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RESEARCH

Energy efficiency and decarbonisation pathways for Australian public hospitals

Jacob Fry[1,2] · Angie Bone[2] · Matthew Hoogland[3] · Peter-Paul Pichler[4] · Tristan Webber[5] · Hiroyuki Yokomizo[1]

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Abstract

Hospitals are significant contributors to the carbon footprint of healthcare. Hospitals can be particularly energy-intensive as these facilities operate continuously, have strict space condition requirements and contain unique energy loads. Energy efficiency is a low-cost decarbonisation pathway for hospitals and offers co-benefits such as improved reliability and resilience, however the magnitude of this opportunity can be difficult to quantify. In this study, the energy efficiency potential of Australian public hospitals in Victoria, Queensland and South Australia is estimated using the NABERS Energy for public hospitals dataset. NABERS is an energy performance indicator that measures operational energy use in hospitals, and other large building types, and encodes information about the energy efficiency potential. In this study, the application of energy efficiency, electrification and grid decarbonisation is modelled from 2024 to 2040. We estimate that by 2040, energy efficiency has the potential to deliver a 15–20% reduction in energy consumption to the existing hospital stock. The combination of efficiency and electrification has the potential to reduce the energy intensity of hospital operations by about 40%. By 2040, emissions are projected to fall by 80% using the combination of decarbonisation strategies. The implementation of decarbonisation strategies is modelled probabilistically and a Monte Carlo approach used to derive uncertainty estimates for these predictions. This analysis assumes that hospital heating and cooling systems have the largest potential for efficiency savings. Quantifying the contribution of these healthcare decarbonisation strategies can assist policymakers in allocating appropriate resources for implementing efficiency and other decarbonisation measures.

Keywords Industrial ecology · Resource efficiency · Decarbonisation · Hospitals · Healthcare

1 Introduction

Healthcare contributes 4–5% of global greenhouse gas (GHG) emissions (Lenzen et al., 2020; Pichler et al., 2019). Decarbonising health care requires a number of strategies at different scales. At a societal level, this includes reducing the overall demand for health services by improving the social determinants of health and strengthening other disease prevention strategies (MacNeill et al., 2021). Within health policy, effective decarbonisation requires ensuring appropriate care while avoiding unnecessary diagnostics and treatments (Brownlee et al., 2017). At the facility level the focus lies on optimising the environmental efficiency of care delivery. Besides reducing upstream emissions through green procurement (Mortimer & Pencheon, 2022) this requires reducing emissions from direct energy use by improving energy efficiency (NHS, 2023) and transitioning to renewable energy sources for the remaining energy demand.

Studies have identified hospitals as a significant contributor to total healthcare GHG emissions, for example (Pichler et al., 2019) attribute ~ 15–50% of healthcare emissions to hospitals internationally and Malik et al. (2018) found public and private hospitals contribute 34% and 10% respectively to total healthcare emissions in Australia. Reducing hospitals' contribution to fossil-fuel related air pollution also contributes to reducing the population health burden and consequent health service demand (Eckelman et al., 2020).

✉ Jacob Fry
fry.jacob@nies.go.jp

1 National Institute for Environmental Studies, Tsukuba, Japan

2 Monash Sustainable Development Institute, Melbourne, Australia

3 Hoogland Consult Pty Ltd, Darwin, Australia

4 Potsdam Institute for Climate Impact Research, Member of the Leibniz Association, Potsdam, Germany

5 DeltaQ Pty Ltd, Canberra, Australia

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Globally, 26% of energy-related emissions are attributed to building operations (IEA, 2023). Hospitals have a somewhat unique demand for energy services and are energy intensive compared to other buildings of similar size (García-Sanz-Calcedo et al., 2019). Hospitals often operate continuously and may also have strict space conditioning requirements compared to other buildings, for example intensive care units (ICUs) and operating theatres, which have tight bands of acceptable temperature and humidity (Sharp, 2020). Infection control strategies can also increase energy consumption in ventilation systems. Hospitals may also contain unique energy load types, for example kitchens, steam production for laundries and autoclaves, refrigeration for pharmaceuticals and morgues, and energy intensive equipment such as Magnetic Resonance Imaging machines (Heye et al., 2020).

Several strategies, or combinations thereof, can be applied to decarbonize the direct energy use of hospitals. One strategy is for hospitals to switch to renewable electricity supply, either through on-site generation or through procurement contracts (Burch et al., 2021). Due to the energy intensity of hospitals, it's unlikely that on-site generation will be sufficient to provide 100% of the hospital's energy requirements, for example PV generation is constrained by available space for PV panels (Coble-Neal & Ablaza, 2022). One mechanism for obtaining more renewable energy is through Guarantees of Origin and Power Purchase Agreements (PPAs), which involve an agreement between a renewable generator (such as a large-scale wind or solar farm) and an energy consumer such as a hospital or state health department (Briggs et al., 2019; DCCEEW, 2025). These agreements are becoming more popular in Australia, for example in Victoria hospitals will purchase 100% renewable electricity by 2025 (Vhba, 2023b). However, concerns remain regarding the effectiveness of PPAs in driving additional renewable capacity and therefore their role in emissions accounts (Bjørn et al., 2022; Brander et al., 2018).

Another method of decarbonisation is electrification, where natural gas and liquid petroleum gas (LPG) are substituted for electric services, such as heat pumps (ASBEC, 2022). Electrification complements the decarbonisation of the electricity grid, since this fuel switching allows hospitals to leverage the declining grid emissions intensity to reduce energy related emissions. Sustainable design and construction of buildings can also be implemented using principles from standards such as GreenStar (Australia), LEED (USA) and BREEAM (UK).

Finally, improving energy efficiency is a key strategy for the decarbonisation of health care (DoHAC, 2023; NHS, 2020) as it reduces the energy required for health care provision. By some estimates, the global energy efficiency potential is under-appreciated, ubiquitous and a low-cost decarbonisation pathway (Cullen et al., 2011; Lovins, 2018). An energy efficiency program in Australia, which targeted the largest energy consumers in the economy, discovered energy savings amounting to 1.5% of national emissions, at a negative abatement cost (\$/tCO_2-e) (Baldwin & Raupach, 2014). The National Australian Built Environment Rating Scheme (NABERS) has been very successful at identifying and driving energy savings in commercial buildings (i.e. offices and shopping centres). Precious (2022) found that participation in the NABERS for offices program was associated with an average 42% reduction in emissions intensity (MJ/m^2) over 14 years. If applied to healthcare facilities, such energy efficiency projects can deliver a number of co-benefits, such as improved resilience to extreme temperatures through increased reliability and reduced demand on energy storage in the event of blackouts (Franconi et al., 2023). Also, reducing energy costs through efficiency can allow financial savings to be redirected to delivering healthcare services (Pearson, 2012).

