption and Grid Impact

The model calculated total electricity consumption for each hour, factoring in the operation of HPs, the energy used in charging or discharging the TES, and existing building demands. These data were vital for monitoring the impact on the low-voltage substation and ensuring that the total demand did not exceed the substation's capacity of 800 kW. Additionally, the model evaluated the peak demand scenarios and provided strategies to mitigate potential overloads, thereby enhancing grid stability. The following equations were used within the model to calculate the electricity demand and peak demand:

$$E_{HP}(t) = \frac{Q_{Heat}(t)}{COP\ (t)} \tag{1}$$

$E_{HP}(t)$ is the electricity demand of the heat pump at time $t$.
$Q_{Heat}(t)$ is the heat demand at time $t$.

$COP\ (t)$ is the coefficient of performance of the heat pump at time $t$, which is a function of the outdoor temperature.

$$E_{total}(\mathrm{t}) = E_{HP}(t) + E_{other}(t) \tag{2}$$

$E_{total}(t)$ is the total electricity consumption in the building at time $t$.
$E_{other}(t)$ represents other electrical loads in the building at time $t$.

$$E_{Peak} = max_{t\,\in\,T}\ E_{total}(t) \tag{3}$$

$E_{Peak}$ is the peak electricity demand over the period $T$.

### 2.5.2. Operational Status and Demand Satisfaction

For each hour, the model generates outputs about the status of HP activation, charging and discharging of the TES, and the building's heat demand satisfaction. These granular data allowed for a precise understanding of how energy resources were being utilised in real-time and were crucial for assessing the responsiveness of the system to the occupants' needs.

The operational dynamics of the TES were critically influenced by the charging and discharging rates, which were designed to optimise both energy use and system durability. During the charging process, the model operated the HP at half its total capacity when charging the TES. This approach was sufficient for the Trent Basin project case to meet the model's objectives and prevent demand from peaking during charging times.

It is important to note that this charging strategy is specific to this model and the Trent Basin project. In real-world applications, the charging process would be controlled by the specific TES technology used and could vary significantly based on the project's unique requirements and constraints.

Conversely, the discharging process in the model was not similarly restricted, allowing the TES units to release stored heat as needed to meet real-time demand. The following equations represent the hourly TES charge state calculations and the corresponding HP consumption:

$$S(t) = S(t-1) \pm Q_{Charge/Discharge}\ (t) \tag{4}$$

$$E_{HP(charging)}(t) = \frac{E_{HP(MAX)}/2}{COP\ (t)} \tag{5}$$

$S(t)$ is the amount of thermal energy available in the TES unit at time $t$.
$Q_{Charge}\ (t)$ is the amount of energy charged into the TES unit at time $t$.
$Q_{Discharge}\ (t)$ is the amount of energy provided by the TES unit at time $t$.
$E_{HP(charging)}(t)$ is the electricity demand of the HP while charging the TES at time $t$.
$E_{HP(MAX)}$ is the maximum capacity of the HP.

### 2.5.3. Carbon Emissions Analysis

Integrating grid carbon intensity data into the model was pivotal for evaluating the sustainability of the energy solutions implemented and for aligning with broader environmental objectives. The optimised model computed the carbon emissions for each operational scenario, providing a quantitative measure of the environmental impact.

The equation used to calculate the carbon emissions related to HP electrical consumption is

$$CO_{2\ Emissions} = \sum_{t=1}^{T} CI\ (t) \times E_{HP}(t) \tag{6}$$

$CO_{2\ Emissions}$ are the carbon emissions related to HP operation in $(\mathrm{kg}CO_2)$ during period of time $T$.

$CI\ (t)$ is the electrical grid's carbon intensity at time $t$ in $(\mathrm{kg}CO_2/\mathrm{kWh})$.

2.5.4. Comparative Scenario Analysis

To demonstrate the efficacy of the optimised model, the outputs of the three scenarios—as introduced in the model development section—are compared. This comparison highlights the advantages of the model in terms of reduced energy consumption, lower carbon emissions, and improved grid stability.

The insights derived from these outputs are critical for ongoing optimisation and decision-making processes. They allow for the continual refinement of operational strategies and provide a robust framework for managing energy efficiently within the Trent Basin project.

