Highlights

- Energy use characteristics in different buildings used for various academic activities such as teaching, research, administration, academic office works, and self-learning
- Energy use characteristics in different buildings used for various disciplines such as Business, Health, Science, Arts, Education and Law
- A literature review of exiting benchmarking and energy characteristic studies in educational buildings such as schools and universities
- Comparative study of statistical benchmarking techniques to find the most appropriate benchmarking technique for higher education buildings including methods such as ordinary least square, corrected least square, data envelopment analysis and stochastic frontier analysis
- Energy use benchmark for higher education campus buildings focused on different disciplines and activities

1

Energy use characteristics and benchmarking for higher education buildings

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Abstract

Higher education buildings serve complex functions by providing spaces for various activities and disciplines. This study aims to understand energy use characteristics of different types of buildings in higher education campuses and to establish an energy benchmark system. The data was collected form 80 university campus buildings in Australia. Energy consumption (EC) and energy use intensity (EUI) as well as related space types and occupancy conditions were analysed. Based on a comparative study of several statistical methods, the stochastic frontier analysis (SFA) method was selected as the most appropriate benchmarking technique for this research. The benchmark values for various activities and disciplines were determined using the SFA statistical technique. Regarding activities, buildings which were used mostly for research had the highest benchmark EUI value at 216 kWh/m²/year and buildings for academic offices had the lowest benchmark value at 137 kWh/m²/year. When considering disciplines, buildings for *Science* had the highest benchmark EUI value at 164 kWh/m²/year and building type can guide university authorities to promote energy efficiency by evaluating energy use, determining feasible energy saving techniques, and forecasting future planning development.

EC	Energy consumption
EUI	Energy use intensity
GFA	Gross floor area
OLS	Ordinary least square
COLS	Corrected ordinary least square
DEA	Data envelopment analysis
SFA	Stochastic frontier analysis
BBR	Building bulk ratio
HVAC	Heating, ventilation and air-conditioning
LAB	Laboratory
СОМ	Computer laboratory
LIB	Open stack library
STD	Studio
CLNC	Clinic
LCTR	Lecture and seminar rooms
RTL	Retail
1	

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Keywords: energy efficiency; university buildings; higher education; energy use benchmark; building types

1 Introduction

There is an international agenda to accelerate the sustainable transformation of the built environment due to rising public awareness regarding the impacts of the built environment on global environmental issues. Recently, there has been a growing interest in sustainability declarations in higher education institutions, as universities play a key role in creating a sustainable future [1]. The scale of investment in green and well-designed campus buildings creates unprecedented openings for sustainable transformations. Sustainably designed or green higher education buildings can make a strong contribution to the spread of sustainability education [2]. Acting as models for communities, universities are innovators through research activities in sustainability transformations [3]. Investment in green buildings and sustainability programs helps universities to promote public relations and increase market share by contributing to campus reputation [4]. This indicates that the environmental performance of universities is directly linked to governmental grant allocation as it helps governments to reach emission reduction goals [5]. As a result of the factors mentioned above, campus sustainability has become a concern for university policymakers and planners [6].

The first step towards campus sustainable transformations is minimizing resource and energy consumption in new and existing buildings [7, 8]. Energy management of buildings in Australia, which has the highest greenhouse gas emissions per capita among the developed countries in the world, is a challenge [9]. Australian university promotion and action plans supported by the United Nations Environment Programme (2014) for green buildings can be divided into three main strategies: energy conservation in the form of revised policies and interventions, energy efficiency through maintenance and management, and renewable energy as an alternative solution [10]. This research aims to target the first strategy by introducing a benchmark system to promote energy efficiency through revised policies and interventions. Energy efficient structures refer to buildings that provide the same amount of services and outputs with less energy when compared to similar buildings [11]. Energy benchmarking is the development of a system which predicts the energy performance of buildings based on a sample of similar reference buildings [12]. Several factors should be considered in an energy efficiency evaluation, including (1) random factors and unusual climate conditions, (2) physical characteristics such as age and number of floors, (3) building management incentives such as heating, ventilation and cooling (HVAC) scheduling, and (4) differences in how building occupants utilize devices such as indoor environmental controls, and plug loads [12].

However, energy efficiency evaluation is different from energy benchmarking. A benchmark is a value of a performance metric, which indicates a point of reference and a threshold to evaluate building performance. A metric is a unit of measurement for services, facilities or components [13]. Energy benchmarking aims to identify indicators of energy assessments, and contributes to the improvement of building energy performance. Energy benchmark systems are normally presented in a form of a benchmark table of energy consumption normalized by floor area and outdoor temperature [11]. For the purpose of energy efficiency, benchmarks are used to forecast demand, stimulate the adoption of new technologies, and promote energy efficiency.

2 Background

Earlier studies have investigated explanatory factors on building energy consumptions and endeavoured to find relationship between energy consumption, and environmental and non-environmental factors. One study found a significant positive correlation between building energy consumption, and building age while outdoor climate showed insignificant influence on energy use [14]. On the contrary, another study [15] implied that energy consumption correlates highly with outdoor temperatures. A series of energy management techniques, such as turning heating systems on and off, and administering an occupancy schedule for heating systems were applied in a university building, and 40% reduction in energy loads were reported [16]. Another study [17] found a potential 6%–30% in energy savings when some energy saving measures were applied, such as changing indoor temperatures, occupant behaviours, and building envelope properties. Using simulation methods, one study [18] showed that there was a 20% to 40% energy saving potential with reasonable paybacks when energy efficient technologies and equipment were applied.

Past research has shown that energy loads, particularly electricity consumption in residential buildings, can be correlated with occupant related activities [19, 20]. Some research has focused on the influence of occupant intervention in reducing energy consumption in commercial and institutional buildings by implementing individual controls and occupancy sensors of indoor environmental conditions and reported considerable energy

savings [21-23]. However, the influence of occupant behaviour on energy consumption in commercial and educational buildings has been an enduring challenge as most buildings of these types are managed by BMS (building management system) and occupants have no or limited controls on indoor environmental conditions [24, 25]. This contradiction has been further exemplified in a study of a university building managed by BMS which found no relationships between occupancy patterns and energy loads [25].

Finding a relationship between energy consumption and occupant behaviour is a challenge because of the stochastic nature of human actions, and the complexity of characterising behaviour [24, 25]. That is why simulation studies often suffer from a lack of accuracy in occupancy patterns, and result in discrepancies between measured and simulated energy consumption data [26]. Thus, occupancy forecasting models based on physical-statistical approaches have been developed in a few studies to predict occupancy patterns to be used in simulation studies, and to improve energy forecast accuracies [22, 26, 27]. One study developed a stochastic behaviour model for users moving in and out of cubicle offices [27]. Some studies found alternative solutions to formulate occupant behaviour and investigate relationships between behaviour patterns and energy consumption in buildings. One study found a positive correlation between Wi-Fi network connection and building energy consumption [24], and demonstrated that Wi-Fi connection was a useful indicator of occupancy patterns in buildings. Another study examined plug load data as an indicator for occupancy patterns to find relationships between equipment loads and cooling energy consumption [28].

Previous studies have emphasized the importance of activity-based benchmarks and highlighted the importance of assessing building environment as an energy use determinant [29]. To understand occupancy activity, occupancy densities could be another important energy demand determinant. The number of visitors, in addition to permanent residents, should be determined to study occupancy patterns as one study showed visitors accounted for 92% of the building occupants [25]. Another study showed that the number of visitors in a building in one hour was equal to the maximum capacity of the building [30].

In order to systematically search for literature published in energy benchmarking for education buildings a systematic quantitative literature review was conducted [31, 32]. Scholarly electronic databases were searched to find original research papers published on the topic "building energy consumption and benchmarks in educational buildings". The searched databases included: Scopus, Science Direct, ProQuest, Web of Knowledge, and Google Scholar. Databases were searched between June 2017 and November 2017. Keywords used for the search included: "energy", "benchmarks", "educational buildings". Table 1 lists some key references and their research findings (Table 1).

