

Article

# Impact of Human Actions on Building Energy Performance: A Case Study in the United Arab Emirates (UAE)

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**Abstract:** There is a growing interest in the literature to understand how actions taken by occupants and facility managers can affect building performance. However, user-centric building energy research: (1) remains understudied compared to design-focused research efforts; (2) overlooks combined effects or uncertainty in multiple parameters; and (3) typically does not cover particular types of buildings (e.g., educational facilities), nor buildings subject to extreme weather conditions. This paper fills an important gap in the literature by proposing a comprehensive energy modeling and analysis framework to quantify the impact of human action on building energy consumption. The framework applies various data analysis methods such as differential, fractional factorial, and Monte Carlo analysis methods, in order to capture potential combined or synergetic effects of human actions on building performance. A case study is then presented on typical educational buildings located in the extreme hot climate of Abu Dhabi, United Arab Emirates (UAE). Results indicate that uncertainty in human actions can lead up to a  $\pm 25\%$  variation from average energy consumption levels, confirming the significant role that people have in making their built environment more efficient and sustainable.

**Keywords:** human actions; uncertainty analysis; building operation; energy consumption; educational buildings; United Arab Emirates (UAE)

## 1. Introduction

The building sector is a major contributor to the high and increasing demands for energy and corresponding carbon emissions [1]. Worldwide, this sector accounts for 30% to 40% of total energy consumption [2]. This ratio is even significantly higher in countries with extreme climate conditions such as the United Arab Emirates (UAE), where more than 70% of the power generated is consumed by buildings [3,4]. Over the life cycle of a typical building, more than 80% of the energy is consumed during the operation phase [5], while the remaining energy mainly goes to the construction and demolition phases. As a result, targeting the operation phase of buildings is essential to achieve long-term energy savings. In general, a building's performance during operation is highly dependent on its design, especially the choice and sizing of its electro-mechanical systems. For this purpose, building energy modeling software is commonly used during the design phase to: (1) simulate the building under study; (2) predict its energy consumption levels during operation; and (3) help designers and engineers choose and size different building systems (e.g., air conditioning units) [6,7]. A large number of building energy modeling tools can be found in the market and in literature; four of the most commonly used tools are: EnergyPlus, IES Virtual Environment, TRNSYS, and eQuest [8].

In practice, while the accuracy of these models is essential for a good building design, important discrepancies are typically observed between their predicted energy consumption levels (obtained

during design) and actual levels (observed during operation). These differences typically vary between 30% and 100% in some cases, and can be attributed to three main factors: (1) inaccurate assumptions regarding external building conditions (e.g., variations in weather conditions); (2) inaccurate assumptions regarding building design (e.g., efficiency of different systems); and (3) inaccurate assumptions regarding human actions and operation (e.g., energy use patterns) [7,9]. While the literature has been traditionally mostly focused on the first two, numerous field studies confirm that human actions and operation patterns have a significant impact on building energy performance and require further study. For instance, Roth et al. [10] estimated that in United States (US) commercial buildings, 20% of the energy consumed by systems such as lighting and the heating, ventilation, and air conditioning (HVAC) can be attributed to undetected faults or poor operational assumptions during the design and commissioning phases. Along the same lines, Granderson et al. [11] argued that poorly operated equipment in commercial buildings account for 10% to 30% of the energy consumed. Finally, additional studies confirm that occupancy actions, such as leaving equipment or lights running after hours, can lead to significant and unnecessary energy use levels (e.g., [12–14]).

In recent years, there has been a growing trend in the literature to study operation and user-centric drivers of building energy performance. One such effort is the Annex 66 project on the “Definition and Simulation of Occupant Behavior in Buildings” by the International Energy Agency (IEA) Energy in Buildings and Community (EBC) programme. The objectives of Annex 66 include: (1) setting up a general occupant behavior definition platform; (2) establishing a quantitative simulation methodology to model occupancy behaviors in the built environment; and (3) understanding the influence of occupancy behavior on the indoor environment and building energy consumption levels [15]). While the three above objectives are essential, the current paper focuses on the latter, particularly on the impact of individual human actions on building energy use.

Various research efforts have aimed to understand and quantify the impact of individual human actions on building energy performance. Delzendeh et al. [16] provide a comprehensive review of these studies, which cover the use of appliances and electrical devices (e.g., [17,18]), lighting usage (e.g., [19–21]), window opening (e.g., [22,23]), and HVAC settings (e.g., [24]). In parallel to the assessment of individual drivers of energy use, Azar and Menassa [25,26] used building energy modeling to simulate the impact of various human actions on the performance of typical US commercial buildings. Through parametric variations, the authors isolated and quantified the effect of lighting, equipment, HVAC, and hot water use patterns on the energy use of the studied buildings. The above studies contribute to an improved understanding of the impact of human actions on the performance of their built environment. However, important gaps can be found in the existing literature, and are yet to be addressed, motivating the need for the current research.

