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RELIABLE AFFORDABLE CLEAN ENERGY

Final Report

AI-ready flexible buildings

Data requirements and feasibility of unlocking flexibility in commercial buildings

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Data requirements and feasibility of unlocking flexibility in commercial buildings

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What is RACE for 2030?

RACE for 2030 CRC is a 10-year co-operative research centre with AUD350 million of resources to fund research towards a reliable, affordable, and clean energy future. www.racefor2030.com.au

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1 Introduction

Buildings play a significant role in energy consumption and the emission of CO_2 worldwide, accounting for approximately 40% of the world's energy consumption and contributing to about 35% of total greenhouse gas emissions (Ürge-Vorsatz et al., 2015; Magni et al., 2021; Pouranian, Akbari, and Hosseinalipour, 2021; X. Zhang et al., 2020; Pervez, Ali, and Petrillo, 2021). The Net Zero roadmap by the International Energy Agency (2021) suggests that to achieve global net-zero emissions by 2050, heating and cooling energy use should drop from 100% in 2020 to 50% by 2030 and finally 20% in 2050. The roadmap expects that *efficiency* is the primary driver of the required reduction in buildings' total final consumption, with an anticipated 350 Mt CO_2 reduction by 2050 achieved through digitalisation and intelligent controls. Deploying such intelligent building controls to retrofit existing buildings is one potential lever to quickly reducing greenhouse gas emissions.

Heating and cooling in office buildings are major contributors to energy consumption, accounting for a significant percentage of building energy usage and CO_2 emissions. While this is a significant outlay, buildings also have the potential to absorb, store, and release the heating or cooling into the building materials, much the same way a battery does. By pre-cooling or preheating the building, "thermal inertia" will, in theory, provide the flexibility to use more variable renewable energy, thus lowering the carbon emissions of the building. However, in practice, this will require greater automation and responsiveness of the buildings to climate, renewable resources, and electricity grid prices.

This project aims to define, test, and document the data produced by new automated systems to determine the optimal times to heat and cool a building. This decision process will also be automated by combining AI-driven predictive modelling with strategic data organisation and innovative optimisation techniques to significantly reduce energy usage and carbon emissions in office buildings while maintaining comfort and productivity.

The core output of the project is a simulation model of an office building (modelled on an existing office building in Monash University), for which we optimise an HVAC control schedule to make the best precooling and preheating decisions. Optimising the control of the building automation and management system (BAMS) to align the energy consumption with periods of low carbon intensity grid power, we are able to reduce the carbon intensity of the building's overall energy requirements by 10%. Extrapolating this result to the entire Monash campus suggests a potential annual reduction of up to 23,000 tons of CO_2-e if this solution is fully deployed across all buildings, although further real-world studies are needed to validate the simulation estimates.

The project's long-term benefits include greater accessibility of the building control data for R&D, developing advanced control models for energy optimisation, significantly reducing carbon intensity in building operations, and setting a precedent for future innovations in sustainable building management.

2 Literature review on building automation

This chapter provides a comprehensive introduction to the foundational concepts of building automation, emphasising the growing significance of data-driven strategies in building energy management across both the design and operational phases. These systems can be used for a range of automation and management tasks such as load forecasting (M. Hu et al., 2023), anomaly and fault detection and diagnosis (Lei et al., 2023), predictive control and thermal comfort (G. Hu and You, 2023), indoor environmental quality (IEQ) monitoring (Majdi et al., 2022), facility and asset management (Ogolla and Kieti, 2022), energy efficiency planning (Verma, Prakash, and Kumar, 2023), security and safety (Hsiao and Hsieh, 2023), occupancy detection (Sayed, Himeur, and Bensaali, 2022), and water usage management (AlGhamdi and Sharma, 2022).

While traditional approaches rely on physical modelling to account for factors like shading, passive heating, orientation, natural ventilation, and geometry, the data-driven approach harnesses empirical data to extract valuable insights. By analysing data related to heating/cooling load, lighting, electricity usage, and occupancy profiles, a more accurate understanding of building performance can be achieved (Pan and L. Zhang, 2020; Che-Ani and Raman, 2019). Collecting and maintaining real-world building energy use data (RBEUD) that represent the actual condition of buildings enhances operational efficiency and contributes to valuable knowledge for future projects. Adopting modern distributed computing platforms, such as cloud computing (Mohamed, Lazarova-Molnar, and Al-Jaroodi, 2016), edge computing (Minh et al., 2022), fog computing (Iftikhar et al., 2022), and hybrid strategies (Himeur et al., 2022), can simplify and support this task by providing seamless connectivity, data pre-processing and storage, and powerful computing resources at various levels. The availability of such data sets plays a pivotal role in informed policy-making and bridging the energy performance gap (EPG), which represents the disparity between mandated energy consumption and actual usage in practice (X. Wang et al., 2023).

2.1 Traditional HVAC Control

Traditional HVAC control methods focus on maintaining indoor environmental comfort by regulating temperature, humidity, and air circulation using set point and feedback control mechanisms. These conventional strategies include manual adjustments, where occupants adjust settings based on comfort levels, and automated systems, which rely on predefined set points for temperature and humidity control and operate independently to maintain a specified comfort range.

Significant energy savings and preservation of human comfort can be achieved by optimising these control strategies, including the use of optimal control strategy curves and operation curves for equipment and devices. Moreover, the advent of intelligent control techniques and user-adaptable comfort control systems signifies a shift towards more responsive and energy-efficient HVAC operation, aiming to align more closely with the specific thermal comfort preferences of occupants (Federspiel, 1992; Mirinejad, Welch, and Spicer, 2012).

Historically, automation, control systems, and material science advancements have been the focal points for improving HVAC efficiency (Aftab et al., 2017). However, the recent integration of AI and machine learning technologies and a global shift towards renewable energy sources have significantly enhanced HVAC operations. This technological evolution reduces the environmental footprint of HVAC systems and revolutionises control strategies and methodologies.

2.2 AI and Machine Learning for HVAC Control Strategies and Algorithms

Recent studies underscore the effectiveness of leveraging predictive control algorithms and deep learning approaches for optimising energy consumption and enhancing thermal comfort within buildings through HVAC systems (Kalaimani, Keshav, and Rosenberg, 2016). Furthermore, the development of intelligent building automation systems, capable of dynamically sensing occupant comfort needs and accordingly scheduling HVAC operations, represents a significant advancement towards more efficient and responsive building environments (Aftab et al., 2017).

Buildings, particularly through their HVAC systems, can enhance grid stability by adjusting their electric loads in response to signals from the grid. This adjustment contributes to maintaining the Networked Energy Management (NEM) frequency balance and overall system stability. By implementing control strategies, HVAC systems in both commercial and residential settings can offer frequency regulation services without significantly impacting indoor climate comfort. Research has explored model predictive control and rule-based control strategies that enable HVAC operations to be dynamically adjusted, taking into account factors like occupant comfort and hardware constraints. Such strategies allow for a more responsive and energy-efficient operation of HVAC systems, providing valuable ancillary services to the grid, such as demand peak reduction and balancing supply and demand, thereby supporting a stable and efficient energy system.