Earlier energy studies have used three different energy models of white-box (Physics-based), black-box (datadriven) and grey-box (a combination of white-box and black-box) to evaluate energy efficiency in educational buildings [28]. White-box models present physics-based evaluations including simulation studies while blackbox models are based on data and statistical techniques of using reference buildings as an evaluation tool such as regression or neural networks [33]. Grey-box techniques are a combination of white-box and black-box models [34]. Table 1 presents some related key studies in educational buildings using white-box, black-box and grey-box techniques.

Source/ date	Method (Approach)	Country (Climate)	Sample	Avg. EUI (kWh/m²/year ⁾	Findings
Sharp [35]/1998	Black-box (COLS)	USA (Temperate)	Schools	-	Beyond floor area, the most predictive variables were the number of workers, number of personal computers, owner-occupancy, operating hours, and the presence of an economizer or chiller.
Kim, Lee and Hong [36]/2012	Black-box (EUI)	South Korea (Temperate)	10 schools	289	Monthly energy consumption of the elementary schools in South Korea, is highest in Dec and lowest in Jan and August. Annual energy use continues to increase due to replacement of cooling/heating systems by electric systems, the installation of electric IT equipment, and the changes in the outdoor temperature.
Hernandez, Burke and Lewis [37]/2008	Grey-box (EUI & Physics- based calculation)	Ireland (Temperate)	88 schools (measured) & 500 schools (calculated)	31 measured 53 calculated	Two methods of energy benchmarking using calculated rating and a measured rating were proposed.
Chow, Ganji, Hackett, Parkin and Fetters	White-box (Simulation)	USA (Temperate)	12 schools	1590	The results show a 20-40% energy saving potential with reasonable paybacks using the available energy efficient technologies.

Table 1. Literature review table of energy consumption studies in educational buildings.

[18]/2003

Butala and Novak [38]	Black-box (EUI)	Slovenia (Temperate)	24 schools	112	Three key energy saving measures were identified as building envelopes, heating devices and systems, and management
Santamouris, Balaras, Dascalaki, Argiriou and Gaglia [39] / 1994	Black-box (EUI)	Greece (Mediterrane an)	238 schools	93 avg.	In Greece, school buildings were identified as the least energy consuming building type as they don't utilized cooling systems and operate for nine months a year.
Dimoudi [40] / 2013	Black-box (EUI)	Greece (Mediterrane an)	77 schools	84 avg. 41 benchmark	Measures to reduce heating energy were identified as the most effective tool to both reduce energy consumption and improve thermal comfort conditions in Greece.
Desideri and Proietti [41] / 2002	Black-box (EUI)	Italy (Mediterrane an)	29 schools	-	38% and 46% savings were reported in thermal energy and electricity consumptions, respectively when energy efficiency measures were applied.
Monts and Blissett [42]/1982	Black-box (OLS)	USA (Subtropical)	342 universities	-	A model incorporating climate, occupancy patterns, HVAC design, and building type explains 42% of the EUI variance in a sample.
Federspiel, Zhang and Arens [43]/2002	Grey-box (COLS, EUI & simulation)	USA (Subtropical)	19 universities	-	The model-based benchmarking method was more accurate when a combination of laboratory and non-laboratory buildings was analysed.
Wang [44]/2016	Black-box (OLS)	Taiwan (Subtropical &Tropical)	51 universities 23 schools	79 universities 26 high schools 17 elementary schools	Universities use 3-4.9 times more energy than schools.
Sekki, Airaksinen and Saari [14] /2015	White-box (OLS)	Finland (Temperate)	80 day-cares 74 schools 13 universities	251 day-cares 214 schools 229 universities	Good positive correlation between building age and energy use was found. Climate was not a good indicator for energy consumption
Chung and Rhee [17]/2014	White-box (Physics- based calculation)	South Korea (Temperate)	11 universities	223	A potential 6%–30% energy savings was found trough changing indoor temperatures, occupant behaviour, and building envelop properties.
Jafary, Wright, Shephard, Gomez and Nair [15]/2016	White-box (EUI)	USA (Subtropical)	4 universities		Energy consumption correlates highly with outdoor temperature.
Yang, Santamouris, Lee and Deb [28]/ 2015	Grey-box (OLS & simulation)	China (Subtropical)	3 universities		This study presents an investigation and discussion on a newly developed methodology for institutional building cooling load consumption modelling and simulation considering occupancy patterns based on plug loads and HVAC loads

Using black-box methods of statistical techniques, the typical energy consumption in school buildings were reported as 289 kWh/m² [36] in South Korea, 112 kWh/m² [38] in Slovenia, and 93 kWh/m² [39] and 84 kWh/m2 [40] in Greece. Using statistical techniques, a benchmark value of 41 kWh/m² for energy use was determined for schools in northern Greece [40]. In another black-box study in Greece [45], a mean energy consumption of 68 kWh/m2 and a benchmark value of 42 kWh/m² was reported using fuzzy clustering techniques. Sharp [35] studied benchmarking for schools in the United States and found that apart from floor area, the most influencing variables for energy intensity were the number of workers and personal computers, owner-occupancy, operating hours, and the presence of an economizer or chiller. Using black-box methods, a regression model incorporating climate, occupancy patterns, HVAC design, and building type was developed by Desideri and Proietti [41] which studied energy saving potentials in 29 school buildings in Italy, and reported a potential of 38% and 46% savings in thermal energy and electricity consumption, respectively. Monts and Blissett [42] found 42% variance in EUI (energy use intensity) in a sample of Texas school and university buildings. Black-box methods have also been used to evaluate energy efficiency in 23 school and 51 university buildings in Taiwan, and typical energy consumption was reported as 16 kWh/m², 26 kWh/m² and 79 kWh/m² in elementary schools, high schools, and university buildings, respectively [44]. In another comparative study [14], the median energy consumption was reported as 251 kWh/m², 214 kWh/m² and 229 kWh/m² in day-cares, schools, and university buildings, respectively.

A number of studies used white-box and grey-box methods to evaluate energy performance of buildings. Using white-box techniques, one study reported a median energy consumption of 223 kWh/m2 analysing 11 university buildings in South Korea. Another study used simulations as a white-box methodology and reported a high benchmark value of 1590 kWh/m2 for school building in the United States. Using a grey-box technique, one study combined measured data of plug loads with simulation techniques to analyse energy efficiency in university buildings in China [28]. Another study in Ireland used a mixture of measured and simulated energy consumption, and reported a benchmark value of 31 kWh/m² through measured data and 53 kWh/m² through

simulations [37]. Using a combination of simulation techniques and statistical methods, Federspiel, Zhang and Arens [43] studied laboratory buildings, and found that benchmarking models were more accurate when a combination of laboratory and non-laboratory buildings was included in the sample data.

Regarding laboratories, a benchmark system based on idealized models of equipment and system performance was developed using simulation techniques in a study by Federspiel, Zhang and Arens [43], which identified HVAC and plug loads as one of the most important factors in high energy consumption in laboratory buildings. By introducing four different benchmarking strategies for laboratories, Sartor, Piette, Tschudi and Fok [46] indicated that laboratory buildings could consume four to 100 times more energy than other campus buildings. One study emphasized the significance of energy benchmarking for laboratories, and listed some key normalizing parameters for laboratories including gross area, lab area, weather, lab type, lab use, occupancy schedule, required ventilation rates and equipment load [13]. Another study by categorizing laboratories into different classes of science, applied science, intervention and analysis indicated that laboratories in average use four to five times more energy than non-laboratories comparing campus buildings [47]. In another study in the United States, energy consumption in laboratories constitute three times more than non-laboratory buildings [48].