Approximately 50–65% of hospital operational energy use can be attributed to Heating, Ventilation, and Air Conditioning (HVAC) systems (Aunión-Villa et al., 2021; Kolokotsa et al., 2012). The remaining energy loads include lighting, medical equipment and domestic hot water (e.g. hot water for cooking and cleaning). Due to its dominance on the energy profile, HVAC is a major focus of energy efficiency opportunity in healthcare buildings. Optimising the energy performance of HVAC systems has been well-practised in Australia across various industries and building types, particularly in sectors with strong take-up of NABERS ratings and thus an associated market driver for NABERS rating improvement, such as commercial office towers and retail shopping centres. While unique challenges apply to healthcare buildings, such as 24/7 operational constraints and infection control requirements, energy efficiency strategies including controls optimisation, retrofit and refurbishment of HVAC systems remain significant opportunities.

Efficiency strategies for operational energy consumption can be characterised into (i) equipment upgrades, (ii) enhanced maintenance, (iii) optimal control and tuning and (iv) retrofit upgrades. Building services equipment, such as large chillers and boilers, can be upgraded for more efficient performance (Ruparathna et al., 2016). Enhanced maintenance programs may utilise digital monitoring to quickly identify and resolve failures such as valves and louvres failing to close properly (Daly et al., 2023). Where feasible, retro-fitting *economy cycle* capability allows air-conditioning systems to take advantage of free cooling from ambient air in suitable conditions. Other strategies include upgrading the building fabric to reduce heat transfer (e.g. with insulation) and replacing gas-fired boilers with electric heat pumps (Foo et al., 2022b).

HVAC systems are complicated and comprise many sensors, valves, actuators and large machinery such as pumps, fans, chillers and boilers. To manage this complexity, large buildings are controlled by automated building management systems. These controls must be properly commissioned and tuned to achieve the design performance (Brown et al., 2006). Over time, building performance can decay as control and sensing hardware deteriorates, therefore performance monitoring is an important tool for achieving and maintaining efficient buildings (Katipamula et al., 2012). Automated fault detection and diagnosis (FDD) tools can be employed to discover performance issues quickly (Wang et al., 2013).

NABERS is an Australian government program that provides a framework for assessing building performance. The scheme provides tools for specific building types, such as commercial buildings (i.e. offices), retail buildings (i.e. shopping centers), data centers, warehouses and public hospitals (NABERS, 2022a), and rating types, such as energy, water and waste. NABERS assesses a building based on operational performance, that is for an energy rating, the energy consumed and emissions produced, while the building is in operation, rather than design characteristics. Operational energy use is important since even newly-constructed buildings may not perform as well as their intended design (Foo et al., 2022a) and older buildings may have many opportunities to realise greater efficiency (CEFC, 2020). The NABERS program is considered an exemplar in energy efficiency policy-making globally (Mallaburn et al., 2021) and has since launched in the United Kingdom.

Under the NABERS scheme, for energy ratings, buildings are benchmarked against the average or median emissions intensity of similar buildings. Building performance is normalised against variables such as size, climate zone, occupancy and function. Hospital NABERS Energy ratings are further normalised against facility type, patient separations (i.e. an ‘episode of care’ for a patient), occupied bed days, aged-care bed days, energy consumption by fuel and region (climate zone) (NABERS, 2022b). This normalisation allows the performance of buildings with different characteristics to be compared to, for example, buildings of different size. The intensity metrics are binned and transformed into a star rating scale between 1 and 6 stars (Bannister et al., 2016) so that a star rating for a NABERS Energy rating is directly connected to normalised emissions intensity. A maximum rating of 6 stars indicates best practice (Precious, 2022) and therefore the rating encodes information about the ability of a building to improve and the latent energy efficiency potential.

In this study, the NABERS for public hospitals dataset is used to model a number of decarbonisation pathways for hospitals: accelerated efficiency, grid decarbonisation and electrification. The NABERS dataset, and therefore this study, covers hospitals in three Australian states: Victoria (Vic), Queensland (Qld) and South Australia (SA). A probabilistic approach is employed to project hospital ratings into the future. NABERS star ratings for each hospital are modelled as sequences that evolve probabilistically over time. Then, machine learning techniques, trained on historical data, are employed to approximate the NABERS algorithms and allow mapping between star rating changes and emissions.

The public hospital dataset used in this study is described in Sect. 2.1. The system boundary of this study is defined in Sect. 2.2. The probabilistic approach to predicting NABERS rating transitions is described in Sect. 2.3. Predictors of energy consumption in hospitals are presented in Sect. 3.1. In Sect. 3.2, decarbonisation pathways are modelled from 2024 to 2040 for each decarbonisation scenario, along with uncertainty estimates. Projected changes to NABERS ratings in the hospital stock are shown in Sect. 3.3. The limitations, future work and policy implications are discussed in Sect. 4. In Sect. 5, the broader implications of this work to healthcare and planetary health are discussed.

2 Method

2.1 Dataset

Hospital NABERS rating data were obtained from the health departments in Victoria (Vic), Queensland (Qld) and South Australia (SA). This dataset contained annual NABERS ratings data for 357 hospitals for the years 2016–2023. Together, the dataset contains 1,714 individual ratings, with each hospital conducting a median of 5 ratings and a maximum of 8 ratings. The ratings for each hospital form a sequence of varying length, in some cases discontinuous with each hospital performing a different number of ratings during 2016–2023. The basis of NABERS ratings across the study period (2016–2023) was constant, so that changes to ratings reflect changes in actual performance and not the underlying rating benchmarks. This dataset contains public hospitals only and is prepared and maintained by individual state and territory health departments in conjunction with the NABERS program (NSW Department of Planning, Industry and Environment). The steps taken for data preparation are described in Supplementary Information SI1-1.

The history of star ratings for each hospital forms a sequence of discrete ratings with values between 0 and 6 in 0.5 star increments i.e. $s \in \{0, 0.5, .., 5.5, 6.0\}$. Our goal is to cast the hospital ratings sequences into the future under a range of scenarios. Unfortunately, the hospitals dataset does not contain site-specific such as which services use energy, mechanical equipment configurations, operations patterns or maintenance schedules.

2.2 System boundary

This study focuses on operational (direct) energy consumption in hospitals, primarily energy consumed by building

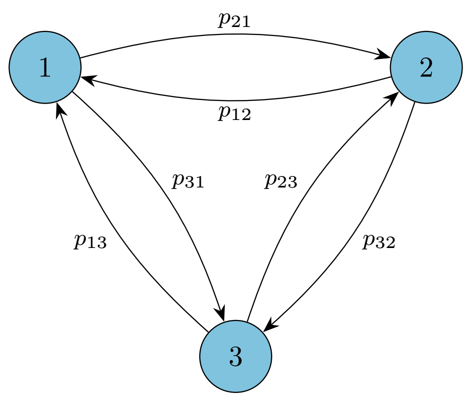

Fig. 1 A simple 3-state system where the probability of transitioning from state $j \rightarrow i$ is given by p_{ij}

services such as HVAC systems. In recent years, healthcare facilities have been outsourcing some energy services, such as laundry, to external organisations. In principle, the NABERS rules require that hospitals disclose whether laundry services are conducted on-site (NABERS, 2022b), however this information was not available in the dataset and therefore not considered in this study. Data on patient transport and electric vehicle energy use are also not part of NABERS and therefore also not included in this study.