2.3 AI-Driven HVAC Control—Buildings that act as batteries of last resort

The integration of renewable energy sources into the electricity grid has led to the need for demand response strategies to mitigate the volatility of renewable energy supply. HVAC systems, particularly in commercial and industrial settings, have been identified as potential candidates for fast-demand response applications (Goddard, Klose, and Backhaus, 2014). The potential of demand response in enabling flexibility for higher renewable energy penetration and efficient resource exploitation has been highlighted, particularly in industrial near-zero-energy buildings (Kampelis et al., 2019). Additionally, research has focused on integrating HVAC operation into demand response programs, emphasising the need for occupant-oriented demand response with room-individual building control (Frahm et al., 2023). Furthermore, an integrated approach to adaptive control and supervisory optimisation of HVAC control systems for demand response applications has been proposed as an effective solution for a scalable and adaptable demand response platform for HVAC systems (Adegbenro, Short, and Angione, 2021).

In the context of microgrids, cooperative algorithms utilising HVAC demand response have been explored to minimise supply-demand mismatch, thereby reducing the need for energy storage devices (J. Ma, X. Ma, and Ilic, 2019). Moreover, control strategies for coordinating the operating schedules of multiple HVAC devices in residential demand response have been investigated, emphasising the inseparability of effective control algorithms from residential demand response based on HVAC systems (Kou et al., 2021). These studies collectively underscore the potential of HVAC demand response to address the challenges posed by integrating renewable energy sources into the electricity grid.

In response to grid shortages or outages, buildings can collectively act as “batteries” to provide load shedding or self-curtailed services by adjusting the set-points of HVAC systems within reasonable ranges. This adaptive management of HVAC systems enables buildings to reduce their electric load dynamically, contributing to grid stability during peak demand times or in situations where the grid’s supply capacity is strained. Conversely, when the grid experiences surplus energy availability due to favorable conditions for photovoltaic (PV) or wind generation, buildings can increase their HVAC consumption flexibly. By doing so, buildings can absorb excess energy, preventing potential waste of renewable resources and aiding in the balancing of supply and demand on the grid.

For instance, research has proposed the concept of a Virtual Battery (VB) control for commercial HVAC systems to adjust power consumption in real-time by regulating zonal airflow rates, demonstrating how buildings can effectively respond to grid signals. Additionally, the integration of HVAC and battery scheduling in buildings has been explored to optimise demand response, showcasing the potential for buildings to manage peak load demands while ensuring thermal comfort and leveraging battery storage.

These approaches highlight the pivotal role buildings can play in enhancing grid resilience and stability. By leveraging HVAC systems' flexibility alongside energy storage solutions, buildings can effectively serve as dynamic assets in the smart grid, adjusting their energy profiles to support grid operations while maintaining occupant comfort.

2.4 Building Automation and Management Systems

A building automation and management system (BAMS) is a sophisticated installation within buildings that plays a crucial role in overseeing and regulating a diverse range of building services. These services include heating, cooling, ventilation, air conditioning, lighting, shading, life safety, alarm security systems, and more. At its core, a BAMS aims to bring automation to technologically-enabled environments by harmonising a multitude of electrical and mechanical devices. These devices are intricately connected through distributed control networks, forming an interconnected ecosystem. BAMSs find wide application across various settings, ranging from industrial facilities and commercial buildings to bustling malls and even residential properties (Domingues et al., 2016). While building automation and management systems theoretically have the potential to provide comprehensive components and functionalities for analysing and operating buildings, there are additional vital tasks that often fall under the responsibility of the operator. In other words, energy management systems can be considered as reactive systems, therefore, it is necessary to develop smarter strategies that are fully focused on energy improvement (Lee, Cha, and Park, 2016). These tasks and strategies include evaluating building performance, detecting unusual energy consumption patterns, identifying efficiency improvements, and ensuring the security and privacy of end-users (Himeur et al., 2022).

Since the early 2000s, the application of virtualisation in data centres has brought about a paradigm shift in digital systems, delivering remarkable improvements in flexibility, availability, and security. BAMSs have embraced this transformative trend by seamlessly integrating wireless technologies like WiFi. This integration has empowered BAMSs with the ability to enable remote access and monitoring, unlocking new opportunities for efficient and effective management of building systems (S. Wang, 2009). Furthermore, this integration has laid a solid foundation for the implementation of cutting-edge algorithms and technologies that support higher-level tasks. These tasks require the utilisation of advanced tools such as big data analytics pipelines, capable of processing vast amounts of interconnected equipment data. Additionally, artificial intelligence and machine learning algorithms play a crucial role in tasks such as load forecasting, water management, indoor environmental quality monitoring, occupancy detection, and energy anomaly detection. By leveraging these innovative approaches, building automation systems collaborate to enhance the overall performance of the building, ensuring optimal efficiency, occupant comfort, and sustainability (Debrah, Chan, and Darko, 2022).

The significance of BAMSs lies in their ability to ensure occupant satisfaction, reduce energy consumption, and streamline efficient building operations. To achieve this, BAMSs provide comprehensive awareness to relevant managers, which is supported by the collection of high-resolution data. This data is acquired through a diverse array of sensors that are strategically deployed and connected to the BAMS using different communication technologies, such as fieldbus and IoT standards (Pandya, 2021; Moudgil et al., 2023; Zaeri et al., 2022). By harnessing these technological advancements, BAMSs empower building managers to make informed decisions and optimise building performance in pursuit of energy efficiency, occupant comfort, and sustainable operation.

The field of building automation has long been dominated by a wide array of proprietary solutions, with ad-hoc approaches often meeting moderate performance requirements. However, driven by the growing market demand for open systems, even industry leaders are gradually shifting away from proprietary designs. Recognising the importance of open systems, official standards bodies are actively involved in ensuring that the standards they develop and publish adhere to the principles of openness. These principles include non-discriminatory access to specifications and licensing. Consequently, the adherence of equipment to formal standards is increasingly becoming a requirement in many procurement processes. Standards directly relevant to building automation system technology are developed both in the United States and by several European and international standards bodies such as ISO[1], CEN[2], and CENELEC[3]. These standards serve as guidelines and benchmarks for the industry, promoting interoperability, compatibility, and the seamless integration of different building automation components (Kastner et al., 2005).