The analysis of energy consumption comparison between university and school buildings show that campus buildings used far more energy than schools because of longer operation periods and higher equipment loads compared with schools [44]. To keep a consistency in energy use patterns and energy loads, in this study we focused on energy consumption in university buildings using statistical methods of real energy data. After normalization of energy data by degree days and gross floor area, the influence of several factors, such as building function, and academic discipline on energy consumption was studied. To overcome the main uncertainties regarding occupancy patterns and intensities, the influence of building function, and academic discipline on energy consumption function, and academic discipline on energy consumption was studied. The complexity of model-based benchmarks, energy benchmarking based on normalized ranking has been utilized in several earlier studies [49]. Thus, this research uses four different approaches of statistical techniques to define energy efficiency, and develop a benchmarking system based on normalized ranking.

This research aims to develop an energy assessment and benchmarking system for university buildings in Australia. Australia has eight climatic zones, based on classifications defined by the Building Code of Australia [50]. However, many major cities, such as Brisbane, Sydney, Adelaide and the Gold Coast, accommodating universities and higher education facilities, are located in subtropical regions. As a result, subtropical climate was selected as a focus for this study to develop an energy benchmark for subtropical climate in Australia. This paper aims to conduct a systematic energy characteristic and benchmarking study using a set of comprehensive statistical methods for higher education building types. The objective of this paper is to offer a first step towards achieving energy efficiency in university campus buildings by evaluating the performance of existing buildings.

A major problem for studying university energy uses is occupancy pattern which involves various activities and disciplines. Each discipline has distinctive characteristics in terms of occupancy and activities. In our research, the four major discipline categories of *Business, Health* and *Science*, as well as *Art, Education and Law (AEL)* were studied. Another focus of this study is campus activities such as teaching, learning, academic office work, research, and administration. Each of these activities requires specific indoor environmental conditions with different occupancy and energy use intensity. Each activity demand different occupancy and operation hours, which in turn influences HVAC and equipment loads. The study would help to identify a pattern of energy consumption across campus activities and disciplines.

3 Method

3.1 Griffith University

This research uses Griffith University as a case study. Griffith University accommodates a wide range of disciplines. Its campuses include spaces such as laboratories for different disciplines, teaching spaces, offices, seminar rooms and communal spaces. This provides an opportunity to have a diverse dataset of buildings, and to develop a benchmarking model for the subtropical climates in Australia. Griffith University has five campuses which are located on the Gold Coast and in Brisbane, two major cities in Southeast Queensland in Australia (See Figure 1). According to Koppen's climate classification, Brisbane and the Gold Coast share a humid subtropical climate with hot and humid summers, and moderately dry warm winters [51]. Due to warm ocean currents, there

is relatively small seasonal temperature variability in both cities. The average temperatures for Brisbane are below 30.3 °C in summer and above 10.2°C in winter; the average temperatures for the Gold Coast are below 28.7°C in summer and above 12.0°C in winter [52]. Average relative humidity ranges from 43% to 59% for Brisbane and 55% to 70% for the Gold Coast [52].



Figure 1. Location of the Gold Coast and Brisbane in Australia ©Google.

Griffith University has 185 buildings across five campuses. These buildings are divided into groups representing major building functions such as academic offices, teaching, research, administration, library, residential, retail, water chilling buildings, and recreational. The categories defined here are adopted and slightly modified from the Higher Education Funding Council for England initiatives [53]. Residential, retail and recreational buildings were excluded from the dataset due to their unrepresentativeness of university building types. For this study, the energy data for these buildings were provided by building energy managers. Electricity is the main energy type used in these buildings and data are monitored and published by smart meters. Since December 2014, energy data at Griffith University have been collected by smart meters and published online by PI Vision software, where it is monitored and controlled by facility managers for energy management and maintenance purposes. The data of monthly and annual energy consumption (kWh) of individual buildings during the years 2015 and 2016 was collected. Several buildings with missing or inaccurate information were excluded from the study. In total, 80 buildings were selected for the statistical benchmarking representing university buildings in the subtropical climate of Queensland in Australia. The sample consisted of 50 academic office buildings, 11 administration offices, 8 teaching buildings, 6 research buildings, and 5 libraries.

A summary of the selected university building types with their characteristics, such as major space function, local indoor environmental controls, annual and daily operating periods, and individual occupancy patterns is presented in Table 2. Campus buildings accommodate a differing proportion of spaces for different activities. For example, a building may have 70% of space used for teaching and 30% for laboratories while another building may have 40% of usable floor area occupied for administration offices and 60% for teaching rooms. Since there is no sub-metering for individual rooms or activities, we categorised buildings into six classes based on the major activity. The criterion was that more than 40% of the usable floor area of a building should be dedicated to that activity. For instance, a building which had more than 40% spaces for laboratories was classified as a research building. Buildings with multiple activities occupying more or less equal proportions were classified as mixed use buildings.

University space type	Major space function	Local indoor environmental controls	Annual operating period	Daily operating period	Individuals occupancy duration	Occupation intensity
Academic office	Cellular offices open-plan offices Meeting rooms	Moderate	All year	9 - 17:30	Variable *mid- to long- term	*low-density
Teaching	Lecture theatres Halls Seminar rooms Tutorial rooms Classrooms	High	Semester time	9 - 17	* Short-term	high-density
Research	Laboratories Workshops Computer terminals	High	All year	24 hours	Variable	low-density
Administration	Administration offices	Moderate	All year	8:30 - 17	Long-term	moderate- density
Library	Resource centres Reading rooms Meeting rooms Book shelves/open stack library	Limited	All year	8 - 19	Variable short to long-term	low-density

Table 2. Case study's Representative space types and their characteristics.

* Short-term is under 2 hours; mid-term is between 2 and 5 hours; and long-term is above 5 hours

* Low-density is 30 or fewer occupants in every 1000 square feet. High-density is more than 30 occupants in every 1000 square feet [54].

Descriptive statistics of the studied buildings regarding building gross floor area (GFA), building age, occupant numbers, and operational hours across the selected campus activities are summarized in Table 3. The average GFA of buildings was the highest for libraries, indicating that library buildings were the largest buildings on the campuses. The average GFA of libraries was almost four times more than academic office buildings. The average age of buildings among different building types ranged from16 to 27 years. The oldest building (86 years) was a teaching building, and the youngest was a mixed use building (3 years). The rationale for counting occupant numbers was as follows: full time staff and students counted for one, and part time students counted for half. As discussed previously, each university building accommodates various spaces and activities. According to our classifications for activity types, for example an academic office building constitutes mainly of offices, but also may include research laboratories, teaching spaces and administration offices. As a result, in listing operation hours, we considered individual spaces rather than the whole building.

	GFA (gross floo	r area)	X	Buildi	ng age			Occup	ant numb	ber		Operati	ng hours		
	m ²				Year	00			People	count			Hours of	count		
-									1							
Building type	Avg.	Max	Min	Std.	Avg.	Max	Min	Std.	Avg.	Max	Min	Std.	Avg.	Max	Min	Std.
Academic offices	1967	4576	292	1337	21	43	10	11	247	503	46	118	12.8	24	8	2.8
Administration	2211	5698	130	1766	27	45	10	11	181	375	20	106	10.6	24	8	5.7
Library	9228	18264	5893	5141	16.2	21	4	7	447	1314	20	505	12.2	15	8	3.8
Research	3527	7811	112	2269	19	43	4	14	191	323	37	106	16	24	8	6.3
Teaching	2912	7272	311	2587	20	86	54	11	230	823	9	273	8	9.5	8	3.4
General	5604	30436	908	5353	21	48	3	12	165	506	8	133	10.6	24	8	4.6

Table 3. Descriptive statistics regarding gross floor area, building bulk ratio, and age of the 80 university buildings.