## 3. Results and Discussion

The outcomes of the active building model simulation for the Trent Basin project are presented and analysed in this section, utilising historical data from 2022. Energy demand patterns are first examined to provide context for the subsequent analysis. Three scenarios are then compared: the baseline scenario with a standard heat pump operation, the fixed threshold scenario, and the active building model with daily optimised thresholds. Key aspects of system performance, including energy consumption, grid impact, and carbon emissions, are evaluated. The effectiveness of the active building approach in optimising energy use, reducing peak demand, and enhancing grid stability while maintaining occupant comfort and reducing carbon emissions is demonstrated through this analysis.

### *3.1. Energy Demand Analysis*

This subsection presents a detailed analysis of the energy demands within the Trent Basin project during the coldest week of the year (7 January 2022–13 January 2022). The heat demand data were modelled using the Integrated Community Design (ICD) tool, while the electricity demand and substation load data were based on actual measurements, providing a real-world snapshot of the current energy usage without heat pump integration.

Figure 3 illustrates the simulated heat demand for a typical building from Category 2 throughout the coldest week of the year, with demand fluctuating between 1 kW and 7 kW, as generated by the ICD tool. The chart captures the fluctuations in heat demand during the day with peak periods during early morning and late evening, which likely reflect occupancy patterns, such as increased heating requirements when residents are home and active, which is crucial for assessing the heating needs under traditional systems.

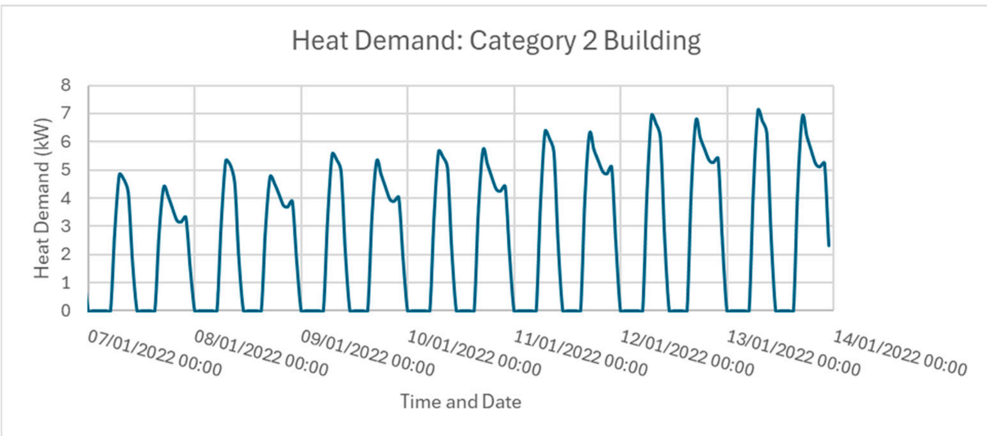


**Figure 3.** Heat demand for Category 2 building during the coldest week of the year.

Subsequently, Figure 4 displays the hourly peak electrical power for this building during the same period as previously noted. This chart captures the maximum power usage for each hour, detailing daily fluctuations and highlighting peak demand times. The sharp spikes seen across the graph occur at various times throughout the week, illustrating the building's maximum electrical load under current conditions without the influence of heat pumps. This detailed insight into hourly peaks is crucial for understanding the building's energy consumption patterns, allowing for more precise energy management and planning to efficiently handle peak loads and enhance overall energy efficiency during extreme weather conditions.