2.3 Probabilistic modelling approach

The lack of site-specific information makes it difficult to model the change in ratings deterministically, therefore a probabilistic modelling approach is taken to project hospital decarbonisation futures. Firstly, hospital NABERS ratings sequences are modelled as Markov chains (Sect. 2.4). Then, hospital ratings are evolved forward in time by first estimating transition probabilities empirically and then randomly sampling from these probabilities at each time step (Sect. 2.5). Changes to ratings are then mapped to changes in fuel consumption and emissions (Sect. 2.6). Several decarbonisation scenarios are then modelled using a Monte Carlo simulation to account for uncertainty and scenario interactions (Sect. 2.7) Fig. 1.

2.4 Markov chains

Markov chains are an approach to modelling transitions between discrete states probabilistically (Albert & Hu, 2019). Markov chains have been used to model sequences in diverse applications such as DNA sequences (Avery & Henderson, 1999), clinical trial outcomes (Hopper & Young, 1988) and web search (Hilgers et al., 2006). For a simple Markov processes, the probability of future states depends only on the current state and not on the sequence of events that preceded it: $P(x_{t+1}|x_t, x_{t-1}, x_{t-2}, ...) = P(x_{t+1}|x_t)$ (Cox, 2017). This means that the path taken to reach a particular state does not influence the probability of moving to another state. The transition between the discrete states $j \rightarrow i$ or $x_t = j$ to $x_{t+1} = i$ can be described by the transition probability p_{ij}.

The transition probabilities can be modelled as a function of a feature vector $\mathbf{x}_t = [x_1, x_2, ..., x_n]$, rather than simply the previous state (Boyle, 1976). This feature vector $\mathbf{x}_t$ may contain both cardinal and ordinal variables. Higher order Markov states can also be defined which depend on some number of preceding states, therefore 'lag' terms can be included in $\mathbf{x}_t$ e.g. $t-1, t-2$ etc.

2.5 Time evolution

In general, Markov chains can be evolved forward in time by randomly sampling from the transition probabilities at each time step. To do this, the transition probabilities should first be derived or estimated, which can be achieved using, for example, logistic regression models (Barratt & Boyd, 2023) or k-nearest neighbours (kNN) approaches (Wang et al., 2020).

In this study, the transition probabilities are estimated using a k-nearest neighbours (kNN) estimator, which is implemented due to both the algorithm's simplicity and transparency (Cover & Hart, 1967). kNN models are sensitive to a number of tuning parameters, such as the number of neighbours k and the similarity metric, therefore a grid-search was conducted to determine the combination of tuning parameters that yield best model performance. To mitigate the risk of overfitting, the model was trained using a cross-validation approach with 15% of the raw data samples withheld from model training to test the out-of-sample prediction error (Yates et al., 2023). Model performance was evaluated as minimising the root-mean-square error (RMSE) (see Supplementary Information SI1-2 for more detail).

At time t, the hospital *state* can be represented by the feature vector $\mathbf{x}_t$, which includes the star rating and other parameters, as shown in Table 1. Here the hospital state at time t can be defined broadly to contain enough information to predict the next state, including lag terms at earlier time steps (Carroll, 2009). For a given feature vector $\mathbf{x}_t$, the kNN method finds records with 'similar' states. Similarity is measured using the Euclidean vector distance metric between the target feature vector and all records in the training data. The k closest records are then aggregated into an estimate of the conditional probability $p_{ij} = P(x_{t+1} = i|x_t = j) = \frac{m}{k}$, where state i occurs m times among the k neighbours (Fu et al., 2018; Zhou, 2004). For example, if among the 10 nearest neighbours, 3 transition from state j to i (e.g. from 3.0 stars to 4.0 stars), the estimated transition probability is 0.3. Therefore, the transition probabilities are derived from the pool of hospitals in similar states in the raw data, and the

Table 1 Parameters defining the state at time t

Category	Parameter	Description
Operational	occupied_bed_days	Occupied bed days at time t
	separations	Separations at time t (separation refers to a patient 'episode of care')
	aged_care_bed_days	Aged care bed days at time t
	occupied_bed_days_gradient	Occupied bed days gradient between t and $t-1$
	separations_gradient	Separations gradient between t and $t-1$
	aged_care_bed_days_gradient	Aged care bed days gradient between t and $t-1$
Energy	electricity	Electricity consumption at time t
	gas	Natural gas consumption at time t
	lpg	Liquified petroleum gas consumption at time t
	diesel	Diesel consumption at time t
	electricity_gradient	Electricity consumption gradient between t and $t-1$
	gas_gradient	Natural gas consumption gradient between t and $t-1$
	lpg_gradient	LPG consumption gradient between t and $t-1$
	diesel_gradient	Diesel consumption gradient between t and $t-1$
Climate	tdd	Total Degree Days (CDD+HDD)
	cdd	Cooling Degree Days
	hdd	Heating Degree Days
Cohort	peer-group-category-code	Peer group category e.g. acute, rehabilitation etc
	remoteness-category-code	Remoteness code e.g. Capital city, outer regional etc
	remoteness-simple-category-code	Simple remoteness code i.e. urban or rural
	climate-zone-category-code	Climate zone e.g. warm temperate, cool temperate etc
Timeseries	stars	Star rating at time t
	stars-1	Star rating at time $t-1$
	stars_gradient	Star rating gradient between t and $t-1$
	year_diff	Years between samples t and $t-1$

current rating is updated based on the past performance of the population.

2.6 Mapping from star rating changes to fuel consumption

As the star rating for each hospital is projected forward in time, the fuel consumption also evolves. The computation of NABERS ratings s can be represented by the function $s = h(\mathbf{y}, \mathbf{z})$, where $\mathbf{y}$ contains hospital operational, climate and cohort parameters, and $\mathbf{z}$ is a vector of fuel consumption i.e electricity [kWh], natural gas [GJ], LPG [L], diesel [L]. Vectors $\mathbf{y}$ and $\mathbf{z}$ are both subsets of the feature vector $\mathbf{x}$ so that $\mathbf{y} \subseteq \mathbf{x}$, $\mathbf{z} \subseteq \mathbf{x}$. The function h is non-linear and not openly published by NABERS; the dataset received by this study contained precomputed star ratings s. To map backwards from star ratings to emissions, a map g is required that computes the updated emissions so that $e_{t+1} = g(\mathbf{y}_t, e_t, s_t, s_{t+1})$. Hospital operating parameters are assumed to remain are unchanged so that $\mathbf{y}_{t+1} = \mathbf{y}_t$.