Kastner et al. (2005) present a general system model that encapsulates most types of BAMS, by separating out the functionality of its individual components across three levels:

- *Field Level*: The field level covers the switches, sensors and actuators that the BAMS is ultimately interacting with to achieve the desired real-world outcomes in the building. Through the field level, the BAMS interfaces with the physical world in a distributed manner, collecting and transforming measurement, counting, and metering data into a format suitable for transmission and processing. Additionally, this level facilitates physical control over environmental parameters through actions such as switching, setting, and positioning in response to system commands.
- *Automation Level*: At the automation level, a wide range of autonomously executed sequences come into play. This level operates on the data prepared by the field level, establishing logical connections and control loops to facilitate efficient operations. The automation level serves as a crucial intermediary between the field level and the management level, providing the necessary intelligence and decision-making capabilities for the smooth and efficient operation of the overall system.
- *Management Level*: At the management level, comprehensive access to information from the entire system is made available. This level presents a unified interface to the operator, facilitating manual intervention when necessary. It provides vertical access to automation-level values, allowing for the modification of parameters such as schedules to adapt to changing requirements. Furthermore, the management level plays a crucial role in monitoring system health and generating alerts for exceptional situations like technical faults or critical conditions. It also encompasses long-term historical data storage, enabling the generation of reports and statistics for in-depth analysis and decision-making.

It is important to highlight that devices within BAMS often incorporate a combination of functionalities from all three levels. This amalgamation of services and requirements necessitates network architectures that can accommodate this diversity. Strictly adhering to a three-tier network structure would introduce unnecessary

[1] International Standards Organization
[2] European Committee for Standardization
[3] European Committee for Electrotechnical Standardisation

complexity when it comes to sharing devices, especially sensors, between different functional domains (Kastner et al., 2005).

Here are the main components commonly found in a BAMS:

- *Sensors*: The devices responsible for capturing data on various aspects of the building environment, such as temperature, occupancy, light levels, and air quality. Sensors provide inputs to the BAMS, enabling effective monitoring and control. Leveraging advanced sensing and metering technologies, data can be gathered from multiple modalities, creating a comprehensive information source for targeted analysis and the development of intelligent and sophisticated tools. Measurement devices increase the observability of the building's transient and dynamic events as well as gather actual data related to diverse functionalities of the building (Himeur et al., 2022). Sensors are either directly connected to controllers via a standard interface or by means of a field network (Kastner et al., 2005).

- *Controllers*: Controllers are responsible for processing the data received from sensors and initiating appropriate actions. They make decisions based on predefined algorithms and control strategies to regulate building systems. The control unit is the central brain of the BAMS generally built upon industry standards and protocols such as BACnet[4], Koinnex (KNX)[5], LonWorks[6], and Modbus (Pricop et al., 2017).

- *Actuators*: Actuators respond to the output signals from a controller and accomplishes actions to operate the final control device, which might be a valve, damper, or switch (S. Wang, 2009). Actuators control functions such as adjusting temperature, operating valves, turning on/off lights, and managing security systems. Similar to sensors, actuators are either directly connected to controllers or through a field network (Kastner et al., 2005).

- *Human-Machine Interface* (*HMI*): The HMI is the user interface through which building operators or occupants interact with the BAMS. It can be a graphical interface displayed on a computer, touch panels, or mobile devices, allowing users to monitor system status, adjust settings, and receive alarms or notifications. Generally, the HMI is developed to monitor the energy management system regarding energy consumption (Hmidah et al., 2022). BAMS'S HMI is built upon supervisory control and data acquisition platforms to provide a unified visualisation for all systems and subsystems which facilitates the task of the operator (Figueiredo and da Costa, 2012; Kastner et al., 2005).

- *Communication Infrastructure*: BAMS components are interconnected through a communication network, allowing data exchange and coordination. This infrastructure may include wired or wireless protocols, such as Ethernet, BACnet, LonWorks, Modbus, or other industry-specific protocols.

- *Supervisory Control and Data Acquisition* (*SCADA*): SCADA systems offer centralised monitoring and control capabilities for large-scale BAMS deployments. These systems empower operators by eliminating the need to handle each piece of equipment locally within a building or complex. Instead, they enable remote monitoring and control, allowing for the detection of abnormal conditions without the requirement of being physically on-site. SCADA systems gather data from various controllers and sensors, providing advanced analytics, data fusion, and reporting functionalities to enhance operational efficiency and decision-making (Nesa and Banerjee, 2017; Kastner et al., 2005).

[4] An object-oriented peer-to-peer network protocol

[5] KNX, is a popular open standard for home and building automation. Twisted pair (TP), power line (PL), radio frequency (RF), and Ethernet (IP) are among the in-house communication possibilities covered by KNX (Shikhli et al., 2022)

[6] A standardised bus system used in centralised and decentralised building automation control (Merz, Hansemann, and Hübner, n.d.)

- *Energy Management System* (*EMS*): An EMS component within the BAMS focuses on optimising energy consumption and efficiency. It analyses energy data, identifies areas for improvement, and implements strategies to reduce energy usage and costs.
- *Integration Gateways*: Integration gateways play a crucial role in ensuring seamless interoperability between various building systems and protocols. These gateways serve as communication bridges, enabling the exchange of data and information between the BAMS and subsystems like HVAC, lighting, security, life safety, and access control. By adopting the gateway approach, control applications on different networks can utilise their native protocols to communicate with one another, while the gateway takes care of establishing the semantic connection. This approach allows for the abstraction and concealment of the complexities associated with specific protocols, as they are handled behind the scenes by the gateway. As a result, integration gateways facilitate smooth and efficient communication between diverse building systems, promoting interoperability and streamlined functionality (Kastner et al., 2005).
- *Databases and Data Storage*: BAMS systems often include databases to store historical data, event logs, and configuration information. These databases support reporting, trend analysis, and long-term performance monitoring.
- *Alarm Management and Notification*: The BAMS includes mechanisms to detect and respond to abnormal conditions or faults. It can generate alarms and notifications, alerting building operators or maintenance personnel of potential issues requiring attention.

3 Methodology

It may be possible to use a building's thermal mass to achieve demand flexibility, if it is known in advance when the flexibility is required. The methodology we use to realise this flexibility is a combination of machine learning and optimisation technology, to ultimately derive a control set-point schedule that reduces (or increases, as required) the energy consumption of the building during the flexibility window.

Figure 3.1 shows the high-level overview of the components that make up the (ideal) methodology. In the data collection phase, sensor readings are collected from the building's sensors and stored in a long-term storage database. Subsequently, the machine learning phase consists of fitting a predictive model to the readings in the database. The predictive model takes the the external (uncontrollable) conditions together with the control signal as input features, and predicts a next temperature (or a temperature trajectory). This predictive model is used in the operational phase by an optimisation model that takes as input the current state of the external conditions together with the predictive model, and produces control set-points (or a control set-point schedule) to be deployed on the building.