First, most studies have mainly considered the impact of individual parameters on energy consumption. The combined effects of parameters, as well as simultaneous uncertainty in all parameters, have rarely been considered. In practice, potential synergies might exist between parameters causing an impact on energy consumption that is larger than the sum of the individual parameters’ effects. Addressing this gap will provide important and comprehensive insights on the true impact of people’s actions on the energy used in buildings. Second, the majority of studies on the energy use patterns of occupants mainly focus on typical commercial or residential buildings. The influence of human actions on educational buildings, such as in a campus environment, has been rarely investigated. This motivates the need to expand the scope of study to educational buildings, (e.g., classroom or dormitory buildings). Such building types might show different sensibilities in their performance to human actions when compared with traditional commercial or residential building types. Finally, the reviewed studies in the literature mostly originate from and focus on regions such as North America or Europe. It is important to expand the scope of analysis to regions with extreme hot climates such as the UAE, where buildings might exhibit different behaviors when subjected to variations in human actions and energy use patterns.

This study proposes an energy modeling and analysis approach to comprehensively evaluate and quantify the impact of human actions on building energy performance. Specific objectives include: (1) determining the direct impact of actions taken by occupants or facility managers on the energy consumption of buildings of different types; (2) identifying potential synergetic or combined effects between parameters; (3) evaluating and comparing the response of buildings to potential uncertainty in human-related parameters; and (4) using the results to recommend user-centric energy-saving solutions. The followed approach is general, and can be applied to any building. In this paper, it is applied to a set of educational buildings in Abu Dhabi, UAE, highlighting the capabilities and uniqueness of the work.

## 2. Methodology

The proposed methodology in this paper has three main steps, which are detailed in the following subsections. In Step 1, the characteristics of typical educational buildings in the UAE are gathered from different sources. Those buildings are categorized as office, classroom, and dormitory (“dorm”) buildings. Step 2 consists of developing and calibrating building energy models to simulate the energy performance of those buildings. Extensive parametric variations are then conducted in Step 3 using different methods, including differential, fractional factorial, and Monte Carlo analyses.

### 2.1. Data Gathering

The data needed to develop the base case energy models are divided between three categories: “Building Design Characteristics”, “Energy Systems Characteristics”, and “Business-as-usual Occupancy Characteristics”. The first covers parameters such as total floor area, floor height, number of stories, glazing fraction, and U-values for roof, walls, and glazing. The second covers the characteristics of various end-use systems such as the HVAC, lighting, and equipment (i.e., plug loads). Finally, the base case occupancy characteristics are factors that affect the operational performance of the building; these include, but are not limited to: people density, occupancy schedule, equipment use patterns, lighting use patterns, and HVAC operation schedule and thermostat temperature set points.

The values of all of the above-mentioned parameters are obtained from a variety of sources, including a report by the Abu Dhabi Urban Planning Council (UPC) [27], a study on the life-cycle analysis of building retrofits at the urban scale in the UAE [3], building standards [28], and other sources covering building benchmarking efforts [29,30]. A summary of the gathered data, which is later used as inputs to develop building energy models, is shown in Table 1. The table includes information for the three types of buildings considered, obtained from a variety of sources that are cited in the table.

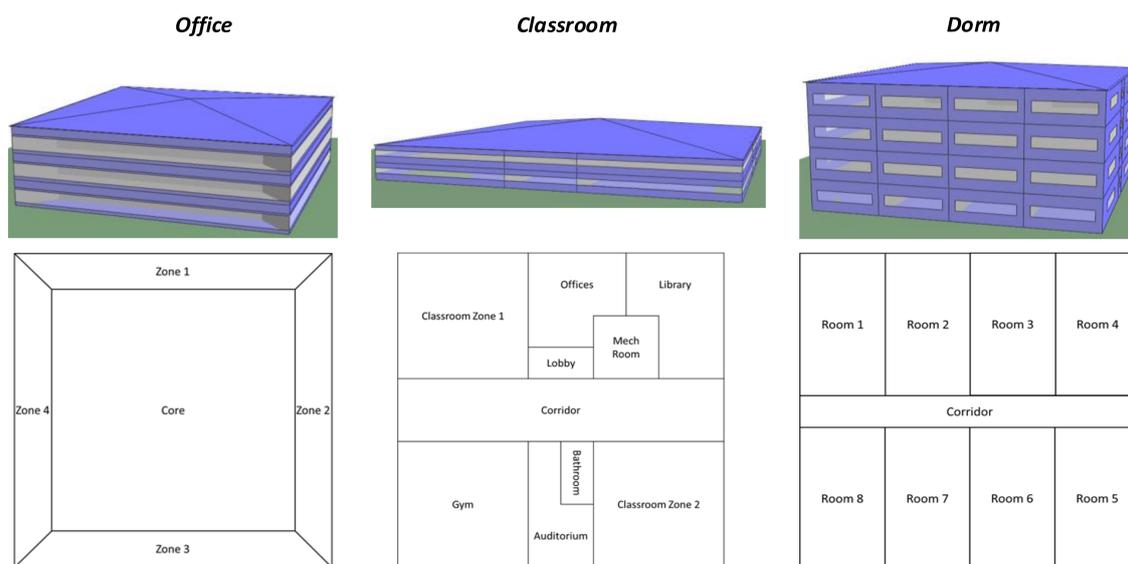
**Table 1.** Modeled buildings' parameters.