Since NABERS does not publish the equations underlying the rating scheme, the map g was approximated by training a random forest regression model on the historical data. Random forest models consist of ensembles of randomised decision trees, which produce predictions by aggregating the predictions of individual trees (Biau & Scornet, 2016; Breiman, 2001). Random Forests have been applied to energy systems in buildings, for example modelling building energy consumption (Wang et al., 2018) and solar thermal generation (Ahmad et al., 2018). This model was also trained using a cross-validation approach with 15% of the raw data samples withheld from model training to test the out-of-sample prediction error. Model tuning parameters were determined by a grid-search which selects the combination of parameters yielding the best model performance. The 'best' model was selected by minimising the root-mean-square error (RMSE) (see Supplementary Information SI1-3 for more detail).

The regression model estimates the updated emissions resulting from a change in the star rating. The ratio of initial emissions e_t to updated emissions e_{t+1} can be expressed as the change in the emissions by fuel type: $e_t/e_{t+1} =$

$\sum_f w_{f,t} / \sum_f w_{f,t+1}$, where $\mathbf{w}$ is a vector of emissions by fuel type f and can be decomposed into $\mathbf{w} = \mathbf{z} \circ \mathbf{d}$, the element-wise multiplication of the fuel consumption $\mathbf{z}$ and emissions intensity by fuel $\mathbf{d}$. Then, rearranging: $\mathbf{z}_{t+1} = [(e_{t+1}/e_t)\mathbf{w}_t]/\mathbf{d}$, so that fuel consumption is updated in proportion to existing fuel shares and the change in total emissions.

2.7 Simulating future scenarios

Emissions and energy consumption are simulated for each hospital ($N = 357$) over each year t (2024–2040). This is repeated for each simulation run ($N = 500$). Each simulation run is probabilistic, since rating sequences evolve according to transition probabilities, therefore a Monte Carlo method is used to estimate the uncertainty in the final results by evaluating many simulation runs together (Tseng et al., 2020).

```
for each simulation run do
    for each hospital do
        for each year in timeseries do
            Derive the next star rating: s_t → s_{t+1} using
            p(x_{t+1} = i | x_t = j)
            Update emissions at next time step:
            e_{t+1} = g(y_t, e_t, s_t, s_{t+1})
            Update fuel consumption: z_{t+1} = [(e_{t+1}/e_t) w_t]/d
```

Algorithm 1: Pseudocode for running simulations of hospital energy consumption and emissions.

A number of future scenarios are simulated to estimate future hospital energy consumption and emissions. These scenarios are implemented sequentially and cumulatively following the mitigation hierarchy approach (Dempsey et al., 2023): firstly, emissions are avoided through energy efficiency measures (Sect. 2.7.2), then decarbonisation of the electricity grid is modelled (Sect. 2.7.3), and finally remaining impacts are reduced through electrification of gas services (Sect. 2.7.4).

2.7.1 Business as usual (BAU)

This scenario forecasts hospital performance with no change to the historical rate of performance improvement. Each hospital's performance is projected forward from the initial state at $t = 0$, the last known state in the dataset.

2.7.2 Accelerated efficiency

A 'best-case' efficiency scenario is simulated by filtering the training data for hospitals that performed well. The following filter criteria was used: (i) hospitals with a rating ≥ 5 stars in the final year of assessment period, or (ii) hospitals that improved by > 2 stars during the assessment period, or (iii) hospitals that improved by ≥ 1 star in the last 2 years of the assessment period. This filtered population is used to determine the transition probabilities in Sect. 2.5 and then each hospital's rating sequence evolved forward in time.

2.7.3 Electricity grid decarbonisation

In Australia, emissions associated with electricity generation are predicted to decrease by 75% between 2023 and 2035 (DCCEEW, 2023). This decrease is driven by the phase-out of coal and gas generation and replacement with renewable energy generation. In this scenario, emissions intensity (kg CO_2-e/kWh) forecasts are used to predict the future emissions resulting from hospital electricity use. These emissions intensity forecasts are region-dependant and obtained for each state from official forecasts (CCA, 2013; DCCEEW, 2023) (see Supplementary Information SI1-4 for more detail).

2.7.4 Electrification

Many hospitals use gas for space heating, sterilisation, domestic hot water and cooking, however these services can be replaced with electric alternatives. Emissions are reduced by increasing the efficiency of heating applications (e.g. via the use of heat pumps and induction cooking) and by leveraging the declining emissions intensity of grid-sourced electricity. In this study, electrification is modelled using a logistic function, resulting in 80% of hospitals electrified by 2040 and the remaining stock electrified by 2050 (this function is plotted in Supplementary Information SI1-5). Logistic 'S' curves are often used to model the diffusion of new technology where learning effects and economies of scale influence the uptake (Fleiter & Plötz, 2013). Progressive electrification of the hospital stock is simulated by sampling from this logistic function and deciding probabilistically whether a hospital is electrified in any particular year. Once the configuration is set to electrified, it remains in that state for the remainder of the simulation.

Electrification is modelled by reducing hospital gas use to zero and increasing electricity consumption proportional to the heating requirement. It is assumed that existing gas consumption is used for space heating or water heating and the assumed average operating efficiency of the gas burners is 85% (η_g) (AHIA, 2024). The coefficient-of-performance (COP) measures the ratio of useful heating performed compared to the supplied energy, with electric technologies having a higher relative COP than gas. The electrified system is modelled by setting 85% of the heating energy provided by electric heat pump compressors operating with a COP of 3.3 (η_{hp}) (AHIA, 2024; A2EP, 2022), and 15% of the heating provided by direct electric heating elements operating with a COP of 1.0 (η_{he}). The energy required by an electrical system (E_e) replacing an existing gas system (E_g) is then: $E_e = E_g\eta_g[0.85(1/\eta_{hp}) + 0.15(1/\eta_{he})]$. The limitations to this approach are discussed in Supplementary Information SI1-5.

3 Results

3.1 Hospital energy consumption

Hospital energy use is plotted with key explanatory variables in Fig. 2. Panel (i) shows patient separations and energy consumption by hospital, with each sample representing one year. The relationship can be approximated as a polynomial with a point of inflection at approximately 1000 separations, after which energy requirements increase approximately linearly. A minority of hospitals exhibit very low numbers of separations, these are small clinics and hospitals in regional and remote areas. Panel (ii) shows occupied bed days and energy consumption by hospital per year, this relationship is also approximately linear after a point of inflection around 500 bed-days. Panel (iii) shows aged-care bed days and energy consumption by hospital. Note only a minority of hospitals reported aged-care beds ($\approx$ 17%). In panel (iv), relative changes in star rating are shown with relative changes in energy consumption. Since the star ratings are limited to half-star increments, 1% random jitter was introduced to the x-axis of panel (iv) for readability.

Hospital fuel consumption mix is depicted with *remoteness* class (ABS, 2021) in panel (v), and with climate zone classification in panel (vi). Panel (v) shows *Remote* and *Regional* hospitals consuming larger volumes of LPG, a fuel often used where no district natural gas supply is available. In general, *Inner Regional* and *Major cities* hospitals consume higher proportions of natural gas than electricity. The secondary axis shows the count of hospitals present in the dataset by *remoteness* class. In panel (vi), gas consumption is higher in areas with cooler weather, which is likely because gas is mainly used for space heating. Hospitals classified as *Very Remote* are in regions with many more cooling degree days (CDD) than heating degree days (HDD), and therefore require little heating and hence no gas consumption. In humid regions, more electricity may be used for latent cooling and dehumidification. Panel (vi) is overlaid with cooling and heating degree-days, plotted on the secondary axis. These proportions represent only the Australian states in our dataset (Vic, SA and Qld) and hence the nationwide proportions may differ.