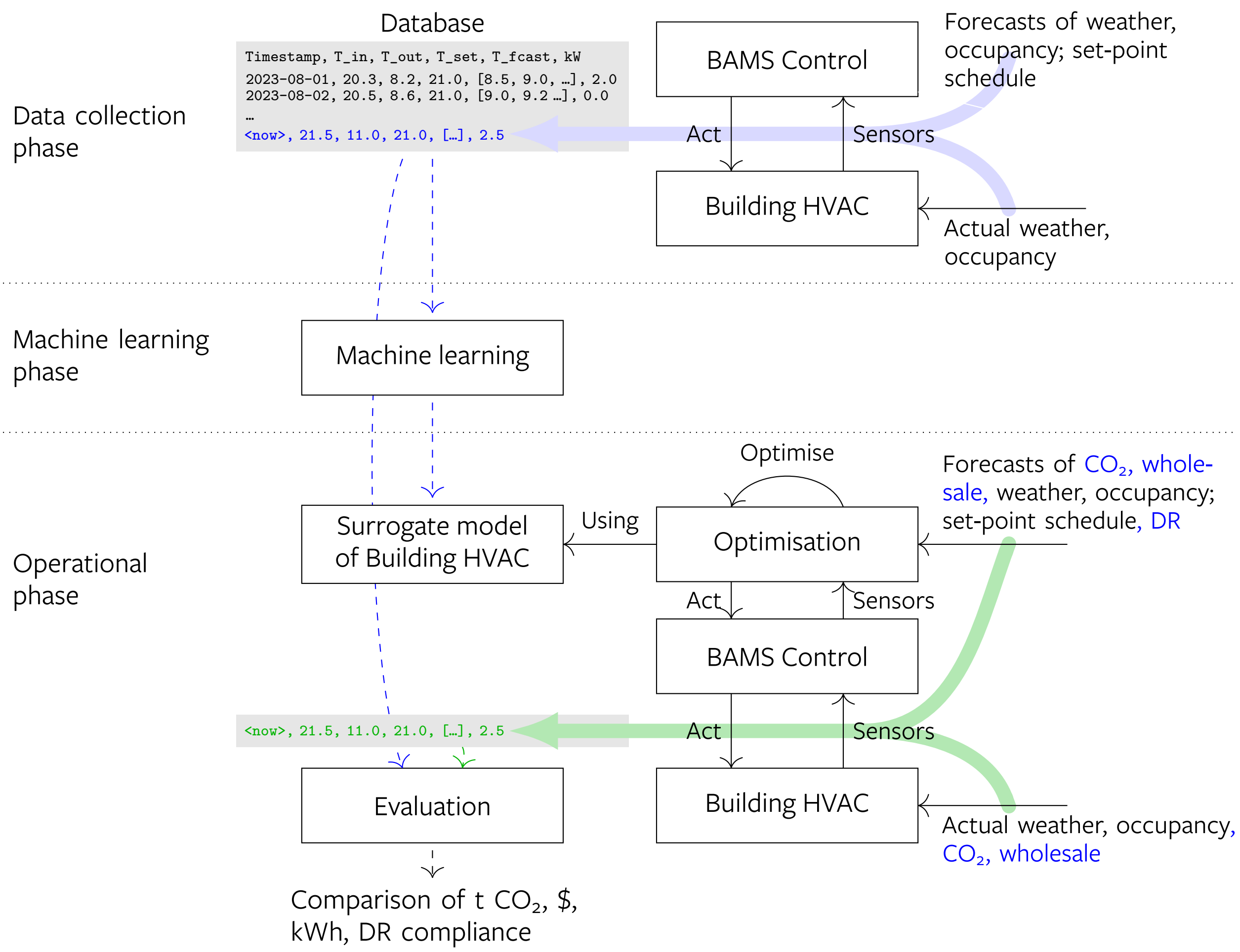


Figure 3.1: Idealised machine-learning and optimisation pipeline to transition from a 'normal' building to a 'flexible' building. An existing building with BAMS is instrumented to collect operational data (data collection phase). A surrogate model is fit to this data to match the building's thermal response under different weather and occupancy modes (machine learning phase). In the operational phase, the real-time BAMS set-point schedule is optimised using the surrogate model and additional forecast information such as the carbon intensity and wholesale electricity price (blue inputs).

This methodology has been shown to work using simulated building models (Lam et al., 2020), demonstrating optimal flexible load responses calculated for the control of up to 20 buildings. However, the practical application of this methodology in the real world faces significant hurdles. Crucially, the quality of the optimised control schedule depends in large part on the accuracy and completeness of the input data used to fit the building model. However, traditionally building operators have had little need to keep accurate historic sensor logs across long horizons, resulting in long lead times necessary to collect enough real-world data to make the application feasible.

Because of the large cost involved in maintaining a high-accuracy data collection framework (including the maintenance and monitoring of sensors for drift), an important question to answer is how much data is needed to make this methodology work. This research aims to answer this question via a simulation approach: by *simulating* the data collection phase at different levels of accuracy and granularity, we can obtain a (best-case) estimation of the amount of data necessary to reconstruct a (sufficiently) accurate predictive model.

3.1 Building simulation software and data

3.1.1 EnergyPlus

EnergyPlus is the official building energy simulation program from the U.S. Department of Energy. It models heating, cooling, lighting, ventilation, water usage, and other energy flows within buildings. A key strength is its ability to perform integrated sub-hourly simulations of interconnected heat transfer paths across the entire building. EnergyPlus accurately accounts for window gains, shading, daylighting, renewables, and construction materials. Its detailed modelling allows the optimisation of energy-efficient building and HVAC designs while considering water use and utility costs. The robust program is widely used by the global building energy analysis community (Fumo, Mago, and Luck, 2010).

The methodology proposed in this study is predicated on data derived from EnergyPlus simulations of HVAC control and building thermal response, with a particular emphasis on the set points representing the thermal zones of the target building. In contrast to collecting real-time building control data from BAMS, EnergyPlus simulation models offer an efficient means of streamlining the data collection and interpretation processes. For intricate commercial buildings, the substantial volume and complex interconnections of HVAC systems, electrical equipment, and other components necessitate extensive data science capabilities for cleaning, interpretation, and analysis. EnergyPlus energy simulation models consolidate the data into a unified format at a controllable scale for subsequent deep-learning model development while comparatively reflecting the salient physical properties of the building under investigation, including size, internal and external materials, and basic HVAC system configuration.

Nonetheless, as a trade-off between resource allocation, time, and accuracy, this study considers the integration of EnergyPlus simulation models for AI-driven control as a reasonable methodology for achieving flexible building goals.

3.1.2 OpenStudio

OpenStudio is a cross-platform suite of software tools developed by the National Renewable Energy Laboratory (NREL) to facilitate whole-building energy modelling using the EnergyPlus simulation engine. A key component is the OpenStudio Application Suite, which provides a user interface and geometry editor for creating, editing, running, and visualising EnergyPlus models.

Given the inherent complexity of constructing a thermal model directly within the EnergyPlus environment, this study utilised OpenStudio to streamline the process of building the foundational 3D model via SketchUp Software and configuring the HVAC system for subsequent EnergyPlus simulations. By leveraging OpenStudio's integrated toolset, the difficulties associated with establishing an EnergyPlus model from the outset were mitigated, enabling a more efficient workflow.

Ultimately, OpenStudio serves as a comprehensive software framework designed to facilitate and expedite building energy modelling workflows by providing a user-friendly interface and development environment for harnessing the robust simulation capabilities of EnergyPlus. As an open-source tool, it benefits from an active developer community contributing to plugins, enhancements, and technical support.

