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Energy Analysis and Forecast of a Major Modern Hospital

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Abstract: Healthcare buildings often have high energy use intensity, which is potentially influenced by a few factors, such as occupancy and climate. A suite of data analysis methods, including principal component analysis and regressions, is applied to analyse monthly electricity data of a modern major hospital in subtropical Australia. The analysis shows that occupancy is not highly correlated with the hospital's electricity use, nor is it important for building energy modelling. However, outdoor environment temperature is highly correlated with the hospital's electricity use. Then, the hospital's electricity uses in 2030 to 2090 scenarios are forecast with future climate files. The impacts are analysed in terms of bill increases and renewable capacity needed to offset the increased electricity use. This study has established a process to predict future hospital energy use using data-driven energy modelling. This succinct article provides vital evidence to support the healthcare sector to continuously improve energy efficiency for health buildings, which is a major asset to adapt to the changing climate.

Keywords: energy modelling; global green and healthy hospitals; healthcare transition; neural network; polynomial; principal component analysis

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1. Introduction

As society develops, more hospitals and healthcare facilities are being built in regions of population growth [1,2]. Hospitals are typically energy-intensive, which results in high greenhouse gas emissions [3,4]. Globally, the healthcare sector contributes 4.4% of all CO_2 emissions, with half of the emissions related to energy [5]. On a per capita level, the top four healthcare emitting countries are the U.S., Canada, Australia, and Switzerland [5]. In Australia, the healthcare sector is estimated to account for 7.2% of the country's carbon emission footprint and its healthcare spending was approximately 9.1% of its gross domestic product in 2014 [6,7]. The public health sector is regularly the leading energy user and emitter for Australian state governments, such as in the state of Victoria [8].

There is diverging evidence to suggest the role of occupancy on building energy use. Occupancy is often a key aspect in building energy data analysis, modelling, and forecasting [9]. Occupancy has been found to be relatively highly correlated with energy use for a health centre in Singapore [10]. However, other evidence suggests a low correlation between occupancy and building energy use in residential aged care facilities [11]. A further study identified that occupancy may not be as significant as the occupants' behaviour in influencing energy use, such as changing air conditioner thermostat settings [12]. Hospitals are a restorative environment with quite strict requirements for the buildings' operation, and there is a gap in understanding how occupancy is correlated with energy use for large hospitals.

In addition to the occupancy, climate conditions, especially temperature data, are often related to electricity use in buildings, suburbs, or at a grid level [13,14]. Climate is also a significant factor impacting energy use in healthcare facilities. For example, a national study found that heating ventilation and air conditioning systems (HVAC) account for around 52% of energy use for U.S. healthcare buildings [15]. Climate change is impactful to people's health and the healthcare sector [16,17]. Nematchoua explored the impact of future climate scenarios on heating and cooling energy for hospitals on six Indian Ocean islands [18]. Overall, there have been limited publications on the impact of future climate on health facilities.

Therefore, this research aims to provide vital evidence to support continuous improvement for hospital building energy efficiency measures and major energy assets, such as strategies to improve the thermal performance of the building envelope, increase the efficiency of space cooling, and reduce the impact of the urban heat island effect. This paper is the first, to the authors' knowledge, to report on a modern major hospital's electricity use forecast in 2030 to 2090 scenarios under the changing climate.

The next section presents the methodology, including a number of data analysis methods and major steps.

2. Inputs and Methods

The research methodology flow is illustrated in Figure 1. Overall, this research applies a suite of data analysis methods to a major modern hospital in subtropical Brisbane, Queensland, Australia [19].

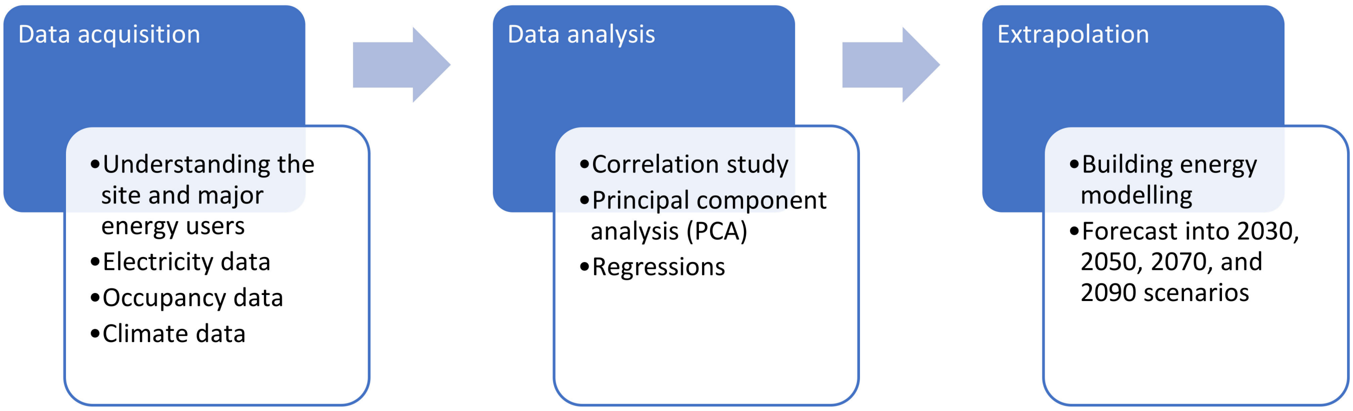


Figure 1. Research flowchart.