The terms used in Table 3 refers to building types. *Academic offices* represents spaces such as cellular and open plan offices for staff and research students, seminar rooms, tutorial rooms, classrooms, and meeting rooms. This building type requires moderate indoor environmental controls. Operation of academic office spaces is all year round with normal daily operation time from 9am to 5:30pm. Occupancy duration varies greatly, from mid to long term, and low density occupancy. *Teaching* represents spaces such as lecture theatres and halls. As teaching spaces are highly dense occupied spaces, they require high indoor environmental controls. The annual operation period is limited to semester periods with operation time between 9am to 5pm. Individual occupancy patterns are short term. *Research* represents spaces such as dry and wet laboratories, laboratory preparation, cold rooms, workshops, and computer terminals. They require high indoor environmental controls and accommodate

spaces with high cooling loads. Due to health and safety factors, high air change rates, approximately four times more than normal office environments, are utilised in laboratories. The operation of research spaces continues during the semester breaks on a twenty-four hour and seven day basis all year round. The occupation density varies with experimental needs. *Administration* represents spaces such as offices for administrative jobs. The indoor environmental controls are moderate with all year operation periods. Daily operation hours are from 8:30am to 5pm in most administration office types. The individual occupancy duration is long term with moderate-density similar to commercial office buildings. *Library* represents spaces such as resource centres, reading rooms, quiet study rooms, group meeting rooms, and library bookshelves or open stacking. The indoor environmental controls are limited as this building type is a low-density space with variable occupancy duration from short to long-term. The annual operating period is all year from 8am to 7pm on normal working days.

Energy demands and reductions also vary according to different academic disciplines. Using normalized ranking benchmarks, one study in 98 university buildings showed that *natural science and technology* disciplines accounted for the largest energy consumption on campus [55]. The reason for the difference in energy use in different disciplines may be explained by the difference in learning methodologies. The *science* discipline places emphasis on experimental learning by having major activities occurring in laboratories and workshops. *Business*, and *AEL* on the other hand place emphasis on theoretical learning, and most activities are undertaken in teaching and learning spaces. The *Health* discipline has an equal distribution of emphasis on both theoretical and experimental approaches. In recognition of this discipline-based variation, disciplinary splits of energy consumption behaviour and energy demands were studied in this paper. Similar to the categorisation of activities, buildings were categorized into groups based on major disciplines with space occupation of more than 40% usable floor area in the whole building. Buildings shared by several disciplines occupying more or less equal proportions were classified as *general*. Based on all the nomenclature in this study, the five groups of buildings were *Business*, *Health*, *Science*, and *AEL*, and *general*.

Academic offices, research and administration buildings accommodate laboratory spaces for different disciplines. The HVAC systems for laboratory buildings operate for twenty-four hours and seven days, yet for offices and teaching spaces, occupancy sensors trigger the systems. Ventilation systems in all buildings are variable air volume (VAV) with chillers for the cooling season and electrical heaters for the heating season. Air handling units distribute the conditioned air through overhead vents in most buildings. There is a variation in terms of equipment loads in different buildings. Laboratories accommodate equipment with higher plug loads and for longer hours than other space types such as offices or lecture theatres. Windows are not operable in most spaces except in a few rooms. Since there are individual controls or thermostats for switching off ventilation systems in some individual rooms when windows are open, building management has a clear rule of discouraging occupants to open windows. This causes interruptions with the central management system, wastage of energy, and possible formation of condensation. The indoor comfort temperature range is set to 23.0° C in winter and 24.5° C in summer. There is an adjustable air mixer in air handling units which mixes outside air with recycled air from indoors to balance CO₂ levels in rooms. Electrical heaters are located in duct works and are used when needed in the heating season.

3.2 Benchmarking method

The benchmarking process based on statistical regression is composed of four steps: (1) the selection of variables; (2) data normalization; (3) multiple linear regression analysis; and (4) benchmarking.

3.2.1 Selection of variables

Benchmarking is independent of the infrastructure of buildings, including HVAC system efficiency, envelope thermal properties, and equipment loads [56]. Accordingly, the aim of this project was to analyse the energy performance of buildings with specific service provisions regardless of individual subsystems such as building thermal envelope, window to wall ratio, or HVAC system efficiencies. Hence, energy is considered as a function of the quantity of services provided. In other words, this paper seeks to identify optimal energy use for given university building services. The following section provides a more extensive explanation of the selected variables for the regression analysis process and for developing a formula for energy benchmarking based on independent variables.

The HVAC requirements, operation hours, and equipment loads in buildings vary greatly depending on space types and activities. As an indicator of energy loads, space types as another important variable was considered in

the regression analysis. Climate also greatly influences the energy consumption of buildings. Since the data were collected from the same period of time (January 2015 to December 2016), normalization was performed to adjust the effect of climate on cooling and heating loads. This is explained more extensively explained in the following section.

The energy used in university buildings, like any other buildings, is influenced by building services provided in the facility. The energy used for providing services such as artificial lighting, electricity supply for equipment, HVAC varies depending on the efficiency of the systems and loads. A framework for representing ontology and relationships between the dependent variable (energy use) and independent variables selected for this study is illustrated in Figure 2.





3.2.2 Data normalization

By assuming a linear relationship between climate (degree days) and energy use, climate normalization is adapted to account for annual climatic fluctuation [57]. As suggested by some researchers [58], adjustments are applied by multiplying the energy data by climate correction factors. In this paper, climate correction factors are defined as average degree days in a ten-year period divided by degree days of an observation year [59]. Degree days, as a sum of cooling and heating degree days, calculate how much the outside temperature is lower or higher than a specific base temperature, which is 18°C for the Australian context [60]. Energy consumption was also normalized by floor area to identify individual building energy use intensity, also called as the energy utilization index (EUI), which is a simple and easily understandable method for energy efficiency evaluation.

3.2.3 Multiple linear regression analysis

Statistical analysis was performed with IBM SPSS Statistics package 22. The multiple linear regression model was validated with a data-splitting method by randomly splitting samples into two parts: two thirds consisting of 53 datasets, and the remaining one third of 27 datasets. Model validation and the data-split method was adopted from Picard and Berk [61]. Multicollinearity between variables was investigated.

3.2.4 Benchmarking techniques

After the regression analysis, benchmarking was performed using four different benchmarking methods, OLS, COLS, SFA, and DEA, in order to reduce benchmarking limitations. The following section provides an overview of each method.

3.2.4.1 Ordinary least square (OLS)

OLS is a linear regression model that determines the efficiency line by minimizing the sum of squares of errors (distance of data points from the line also to be known as residuals). Based on sample information, OLS represents average practices. OLS applies regression analysis principles to determine the relationships between the variables and predict the energy intensity of buildings based on a simple linear regression model [62]. In this method, average energy efficiency level can also be estimated with the help of the regression line. Buildings with energy intensity higher than the average line are considered energy inefficient, and buildings under the

regression line are considered efficient. Residuals as the difference between the observed energy use and the predicted energy use can be used as a measure of efficiency and to establish distributional benchmarking tables. This method was introduced by Sharp [63], and was later used as a basis for developing the Energy Star modelling [64]. The typical OLS regression model is formulated as [65]:

$$Y = a + b_1 x_1 + b_2 x_2 + \ldots + b_k x_k;$$

(eq.1.)

where Y is the dependent variable; a is the intercept; $b_1, b_2, ..., b_k$ are the regression coefficients; $x_1, x_2, ..., x_k$ are the significant independent variables. An example which used the OLS method in estimating the impact of cost inputs was research by Banaeian, Omid and Ahmadi [66] which performed an energy and economic analysis of greenhouse strawberry productions.

3.2.4.2 Corrected ordinary least squares (COLS)

A more advanced version of the OLS method initiated by Winsten [67] is COLS, which is performed in two stages. At the first stage, the regression line is determined using the OLS method in which some of the residuals are negative and some positive. At the second stage, the regression line is shifted downward in a way that all the residuals become positive. This means that the most energy efficient observation is considered as the efficient standard and the rest of the observations as inefficient. Instead of considering the mean value for defining efficient EUI, the COLS method uses the lowest EUI to calculate the residuals and efficiency. The COLS estimates the frontier line based on the single best practice. The downfall, however, is that the results are highly dependent on the performance of the most efficient building in the database, and have no recognition of stochastic errors [12]. COLS shares some similarities with the DEA method, as both methods assume residuals are due to inefficiencies. This is further developed in Section 3.1.5. Again similarly to DEA, COLS ranks all efficiencies on a 0 to 1 scale with 1 being the most efficient building. A review paper by Banker, Gadh and Gorr [68] comparing COLS and DEA methods indicated that COLS performs better with sample sizes of 50 or over.