3.1.3 Climate data

In order to simulate a range of different potential weather conditions, EnergyPlus needs access to a weather data file that represents the typical meteorological year. We make use of the existing dataset of EnergyPlus weather data files for Australia produced by CSIRO (Ren, Tang, and James, 2021). This dataset is based on historical weather data drawn from the years 1990 to 2015, containing hourly observations for an entire year. Since we are modelling a building located in Clayton, Victoria, the closest data file is 'Melbourne RO', which is the one that we used in our simulations.

A major challenge in performing validated studies into optimised building control is the fact that virtually no dataset for climate and weather data contains forecast data in addition to the true signal. Without access to forecast data, studies must either assume perfect forecasts or attempt to produce reasonably realistic forecast errors. Unfortunately, due to the complexity in weather prediction, successfully creating realistic forecast errors is unlikely. Because of this, for our study we will also restrict ourselves to perfect forecasts, which will result in over-estimation of the true best performance, but represents the best *possible* outcome.

3.2 Simulating a multi-purpose university campus building

For testing the methodology proposed in Figure 3.1 we developed an EnergyPlus model of a multi-purpose campus building housing both office workers, lecture halls and breakout spaces for collaborative work. We patterned our building model on the recently delivered 'Woodside Building for Technology and Design' on Monash' Clayton campus. This building has several properties that make it particularly suitable for this study: it has multiple thermal zones across several open and confined spaces, it houses both research labs and student lecture halls, and it has a high thermal capacitance owing to its Passivhaus design (Grimshaw, 2020).

3.2.1 EnergyPlus model design parameters and floorplan

The project employed Sketchup and OpenStudio for constructing the EnergyPlus model, utilising the real-world geometric dimensions (120 x 42 x 25 metres) and fundamental material data. Compliance with AIRAH Standard 189.1-2009, the Building Code of Australia (NCC Volume 1), Australian Standard 1668.2, and the AIRAH Technical Handbook was maintained to establish parameters for both the exterior and interior building materials, the type of building, default electrical equipment, occupancy, and predefined schedules for each thermal zone.

For this project, three EnergyPlus simulation models were developed, each progressively increasing the number of thermal zones to more accurately represent the complexity of the thermal dynamics and real-time HVAC control operations. Taking the 35 thermal zones model as an example, the building is segmented into five floors. Each floor is partitioned into a primary space flanked by six smaller, interconnected spaces, as shown in Figure 3.2.

While the true architectural complexity of the real-world building is more intricate, this project employs the building's total annual energy consumption data to ensure the approximation matches in terms of the simulated energy consumption, the number of thermal zones, HVAC configurations, and building material configuration. The model thus serves as a close representation of the real building's thermal behaviour and energy dynamics.

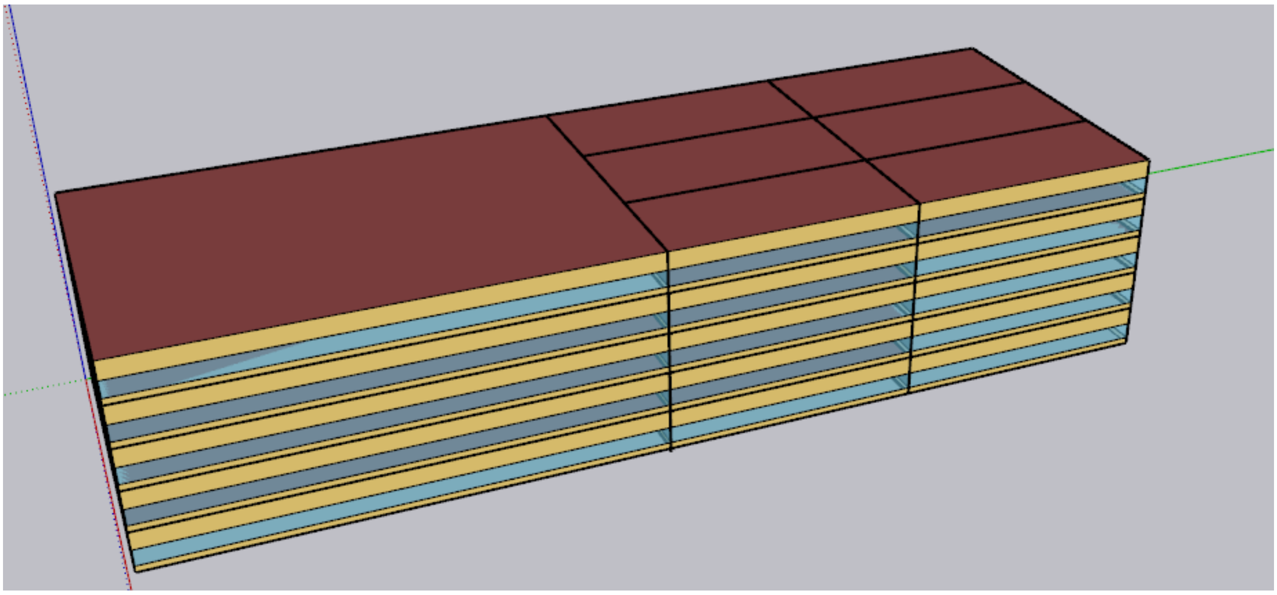


Figure 3.2: Most granular version of the EnergyPlus simulation model, showing the subdivision of each floor into 7 zones. One large open space (left) and 6 equally-sized zones (right), of which one zone is entirely in the interior.

3.2.2 Simulating the HVAC System

The HVAC system within the building simulation incorporates a comprehensive climate control solution tailored for both efficiency and comfort. The system features packaged rooftop air conditioners, designed for ease of installation and maintenance, providing reliable and centralised cooling throughout the building. Additionally, the simulation includes a variable air volume (VAV) system with reheat capabilities, ensuring precise temperature control across different zones and the ability to adjust airflow based on occupancy and thermal demand, thereby reducing energy consumption. Service hot water systems are integrated into the design to meet the building's hot water needs for various uses such as restrooms and kitchen facilities. This multi-faceted approach to HVAC ensures that the building maintains optimal indoor air quality and comfort while striving for energy efficiency.