2.1. Data Acquisition

At the data acquisition step, the site building types, operation mode, and major energy users were identified. In this research, the defined period is each calendar month because, in the Australian context, metering and billing are applied monthly for commercial and industrial (C&I) customers.

Monthly electricity use data and occupancy data can be obtained from site facility management. Occupancy data included occupied bed days and separations in each month. Occupied bed days are "the total number of bed days of all admitted patients" in a defined period [20]. Separations are the total number of patients who are recorded as having "cessation of treatment and/or care and/or accommodation" in a defined period [20].

Climate data can be obtained from a local Australian Bureau of Meteorology weather station (Table 1). Monthly climate data were used, and daily maximum and minimum temperatures were obtained from an Australian Bureau of Meteorology station, No. 040842 [21].

Table 1. Data types and description.

No.	Description	Units
1	Monthly electricity use	Kilowatt-hours (kWh)
2	Daily maximum temperatures	Degree Celsius (°C)
3	Daily minimum temperatures	Degree Celsius (°C)
4	Monthly separations	Separations (SPR)
5	Monthly occupied bed days	Occupied bed days (OBD)

2.2. Data Analysis

After the site was understood and relevant data were obtained in the previous stage, this stage analysed the relationship between monthly electricity use data and occupancy data, and between monthly electricity use data and temperature data.

Three common analytical methods were applied: Pearson correlation coefficient (PCC), principal component analysis (PCA), and regression [22]. PCC has low computational requirements and can time-efficiently provide an overview of correlations between many sets of variables. Equation (1) calculates PCC, which is a value between −1 and +1, as an indicator for the relationship between changes in variable A and changes in variable B [23,24]. PCC $\rho_{A,B}$ is obtained using covariance between variable A and variable B $COV(A,\ B)$ divided by the standard deviation of A σ_A and the standard deviation of B σ_B.

$$\rho_{A,B} = \frac{COV(A,B)}{\sigma_A \sigma_B} \tag{1}$$

Principal component analysis (PCA) uses the singular value decomposition method to identify another set of numerical components which may have fewer dimensions than the input datasets [10,25]. In this way, a reduced number of inputs may be identified with a similar accuracy in energy modelling. Consequently, reduced model complexity and lower computational overheads may be achieved.

In the regression part, polynomial fitting and artificial neural networks (ANN) are applied to the datasets. The models' accuracy comparisons are undertaken to select the most accurate model. First-order polynomial fitting Equation (2) and second-order polynomial fitting Equation (3) are used in this research. $\boldsymbol{X}$ are monthly input variables used as matrix forms in (2) and (3). Also in (2) and (3), $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\eta}, \boldsymbol{\theta}$ are fitted coefficients for the two polynomial equations.

$$\text{1st order polynomial}: \ E = \boldsymbol{\alpha X} + \boldsymbol{\beta} \tag{2}$$

$$\text{2nd order polynomial}: \ E = \boldsymbol{\delta X}.^2 + \boldsymbol{\eta X} + \boldsymbol{\theta} \tag{3}$$

A single hidden-layer feedforward ANN with N number of hidden neurons and activation function g is presented in Equation (4) [26]:

$$G_N(X_t) = \sum_{i=1}^{N} \beta_i g(W_i \boldsymbol{X}_t + b_i) \ \ with\ t = 1, \ldots,\ T \tag{4}$$

where W_i is the input weight vector; β_i is the output weight vector; b_i is the bias term; g is the activation function; T is the number of samples. The activation function is a smooth bounded monotonic function, often a sigmoid [27]. A backpropagation method has been commonly used to train neural network models [28]. Cross-validation is useful in terms of identifying the optimal ANN model for a given set of input variables [29].

For model Equations (2)–(4), inputs can include different combinations of monthly variables, such as monthly temperature variables, monthly occupancy variables, and a combination of both. Daily temperature inputs (row 2 and 3 of Table 1) are calculated into monthly intervals as a type of input variable. The three different models and combinations of inputs are evaluated with root mean squared errors (RMSE) and mean absolute errors (MAE) [30]. The model with the highest accuracy is selected for the next stage.

2.3. Forecasting

The Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia's national science agency, has released future weather files for Australian climates in 2030, 2050, 2070, and 2090 scenarios [31], as described in Table 2. The temperature variables from these files are then recalculated into various monthly inputs, which are inserted into the best model identified out of Equations (2)–(4) to forecast the site's future electricity use.

Table 2. Australian future climate scenarios.