3.2 Projected decarbonisation pathways

Total energy consumption for the hospitals in this study (Vic, Qld and SA) was on the order of 8.75 PJ in 2019. Comparing this to Burch et al. (2021), who considered all Australian states and territories, this represents about 59% of total public hospital energy consumption in Australia. The projected decarbonisation pathways for each scenario are shown in Fig. 3, panels (i) and (ii). By 2040, energy efficiency has the potential to deliver 15–20% reduction in energy consumption to the hospital stock. By 2040, emissions can be expected to fall by 80% using the combination of strategies. Remaining emissions are attributable to the residual electricity grid emissions and remaining gas usage. In 2040, 10–15% of the current hospital stock remain unelectrified, which is constrained by the electrification rate (as described in Sect. 2.7.4). In panels (ii) and (iv), grid decarbonisation is not plotted, since this strategy does not reduce the energy consumption of hospitals, rather the emissions intensity of supplied electricity. Note that measures of absolute energy and emissions reduction assume that the hospital stock and operations remain unchanged, with future changes to the hospital stock not modelled here.

Panels (iii) and (iv) in Fig. 3 depict confidence bounds for each scenario, estimated from 500 Monte Carlo runs. The outcomes for each scenario are approximately normally distributed and projection bounds calculated as a 95% confidence interval, two standard deviations from the mean. The uncertainty is largest for the BAU and efficiency scenarios, reflecting the random sampling of the NABERS rating sequences. For these scenarios, the magnitude of the uncertainty also grows with the forecast horizon. The grid decarbonisation has the effect of squashing-out uncertainty in the emissions prediction. The uncertainties are shown in Table 2 for 2030 and 2040 (see Supplementary Information SI-6 for individual Monte Carlo run results).

Panel (v) depicts the change in emissions and energy intensity of bed-days, indexed to 2023. All three strategies contribute to declining emissions intensity of delivering hospital services, with a combined 70% reduction in intensity by 2040. The combination of efficiency and electrification has the potential to reduce the energy intensity of hospital buildings by about 40%. While electrification contributes to the reduction in energy intensity through improved COP, it's is not possible to reduce energy intensity to zero due to the thermodynamic limits of thermal conditioning, regardless of the fuel source consumed. Panel (vi) shows changes to fuel consumption, indexed to 2023. It can be seen that electricity consumption initially decreases as a result of efficiency measures, then increases again as gas services are progressively replaced with electric services.

3.3 Rating transition time evolution

Hospital energy ratings improved on average by 0.43 stars during the assessment period (2016–2022). 172 hospitals (48%) underwent a performance improvement while 74 hos-

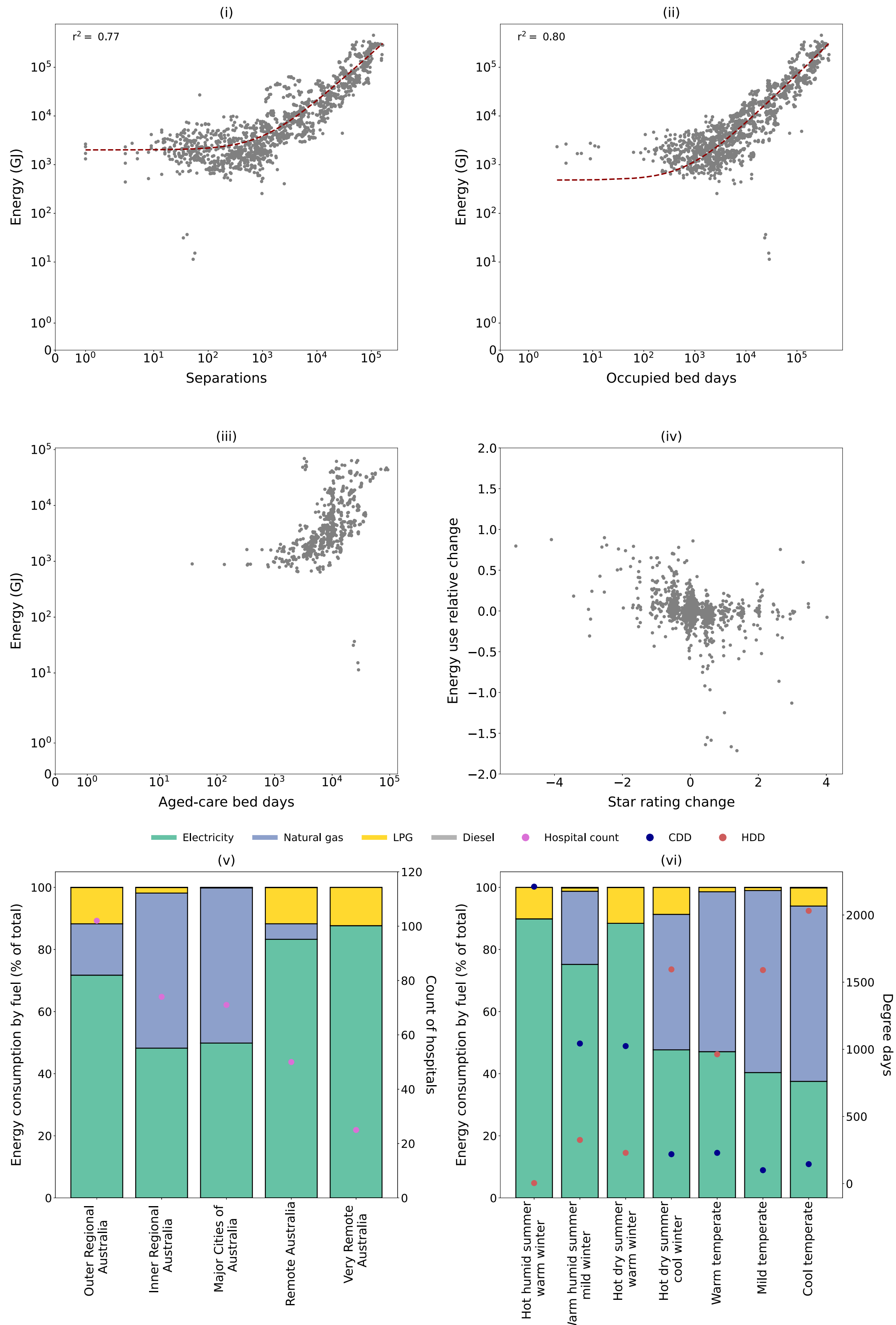

Fig. 2 **i** Patient separations and energy consumption (GJ), **ii** occupied bed days and energy consumption (GJ), **iii** aged-care bed days and energy consumption (GJ), **iv** relative change in energy consumption and relative change in star rating, **v** remoteness classification and fuel use mix, with count of hospitals overlaid, and **vi** climate zone and fuel use mix, with heating degree-day (HDD) and cooling degree-day (CDD) overlay. The data for this figure can be found in Supplementary Information SI2-8