Parameter	Units	Office	Classroom	Dorm
Typical Total Floor Area [27,29]	m <sup>2</sup>	4982	19,592	3135
Building Width (calculated)	m	40.8	100.0	28.0
Building Length (calculated)	m	40.8	100.0	28.0
Floor Height [29]	m	4.0	4.0	3.1
Number of Stories [29]	Floors	3	2	4
Location	—	Abu Dhabi	Abu Dhabi	Abu Dhabi
Glazing Fraction	—	50%	33%	15%
Window-to-Wall Ratio (WWR) [27,29]	—	50%	33%	15%
People Density [28]	m <sup>2</sup> /person	18.6	3.7	9.3
Minimum Fresh Air [27]	L/s/person	10	10	2
Infiltration Rate [30]	Air changes per hour (ACH)	0.5	0.5	0.7
Equipment Intensity [27,28]	W/m <sup>2</sup>	15.0	15.0	6.4
Lighting Intensity [27,28]	W/m <sup>2</sup>	10.0	10.7	6.6
Domestic Hot Water (DHW) [28]	L/Person	3.8	6.8	48.1
Wall U-Values [3]	W/m <sup>2</sup> ·K	1.7	1.7	1.7
Roof U-Values [3]	W/m <sup>2</sup> ·K	0.5	0.5	0.5
Glazing U-Values [27]	W/m <sup>2</sup> ·K	2.4	2.4	2.4
Occupants Maximum Sensible Gain [28]	W/Person	73.3	73.3	73.3
Occupants Maximum Latent Gain [28]	W/Person	58.6	58.6	58.6
Occupancy, Equipment, Lighting, and HVAC Profiles [28] (Refer to Appendix A for more details)	—	Table 5-J Schedule A	Table G-K School Occupancy	Table 5-M Schedule D
HVAC Occupied [27] & Unoccupied Set points	°C	Occupied: 22 Unoccupied: 24	Occupied: 22 Unoccupied: 24	Occupied: 22 Unoccupied: 24
Cooling System Type [29]	—	PACU (packaged air conditioning unit)	Chiller—air cooled	PACU—SS (Split System)
Air Distribution [29]	—	MZ VAV (multi-zone variable air volume)	MZ VAV	SZ CAV (single-zone constant air volume)

Note: In Deru et al. [29], it is assumed that the classroom and dorm buildings are equivalent to secondary school and mid-rise apartment buildings, respectively.

## 2.2. Energy Modeling

Three prototype building energy models are developed in IES-VE (Integrated Environmental Solutions—Virtual Environment), which is a commonly used building energy modeling software [8]. The models are representative of archetype office, classroom, and dorm educational buildings in the UAE, which were described in Table 1. Figure 1 illustrates the geometries of three models in IES-VE. The general floor layouts are adapted from Deru et al. [29], while a square shape is chosen for all of the buildings to minimize the effect of building orientation on performance. Following the geometry development, the parameters of Table 1 are assigned to the three models, hence adding the building material, energy systems, and base case occupancy layers of information. As for the outdoor weather conditions, they are obtained from the weather files of Abu Dhabi airport for the year 2014, which include variables such as hourly temperatures, humidity, and air speed [31]. It is important to note that no studies were found that explicitly define typical HVAC unoccupied set point temperatures in UAE buildings. Given the academic nature of the facilities, which are typically open to students and/or staff around the clock, values of 24 °C are chosen to reflect more relaxed temperature values compared to occupied set points (i.e., 22 °C), while maintaining acceptable indoor conditions in case the space becomes occupied beyond regular working hours. Moreover, choosing unoccupied temperature settings that are close—or even similar—to those of occupied hours is common when modeling buildings in the UAE and other Arabian Gulf countries such as Kuwait [3,32,33], which further supports the choice of 24 °C as a set point for unoccupied periods.



**Figure 1.** Geometry and layout of the base case models.

Next, the building energy models are run, generating energy intensity estimates (i.e., site electricity demand) of 257.1 kWh/m<sup>2</sup>/year for the typical office building, 195.1 kWh/m<sup>2</sup>/year for the classroom building, and 363.9 kWh/m<sup>2</sup>/year for the dorm building. In the UAE, the vast majority of the electricity delivered to the building sector is generated from natural gas power plants. According to Sgouridis et al. [34] an average of 8.28 MJ of fossil primary energy is needed for 1 kWh of residential electricity delivered. Consequently, the primary energy intensity of the three modeled buildings are estimated at 2.13 GJ/m<sup>2</sup>/year, 1.16 GJ/m<sup>2</sup>/year, and 3.01 GJ/m<sup>2</sup>/year, respectively.

Following the model development, it is important to verify that the energy predictions of the models are close in value to the energy consumption that is observed in actual buildings of similar characteristics. When developing an energy model of a typical or prototype building, a common practice is to compare the model's predictions to those collected from a stock of similar buildings [25]. One commonly used building database for this purpose is the Commercial Buildings

Energy Consumption Survey (CBECS) [35], which gathers data from thousands of commercial buildings in the US. The CBECS is commonly used for benchmarking building performance and developing typical or reference energy models [29,35].