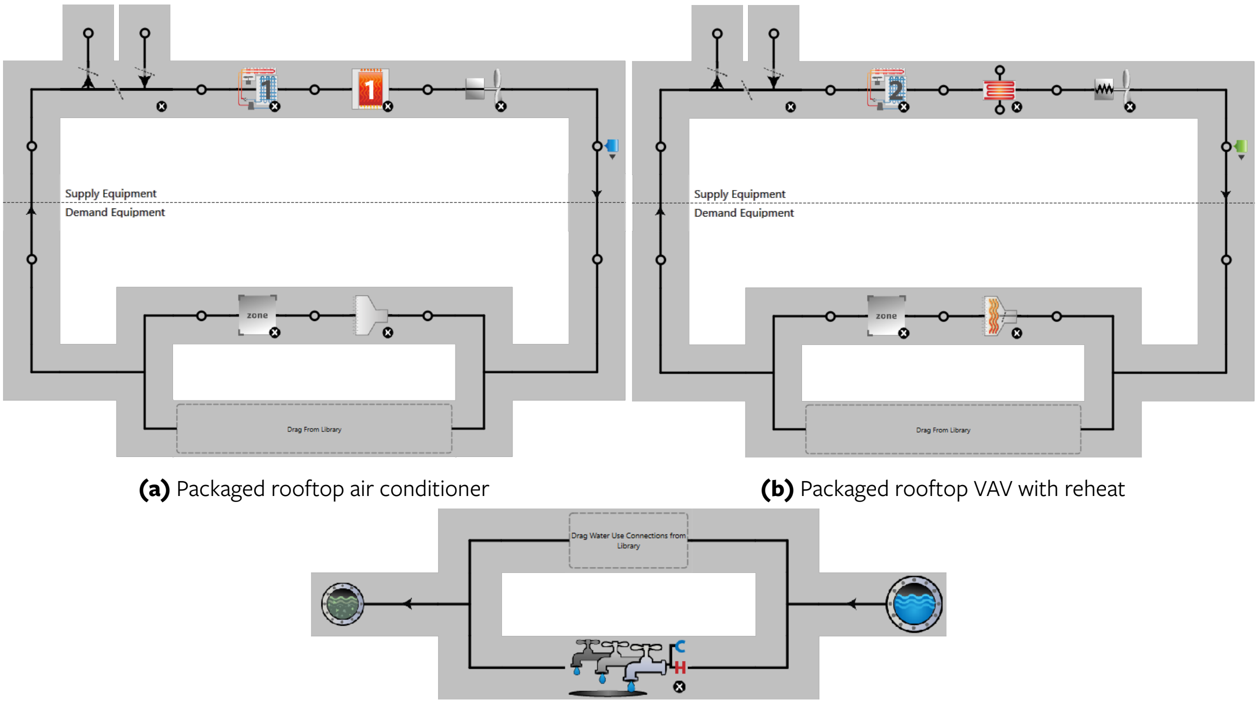
To streamline the thermal simulation process within the EnergyPlus model and place greater emphasis on the application of deep learning and optimisation methods for HVAC control, this project consolidates all the building's thermal zones into a unified HVAC system as detailed in Figure 3.3

3.2.3 Simulating the Occupancy Schedule

An accurate representation of occupancy patterns is crucial for predicting building energy consumption in EnergyPlus simulations. Occupancy directly impacts heating/cooling loads through heat gains from occupants as well as equipment and lighting usage schedules tied to occupancy.

University buildings often exhibit highly variable and intricate occupancy schedules, necessitating the consideration of cyclic academic calendars, seasonal variations, weekday and weekend differences, and other pertinent factors. To accurately capture these complexities within the EnergyPlus modelling framework, this study employed a stochastic approach to generate occupancy data profiles grounded in existing spatial-temporal occupancy pattern studies (Ju et al., 2023).

Specifically, the occupancy modelling process accounted for the dynamic nature of university facilities by incorporating the following elements: cyclic academic calendars to reflect higher occupancy during instructional periods and lower occupancy during breaks, seasonal fluctuations to capture variations in occupancy patterns



(a) Packaged rooftop air conditioner **(b)** Packaged rooftop VAV with reheat

(c) Service Hot Water

Figure 3.3: The EnergyPlus components used in the simulated building's HVAC system.

across different times of the year, and distinctions between weekday and weekend occupancy levels to account for the diverse activities and schedules inherent to university campuses.

By integrating these factors, the generated occupancy data aimed to provide a comprehensive and realistic representation of the spatio-temporal dynamics governing occupancy within the context of a university setting. This approach facilitated a more accurate assessment of the energy consumption profiles and HVAC system requirements within the EnergyPlus simulations, thereby enhancing the reliability and applicability of the modelling outcomes.

3.3 Optimisation algorithms for flexible building control

Optimisation refers to the process of finding an assignment of values to decision variables x that maximises (or minimises) the objective function $f(x)$, possibly subject to some constraints on the kind of values that x are allowed to take. Informally stated, the optimisation problem for flexible building control can be stated as follows:

$$\begin{aligned} \text{minimise } &\langle \text{energy consumption during flexibility request} \rangle \\ \text{subject to } &\langle \text{occupant comfort constraints} \rangle \\ &\langle \text{plant operational constraints} \rangle \end{aligned} \tag{3.1}$$

In this model sketch, occupant comfort constraints relate to maintaining comfortable indoor temperature and humidity in occupied zones of the building, while plant operational constraints refer to any restrictions that might apply to the control signal (for example, to avoid excessive wear on the HVAC plant due to frequent switching).

There are multiple ways to implement such an optimisation task; the choice of approach depends on the runtime and accuracy requirements. Exhaustive search methods can find a solution that is proven globally optimal, at the cost of imposing some mandatory structure on the kind of constraints that can be encoded, while trial-based search methods are open-ended in the kinds of functions they can optimise over, at the cost of being unable to provide accuracy estimates or optimality guarantees. In this work, we focus on the exhaustive search methods, because we want to measure the accuracy of the prediction models, a measure which would be affected by finding sub-optimal solutions due to the optimisation method.

We use the MiniZinc language and compiler to rapidly prototype the constraint optimisation programs. MiniZinc is developed at Monash as a domain-specific language that can transcribe an optimisation program specified at a high level of abstraction into a low-level formulation that can be interpreted by one of the many commercial and open-source solvers available. Although MiniZinc can compile to different solver paradigms (i.e., Constraint Programming, Mixed-Integer Programming, and Satisfiability solvers), we will explicitly target Mixed-Integer Programming solvers because we will need to deal with floating-point quantities (i.e., temperature) which are generally not handled efficiently in the other solver types.

Several recent works have explored the inclusion of neural networks into Mixed-Integer Programming (MIP) models, with Anderson et al. (2020) giving a mathematical treatment of an efficient formalism to capture the operations of a ReLU-based neural network in a MIP.

4 Simulation experiments

Computer simulation models for heating and cooling loads have been around for a long time, with one of the earliest proposed by Mortensen and Haggerty (1988). This simple model mirrors an electric circuit with a single resistance, capacitor, and a current source. Figure 4.1 demonstrates the response of an example instance of such a thermal model. The thermal response is an exponential decay across the full range of temperature, however, it is approximately linear in the thermal comfort range around the usual set-point $\theta_{\text{set}} \approx 21$°C. This comfort range is annotated by a dead-band around the set-point ranging from θ_{Δ^-} to θ_{Δ^+}. Temperatures inside this dead-band range are assumed to be 'sufficiently comfortable' for the occupant of the zone (or otherwise acceptable for the thermal demands of the zone, in case the model is for a different kind of zone like a refrigerator).