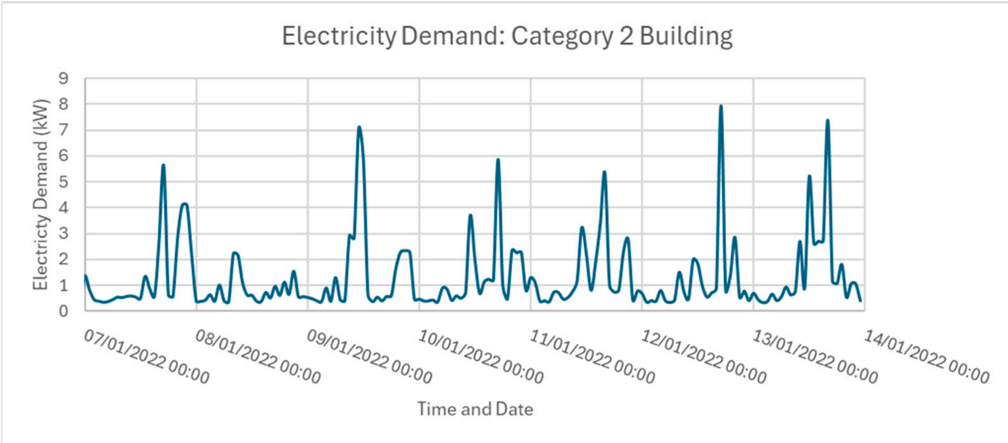


**Figure 4.** Hourly peak electricity power for Category 2 building during the coldest week of the year.

Figure 5 illustrates the low-voltage substation demand during the same week, representing the total maximum power demand for all buildings, assuming the maximum power for each household occurs simultaneously within each hour period. The peak demand reaches around 300 kW, while the base demand is approximately 45 kW. It is important to note that this figure represents the maximum power for each hour, aggregating the combined demand of all houses. Additionally, as mentioned in the methodology section, this analysis assumes the scenario where only buildings from the Trent Basin project are connected to the substation; there may be other loads, such as businesses, industries, or additional residential units connected to the substation. These data offer a crucial baseline for understanding how the substation manages loads without the influence of heat pumps.

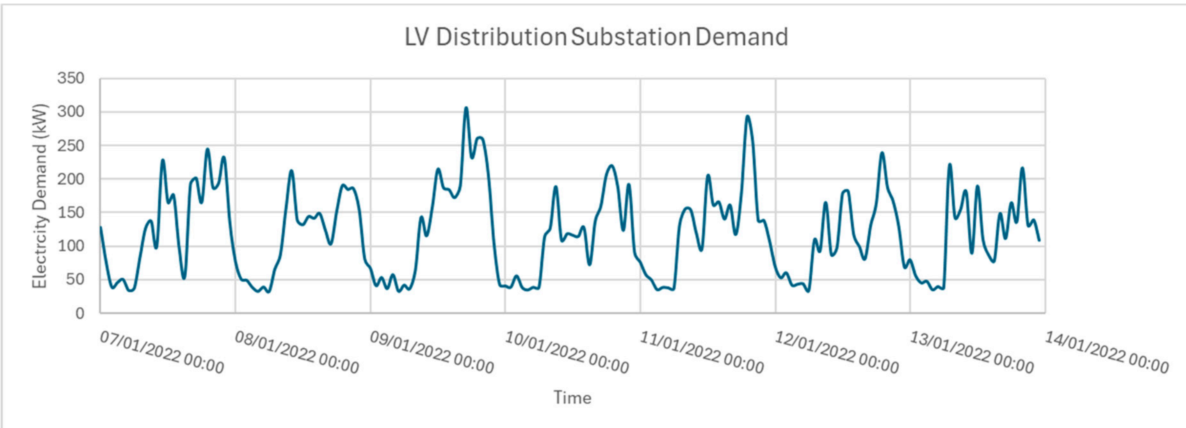


**Figure 5.** Hourly peak electricity power at the LV distribution substation during the analysed week.

To provide context for the subsequent scenario analyses, Figure 5 illustrates the relationship between the COP of a Category 2 HP and the outdoor temperature during the analysed week. This graph demonstrates the inverse relationship between the outdoor temperature and heat pump efficiency, which is crucial for understanding the variations in electricity demand for heating in the following scenarios.

As shown in Figure 6, the COP fluctuates between 2.9 and 3.4 during the analysed week, while the outdoor temperature varies from near 0 °C to about 10 °C. These variations in temperature and the resulting changes in COP play a significant role in the energy demand patterns and system performance across different scenarios, which will be explored in the following subsections.