In the UAE, and in the absence of such consumption benchmarks, the authors compared the energy predictions of the models to those of individual buildings in Abu Dhabi of a similar type (i.e., office, classroom, and dorm) and size (i.e., number of floors and floor area). More specifically, energy consumption data was obtained from 12 buildings including four office, five classroom, and three dorm buildings, whose characteristics are presented in Table 2. It is important to note that these buildings were not used in the model development phase, hence separating the data that was used to develop the models from the one that was used to validate them.

**Table 2.** Surveyed buildings' characteristics.

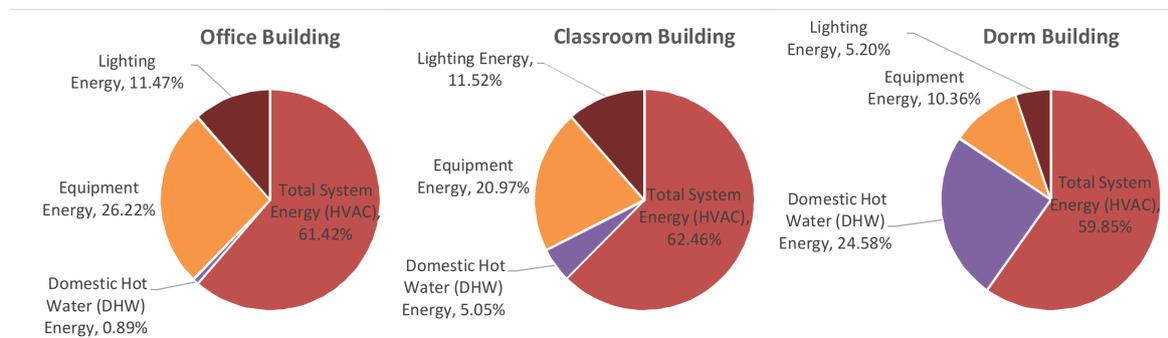
Building	Year Built	Floors	Percent Glazed (Front/Right)	Glazing Type (Front/Right)	Tinting Type (Front/Right)	Shading (Front/Right)
Office #1	1990–1994	2	80–100%/<20%	Single/n/a	None/n/a	No/No
Office #2	2000–2004	2	20–40%/n/a	Single/n/a	Tinted/n/a	No/n/a
Office #3	2005–2007	2	<20%/<20%	Single/n/a	Tinted/n/a	No/No
Office #4	2008–2012	2	<20%/<20%	Dble./Dble.	Reflect./Reflect.	No/No
Class. #1	1990–1994	1	60–80%/60–80%	Single/Single	Reflect./Reflect.	Yes/Yes
Class. #2	<1990	2	40–60%/40–60%	Single/Single	Tinted/Tinted	Yes/Yes
Class. #3	1990–1994	2	<20%/<20%	Single/Single	Tinted/Tinted	No/Yes
Class.#4	2000–2004	3	20–40%/<20%	Single/Single	Reflect./Reflect.	No/No
Class. #5	1995–1999	2	40–60%/20–40%	Single/Single	Tinted/Tinted	Yes/Yes
Dorm #1	n/a	4	<20%/<20%	Single/Single	Tinted/Reflect.	No/No
Dorm #2	n/a	4	20–40%/<20%	Dble./Single	Tinted/None	No/Yes
Dorm #3	2008–2012	4	0%/20–40%	Single/Single	None/None	No/No

The average energy intensities of the buildings described in Table 2 are presented in Table 3, along with the differences, or deviations, between the models' predictions. The results show that the differences do not exceed 5.4%, and are within the acceptable error range of 10% [25]. Nonetheless, the authors acknowledge that collecting data from a larger number of buildings could have further ensured the validity of the models. Since such a task is beyond the scope of the current study, a subset of the CBECS was also used to compare the predictions of the models to additional buildings of similar characteristics as an additional mean of validation. This was done by filtering the CBECS data to only show buildings that have similar characteristics to the three types of buildings considered in this study. These characteristics include building type, size, and weather zones in order to ensure that the surveyed buildings are in climate conditions similar to those encountered in the UAE (i.e., very hot and dry such as in CBECS weather zone 5) [35]. The filtering process identified a total of 54 office, 59 classroom, and 37 dorm buildings that fit these criteria. The average energy intensities of those buildings are also shown in Table 3. When compared to the base case energy predictions of the models, the differences do not exceed 9.0%. Therefore, the obtained results are here again within the acceptable 10% error range, re-confirming the accuracy of the models and their adequacy for conducting further analysis.

**Table 3.** Comparison of energy intensity values. CBECS: Commercial Buildings Energy Consumption Survey.

	Models	Abu Dhabi Buildings		CBECS Buildings	
	Energy Intensity [kWh/m <sup>2</sup> /Year]	Energy Intensity [kWh/m <sup>2</sup> /Year]	Difference with Models [%]	Energy Intensity [kWh/m <sup>2</sup> /Year]	Difference with Models [%]
Office	257.1	243.1	+5.4	278.1	−8.1
Classroom	195.1	205.1	−5.2	191.8	+1.7
Dorm	363.9	354.5	+2.6	331.2	+9.0

Finally, Figure 2 illustrates the distribution of the energy consumption of the base case models by end use. As expected, HVAC is the largest consumer given the hot weather of Abu Dhabi, followed by equipment loads for office and classroom buildings, and domestic hot water (DHW) heating energy for the dorm building.