Future Scenario Names	Description	Pathways
2030	representing a typical year between 2020 and 2040	• Business as usual pathway, Representative Concentration Pathway 8.5 (RCP8.5) [32] • Emission middle pathway (RCP4.5) • Negative emission pathway (RCP2.6). RCP2.6 is the only pathway to maintain the average temperature increase <1.5 °C [33].
2050	representing a typical year between 2040 and 2060	
2070	representing a typical year between 2060 and 2080	
2090	representing a typical year between 2080 and 2100	

For this data-driven research, the following facts and assumptions are included:

- No significant expansion is considered for the site precinct. The case study is a modern major urban vertical hospital and the physical site boundary is limited.
- Like-for-like replacements are considered for existing facility assets when they are out of service lifetime. Potentially new assets would have higher efficiency for the same output rating.
- Increased energy use due to new clinical equipment is largely offset by energy efficiency improvements from other facility assets.
- Indoor thermal comfort is maintained through the 2030 to 2090 scenarios. For example, HVAC systems fully meet the thermal conditioning and ventilation needs of the site buildings.

The next section provides a site description first, followed by data analysis and forecast results into 2030 to 2090 climate scenarios.

3. Case Study Results

3.1. Case Study Site

The site is Queensland Children's Hospital (QCH, coordinates: 27.4839° S 153.0279° E), a major modern hospital precinct commissioned in November 2014. The hospital precinct has three buildings with a total floor area of 134,800 m^2. The site is in Australian Climate Zone 2, with warm humid summers and mild winters, and its Köppen Climate Classification is Cfa (Humid, Subtropical).

QCH is Queensland's only quaternary hospital for children's health and it accepts patients for the whole state of Queensland and northern New South Wales. QCH is also a COVID-19 hospital with negative pressure wards. Each year, QCH services an average of 100,000 occupied bed days and 40,000 separations (definitions in Section 2.1).

The QCH precinct uses a total of 26 to 27 GWh of electricity annually [19,34]. The HVAC system accounts for the largest share of electricity use onsite. Natural gas is used onsite to produce hot water (for domestic hot water and space heating) and steam, which will be studied in a future project and is beyond the scope of this article.

Exploratory data analysis indicates that the site energy is related to ambient temperature, as shown in Figure 2. Electricity use is regularly high in summer months from December to March, between 75 MWh/day and 87 MWh/day. Winter months from June to August tend to have lower electricity use, ranging between 65 MWh/day and 68 MWh/day. Mild months (April, May, September, October, November) are the 'shoulder seasons', transitioning between summer and winter.

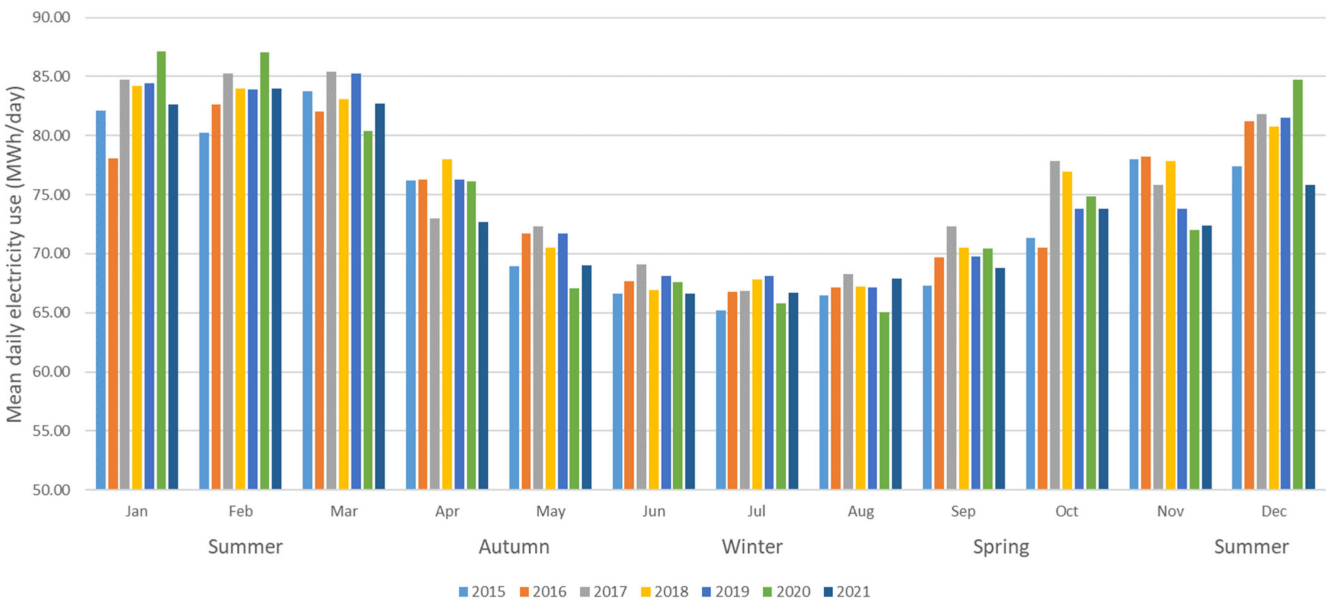


Figure 2. Monthly mean daily electricity use (MWh/day).