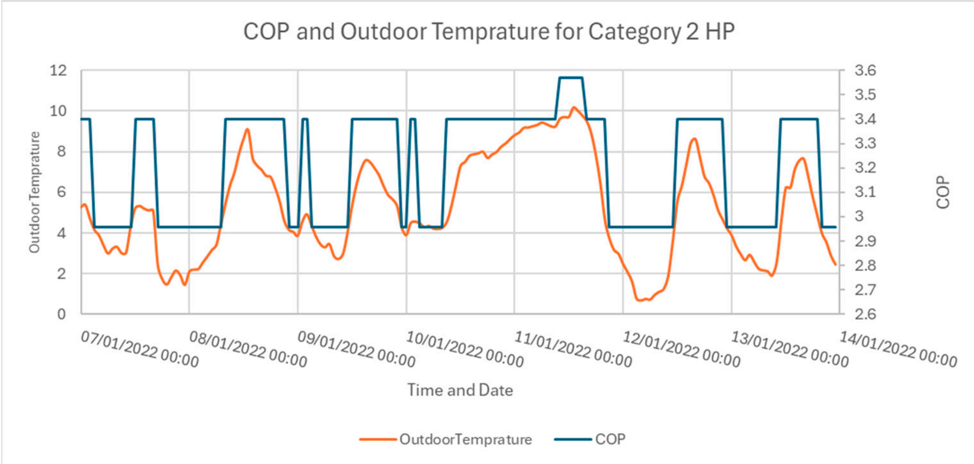


**Figure 6.** COP and outdoor temperature for Category 2 HP over the analysed week.

### 3.2. Baseline Scenario

In this section, we explore the baseline scenario, where heat pumps are installed without any thermal storage, to directly meet the heating demand of the buildings within the Trent Basin project. This scenario serves to illustrate the impact of heat pump integration on both individual building electricity consumption and the overall load on the low-voltage substation.

Figure 7 presents a comprehensive view of the energy dynamics in the same building presented in the energy demand analysis subsection and during the same week, including the heat demand in kW, the electricity demand from the heat pump alone, and the total electricity demand for the building, which combines the heat pump load with other electrical loads within the building.

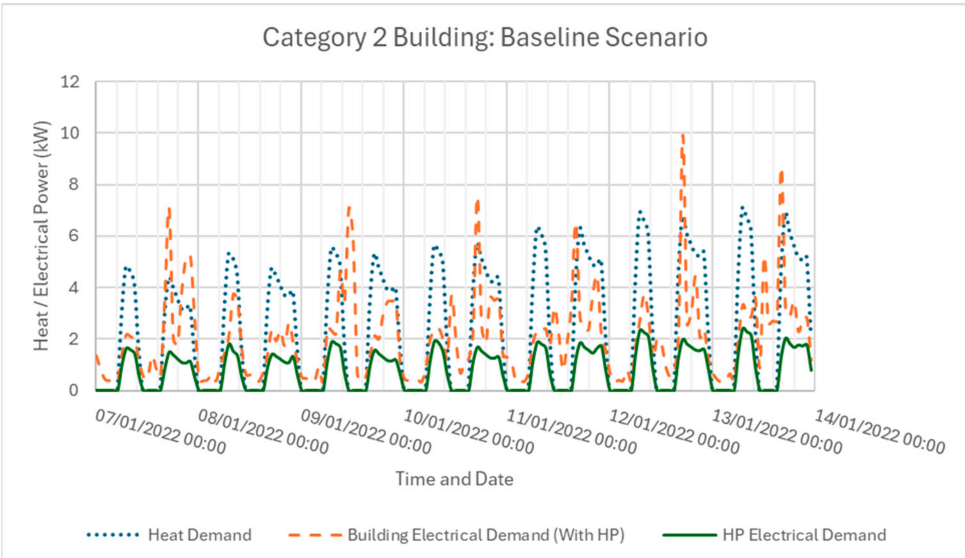


**Figure 7.** Baseline scenario energy dynamics for building from Category 2.

It can be observed from the figure that the total electricity demand for the building peaks around 10 kW on certain days, reflecting the combined impact of the heat pump and other household electrical loads. The heat pump, with a capacity of 6 kW and a Coefficient of Performance (COP) of around three, based on the manufacturer's data sheet and outdoor temperature, operates efficiently. This results in a peak electricity demand from the heat pump alone being just below 2 kW. The efficiency of the heat pump minimises its impact on the building's overall electricity consumption while effectively meeting the heating demands.

### *3.3. Fixed Threshold Model Scenario*

This section presents the results of the simulation model integrating heat pumps with thermal storage using fixed thresholds. The analysis focuses on a typical building from Category 2, equipped with a 6 kW heat pump and a 15 kWh thermal storage unit, before examining the broader impact on the Trent Basin project.

The model employs two fixed thresholds, 140 kW and 180 kW, to optimise energy usage by activating the heat pump and thermal storage based on real-time electricity demand and grid conditions. These thresholds determine when to activate the heat pump, charge the thermal storage, or use stored energy.

Figure 8 displays the state of charge of the thermal storage, the total electricity demand from the heat pump and the building, and the building's heat demand over a week-long period. It demonstrates how the thermal storage discharges to meet heating needs during peak hours, reducing the direct load on the heat pump and, consequently, on the substation.