**Figure 2.** Baseline energy consumption distribution by end use.

### 2.3. Parametric Variation

Three different parametric variation methods are used in this study as detailed next: differential analysis [36,37], fractional factorial analysis [38,39], and Monte Carlo analysis [40,41]. Prior to proceedings, it is important to highlight that the literature lacks a standard on the design of parametric variation experiments, in particular, the choice of the ranges over which to vary each parameter. Consequently, the authors adopted a conservative approach by using ranges that are smaller than or equal to those used in previous comparable studies [25,26,42]. This ensures that the variations simulated in this study are in line with previously published work on the topic, which helps confirm the validity of the experimental design. In this study, the parametric variation is performed by directly changing the input parameters of the building energy models, running them, and observing the changes in their energy predictions. Such an approach is adequate, since the number of runs is not significantly high. For cases where the number of runs are excessive, a surrogate statistical or machine learning model can be trained to mimic the behavior of the building systems and predict their outputs (e.g., energy use levels) for a given series of inputs (e.g., design and operation characteristics). Once a model is trained and validated, a high number of simulations can be conducted at a significantly lower time than when the building energy models are used directly [43].

#### 2.3.1. Method 1: Differential Analysis

The goal of this method is to quantify and isolate the effect of each parameter on the total energy consumption, which is achieved by gradually changing its initial value while fixing all of the other parameters at their baseline values [36,37]). Seven human or operation-related parameters are tested for the three developed energy models.

As shown in Table 4, the first two parameters are equipment and lighting use during unoccupied periods. The focus on the unoccupied period helps simulate scenarios where lighting systems or equipment (i.e., plug loads) are left running while a space is unoccupied, potentially indicating an inefficient operation of these systems. Four values are used: 0%, 10%, 20%, and 30%, where a value of 30% represents a scenario where 30% of the equipment or lighting systems are left running after hours (e.g., at night or over the weekend). The third parameter consists of shifting building schedules by  $\pm 1$  h and  $\pm 2$  h. This helps test potential uncertainty in building schedules or specific strategies such as “green scheduling”, where building operation schedules are shifted to save energy, mainly through reduced cooling or heating loads. Then, window opening is tested using three different scenarios. The first represents a daily opening of half of the windows for 1 h (at 8 a.m.), the second scenario has an opening duration of 2 h (1 h at 8 a.m. and another at 1 p.m.), and the third scenario has an opening

a duration of 3 h (at 8 a.m., 1 p.m., and 6 p.m.). While the opening of windows in air-conditioned buildings is not extremely common nor recommended, studies confirm that such actions are observed in actual buildings [44,45], which motivated their consideration in the current analysis. It is important to note that the parametric variation does not consider the probability or frequency of such actions occurring; rather, it aims to simulate the impact that they will have on building performance in the case of their occurrence. Lastly, different settings for HVAC set point temperatures for occupied and unoccupied periods are simulated. A variation of  $\pm 2$  °C from the base case values is particularly tested for occupied and unoccupied periods.

**Table 4.** Differential analysis parameters.

Parameter	Scenarios
Equipment use during unoccupied periods	0%, 10%, 20%, and 30%
Lighting use during unoccupied periods	0%, 10%, 20%, and 30%
Shifting schedules	Baseline schedule varied by $\pm 1$ h and $\pm 2$ h
Window opening	1 h (8 a.m.), 2 h (8 a.m. + 1 p.m.), 3 h (8 a.m. + 1 p.m. + 6 p.m.)
HVAC occupied set point	Baseline value (22 °C) $\pm 2$ °C
HVAC unoccupied set point	Baseline value (24 °C) $\pm 2$ °C
HVAC occupied and unoccupied set points simultaneously	Baseline values (22 °C and 24 °C) $\pm 2$ °C

Equation (1) is used to calculate the main effect of each factor, which was adapted from the work of Hamby [37]:

$$Eff_A = \frac{EI_{test} - EI_{base}}{EI_{base}} \quad (1)$$

where,  $Eff_A$  is the main effect of parameter A,  $EI_{test}$  is the energy intensity predicted by the model when parameter A is at the test level, and  $EI_{base}$  is the energy intensity when all of the parameters are at their base levels. The number of simulations required for this method are 21 for each model, and 63 for the three models.

### 2.3.2. Method 2: Fractional Factorial Analysis

Fractional factorial analysis is used to analyze the interactions between the parameters, as well as any combined effect that they may have on building energy use [38,39]. This technique helps identify potential synergies between parameters, where the combined effect of two parameters might be higher than the sum of their individual effects. Equation (2) is used to calculate this effect, which was adapted from the work of Langner et al. [38]:

$$Eff_{ab} = \frac{(\overline{EI}_{ab} + \overline{EI}_{AB}) - (\overline{EI}_{Ab} + \overline{EI}_{aB})}{\overline{EI}} \quad (2)$$

where,  $Eff_{ab}$  is the combined impact of parameters a and b,  $\overline{EI}$  is the energy intensity average of all of the simulations,  $\overline{EI}_{ab}$  is the energy intensity average of the simulations where the parameters a and b are at their base levels,  $\overline{EI}_{AB}$  is the average of the simulations where the parameters A and B are at their test levels, and  $\overline{EI}_{Ab}$  and  $\overline{EI}_{aB}$  are the averages of the simulations where one parameter is at the test level, while the other at the base level.