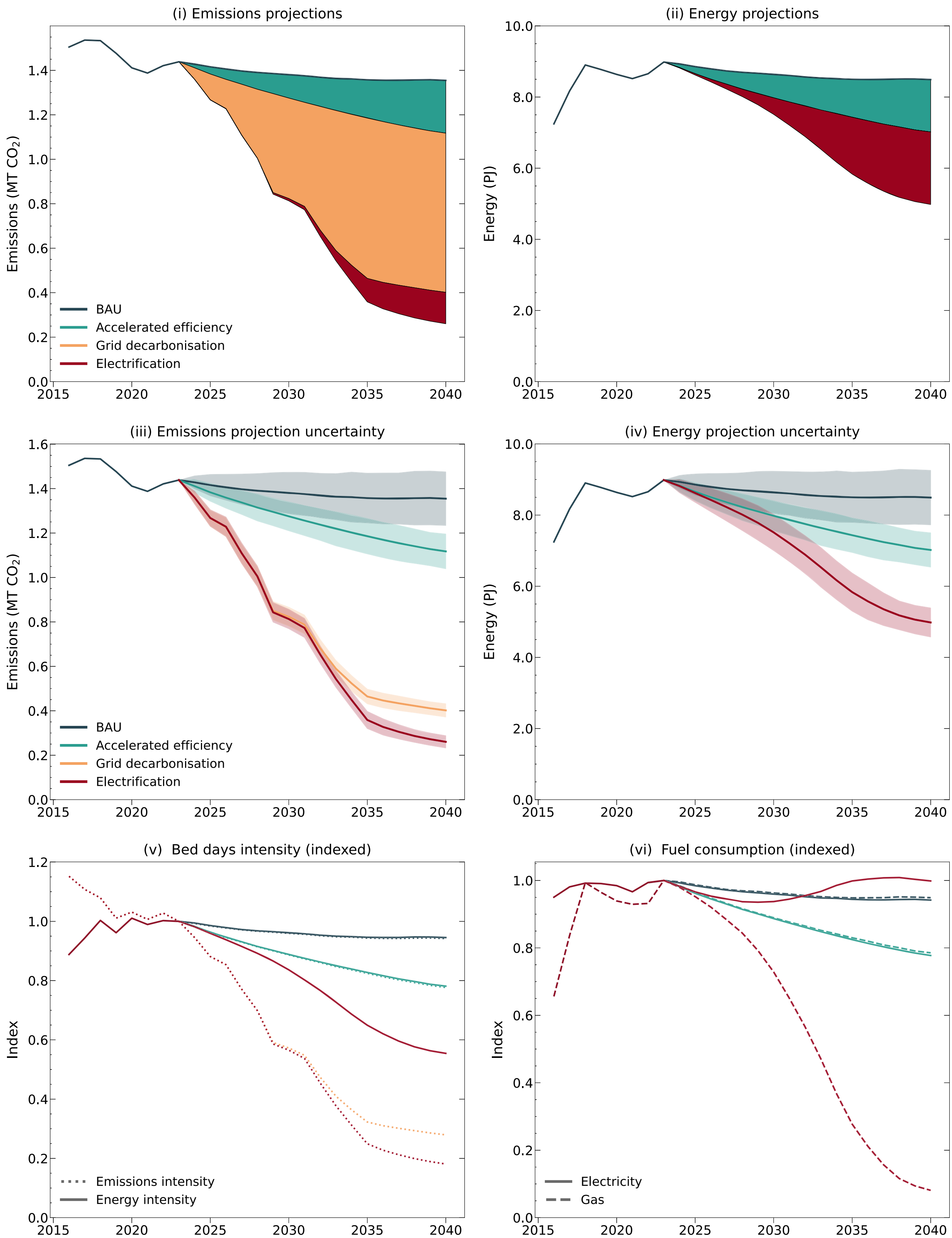

Fig. 3 Projected hospital futures under multiple decarbonisation scenarios, with scenarios applied cumulatively. Panels **i** and **ii** show emissions and energy reduction waterfall plots by scenario, **iii** and **iv** emissions and energy projections with confidence bounds (confidence bounds shown in a lighter shade around the mean line), **v** indexed bed-days emissions and energy intensity and **vi** indexed fuel consumption. The data for this figure can be found in Supplementary Information SI2-9

Table 2 Simulation uncertainties in 20,230 and 2040, with the mean simulation value μ, the standard deviation σ and the 95% confidence interval (2σ) as a percentage (%) of the mean value

Scenario	Indicator	2030			2040		
		μ	$\pm\sigma$	2σ %	μ	$\pm\sigma$	2σ %
BAU	Emissions (MT CO_2)	1.383	0.038	11.03	1.379	0.052	15.09
	Energy (PJ)	8.667	0.283	13.08	8.628	0.33	15.31
Efficiency	Emissions (MT CO_2)	1.256	0.022	7.04	1.139	0.033	11.61
	Energy (PJ)	7.858	0.131	6.68	7.13	0.187	10.51
Grid decarbonisation	Emissions (MT CO_2)	0.811	0.014	7.11	0.408	0.011	10.94
	Energy (PJ)	7.858	0.131	6.68	7.13	0.187	10.51
Electrification	Emissions (MT CO_2)	0.798	0.016	8.02	0.248	0.009	14.55
	Energy (PJ)	7.28	0.195	10.74	4.827	0.126	10.45

pitals (21%) performance decreased. 111 (31%) hospitals remained unchanged. Among hospitals which improved, the mean improvement was 1.3 stars, while among hospitals whose performance declined, the mean change was −1.0 stars. Note that the raw ratings data is limited to 0.5 star increments. Further detail on the distribution of performance is given in Supplementary Information SI1-7.

Figure 4 depicts the rating transitions between initial and final measurements. Panel (i) shows all transitions in the raw data while (ii) shows transitions for only 'best-performers' as defined by the criteria in Sect. 2.7.2. Colour intensity is proportional to the count of hospitals in each bin and the dotted pink line of equality separates the hospitals which have improved (above the line) from those that declined (below the line). The hospitals can be grouped by historical performance: A: hospitals with performance improvements (transitioned from $\leq 3 \rightarrow > 3$ stars), B: consistently high-performing hospitals (>3 stars), C: low performers (≤ 3 stars), D: hospitals whose performance declined ($> 3 \rightarrow \leq 3$ stars).