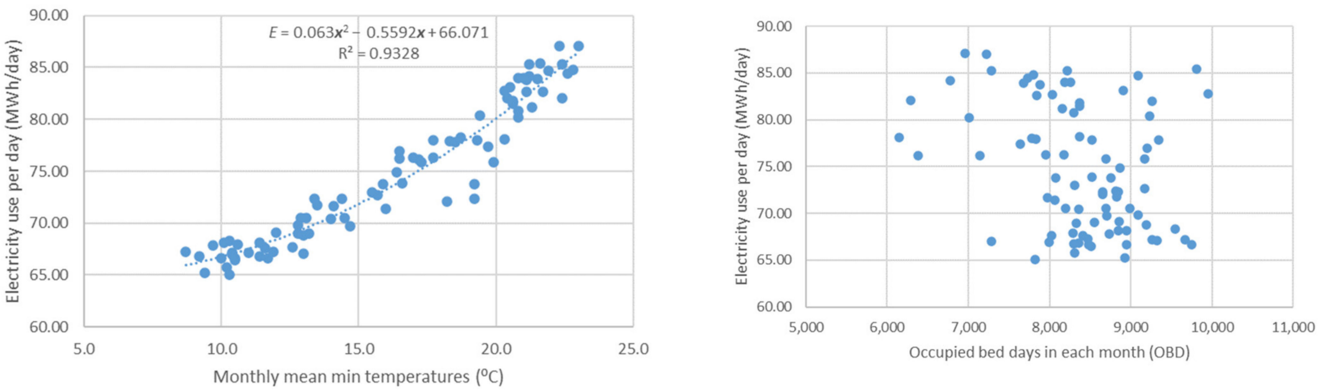
3.2. Correlation Study

Table 3 presents PCC values for monthly mean daily electricity use vs. six temperature variables, and monthly mean daily electricity use vs. four occupancy variables. Overall, monthly mean daily minimum temperatures have the highest PCC values with monthly mean daily electricity use. Regarding the temperature variables, monthly mean daily minimum temperatures and monthly lowest temperatures have the highest PCC values with monthly mean daily electricity use. No occupancy variable is highly correlated with the site energy use, while occupied bed days (OBD, row 9) and separations in each calendar month (row 7) have the highest PCC values among occupancy variables as inputs. All the PCC values can be considered statistically significant as all the *p*-values are less than 0.05 (if 0.95 is considered as the cut-off).

Table 3. Pearson correlation coefficients.

No.	Types	Monthly Mean Daily Electricity Use vs.	PCC	*p*-Values
1	Temperature variables	Monthly mean daily maximum temperatures (MMAX)	0.932	5.320×10^{-38}
2		**Monthly mean daily minimum temperatures (MMIN)**	**0.956**	$\mathbf{1.626 \times 10^{-45}}$
3		Monthly highest temperatures (MHT)	0.775	5.397×10^{-18}
4		Monthly lowest temperatures (MLT)	0.938	2.317×10^{-39}
5		Monthly lowest daily maximum temperature (MLMT)	0.849	2.113×10^{-24}
6		Monthly highest daily minimum temperature (MHLT)	0.922	1.423×10^{-35}
7	Occupancy variables	Separations in each calendar month (SPR)	−0.300	0.006
8		Separations per day in each calendar month (SPR/D)	−0.224	0.041
9		**Occupied bed days in each calendar month (OBD)**	**−0.331**	**0.002**
10		OBD per day in each calendar month (OBD/D)	−0.279	0.010

Then, the variables with the highest PCCs (row 2 and row 9 of Table 3) are plotted against the monthly mean daily electricity use values. Figure 3a presents the scatterplot for monthly mean daily electricity vs. monthly mean daily minimum temperature. A second-order fitting is also presented in the figure, with quite a good R^2 value (goodness of fitting). However, there is no visible relationship shown between OBDs and the electricity use variable in Figure 3b.



(**a**) (**b**)

Figure 3. Scatterplots: (**a**) monthly mean daily minimum temperature vs. monthly electricity use per day; (**b**) monthly occupied bed days vs. monthly electricity use per day.

Figure 4 shows cross-correlations calculated for the ten variables in Table 3. All the temperature variables are quite highly correlated, with PCC between 0.7389 and 0.9721, in the top left corner of Figure 4. Occupancy variables are mostly highly correlated with each other, with PCC between 0.6482 and 0.9583, in the bottom right corner of Figure 4. This indicates that for the site energy modelling, there is probably no need to have more than one variable out of those temperature variables, nor to have more than one variable from those occupancy variables. The next step, principal component analysis (PCA), helps to further determine key input variables, rather than having redundant variables of a similar nature.