The total number of simulations required for this analysis is  $P^2$ , where P is the number of parameters. Four parameters are chosen at this stage: (a) combined equipment and lighting unoccupied usage; (b) window opening; (c) HVAC occupied and unoccupied set points; and (d) shifting schedules. Therefore, a total of 48 simulations is needed, 16 simulations for each building type. The values that are used as the base and test values for the three buildings are shown in Table 5. The 16 combinations for each model are later shown in the results section.

**Table 5.** Base and test values for the fractional factorial analysis.

Parameter	Base	Test
Equipment & Lighting	Unoccupied 0%	Unoccupied 30%
Window Opening	None	3 h (8 a.m. + 1 p.m. + 6 p.m.)
Shifting HVAC set points by 2 °C	22 °C (occupied)	20 °C (occupied)
	24 °C (unoccupied)	22 °C (unoccupied)
Shifting Schedules	None	−2 h

### 2.3.3. Method 3: Monte Carlo Analysis

Monte Carlo analysis (MCA) is one of the most commonly used techniques for carrying out global sensitivity and uncertainty analyses [40,41]. It allows studying how potential uncertainties in model input values propagate to produce variations in overall model outputs (i.e., energy predictions). In this study, random sampling (i.e., uniform distribution) is used to randomly perturb the model inputs without assuming or forcing particular distributions. While other distributions (e.g., triangular, normal, log-normal, etc.) can be also applied, the literature lacks empirical data on the human-related parameters that are studied to force a particular distribution on the simulation of uncertainty. Consequently, a uniform distribution was chosen to avoid making such assumptions, especially that the goal of the analysis is to capture the potential variability in energy consumption from human actions.

Multiple iterations are needed for this type of analysis. A total of 60 iterations are used in this paper, a number that is considered adequate for Monte Carlo simulations independently of the number of parameters varied [40,41]. The considered input parameters are presented in Table 6, along with their ranges of variation (i.e., lower and upper bounds of the uniform distribution function).

**Table 6.** Monte Carlo analysis input parameters and range.

Parameter	Range
Equipment use during unoccupied periods	0%, 10%, 20% and 30%
Lighting use during unoccupied periods	0%, 10%, 20% and 30%
Window Opening	None, 1 h (8 a.m.), 2 h (8 a.m. + 1 p.m.), 3 h (8 a.m. + 1 p.m. + 6 p.m.)
Shifting HVAC set points	Occupied Period: 20 °C, 21 °C, 22 °C, 23 °C, and 24 °C Unoccupied Period: 22 °C, 23 °C, 24 °C, 25 °C, and 26 °C
Shifting Schedules	−2 h, −1 h, None, +1 h, +2 h

## 3. Results

The following subsections present the results of the three parametric variations methods conducted, namely differential, fractional factorial, and Monte Carlo analysis, respectively. A general discussion of the results follows.

### 3.1. Differential Analysis Results

Figure 3 summarizes the results of the differential analysis where the parameters of Table 4 are individually varied for each model. In general, the dorm building shows the highest energy intensity levels, exceeding 300 kWh/m<sup>2</sup>/year. This high energy intensity of the dorm building is mainly due to its demand for domestic hot water, as opposed to the classroom building and office buildings, which require minimal to negligible levels of hot water (refer to Figure 2).