3.2.4.3 Stochastic frontier analysis (SFA)

The SFA model is a parametric frontier method, which uses regression analysis and a mathematical formula to form the frontier line, assuming the existence of a parametric function between production inputs and outputs [69]. This method is claimed to control a range of economic and other influencing factors, and to measure energy efficiency. The method was initiated by Aigner, Lovell and Schmidt [70] and Meeusen and van Den Broeck [71] independently in 1977. Being a stochastic approach, SFA acknowledges the possibility of statistical noise or random errors such as measurement flaws. In fact, SFA assumes that errors or residuals consist of two parts: statistical noise and systematic inefficiencies [72]. In other words, the COLS method assumes that all the residuals are due to inefficiencies, while SFA separates random errors from inefficiencies. This potentially leads to a more accurate estimation of efficiency when errors are discriminated because the distance between the data points is closer to the efficiency line in SFA in comparison with the COLS method [69]. The regression functional form is an econometric technique which uses regression analysis to estimate the energy efficiency of buildings [73]. Some interesting examples of using SFA for energy benchmarking include works by [74], Buck and Young [75], and Boyd [76]. A SFA model can be formulated as Eq. (2) where the U_k is systematic efficiency which must be positive, whereas the V_k is statistical noise of k^{th} sample building. $y_k = f(x_{1k}, x_{2k}, \dots, x_{Mk}, U_k, V_k)$ (eq.2.) [69]

The functional form f aims to generalize the likelihood functions of stochastic frontier estimation and stochastic errors have been addressed in numerous studies [77-79]. One of the most common methods for specifying functional forms and distribution of inefficiencies using SFA is extensively described by Zhou, Ang and Zhou [80]. One of the advantages of SFA is that, unlike OLS and COLS, it reduces reliance on the performance of a single efficient building. However, one of the biggest drawbacks of the method is that if there are no measurement errors, some of the residuals, which are here due to systematic inefficiencies, will be wrongly regarded as statistical errors [81].

3.2.4.4 Data envelopment analysis (DEA)

DEA is a non-parametric approach which classifies buildings into different classes and then compares the energy performance based on the best performing building in each class [82]. The DEA method was built upon works of Farrell [83] in 1957, who developed a mathematical programming model to determine the relative efficiency of comparable entities. Regression models determine energy efficiency by comparing buildings with the average trend over the entire population, while DEA models compare buildings with the best performing buildings in each class. The main advantage of DEA is that it is not based on any presumptions regarding the correlations between inputs and outputs [84]. The DEA method uses measured data to determine the frontier

line, so it is data-driven frontier analysis [85]. The DEA efficiency measure is used to rank decision making units (DMUs) or buildings in this context [86]. In this model, for each building a measure of input factors is dedicated to transform multiple input factors such as usable floor area, occupant population, and equipment efficiency into a single indicator. Efficiency scores are calculated by the Eq. (3):

Efficiency = weighted sum of outputs / weighted sum of inputs

(eq.3.) [12]

In the DEA method, models could be input oriented, which minimizes input for a given output, or output oriented, which maximizes output for given input factors [87]. The efficiency scores in the input oriented method is a value between 0 and 1, while in the output oriented method, the value ranges between 1 and infinity with 1 being the frontier factor in both methods [88]. The most common DEA models can be classified into two categories of constant returns to scale also known as CRS [89], and variable returns to scale as VRS[90]. The CRS method was pioneered by Charnes, Cooper and Rhodes [91] in 1978, whereas VRS was developed by Banker, Charnes and Cooper [92] in 1984.

Each benchmarking method, mentioned above, has its advantages and disadvantages. The reason for using the four different benchmarking methods was to limit biases because benchmarking is relatively subjective to the method which is used for defining efficiency. Based on the benchmarking technique, the energy efficient buildings are defined in different ways. A building which is efficient in the DEA method, for example, may not be energy efficient if the SFA techniques are applied. The main weakness of OLS and COLS is that they reflect a combination of relative efficiency. In particular, OLS calculated the fitted average to estimate efficiency, while ignoring the theoretical notion of energy efficient [63]. This makes the efficiency line relative efficiency depending on the performance of a single building. SFA differentiates random errors from relative inefficiencies, and unlike the other frontier method of COLS, estimates the efficiency model with consideration of possible random errors [81]. DEA envelopes the buildings with the outermost energy efficient buildings and determines frontiers using the most efficient practices [93]. The disadvantage of DEA is that some outlier buildings may fall on the enveloping line and be considered as efficient practices [12].

4 Results and analysis

First, energy characteristics and statistical differences between different academic activities were examined, followed by a correlation analysis. Second, energy characteristics and statistical analysis between different disciplines were explored along with a correlation analysis. Then, a regression model was developed on the prediction of EC and EUI to explore various building characteristics. Finally, the benchmarking process using the different statistical methods was conducted.

4.1 Energy characteristics across different academic activities

The difference in energy use between different types of campus buildings can be seen in Table 4. Libraries and research buildings on average consumed more energy than other types of buildings on campus, with the mean value almost four times more than academic office buildings. In addition, the variation in energy use per activity was significant, as shown by the standard deviation. Mixed use buildings had the largest standard deviation. However, the average EUI values were higher in research buildings. The standard deviation showing the variation in energy intensity in buildings was also higher in research buildings. The second most energy intensive activity was teaching. The analysis of the main statistical features of the EC and EUI values showed that the distribution of the energy use patterns was dissimilar among various building types (Figure 3).

Table 4. Average energy consumption (EC) and energy use intensity (EUI) during the two-year period 2015 and 2016.

Function (number*)	Energy consumption (EC) (kWh/year)				Energy use intensity (EUI) (kWh/m ² /year)			
	Avg.	Max	Min	Std.	Avg.	Max	Min	Std.
Academic offices (11)	255,096	1,198,074	29,564	330,738	121	267	43	76
Administration (15)	327,690	1,379,355	13119	367,538	135	272	40	68
Library (5)	1,162,088	1,912,679	459,286	536,301	148	84	50	233
Research (10)	1,146,690	2,246,659	13,605	604,963	379	908	121	243

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In order to statistically test the effects of academic activity types on energy intensity, a more detailed analysis of energy intensity investigating monthly usage was carried out. A comparison of monthly EUI, building types, university teaching days and outdoor degree days is illustrated in Figure 4. The annual Griffith university semester breaks are one month during July in winter, and two months starting from the middle of December until toward the end of February in summer. While most teaching activities are suspended during breaks, many research students and staff remain at laboratories during these periods. In addition, HVAC systems are continuously supplied in laboratories even during non-occupied intervals due to safety and maintenance reasons. Laboratory equipment is also used during university semester break. This increases the energy intensity in research buildings even during semester breaks.

However, most other activities stop during semester breaks. The plot of degree days shows that January and February had the highest cooling degree days; however, since these two months had few teaching days, energy consumption did not peak during these two months. Similarly, in July, heating degree days were at a peak, and since this period was campus winter break, energy loads did not peak during this month. EUI in spaces accommodating teaching and administration activities did not directly follow the outdoor climate loads. Nonetheless, research buildings had a closer correlation with outdoor climate conditions, as many research activities continue during holiday periods. However, even for research buildings the monthly energy loads did not peak at the time of the outdoor climatic peaks since none of the research buildings were fully dedicated to research spaces. Most research buildings also had office and other space types. The EUI peaked in October, when both cooling loads and teaching days were relatively high.



Figure 4. Monthly EUI of all building types and average degree days in 2016.

A Pearson correlation analysis was conducted to determine the correlations between energy use and building types (see Table 5). The EC strongly correlated with teaching and research, which means that most energy on campus was consumed for teaching and research activities. This is a result of both the size of these building types and energy intensity. However, EUI only strongly correlated with the research building type, demonstrating the high HVAC and equipment loads in this building type.

Table 5. Correlation analysis of different building types with EC and EUI.