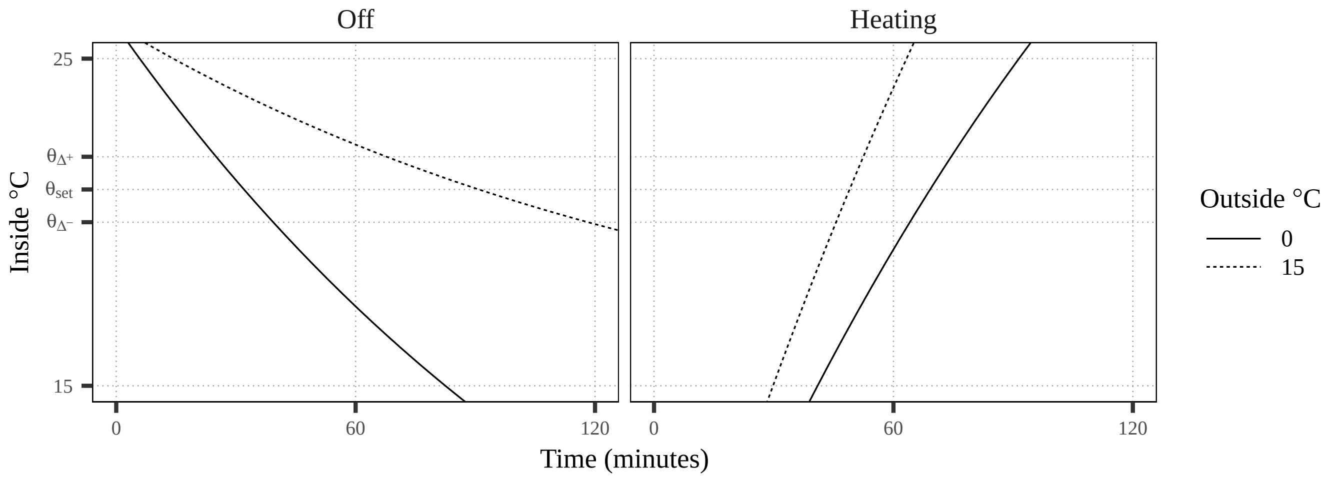


Figure 4.1: Thermal response curves of the simplest thermal simulation model under cooling ('off') and heating ('on') operation, for different external conditions.

A simple flip-flop hysteresis controller for such a dead-band system will keep the temperature within the indicated bounds at all times, while allowing for some modicum of operator flexibility. Figure 4.2 (left) shows a simulation of an aggregate of 200 thermal loads with small random variation in thermal parameters, operating under hysteresis control. The first 10 loads are shown in light grey dashed lines, demonstrating how the direction of temperature change inverts at the dead-band edges. At $t = 400$, the flexibility of the array is called upon, by manually overriding all the hysteresis controllers to the 'off' or 'cooling' setting, independently of their current mode or temperature. As a result, the load demand of the aggregate immediately drops to 0, however, it rebounds relatively quickly as the devices reach the lower dead-band edge.

By contrast, Figure 4.2 (right) demonstrates an optimal coordinated flexibility response. Under this condition, the thermal zones are optimised for *minimum* energy usage at all times, but with an additional constraint to ensure that every device is at maximum θ_{Δ^+} at $t = 400$. As a result of this control operation, the demand for power rapidly ramps up to maximum at the time leading up to the demand-response event. However, once the event hits, demand can stay at 0 for over half an hour without breaching any of the devices' comfort bounds. Note that both control mechanisms guarantee the comfort limits at all times.

Hypothesis 1. Optimal (minimum) energy operation of thermal zones and optimal (maximum) flexibility operation of thermal zones are *orthogonal* concerns that can *both* be targeted at the same time.

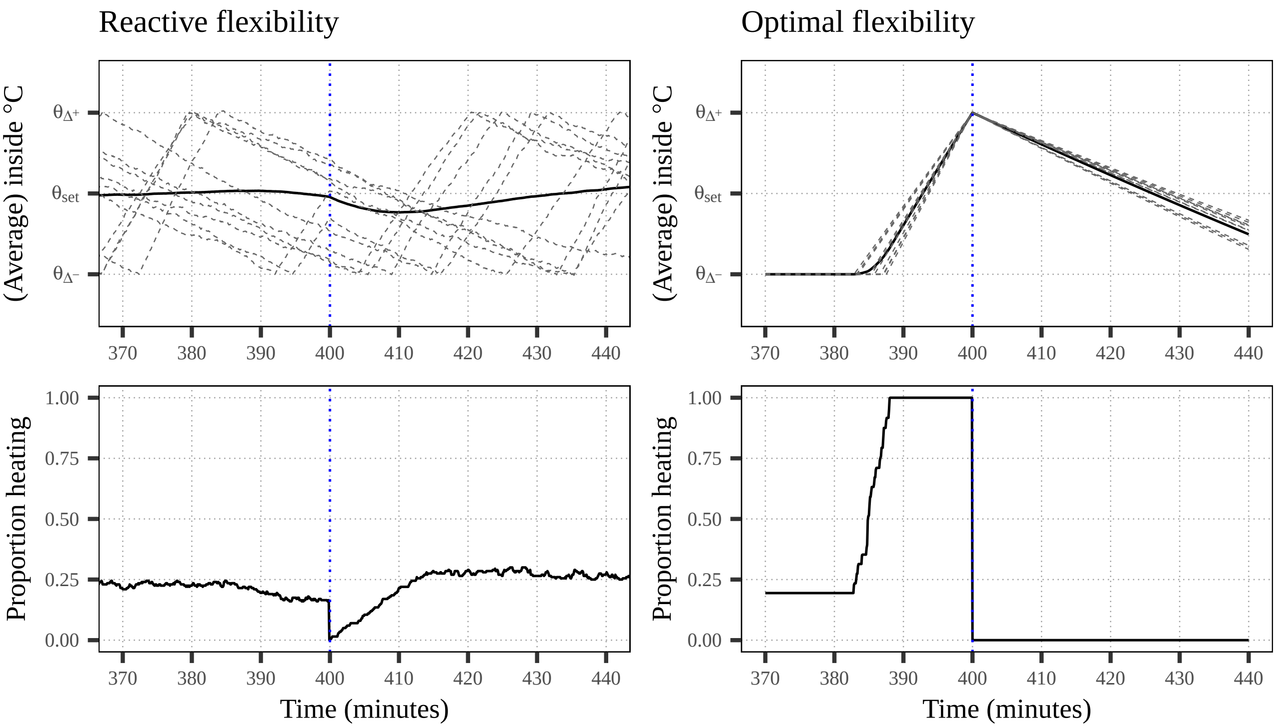


Figure 4.2: Flexibility response of an aggregate of 200 buildings under reactive control (a one-time deactivation of heat-pumps), versus a planned optimal trajectory for the same trajectory.

Hypothesis 2. Controlling for optimal flexibility requires proactive, planning control over a future horizon, involving concerns of *forecasting* and predictive *what-if models*.