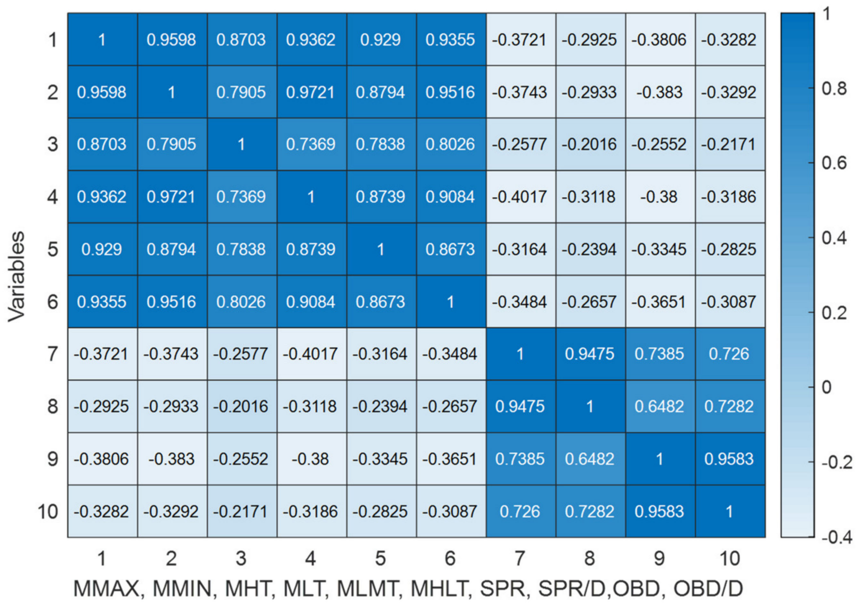
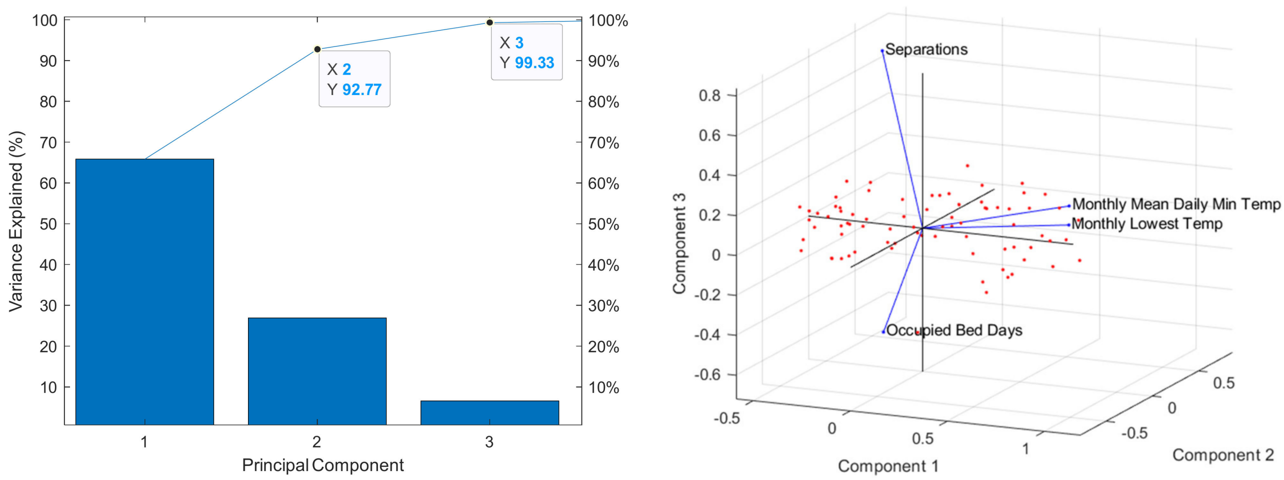


Figure 4. Cross-correlations of potential input variables.

3.3. Principal Component Analysis

PCA can help to mathematically identify the principal components that are impactful for modelling and improve the multicollinearity issue. Two temperature variables and two occupancy variables were used in the principal component analysis, namely monthly mean daily minimum temperatures, monthly lowest temperatures, separations, and occupied bed days in each calendar month. The four variables were selected due to their leading PCC values in the previous analysis. PCA transforms input variables into another set of orthogonal principal components (PC).

Scree plots and analysis of PC can help to identify impactful PC and remove redundant variables. Figure 5a shows the scree plot of three principal components. The first principal component can explain 65.84% of variance; the first two PC together can explain 92.77% of variance, and the three PC together can explain 99.33% of variance.



(**a**) Scree plots (**b**) biplots

Figure 5. PCA plots: (**a**) scree plots to show principal components for percentages of variance explained; (**b**) biplots to show impacts of input variables on principal components.

Figure 5b shows the impacts of input variables on the three principal components. MDMIN and MLT are very close to each other and have similar impacts on the first PC. This indicates a need of having one of the two variables, rather than having both. SPR and OBD have similar impacts on the first PC and an opposite directional impact on the third PC. All four variables have similar impacts on the second PC.

3.4. Regressions

After the previous PCC and PCA analysis, monthly mean daily minimum temperatures (MMIN) were selected as the temperature input for the case study energy modelling. The occupancy modelling inputs can be either occupied bed days or separations.