In general, there was a tendency for hospitals to remain at their current rating, corresponding to transitions falling along the pink line. In panel (i), quadrants (B) and (C) are most populated, suggesting there is inertia for hospitals to remain in either high-performing or low-performing states. There were relatively few transitions from B→D, indicating high-performing hospitals are unlikely to significantly regress. Panels (iii) and (iv) show the proportional rating stocks for the BAU and efficiency scenarios. Under the BAU scenario, the proportions of 3 and 4-star hospitals remains relatively constant, while 1 and 2-star hospitals are gradually replaced. Under the efficiency scenario, the proportion of 6-star hospitals grows, while the proportion of 5-star hospitals remains relatively constant. In this scenario, the proportions of 1 and 2-star buildings disappear from the hospital stock by 2035, and only a small number of 3 and 4-star hospitals remain by 2040.

4 Discussion

Our results suggest that the combination of efficiency, grid decarbonisation and electrification strategies could deliver an 80% reduction in emissions by 2040. By comparison, the NHS is targeting net-zero direct emissions by 2040 (NHS, 2020). Energy efficiency contributes to a 15% reduction in emissions and 17% reduction in energy consumption, findings consistent with global estimates of energy efficiency savings in buildings of 20–30% by 2050 (IEA, 2021). The combination of strategies reduces hospital emissions intensity by 70% and energy intensity by 40% by 2040. Both energy efficiency and electrification reduce the energy intensity of hospital operations, while grid decarbonisation only reduces emissions intensity. According to official forecasts, decarbonisation of the electricity grid will sharply reduce the GHG intensity of hospital electricity supply in the next two decades (DCCEEW, 2023). While electrification improves the energy efficiency performance of hospitals, the abatement potential of this strategy is strongly coupled to the grid emissions intensity. While the data used in this study comprised only a subset of Australian public hospitals, we suggest that these results may have general applicability to Australian hospitals and internationally.

In this study, uncertainty arising from projecting decarbonisation pathways was quantified, however other sources of uncertainty remain unaccounted for. This study did not consider future demand for hospital services or construction of new hospitals, rather the performance of the existing hospital stock was projected forward. There is also uncertainty in the future grid emissions intensity; while the Australian energy generation sector is expected to decarbonise, this is reliant on national energy policy. This uncertainty in future grid emissions intensity also directly influences the abatement potential of electrification, however this uncertainty was not quantified here. In this study, top performing hospitals were considered demonstrative of best performance. However, it's possible that even better performance is achiev-

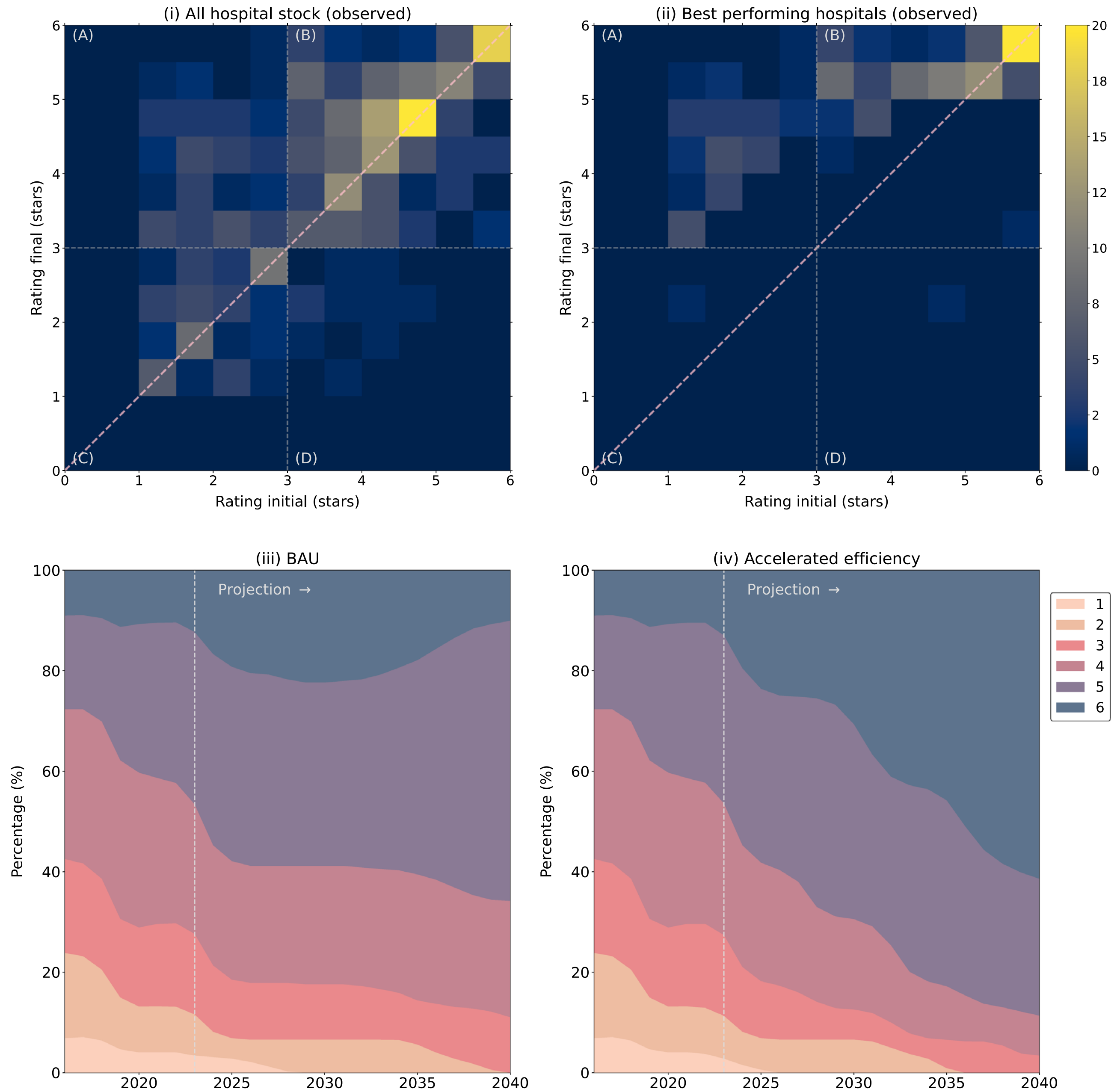

Fig. 4 Panels **i** and **ii** show 2D histograms of transitions from initial to final ratings, with colour scaled proportionally to the number of hospitals in each bin, as observed in the raw data. Note the transitions from initial to final rating states are shown and not the intermediate states. Panel **i** shows all hospitals while **ii** shows hospitals filtered for 'best performers'. Proportions of the hospital stock in each NABERS rating band, historically and projected into the future, are shown for the BAU and efficiency scenarios in panels (**iii**) and (**iv**) respectively (half star increments not shown). The data for this figure can be found in Supplementary Information SI2-10

able, in which case this study represents a conservative estimate of the efficiency potential.

Climate change may also increase hospital cooling loads in coming decades, which will alter the energy requirements and decarbonisation trajectories presented here. For example, Miller et al. (2022) estimate the future warmer climate will cause energy consumption increases for hospitals in Melbourne, Sydney and Brisbane of 1–7% by 2050 and a 6–12% by 2090. However, in cooler cities such as Hobart, HVAC consumption may decrease due to reduced heating loads in the winter. In this study an average heat pump COP of 3.3 was used. However, heat pump COP will vary with climate, equipment condition and potential future technology advancements, and actual COP likely ranges between 2.5 to 4.0 across the industry.