		Teaching	Academic	Research	Administration	Libraries
			offices			
EC	Pearson correlation	0.558	0.097	0.657	0.155	0.252
	Sig.	0.000	0.196	0.000	0.085	0.012
EUI	Pearson correlation	-0.130	0.072	0.291	-0.054	0.004
	Sig.	0.126	0.263	0.004	0.317	0.485

4.2 Energy characteristics across disciplines

The distribution of energy use between different disciplines can be seen in Table 6. The *Business* buildings consumed more energy than other disciplines, with the average for *Business* almost three times more than the average for *Health*. In addition, the table shows the standard deviation for each discipline. The largest variation belonged to general buildings, which accommodated spaces for general services for the campus buildings. EUI had the highest value in the *Science* discipline indicating that the *Science* group was the most energy intensive among the disciplines. The maximum energy intensive building in the whole dataset also belonged to the *Science* group. The standard deviation of EUI was also the highest for the *Science* group.

Discipline (number*)	Energy consumption (EC) (kWh/year)				Energy use intensity (EUI) (kWh/m ² /year)			
	Avg.	Max	Min	Std.	Avg.	Max	Min	Std.
AEL (21)	593863	2132816	13119	595674	145	408	18	93
Business (5)	906662	2135455	125051	824880	185	334	98	92
Health (7)	253470	698633	14845	249110	121	267	43	78
Science (14)	502723	1615159	13605	512601	210	908	43	234
Mixed (8)	751151	1334741	35319	423875	162	227	94	48
General (25)	858683	5095378	72667	1033691	181	551	46	137

Table 6. Average energy consumption (EC) and energy use intensity (EUI) during the two-year period 2015 and 2016.

The correlation analysis between the various disciplines and their EC as well as EUI was studied. As shown in Table 7, no significant correlations were found when comparing energy use among the disciplines. However, only the *Business* school attained a positive correlation with EC, indicating that EC was slightly higher in the *Business* discipline. The *Business* school along with *Science* also obtained a positive correlation with EUI, suggesting that energy intensity was also slightly higher in these two schools. This may be because *Science* had more laboratories and *Business* had more lecture theatres than other disciplines, which accounts for high energy intensity spaces on campus. Nonetheless, the p-value or the significance of the correlations was low and regressing the EC and EUI with disciplines was not significant.

Table 7. Correlation analysis of various disciplines with EC and EUI.

		AEL	Business	Health	Science	
EC	Pearson correlation	-0.011	0.128	-0.146	-0.116	
	p-value	0.460	0.129	0.099	0.153	
EUI	Pearson correlation	-0.112	0.025	-0.097	0.049	
	p-value	0.162	0.414	0.197	0.332	

4.3 Regression analysis

A detailed regression analysis of specific spaces such as Laboratory (LAB), computer room (COM), open stack library (LIB), studio (STD), clinic (CLNC), lecture rooms (LCTR), retail (RTL), GFA and AGE was performed. LAB, COM, LIB, CLNC, RTL and GFA attained a strong positive regression with EC, suggesting that EC increased concurrently with the size of these space types. In particular, laboratory floor area and GFA had a higher positive regression with EC. Therefore, the increase in size of laboratories and building floor areas translated into increased energy loads. The correlation analysis of EUI and various factors revealed that the EUI only regressed with laboratory floor area (see Table 8). This means that the energy intensity was not attributed to COM, LIB, STD, CLNC, LCTR, RTL, GFA, and AGE. The interesting observation was that EUI did not regress particularly with age, rejecting the idea that older buildings are more energy intensive. The stepwise regression model for EC and EUI is presented in Table 9. The stepwise regression only included variables with p-value less than 0.05 to develop a regression equation model. The P-value is the probability of the condition that results have happened by chance. As indicated in Table 8, the regression model developed for EC prediction had a relatively high adjusted R-squared of 0.821 with the overall p-value of 0.000. This proved that the model developed for the EC prediction was significant.

Table 8. Correlation analysis of various factors to energy use intensity (EUI) in university buildings.

		LAB	COM	LIB	STD	CLNC	LCTR	RTL	GFA	AGE	Sig.	R-squared
EC	В	440.12	374.12	376.92	36.70	476.40	-8.09	529.54	63.82	-2009.05	0.000	0.82
	Sig.	0.000	0.027	0.002	0.746	0.013	0.933	0.003	0.000	0.556		
EUI	В	0.076	0.006	0.061	-0.028	-0.012	-0.031	0.076	-0.008	-2.004	0.103	0.180
	Sig.	0.004	0.926	0.178	0.527	0.864	0.407	0.258	0.159	0.141		

Priority of independent	Unstandardized coefficients	t value	p-value
Dependent variable: EC	coefficients		
Lab	436.793	7.44	0.000
Com	397.501	2.58	0.012
STC	379.396	3.60	0.001
CLNC	480.719	2.66	0.010
RTL	531.098	3.21	0.002
GFA	64.625	4.63	0.000
constant	47090.23	0.82	0.416
Model: Total annual energy consumption	(kWh/year)		~
$R^2 = 0.821$			
Adjusted $R^2 = 0.806$			
F value = 55.88			
p-value = 0.000			
Dependent variable: EUI			
Lab	0.048	2.49	0.015
constant	150.494	9.00	0.000
Model: Total annual energy consumption	(kWh/year)		
$R^2 = 0.073$			Y
Adjusted $R^2 = 0.061$			
F value = 6.18			
p-value = 0.015			

Table 9. Stepwise multiple regression analysis on total energy consumption (EC) and energy use intensity (EUI).

The adjusted R-squared was quite low for the regression model developed for EUI with the value of 0.061. However, the F-value, which was the ratio of the model mean square to the error mean square, revealed that the equation was a valid predictive model. F-value shows whether a regression model has statistically significant predictive capability. When the F-value is high (6.18 in this model), the null hypothesis is rejected and this proves that the model has a strong predictive capability.

4.4 Benchmarking

Based on the regression model, this section presents the procedure to develop benchmarks for university buildings using the four statistical methods in 3.2.4. A scatter plot of predicted and observed EUI was generated to illustrate the data spread based on the normal regression analysis (OLS) discussed in the previous section (Figure 5). The grey line's equation is Y = X, meaning that if a data point falls on this line, the predicted EUI is equal to the observed EUI. Based on the OLS method, the data points above the grey line represent the efficient buildings, while the dots below the grey line represent inefficient buildings. The COLS method has the equation equal to OLS, plus an intercept in a way that no data-point is above the efficiency line (Figure 5). All other buildings under the orange line are regarded as inefficient in the COLS method. The frontier method of DEA purports to estimate the efficiency line by the best practice in the data sample. The efficiency line in DEA is defined by buildings which have maximum predicted EUI for minimum observed EUI. The yellow line in Figure 5 represents the DEA benchmarking line by joining the boundary points of the most efficient buildings defined by DEA. In the DEA method, the most efficient buildings are regarded as efficient decision-making units and the rest of the practices are accounted as inefficient units. The SFA efficiency line is defined similar to the COLS method. It uses the OLS regression line, yet it allows an estimation for random errors and reduces the reliance on the performance of a single building. The SFA efficiency line is presented by the blue line in Figure 5.



Figure 5. Scatter plot of the predicted and observed EUI and graphical illustration of benchmarking with various methods.

The efficiency scores were determined by measuring how far each utility is below the efficiency line in each method. The efficiency score of 1 assumes that the practice is efficient. With the OLS method 60% of the buildings in the database are energy efficient, while in other methods a smaller proportion of the buildings are considered efficient (Table 10). With the COLS method, only one building with EUI of 121 (kWh/m²) was scored as efficient, and the rest of the buildings were inefficient compared to the performance of this single building. Determining the efficiency of the whole dataset based on the performance of a single building is one of the main weaknesses of this method. While being still a frontier method, SFA uses a larger population of building performances for efficiency approximation. In the SFA method, 7% of the buildings were marked as efficient. The minimum EUI for the efficient buildings was 43 (kWh/m²), whereas the average EUI among the efficient buildings was 153 (kWh/m²). DEA is another frontier method and it uses more than one building performance to define the efficiency line. However, some of the most energy intensive or very low energy intensive buildings, which may not represent the typical university building energy performance, were considered to define the efficiency line. For example, with the DEA method, one of the buildings with EUI of 908 kWh/m²/year was scored as efficient, while the predicted EUI was almost a third of the observed EUI. This means when using the DEA regression equation, this building was far below the efficiency line. As a result, the SFA model seemed to be the most accurate frontier method to determine building efficiencies and define benchmarking for university building types, due to the large variation in the activities and consequently energy intensity.