Next, 2015 to 2020 data were used as the training datasets for model fitting and the latest 2021 data were used as the testing dataset to calculate the root mean squared error (RMSE) and mean absolute error (MAE) for the fitted models, as shown in Table 4. For the three types of fitting, both RMSE and MAE show that modelling with monthly mean minimum temperature inputs (MMIN) led to the best outcome because of the lowest RMSE and MAE values in each type of modelling, i.e., rows 1, 4, and 7. Modelling accuracy dropped when either occupied bed days (OBD) or separations (SPR) were added. The models with SPR tended to have higher accuracy than the models with OBDs.

Table 4. Model accuracy comparisons.

No.	Description	RMSE	MAE
1	1st order polynomial with MMIN	**2.6639**	**1.9587**
2	1st order polynomial with MMIN and OBD	2.8670	1.9970
3	1st order polynomial with MMIN and SPR	2.7079	1.9611
4	2nd order polynomial with MMIN	**2.3618**	**1.4807**
5	2nd order polynomial with MMIN and OBD	2.6299	1.7080
6	2nd order polynomial with MMIN and SPR	2.3974	1.5322
7	ANN with MMIN (10 neurons)	**1.8093**	**1.4593**
8	ANN with MMIN and OBD (15 neurons)	2.3234	1.8113
9	ANN with MMIN and SPR (11 neurons)	2.0346	1.5951

Overall, ANN with monthly mean minimum temperature inputs (MMIN) on row 7 has the lowest RMSE, which is 23% better than row 4's, and row 7's MAE is also slightly better than row 4's MAE. In the next section, ANN with MMIN inputs is used to forecast electricity use for the case study's 2030 to 2090 scenarios.

3.5. Forecast into 2030–2090 Scenarios

Figure 6 shows the case's yearly electricity use forecast into 2030, 2050, 2070, and 2090 scenarios. In the business as usual (RCP8.5) scenario, more than 10% electricity use increase is forecast to happen by the period 2080 and 2100. In the best negative emission scenario (RCP2.6), the site's yearly electricity use is predicted to have a mild increase of 1.4% by the end of the century. Data for the figure are provided in Table 5. These predictions are for typical yearly electricity use in each 20-year period. The potential financial and societal impacts are discussed in the next section.

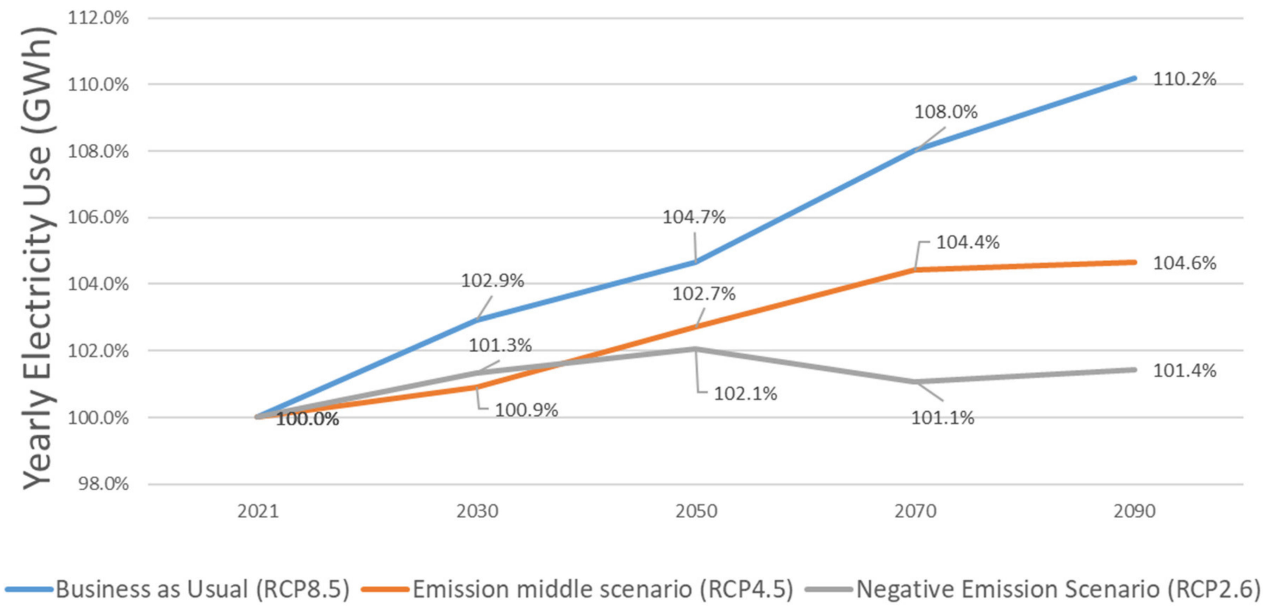


Figure 6. Benchmarking of electricity forecast into 2030–2090 scenarios.

Table 5. Electricity use forecast into future climate scenarios.