This study uses a property of the NABERS for public hospitals dataset that star ratings encode energy efficiency potential. Detailed, facility-level, information about the equipment and configuration of building services would improve these estimates of energy efficiency potential. Such data could be compiled to assist with future studies and could be obtained through energy audits and metering of important loads for each hospital, though this is a significant undertaking. This site-level detail would also reduce uncertainty in the probabilistic model and the electrification scenario, where assumptions were made about which hospital services currently consume gas. A regression model was used to map between fuel consumption and NABERS ratings, which introduces further uncertainty into our results (see model error in Supplementary Information SI1-3). This model would not be necessary were the NABERS equations publicly available.

While new hospitals will likely be fully electric (Vhba, 2023a), challenges remain in electrifying the existing hospital stock. Electrification can be complex and expensive to implement in remote and rural areas, for example due to local electricity grid capacity and access to skilled workers. In addition, disruption of service in frontline health facilities for major electrification works presents difficulties. Removing gas-fired equipment and installing replacement electric equipment can be expensive, so these works may be scheduled when the existing equipment has naturally reached end-of-life. In general, equipment and capital upgrades are more expensive than Building Management System (BMS) tuning, so these opportunities should be targeted first.

Energy efficiency in hospitals and decentralised energy generation can contribute to climate-resilience through reducing vulnerability to energy-supply shocks and allowing hospitals to remain functional to service their communities (Fallah-Aliabadi et al., 2020). Climate-related disasters, such as extreme heat and storms, may cause power blackouts and see hospitals receive an influx of patients requiring care (Paterson et al., 2014). While Australian hospitals are currently required to retain diesel stocks for on-site generators in the event of electricity supply issues, these stocks may be depleted during large disasters. Furthermore, regional and rural hospitals may become isolated, due to floods or fire, and not receive deliveries of diesel and LPG (Yusoff et al., 2017). On-site renewable generation with battery backup can contribute to resilience of energy supply during these extreme events, however the size of hospital energy loads compared with battery capacity limits this. Efficient hospitals may also have a greater ability to cope with extreme temperatures, as greater reserve capacity will exist in HVAC systems, as well requiring less fuels during shortages.

A number of factors can prevent efficiency opportunities in large buildings from being realised. One survey of commercial building professionals in Australia identified a number of barriers for efficiency strategies, including: cost of upgrades, lack of on-site manager whose responsibility includes efficiency, lack of access to information and efficiency expertise (DCCEEW, 2024). Other reasons that prevent uptake of efficiency measures include: imperfect information (e.g. the size of the efficiency gain may be difficult to quantify), hidden costs (e.g. efficiency upgrades may lead to unwanted side effects) and access to capital (e.g. accessing funds to pay for efficiency upgrades upfront) (Brown et al., 1998; Fleiter et al., 2011).

A number of strategies can reduce the barriers to realising these efficiency opportunities. Undertaking of regular energy audits for each hospital by trained professionals can reveal energy efficiency opportunities and other maintenance issues. Energy Performance Contracts (EPCs) provide a pathway for funding efficiency upgrades while sharing the project risks (AEPCA, 2000). All Australian states and territories should be encouraged to participate in the NABERS scheme, which could be expanded to also include private hospitals (DoHAC, 2023). Asset Management Plans provide a strategic approach to building upgrades to achieve efficiency goals, for example planning for equipment replacement at end-of-life. Life cycle planning can also help understand the environmental trade-offs between retrofit efficiency upgrades in older buildings and the impacts embodied in constructing new buildings (Rauf & Crawford, 2015). Digitalisation and analytic monitoring tools can also deliver energy efficiency savings through, for example, optimising HVAC system controls (White et al., 2023).

Achieving the net zero target by 2050 (WHO, 2021) will be challenging for healthcare and hospitals; while grid emissions are declining in Australia the electrification of existing hospitals is likely to proceed slowly. While the contribution of efficiency to hospital decarbonisation is generally acknowledged (Fritz et al., 2025), the magnitude of the efficiency potential is difficult to estimate, which frustrates funding efforts. Efficiency measures deliver secondary benefits such as energy cost savings and risk mitigation against future energy price rises (IEA, 2025), though also compete with other methods of decarbonisation for funding. Estimates of the energy efficiency potential in this study can aid the allocation of scarce healthcare decarbonisation funding.

5 Conclusion

This study modelled a number of decarbonisation strategies for hospital operational energy use. These strategies are complementary and should be implemented in parallel for maximum effect. Transitioning from fossil fuels to on-site renewables or grid electricity is necessary to achieve zero emissions, while electrification allows hospitals to benefit from declining grid emissions. Importantly, energy efficiency improvements serve a dual purpose: facilitating decarbonisation at the facility level and reducing the overall demand for low-carbon electricity at the national level. This reduction in overall energy demand mitigates the non-trivial upstream environmental impacts associated with renewable energy infrastructure, including emissions from steel production and biodiversity impacts from mining activities. Consequently, reducing energy demand directly supports national climate commitments under the Paris Agreement by reducing both the environmental and financial costs of expanding renewable energy capacity.

However, these technical interventions must be situated within a broader context, for example, as established by the planetary health framework (MacNeill et al., 2021). While energy efficiency and electrification are important strategies for reducing the environmental footprint of health facilities, they represent the last step in a hierarchical approach to sustainable health care. Investment decisions to optimise infrastructure should be preceded by broader systemic efforts to reduce overall demand for health services through improved social determinants of health and enhanced disease prevention. In addition, the health care system should be incentivised to provide appropriate, high-quality care, avoid unnecessary or harmful interventions and focus on green procurement for goods and services where clinically equivalent options exist. This hierarchical approach ensures that environmental efficiency measures target genuinely essential health services rather than optimising unnecessary care, thereby targeting limited resources where they will provide the greatest benefit to both human health and environmental sustainability.

Supporting information

Supplementary Information SI1 (SI1-1 - SI1-7) contains further information on data preparation, predictive model training, grid emissions intensity, electrification and uncertainty.

Supplementary Information SI2 (SI-8 – SI-10) provides the data used in figures 2,3 and 4 in the manuscript.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44498-026-00069-1.

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Author contributions J.F., A.B. and M.H. designed the study; J.F., M.H. and T.W. performed the analysis; M.H. and P.P. reviewed the analysis; J.F., P.P, M.H., T.W. and H.Y. wrote the manuscript; all authors reviewed the manuscript.

Data availability Licensing restrictions prevent us from sharing the NABERS Energy for public hospitals rating data. However, these data may be available on request through the state health departments.

Declarations

Conflict of interest At the time of writing, authors Matthew Hoogland and Tristan Webber were engaged in energy efficiency consulting. Matthew Hoogland also works with NABERS to support rules development, quality assurance and assessor training.

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