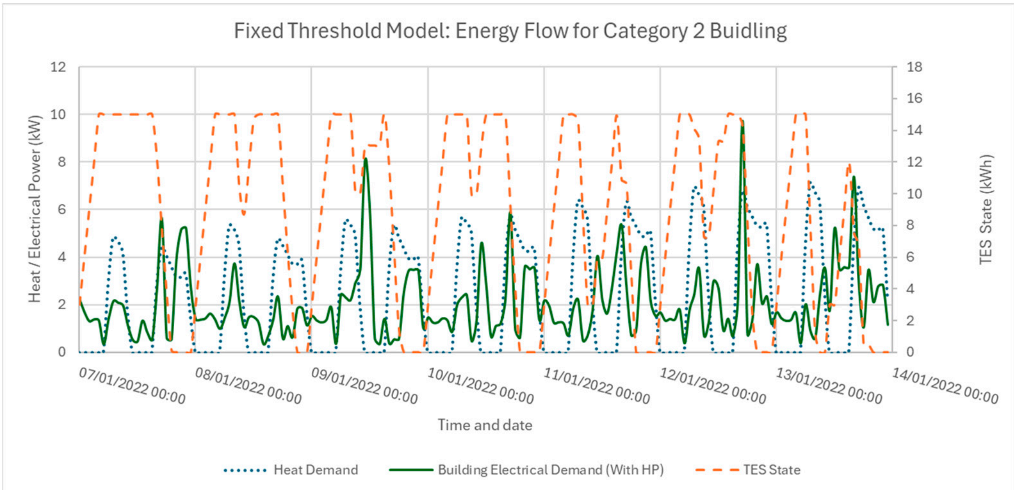


**Figure 8.** Fixed threshold model scenario energy flow in building from Category 2.

This fixed threshold approach shows improvements over the baseline scenario, with some smoothing of electricity demand peaks. The thermal storage acts as a buffer, allowing for a more balanced use of the heat pump throughout the day. However, the fixed nature of the thresholds limits the system's ability to adapt to varying daily conditions.

While this scenario demonstrates the potential benefits of integrating thermal storage with heat pumps, there is still room for further optimisation, as will be explored in the subsequent active building model scenario.

### *3.4. Active Building Model Scenario*

The active building model scenario represents the most advanced approach in our study, employing daily optimised thresholds for each building. This section examines the performance of a typical building under this model and its implications for the broader Trent Basin project.

Unlike the fixed threshold scenario, the active building model dynamically adjusts its thresholds daily to optimise energy usage. The following Table 3 illustrates the daily variations in Threshold 1 (T1) and Threshold 2 (T2) for a typical building over a week. These daily adjustments allow the system to adapt to changing conditions, potentially offering more efficient energy management than the fixed threshold approach.

**Table 3.** Summary of the LV substation operating thresholds within the active building model during the analysed week.

| Day | T1 (kW) | T2 (kW) |
|---|---|---|
| 1 | 170 | 40 |
| 2 | 110 | 140 |
| 3 | 30 | 160 |
| 4 | 140 | 80 |
| 5 | 180 | 40 |
| 6 | 110 | 100 |
| 7 | 140 | 90 |

Figure 9 demonstrates the intricate interplay between heat demand (blue line), building electrical power, including the heat pump (green line), and the thermal energy storage (TES) state (orange line). The dynamic nature of the system is evident in the varying patterns of TES charging and discharging, which align with the fluctuations in heat demand and electrical power consumption. The active building model's ability to adjust thresholds daily allows it to account for changing conditions, potentially leading to more optimal heat pump and thermal storage utilisation. The energy flow patterns shown in the figure reveal how the system manages to balance heat demand with electrical power consumption, using thermal energy storage as a buffer.