Method	Database efficiency	Min EUI among	Avg. EUI
	Percentage	Efficient buildings	among
			Efficient buildings
OLS	60%	18	109
COLS	1%	121	121
SFA	7%	43	153
DEA- input -VRS	6%	18	332

Table 10. Benchmarking using various statistical methods comparing the efficiency of the buildings in the database and average predicted and observed EUI for the efficient buildings.

Based on the multiple regression models and the SFA benchmarking method, energy benchmarking was developed for different building types (Table 11). As expected, research buildings were the most energy intensive and the benchmarked EUI was computed as 216 kWh/m²/year. The rest of the building types had closer benchmarked EUI values compared to the value for research buildings. Libraries and mixed use buildings had a value of 145 kWh/m²/year. Teaching buildings were fourth with a benchmarked EUI score of 149 kWh/m²/year, followed by administration buildings with a value of 140 kWh/m²/year. The least energy

intensive building type was academic office buildings with a benchmarked value of 137 kWh/m²/year. A graphical illustration of benchmark EUI values for different building types are presented in Figure 6.

Building Type	Avg. Observed EUI (kWh/m ² /year)	Avg. predicted EUI (kWh/m ² /year)	Benchmarked EUI (kWh/m ² /year)
Academic offices	121	142	137
Administration	134	148	140
Library	148	160	145
Research	379	279	216
Teaching	145	149	149
Mixed	148	171	142





Figure 6. Boxplot illustration of benchmarked EUI values for different building types.

Based on the same SFA method, energy benchmarking was also developed for different disciplines (Table 12). The benchmarking values for the different disciplines were not as diverse as they were for the different activities. *Science* was the most energy intensive discipline and the benchmarked EUI was computed as 164 kWh/m2/year. *Business* was the second most energy intensive discipline with a value of 156 kWh/m2/year. The next was *AEL* with a benchmark value of 143 kWh/m2/year. The least energy intensive discipline was *Health* with a benchmark value of 121 kWh/m2/year. An illustration of benchmark EUIs for different disciplines are presented in Figure 7.

Discipline		Avg. Observed EUI (kWh/m ² /year)	Avg. predicted EUI (kWh/m ² /year)	Benchmarked EUI (kWh/m ² /year)
AEL		145	137	143
Business		185	219	156
Health		121	145	136
Science		210	171	164
General		181	192	155
Mixed		162	174	149
	1000 900		Т	
EUI (kWh/m2/year)	 800 700 600 500 400 300 200 100 			 Benchmark Average

Table 12. Benchmarking EUI values for different building types in terms of disciplines.



Business Health Science General Mixed

Discipline

4.5 Comparison with international energy benchmarks

Art

This section provides a comparison study of the average energy consumption (the most simple and common benchmarking indicator) of campus building in the subtropical climate across the world including the USA, South Korea, China, Japan, and Australia. The average energy consumption of campus buildings in this study was 170 kWh/m², which was higher than average energy use in Taiwan campus buildings with a value of 79 kWh/m² (Table 13). Yale University showed the highest energy consumption across campus buildings in the subtropical climate with an average value of 739 kWh/m². Cornell University had comparatively lower energy consumption in the USA with an average value of 265 kWh/m² when compared to Yale University. Japanese universities had the second highest energy intensive campus buildings in comparison with other countries with values of 472 kWh/m², 465 kWh/m², and 582 kWh/m² for Osaka University, Keio University and Kyoto University, respectively. Studies in South Korea (223 kWh/m²) and China (204 kWh/m²) showed that average energy consumptions are higher in those countries than Australia. Within Australia, this study showed that average energy consumption of campus buildings at Griffith University (170 kWh/m²) was slightly lower than those at the University of Sydney with an average value of 201 kWh/m².

	Average EUI (kWh/m ²)	Campus	Climate	Data years	Date	Reference / date
USA	739	Yale University	Humid subtropical	4	2010-2013	Ma, Lu and Weng [94] / 2015
	265	Cornell University	Humid subtropical	2	2012-2013	Ma, Lu and Weng [94] / 2015
South Korea	223	A university in Seoul	Humid subtropical	1	2012	Chung and Rhee [17] / 2014
China	204	Eight universities in Changchun	Humid continental	1	2012	Lo [95] / 2013
Taiwan	79	51 universities in Taiwan	Humid subtropical	1	2015	Wang [44] / 2016
Japan	465	Keio University	Humid subtropical	3	2010-2012	Ma, Lu and Weng [94] / 2015
	472	Osaka University	Humid subtropical	3	2010, 2012-2013	Ma, Lu and Weng [94] / 2015
	582	Kyoto University	Humid subtropical	4	2010-2013	Ma, Lu and Weng [94] / 2015
Australia	201	Sydney University	Humid subtropical	5	2009-2014	Obrart [96] / 2015
	170	Griffith University	Humid subtropical	2	2015-2016	This study

Table 13. Average energy consumption of campus buildings across various countries.

4.6 Comparison with national energy benchmarks

A number of green rating tools and schemes have been developed to promote energy efficiency in Australian commercial buildings. The two noteworthy rating systems for commercial buildings in Australia are NABERS and TEFMA. NABERS (National Australian Built Environment Rating Scheme) measures the environmental performance of buildings in terms of energy efficiency, water usage, waste management and indoor environment quality and their environmental impact [97]. NABERS energy assessment in commercial buildings considers gross floor area, the number of computers (as a measure of occupancy), the hours of operation (as a measure of a level of occupancy), climate, and energy use. In commercial building sector, NABERS performance evaluation includes buildings such as offices, hotels, shopping centres, and data centres. NABERS energy assessment using either NABERS prescriptive assessment, or energy modelling based on Building Code of Australia (Section J, Energy Efficiency, and Section JV3, methodology) is not valid for the comparison of energy use in different campus building types in terms of disciplines and activities.

TEFMA (Tertiary Education Facilities Managers Association), is a comprehensive source of information for the Group of Eight Universities (G08) in Australia including costs and energy use [98]. The problem with TEFMA energy benchmark is the aggregation of campus data, which is not suitable for energy comparison studies.

As mentioned above, the NABERS energy tool is designed for commercial, and not for campus buildings due to the great diversity in energy use. Accordingly, a comparison study of national benchmarks is performed with TEFMA and Australian national energy baselines published by the Department of Climate Change and Energy Efficiency.

Analysing the G08 campuses, TEFMA divides university buildings into two groups of *general purpose* with an average energy consumption of 167 kWh/m², and *service and equipment intensive* with an average energy consumption of 611 kWh/m2 (Figure 12) [96]. National energy baseline for Australian campus buildings published by the Department of Climate Change and Energy Efficiency, indicates an average energy consumption of 242 kWh/m2 for campus buildings all across Australia [99]. Our study provides a more detailed benchmarking for different building types by indicating 379 for research buildings, and a value from 121 to 148 for buildings such as academic offices and libraries. This comparison analysis also shows that our benchmark values are much lower than TEFMA and Australian national energy consumption. As shown in Table 14, the resolution of building functionality in campus buildings is relatively poor across TEFMA and Australian

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national baselines. Therefore, it is important to enhance functionality distinction between campus building types to be able to provide an accurate benchmarking system for campus buildings.

Building types	TEFMA [96] (kWh/m ²)	National baseline [99] (kWh/m ²)	This study (kWh/m ²)
Academic offices			121
Administration	170	2.12	134
Library	172	242	148
Teaching			145
Research	555		379

Table 14. Energy comparison study with national benchmarks and energy rating tools.