This optimal control methodology can equally be applied to minimise the carbon intensity of the energy consumed, if a forecast of carbon intensity is available. Figure 4.3 demonstrates this principle with the same aggregate of thermal loads, but now optimising the number of devices on ($p_{t,i} = 1$), times the carbon intensity C_t at time t, across the entire planning horizon h:

$$\begin{aligned} \text{minimise} \; & \sum_{t=1}^{h} C_t \sum_{i=1}^{n} p_{t,i} \\ \text{subject to} \; & \theta_{t,i} = f_i(\theta_{t-1,i}, p_{t,i}) && \forall t, i \\ & \theta_{\Delta^-} \leq \theta_{t,i} \leq \theta_{\Delta^+} && \forall t, i \\ & 0 \leq p_{t,i} \leq 1 && \forall t, i \end{aligned} \tag{4.1}$$

Such an optimisation model is readily solvable if the transfer function of zone i, f_i can be encoded linearly (e.g., multi-linear regression model, or neural network with ReLU activation functions). In the case of these simple thermal models which can be encoded *directly*, optimising such a model takes less than a second on a modern desktop PC, for a control horizon several hours out. As Table 4.1 shows, compared to optimising for only energy consumption ($\sum_{t=1}^{h}\sum_{i=1}^{n} p_{t,i}$), optimising for carbon intensity reduces the carbon impact by approximately 11%, at the cost of 2.4% more power (for this particular instance, on a per-unit basis because the power consumption of the heaters is not dimensioned).

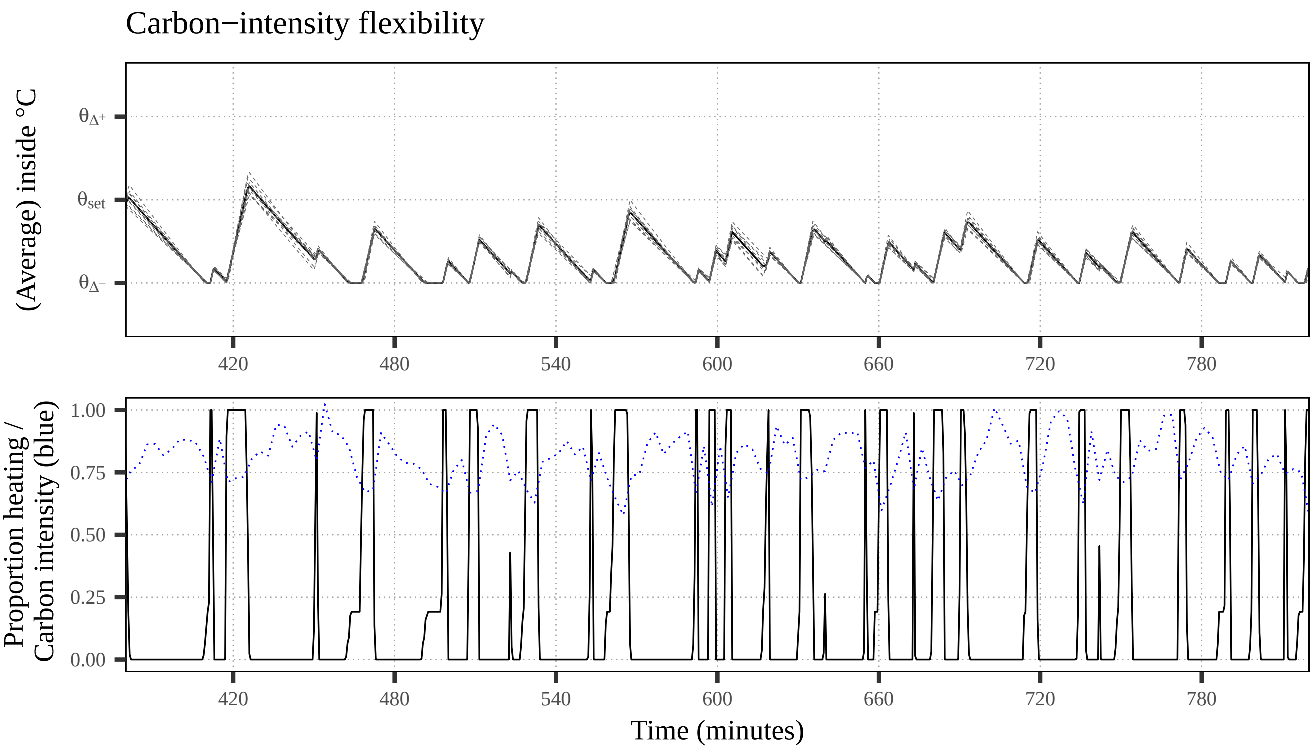


Figure 4.3: Optimal flexibility response of an aggregate of thermal loads against a carbon intensity signal.

Table 4.1: Effect of optimising for minimum grid carbon emissions versus minimum building energy consumption.

	Solution metric:	
Objective:	Total carbon (p.u.)	Total energy (p.u.)
Minimise carbon	2637.4	3840.6
Minimise energy	2966.5	3753.9

5 Discussion—Challenges and Opportunities

Buildings have a potential role to play in our future electricity grid, if a sufficient volume of HVAC load can be converted into flexible demand. This project investigated and demonstrated the software and data side of the methodology required to enable AI-ready flexible buildings. Nevertheless, many challenges remain before widespread real-world adoption of the technology is possible:

- Not every building is suitable for this methodology. Only buildings with sufficient thermal mass and sensor instrumentation are suitable candidates.

  Recommendation: Building energy efficiency comes before energy flexibility. Existing building stock should be improved and upgraded, including enhancing their sensor coverage, and long-term data collection should be established where possible.

- Application of this methodology requires a deliberate dedication of building managers to up-front data collection. However, it may only be cost-effective to apply this methodology once a building is being refurbished for energy efficiency. After refurbishing, its thermal dynamics will have changed, and historic data will not be relevant any more.

  Recommendation: Future work should look into algorithms to safely transfer simulation-trained thermal models to real-world buildings, together with rapid model adaption mechanisms.

- Current methodology assumes bespoke thermal models and optimisation formulations will be created for each building. These must be aligned to the available sensor data and available actuators. Wide adoption of this methodology can only be achieved if it can be simplified into a product.

  Recommendation: Future work should look into automatic model extraction from schematics, for example by making use of building ontology to map concepts in BAMS to the methodology.

By fitting a machine learning model of a building that captures enough of the thermal dynamics, we can apply optimisation algorithms to improve the load profile of a building to target a control signal such as grid carbon intensity. We have demonstrated this methodology on a high-accuracy simulation model running in EnergyPlus, proving the concept is possible. With sufficient forecast information and high thermal model accuracy, the carbon intensity of the building's heating and cooling requirements may be reduced by up to 11%. However, real-world validation experiments are necessary to validate the findings of this study under more realistic conditions such as uncertainty over the forecast data and sensor drift, to understand how much of the ideal carbon reduction can be achieved in practice.

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