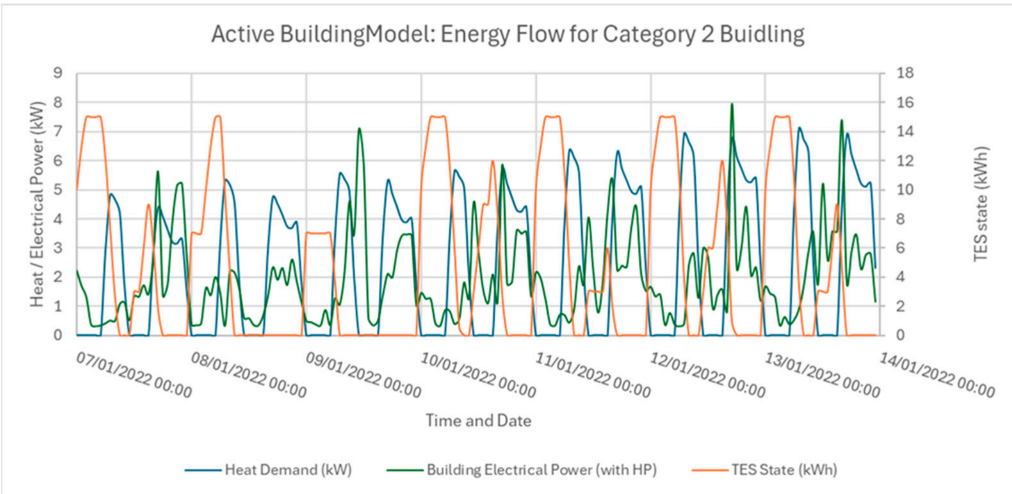


**Figure 9.** Active building model scenario energy flow in building from Category 2.

*3.5. Comparison of Scenarios*

To evaluate the effectiveness of the different control strategies, the performance of the three scenarios: baseline, fixed threshold model, and active building model, was compared. This comparison focuses on their impact on the total electrical power demand, key annual metrics, and the frequency of high peak power occurrences.

Figure 10 illustrates the hourly peak electrical power on the LV substation for all three scenarios over the coldest week of the year. The baseline scenario (orange line) exhibits the highest and most volatile demand patterns, with frequent sharp peaks reaching up to 500 kW. The fixed threshold model (blue line) shows a more balanced profile with reduced peak heights, generally staying below 400 kW. The active building model (green line) demonstrates the most stable demand pattern, effectively flattening many of the peaks seen in the other scenarios and rarely exceeding 350 kW.

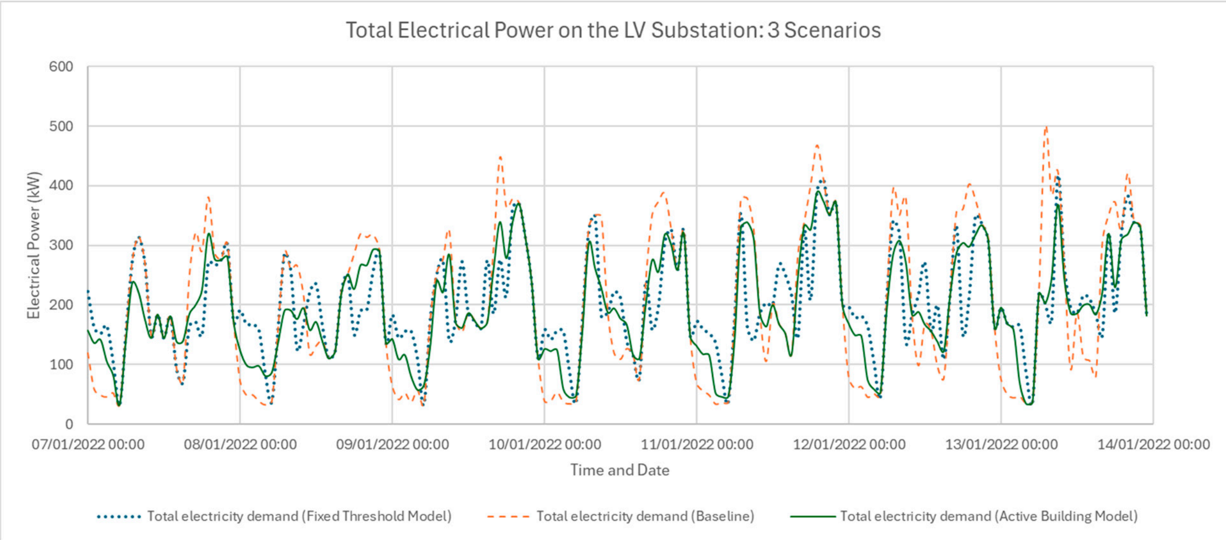


**Figure 10.** Comparison of the total electrical power on the LV substation between the 3 scenarios.

This weekly pattern provides insight into the broader annual performance of each scenario, which is summarised in Figure 11, presenting key yearly metrics.