Climate Scenario Names	Description	Emission Business as Usual (RCP8.5)	Emission Middle Scenario (RCP 4.5)	Emission Negative Scenario (RCP2.6)
2021	Yearly electricity use (GWh)		26.846 (base)	
2030	Typical yearly use between 2020 and 2040 (GWh)	27.632	27.089	27.206
	Increase compared to 2021	2.9%	0.9%	1.3%
2050	Typical yearly use between 2040 and 2060 (GWh)	28.094	27.572	27.397
	Increase compared to 2021	4.7%	2.7%	2.1%
2070	Typical yearly use between 2060 and 2080 (GWh)	28.995	28.033	27.133
	Increase compared to 2021	8.0%	4.4%	1.1%
2090	Typical yearly use between 2080 and 2100 (GWh)	29.579	28.093	27.230
	Increase compared to 2021	10.2%	4.6%	1.4%

4. Discussion

Across Australia, there are over 1300 public and private hospitals and 148 of these are major hospitals with over 100 beds [1,35]. QCH is one of the major hospitals. As the climate changes, there is a need to better understand the impact of the future climate on energy use, to better future-proof energy sustainability and financial sustainability for our healthcare sector. The following paragraphs discuss the implications of this research for operational expenditure, renewable energy, policy, and future developments.

4.1. Implication for Operational Expenditure

Assuming an electricity price of AUD 0.15/kWh in 2021 with a 2.5% per year cost increase [36–38], the site's yearly electricity bill increases (above current baseline) for the 2030 to 2090 climate scenarios are presented in Table 6. The site's electricity costs, a combination of increased energy use and increased cost per unit, places a very high financial burden on the hospital in the business as usual scenario (exceeding 1 million dollars for 2070 and 2 million dollars for 2090). On the positive side, the negative emissions scenario (RCP2.6 scenario) results in a much smaller cost increase. The public resource saving would be in the order of AUD 214,000 in 2050 and AUD 1,937,000 in 2090, if the RCP2.6 scenario occurs instead of RCP8.5. It is unclear whether any public health departments, already under financial pressure, have planned for the likelihood of significantly higher energy bills in the future.

Table 6. Yearly bill increase in future climate scenarios.

Climate Scenarios	Business as Usual (RCP8.5) [a,b]	Emission Middle Scenario (RCP4.5) [a,b]	Negative Emission Scenario (RCP2.6) [a,b]	Savings Comparing RCP2.6 to RCP8.5
2030	$147,255	$45,602	$67,501	$79,754
2050	$383,318	$223,028	$169,246	$214,073
2070	$1,081,181	$597,236	$144,658	$936,523
2090	$2,253,117	$1,027,949	$316,407	$1,936,710

Notes: [a] Electricity is assumed to be AUD 0.15/kWh in 2021 excluding goods and services tax. [b] Electricity price is considered to increase 2.5% annually, in line with Australia's official long-term inflation target [36].

4.2. Implication for Renewable Energy

Renewable energy has been a significant part of the public sector's procurement strategy and it has been demonstrated to be effective in terms of carbon emission reductions [39]. Most Australian states and territories have set targets for achieving net zero carbon emissions and for increasing the share of renewable energy in the electricity sector. The outcome of this is demonstrated in the rising share of renewable energy as a share of national electricity, and the rising (but still small) share of public hospital energy use being met by renewables (Table 7, [39]).

Table 7. Renewable energy baselines and percentages.

Energy	2016/17	2017/18	2018/19
National baseline renewables	15.7%	17.0%	24.0%
Total hospital energy consumed	4,132,162 MWh	4,213,694 MWh	4,121,911 MWh
Hospital renewable energy produced	13,651 MWh	18,350 MWh	94,415 MWh
Hospital energy % renewable	0.33%	0.44%	2.29%

Solar photovoltaic (PV) is one of the more common renewable technologies [40]. For this research, analysis was undertaken to determine the size of PV system (kWp) required to meet the increased electricity demand into the future. Table 8 shows that for the RCP8.5 and RCP4.5 scenarios, continuously increasing new PV capacity is needed to offset the site's electricity use increase. Note that each future climate scenario is for a typical 20-year period, which is shorter than the expected life of PV panels (currently guaranteed performance over 25 to 30 years [14,41]). An implication of this is that new investments need to be put into place to construct new solar generation to meet the increased electricity use, as well as coping with declining efficiency for solar panels. It is also worth pointing out that this analysis only considers PVs to cover the increase in electricity demand, not the baseline use.

Table 8. New solar capacity to offset the increased electricity use compared to 2021 (kW peak).

Climate Scenarios	Business as Usual (RCP8.5) [a]	Emission Middle Scenario (RCP4.5) [a]	Negative Emission Scenario (RCP2.6) [a]
2030	513	159	235
2050	815	474	360
2070	1402	775	188
2090	1783	814	250

Note: [a] 1 kW peak solar photovoltaic systems in this region generate a yearly average of 4.2 kWh/day.