5 Discussion

This study used the energy data for campus buildings to develop benchmark energy targets for various university building types. Due to the complexity, benchmarking for universities had never been thoroughly studied. The study showed that energy use and energy intensity was different among various disciplines. This emphasizes the psychological influence that Sorrell [100] and Tobias Brosch, David Sander and K.Patel [101] have indicated where different disciplines are different in terms of being either neglectful or optimistic about the potential to reduce energy demands.

This research used statistical techniques to identify a reliable energy predicting equation for EC and EUI. Each individual campus building accommodates a variety of spaces with different energy loads (HVAC, equipment etc.). Due to the lack of sub-metering for different spaces, and in order to find correlations between space activities and energy loads, we divided buildings into groups based on proportional floor area. For example, buildings with more than 40% of laboratories are considered as laboratory buildings, while a building with 10% laboratory space was not considered as a laboratory building. This categorization reduces the significance of correlation studies, yet this limitation was inevitable due to a lack of energy consumption sub-metering for individual functional areas [96].

The highest amount of energy on campus was consumed in libraries due to the size of these buildings. The standard deviation of EC for mixed use and research buildings were the highest, suggesting that the total energy use for these building types differ. The energy use intensity was the highest in research and teaching buildings. Academic office buildings had the lowest average EC and EUI values, and this could be associated with both the size and the nature of occupant indoor activities.

The regression analysis revealed that EC regressed with building size and type, and EUI only regressed with building type, particularly with laboratory floor area. Based on the regression model for EUI, energy benchmarking using various popular statistical methods of OLS, COLS, SFA and DEA was performed. The application of the OLS method in energy benchmarking is the estimation of average energy consumption using regression analysis. Being an average method, the OLS method estimates the efficiency line based on average energy use. The main weakness of the OLS method is that all residuals are considered as relative efficiency levels, ignoring unexplained factors and data errors. In the study, with the application of the OLS benchmarking technique, 60% of the entire building population was efficient. The 60% efficiency of the dataset seems unexpectedly high as only two buildings in the dataset are rated as highly energy efficient and have green building certifications. The COLS technique is an extension of the OLS method that shifts the regression line upwards in a way that the regression line envelopes all buildings [12]. However only a single building in this study fell on the orange line which represents the COLS regression equation. This means that the energy efficiency line defined by the COLS technique is highly dependent of the performance of a single building. This reduces the appropriateness and reliability of the COLS method for benchmarking. In our dataset, there was an uneven distribution of building size categories and energy intensity. For example, there was only a single building with EUI of more than 900 kWh/m² and all the other EUI values were less than 600 kWh/m². As a result, in the DEA method, which develops the efficiency line by enveloping all buildings with linear programming, some outliers were considered as efficient due to the lack of comparable buildings. In this case, the most energy intensive building with EUI of 908 kWh/m² was considered efficient. Based on the comparison, the SFA technique seemed the most appropriate method of benchmarking due to considering both the average

functioning to develop the efficiency line, as well as being a frontier method and considering the highest energy efficient buildings as assets.

Laboratories, supplied by intensive HVAC and equipment loads, consumed more energy than normal academic office space types. In a study in the University of California, laboratories were three times more energy intensive than non-laboratory [43]. Another study indicated that laboratories on average consumed four to five times more energy than non-laboratory space types [47]. The high HVAC and equipment loads in laboratories are mainly due to high air change rate with a 100% outside air supply and air exhausts though fume hoods and local exhaust devices. The high air change rate results in high chiller power consumption to run fans and condition such large quantities of air. In this study, through the regression analysis and benchmarking process, it was confirmed that the energy intensity of university buildings was a function of building types, and particularly laboratory floor area. This study showed that laboratory buildings at Griffith University were three times more energy intensive than academic offices and administration buildings, and two and half times more energy intensive than libraries, teaching and mixed use buildings.

An extreme variability in energy intensity in campus buildings has been found, particularly in laboratories with diverse end-use of energy and occupancy patterns [99]. For example, one laboratory building may be used for a few hours, while another research laboratory may have a 24/7 operation schedule. This is because of diverse energy intensity and occupancy patterns which leads to great variation in equipment loads.

The interesting observation was that EUI did not correlate particularly with age. This contrasts with some previous studies [43] and suggests a strong correlation between building age and laboratory building energy intensity. University semester breaks happen in months with peak cooling and heating loads. The only space type which continues operating during these periods is laboratories. Another finding is that energy loads in research buildings correlated more with climate parameters compared to other building types.

The ASHRAE Standard 90.1 proposed baseline values in university buildings as 403 kWh/m² for electricity and 733 kWh/m² for gas [102]. According to the proposed model by Labs21 from a research centre in the University of California, 45% reduction of ASHRAE Standard 90.1 is recommended for research buildings in the USA [103]. The benchmarking model in this research proposed baselines for Australian subtropical climate particularly with reference to Southeast Queensland universities. Based on activity types, EUI values ranged from 121 kWh/m2/year in academic office buildings to 379 kWh/m2/year in research buildings. However, based on the benchmarking technique (SFA), the benchmark value for research buildings was 216 kWh/m2/year as the highest energy intensive building type and 137 kWh/m2/year for academic office buildings as the lowest energy intensive building. Benchmarking values across various disciplines were the highest for *Science* (164 kWh/m2/year) and the lowest for *Health* (136 kWh/m2/year). This suggests that *Science* was the most energy intensive discipline as it accommodated more spaces for laboratories with higher HVAC and equipment loads. The other disciplines had greater emphasis on theoretical methods and most activities were undertaken in teaching and learning spaces.

The comparison study with international (the USA, South Korea, China, Taiwan, Japan and Australia) and national (TEFMA and national baselines) campus energy consumption showed that the benchmark developed in this study stands within the acceptable range to promote energy efficiency in Australian campus buildings. However, the comparison study showed that a high degree of resolution in terms of activity, energy intensity, and occupancy is necessary to be able to evaluate energy performance and efficiency based on building types, particularly in campus buildings. The higher resolution of details in building characteristics and factors results in more accurate energy models for buildings [99].

6 Conclusion

A considerable difference was observed in energy use intensity in research buildings compared with other building types, such as those for teaching, academic offices, administration offices, and libraries. A more subtle difference was found in energy intensity among disciplines, while energy consumption values regressed with building size, and energy intensity regressed with building type and particularly with laboratory floor area. The benchmarking process using various statistical methods was performed. Among the various statistical benchmarking techniques utilized in this research, the SFA method was found to be the most appropriate for university building type due to large variations in energy intensity and the existence of several outliers. Based on the SFA energy benchmarking, 7% of the buildings in the dataset were energy efficient. The research

building was the most energy intensive with observed average EUI values three times more than academic offices, and administration buildings, and two and half times more than libraries, teaching and mixed use buildings. The highest energy benchmark values belonged to research buildings (216 kWh/m²/year), and the lowest energy benchmark values belonged to academic office buildings (137 kWh/m²/year). In terms of disciplines, the benchmark EUI value was the highest for *Science* with 164 kWh/m2/year, and the lowest for *Health* with 136 kWh/m2/year. These values provided a matrix of benchmark values, which are suitable for use in policymaking and energy performance assessment techniques in campus buildings.

Nonetheless, the major limitation of the benchmarked method utilized in this study was that only buildings from a single university were studied. This would result in some inefficient buildings being benchmarked as efficient. However, no benchmarking systems for Australian university buildings are yet developed and the method utilized here will be used to adjust this presented benchmark by expanding the dataset to other universities in the same climate. Energy efficiency leaders and energy policy makers can adopt benchmarked-based energy targets as an assessment tool to design and evaluate higher education campus building energy efficiency. Energy benchmarks and energy performance targets play a key role in continuing university leadership in building energy efficiency and reaching emission reduction goals. Similar studies in other climatic locations and with case studies from various universities are recommended for future research in order to extend on this study a more validated and provide reliable energy benchmarking systems for campus buildings across the subtropical climate.

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