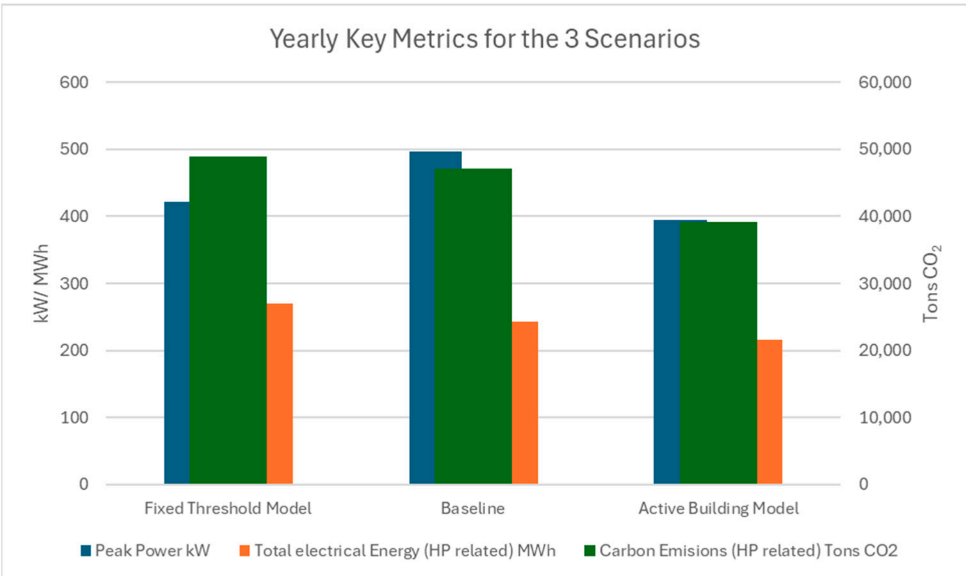


**Figure 11.** Comparison of yearly key metrics for three scenarios.

For the peak power demand, the baseline scenario exhibits the highest peak power demand at approximately 500 kW. The fixed threshold model shows a notable reduction to about 420 kW, representing a 16% decrease. The active building model achieves the most substantial reduction, lowering the peak to around 395 kW, which translates into a 21% decrease from the baseline. This significant reduction in peak demand demonstrates the active building model's superior ability to manage load and potentially alleviate stress on the local grid infrastructure.

In addition to the peak electrical power, the total electrical energy and carbon emissions related to the HP operation were analysed. While similar energy consumption could be expected across scenarios, given that they all meet the same heat demand, the results show notable differences.

The fixed threshold model, despite showing improvements in peak demand, unexpectedly consumes more electrical energy (270 MWh) than the baseline (245 MWh). This 10% increase suggests that the fixed threshold model is triggering heat pump operations during periods of lower Coefficient of Performance (COP), such as colder nighttime hours in winter when ambient temperatures are lower. Consequently, carbon emissions for this model are also higher at about 49,000 tons, a 4% increase from the baseline's 47,000 tons.

In contrast, the active building model demonstrates the most efficient use of electricity, reducing consumption to about 215 MWh, a 12% reduction from the baseline. This translates to the lowest carbon emissions at approximately 39,000 tons of $CO_2$, a significant 17% reduction from the baseline. The superior performance of the active building model can be attributed to its ability to optimise operation times for each building individually, likely prioritising periods of higher COP and avoiding less efficient operating conditions.

These results underscore the importance of not just managing peak demand but also considering the efficiency of heat pump operations when designing control strategies. The active building model's approach of optimising at the individual building level proves to be the most effective strategy for managing total electricity consumption and reducing carbon emissions while still meeting all heating demands.

To further assess the impact of each scenario on grid stability, the annual number of hours where the peak demand on the LV substation exceeded certain thresholds were analysed. Figure 12 illustrates this analysis.