4.3. Implication for Policy and Future Developments

As the data analysis section shows, occupancy is not highly correlated with the site's monthly energy use. There are a few potential reasons for why occupancy does not matter much for a major hospital in a warm climate:

- For the case study, cooling is the dominant HVAC operation mode; electricity is the energy source for cooling. The major hospital is built with concrete and steel structures. Cooling to remove occupants' metabolic load would probably be much less than the cooling needs for buildings' thermal mass in the warm climate.
- The HVAC settings in hospitals are typically determined by standards and regulations based on health, safety, and clinical reasons. The HVAC is typically centrally controlled, with little potential for patients and clinicians to change the thermostat settings. This particular hospital is air-conditioned 24-7 and uses 100% fresh air. This case study provides evidence from another angle to support [12]: occupancy may not be as significant as occupants' behaviour in influencing energy use.

The consistent high correlation between electricity uses and temperature indicates a strong need to have a better building envelope for healthcare purposes, potentially through continuous improvement of health building guidelines [42]. Another related aspect is to have operational improvement for major space cooling-related equipment, such as optimising chillers' staging and control [43]. Renovations between 2025 and 2090 may be great opportunities to improve the hospital building envelope and adopt energy efficiency technologies wherever technically feasible and financially viable.

A limitation of this study is that it was based on typical meteorological future climate files. The electricity use forecast results are for typical years within each 20-year period until the end of this century, rather than for years of extreme events, such as some years with extended periods of heatwaves. Higher levels of energy use increase would probably occur in future years, with increased intensity, magnitude, and duration of heatwaves as a result of climate change. This means that there is a need for the development of 'extreme weather' climate files that consider events such as extended periods of heatwaves. Such events are known to have an impact on energy, through increased utilisation of air conditioning, reduced efficiency of air conditioners and the electricity network, and increased risk of power failure [44]. Extreme weather climate files would enable modelling and simulation to understand the extent of the energy impacts and make decisions to avoid or limit the negative impacts [45].

5. Conclusions

This research has applied a suite of data analysis tools to model and forecast the energy use of a major modern hospital in subtropical Australia. Pearson correlation coefficients, principal component analysis, polynomial models, and artificial neural network models were used in the analysis and modelling process. With projected future weather files (2030, 2050, 2070, and 2090 scenarios), the hospital's energy use was forecast to 2030 to 2090 with three RCP pathway scenarios, namely business as usual, a mid-emission scenario, and a negative emission scenario.

The data analysis results show that there is a low correlation between the case hospital's occupancy and electricity use, but a high correlation with outdoor temperature. This highlights the need for a strong focus on improving the thermal efficiency of the building envelope (to minimise the growth in cooling load) as a priority.

Without addressing hospital buildings and HVAC systems, the changing climate is likely to significantly impact the hospital financially. For 2080–2100, the annual electricity bill could increase by more than AUD 2 million compared to 2021 in the business as usual scenario. This would impact the Queensland state budget, where public health regularly accounts for over 30% of the state's budget [46]. Savings through hospital energy sustainability projects can offer an opportunity to alleviate some of the budgetary pressure.

This paper's energy data analysis did not include energy for water heating, but water heating is a key factor of hospital energy use. Current Australian hospitals mostly use natural gas as the primary energy source to produce hot water or steam [47]. However, there are no data available for hot water use in this case study. A potential research direction is to analyse water heating energy use's correlation with occupancy and explore scenarios of major hospitals with heating fully electrified.

It is likely that major modern hospitals in all climate zones of Australia will have cooling energy highly correlated with climate regardless of occupancy. Future work will test this inference and extend this analysis to include all states and territories of Australia (i.e., a range of climate zones). The outcomes of this data analysis approach to energy forecasting may also be compared with the outcomes of a building simulation approach. It is hoped to demonstrate that data analysis tools can be successfully used for this purpose in the absence of a building model, or in conjunction with a building simulation approach.

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Data Availability Statement: The climate dataset is publicly available on the Australian Bureau of Meteorology site: http://www.bom.gov.au/Climate (accessed on 3 March 2022). The raw data related to the site are proprietary. If there is an interest in collaboration, please contact the corresponding author.

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Abbreviations

Acronyms	Description
PCC	Pearson Correlation Coefficient
PCA	Principal Component Analysis

NN	Neural Network
LR	Linear Regression
CSIRO	The Commonwealth Scientific and Industrial Research Organisation
OBD	Occupied Bed Days in a Calendar Month
OBD/D	Occupied Bed Days per Day in a Calendar Month
SPR	Separations in a Calendar Month
SPR/D	Separations per Day in a Calendar Month
MMAX	Monthly Mean Daily Maximum Temperature
MMIN	Monthly Mean Daily Minimum Temperature
MHT	Monthly Highest Temperature
MLT	Monthly Lowest Temperature
MLMT	Monthly Lowest Daily Maximum Temperature
MHLT	Monthly Highest Daily Minimum Temperature
RCP	Representative Concentration Pathway
SVD	Singular Value Decomposition
RMSE	Root Mean Squared Error

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