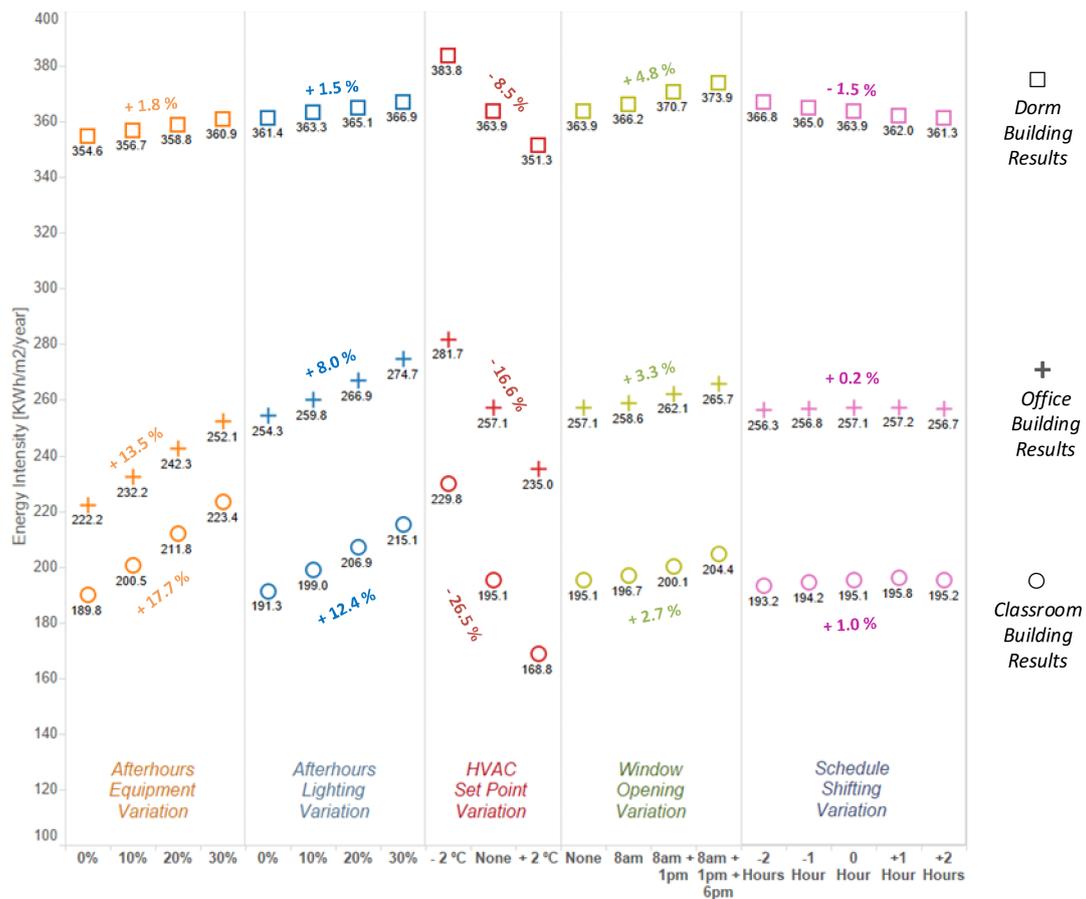


Figure 3. Individual parametric variation effects.

When analyzing the results of the differential analysis, the most influential parameter is the HVAC temperature set point. As shown in Figure 3, varying this parameter by  $\pm 2$  °C leads to important differences in building energy intensity, reaching up to 26.5% for the classroom building. Put differently, if building occupants set the thermostat temperatures at 2 °C higher than the baseline values, instead of 2 °C lower, they can reduce the energy consumption of their buildings by an estimated 26.5%. Such a finding is significant, and can be attributed to the HVAC system's large share of total energy use, given the hot weather conditions of the buildings under study. As previously shown in Figure 2, this ratio exceeds 60% for the three considered building types.

As for the equipment and lighting use after hours, a maximum of 17.7% difference in energy intensity is observed for the classroom building when varying after-hours equipment use from 0% to 30%. The office building also showed important variations in energy intensity, with 13.5% and 8.0% for the after-hours equipment and lighting variation, respectively. The dorm building, on the other hand, showed a lower sensitivity to these input parameters, with its differences in energy intensity not exceeding 2%. This can be attributed to two main factors. Firstly, as previously shown in Figure 2, the equipment and lighting end uses are less dominant in the dorm building, given the importance of the domestic hot water end use. Secondly, as per the equipment and lighting schedule patterns used in the base case [28], the difference between the energy consumption patterns of occupied and unoccupied periods is less significant for the dorm building. In other words, for this building type, some appliances (e.g., refrigerator) and systems (e.g., air conditioning) operate to some degree independently of whether the space is occupied or not, decoupling an important portion of the energy demand from the occupancy status. On the other hand, since office and classroom buildings

are typically unoccupied at night and on weekends, larger energy differences are typically expected between occupied and unoccupied periods.

As for the window-opening scenarios, a maximum of a 4.8% increase in energy is observed when opening the windows three times a day as opposed to none. This occurs in the dorm building, which has a type of HVAC system (i.e., SZ CAV) that is typically less efficient than the one used in the other buildings (i.e., MZ VAV) (refer to Table 1). Therefore, when windows are opened, the HVAC system of the dorm building requires a higher amount of energy to cool down and replace the hot air coming into the building, which can explain the observed higher sensitivity of the dorm building to window openings.

Finally, shifting the building schedule by  $\pm 2$  h did not show a significant impact on energy intensity. A maximum of 1.5% difference in energy intensity is observed for the dorm building, a difference that is considered minimal when compared to the results of the other parametric variations. In summary, the classroom building showed the highest sensitivity to variations in equipment, lighting, and HVAC-related parameters, while the dorm building is the most sensitive to changes in window-opening frequency and building schedules.

### 3.2. Fractional Factorial Analysis Results

The four parameters analyzed using the fractional factorial method are: (a) combined equipment and lighting unoccupied usage (EL); (b) window opening (WO); (c) HVAC occupied and unoccupied set points (HVAC); and (d) shifting schedules (SS). Table 7 below shows the results of all 16 simulations needed for the analysis, with the respective energy intensities obtained for the three building types considered. Table 8 shows the calculated relative effects of each pair of parameters on the three models, which were computed using Equation (2). In general, all of the observed effects are consistently low, indicating an absence of combined parameter effects. The findings indicate that when two parameters are varied simultaneously, the resulting impact on energy intensity is not significantly different than the sum of their individual effects. The relatively highest impact is observed between parameter A (combined equipment and lighting unoccupied usage) and D (shifting schedules), with an absolute value of 0.058 for the classroom building. While still minimal in value, this effect can be due to the internal heat gain generated from an increase in equipment and lighting use, which requires the HVAC system to reject this heat and keep the indoor conditions stable. The energy required for this process is dependent on the outdoor air conditions, since the HVAC needs to bring in and cool outside air prior to distributing it in the building. In turn, these conditions depend on the time of the day, which can explain the combined effect with parameter D (shifting schedules).