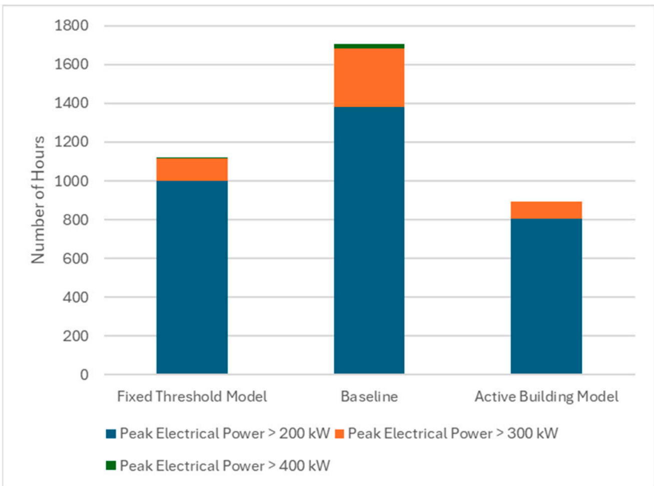


**Figure 12.** Annual number of hours exceeding 200 kW, 300 kW, and 400 kW peak electrical power for three scenarios.

The baseline scenario shows the highest frequency of peak demand events, with over 1400 h exceeding 200 kW and a significant number of hours above 300 kW and 25 times above 400 kW. The fixed threshold model reduces these occurrences, particularly for the higher thresholds, where the substation only exceeds 400 kW three times during the whole year. The active building model demonstrates the most significant improvement, with the fewest hours exceeding all thresholds, particularly above 300 kW and 400 kW.

These results underscore the effectiveness of the active building model in managing peak demand, reducing overall energy consumption, and minimising carbon emissions. Its ability to dynamically adjust to changing conditions on a building-by-building basis proves superior to both the baseline and fixed threshold approaches. This adaptive strategy not only enhances energy efficiency but also contributes to grid stability by significantly reducing the frequency and magnitude of high-demand events.

## 4. Conclusions and Future Work

This study demonstrates the potential of integrating TES units with HPs to manage peak electricity demand in community heating systems. By comparing three scenarios—baseline, fixed threshold model, and active building model—we have identified significant improvements in energy management and grid stability.

The active building model emerged as the most effective approach, achieving approximately a 21% reduction in peak demand compared to the baseline scenario, lowering it from 500 kW to 395 kW. This decrease in peak loads on the LV substation offers a promising pathway to decarbonise heating systems while maintaining grid stability. The model also showed improvements in overall energy efficiency and carbon emissions, with a 12% reduction in total electrical energy consumption and a 17% decrease in carbon emissions compared to the baseline. In contrast, the fixed threshold model demonstrated a 16% reduction in peak demand but showed increases in energy consumption by 10% and emissions by 4%, highlighting the importance of dynamic optimisation in achieving comprehensive energy efficiency.

These findings have important implications for the transition to low-carbon heating systems. The reduction in peak demand suggests that the integration of TES and HPs could delay the need for costly infrastructure upgrades, providing a more gradual and manageable transition to fully electrified heating. The active building model's ability to smooth out demand peaks contributes to enhanced grid stability, which is crucial as we move towards increased the electrification of heating and transport. The model demonstrates that it is possible to make progress in decarbonising heating systems without immediately requiring extensive enhancements to electricity infrastructure.

While this study provides valuable insights, it is important to acknowledge certain limitations. The model assumes that the 76 houses represent the total load on the substation, which may not fully reflect real-world conditions where other loads are likely present. Additionally, the study uses historical data as a proxy for forecasts, which may not capture the unpredictability of real-time energy demand and weather patterns. The simplified sizing strategy for HPs and TES units, while practical for this study, may not be optimal in all real-world scenarios. These limitations provide opportunities for further refinement in future research.

Future work should focus on expanding the model to incorporate a more comprehensive representation of the LV substation, including other potential loads such as businesses, additional residential buildings, and electric vehicles. This would provide a more realistic assessment of the substation's total load and the model's effectiveness in a real-world scenario. Investigations into advanced TES technologies, such as phase change materials, could reveal further improvements in system performance and efficiency.

Exploring how changing energy demand patterns due to factors like improved building insulation or changing occupancy behaviours might affect the long-term effectiveness of the proposed system would be valuable. A detailed cost–benefit analysis to assess the economic viability of implementing TES and HPs on a community scale, including potential savings from delayed infrastructure upgrades, would provide crucial information for decision-makers. Future work should also address the incorporation of time-varying electricity prices and system costs into the optimisation model, considering different electricity unit prices per hour to provide a more comprehensive economic assessment of the proposed strategies.

Further research could examine how the active building model could be optimised to work in conjunction with local renewable energy generation, such as solar PV or wind power. Extending the simulation period to assess the model's performance over multiple years, accounting for seasonal variations and long-term climate trends, would provide insights into its long-term viability. Finally, it would be beneficial to investigate the impact of user behaviour and preferences on the system's performance.

By addressing these areas, future research can build upon the promising results of this study, further refining and validating the active building model as a key strategy in the transition to sustainable, low-carbon community heating systems.

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