Finally, in order to ensure that the results are not dependent on the specific values used in Table 5, the analysis was repeated with different “test” levels for parameters A to D. Values at the middle of the ranges presented in Table 5 are particularly chosen. The obtained results were similar to the ones presented in Table 7, showing very weak combined effects between the parameters. The consistency in the results can be attributed to two main factors. Firstly, the fractional factorial analysis measures the potential synergy between two parameters in a relative manner, rather than an absolute manner. As shown in Equation (2), the combined effect is a unit-less coefficient that compares the simultaneous effect of any two parameters with the summation of their individual effects [38,39]. Secondly, buildings typically exhibit linear relationships between the characteristics of their end-use systems (e.g., lighting, equipment, and HVAC) and energy use levels [46–49]. Such linearity helps explain the low synergies that are observed between parameters, which is shown to be independent of the specific base and test values used in the analysis.

Table 7. Fractional factorial analysis runs.

Run	Parameter				Energy Intensity (kWh/m <sup>2</sup> /Year)		
	-A- (EL)	-B- (WO)	-C- (HVAC)	-D- (SS)	Office	Classroom	Dorm
1	Base	Base	Base	Base	257.1	195.1	363.9
2	Base	Base	Base	Test	256.3	193.2	366.8
3	Base	Base	Test	Base	281.7	229.8	383.8
4	Base	Base	Test	Test	281.4	229.3	386.2
5	Base	Test	Base	Base	265.7	204.4	373.9
6	Base	Test	Base	Test	265.5	203.0	376.6
7	Base	Test	Test	Base	291.3	238.5	394.8
8	Base	Test	Test	Test	291.8	237.7	396.6
9	Test	Base	Base	Base	270.0	242.8	363.9
10	Test	Base	Base	Test	259.6	227.2	365.0
11	Test	Base	Test	Base	294.8	277.1	383.9
12	Test	Base	Test	Test	284.8	262.8	384.4
13	Test	Test	Base	Base	278.8	251.4	374.0
14	Test	Test	Base	Test	268.9	236.4	374.8
15	Test	Test	Test	Base	304.4	285.1	394.8
16	Test	Test	Test	Test	295.4	270.8	394.8

Table 8. Fractional factorial combined parameters' effects.

A&B [EL&WO]		A&C [EL&HVAC]		A&D [EL&SS]		B&C [WO&HVAC]		B&D [WO&SS]		C&D [HVAC&SS]	
Office Building Results											
$\bar{EI}$	277.97	$\bar{EI}$	277.97	$\bar{EI}$	277.97	$\bar{EI}$	277.97	$\bar{EI}$	277.97	$\bar{EI}$	277.97
$\bar{EI}_{ab}$	269.13	$\bar{EI}_{ac}$	261.15	$\bar{EI}_{ad}$	273.95	$\bar{EI}_{bc}$	260.75	$\bar{EI}_{bd}$	275.90	$\bar{EI}_{cd}$	267.90
$\bar{EI}_{AB}$	286.88	$\bar{EI}_{AC}$	294.85	$\bar{EI}_{AD}$	277.18	$\bar{EI}_{BC}$	295.73	$\bar{EI}_{BD}$	280.40	$\bar{EI}_{CD}$	288.35
$\bar{EI}_{Ab}$	277.30	$\bar{EI}_{Ac}$	269.33	$\bar{EI}_{Ad}$	287.00	$\bar{EI}_{Bc}$	269.73	$\bar{EI}_{Bd}$	285.05	$\bar{EI}_{Cd}$	293.05
$\bar{EI}_{aB}$	278.58	$\bar{EI}_{aC}$	286.55	$\bar{EI}_{aD}$	273.75	$\bar{EI}_{bC}$	285.68	$\bar{EI}_{bD}$	270.53	$\bar{EI}_{cD}$	262.58
$Eff_{ab}$	0.000	$Eff_{ac}$	0.000	$Eff_{ad}$	-0.035	$Eff_{bc}$	0.004	$Eff_{bd}$	0.003	$Eff_{cd}$	0.002
Classroom Building Results											
$\bar{EI}$	236.54	$\bar{EI}$	236.54	$\bar{EI}$	236.54	$\bar{EI}$	236.54	$\bar{EI}$	236.54	$\bar{EI}$	236.54
$\bar{EI}_{ab}$	211.85	$\bar{EI}_{ac}$	198.93	$\bar{EI}_{ad}$	216.95	$\bar{EI}_{bc}$	214.58	$\bar{EI}_{bd}$	236.20	$\bar{EI}_{cd}$	223.43
$\bar{EI}_{AB}$	260.93	$\bar{EI}_{AC}$	273.95	$\bar{EI}_{AD}$	249.30	$\bar{EI}_{BC}$	258.03	$\bar{EI}_{BD}$	236.98	$\bar{EI}_{CD}$	250.15
$\bar{EI}_{Ab}$	252.48	$\bar{EI}_{Ac}$	239.45	$\bar{EI}_{Ad}$	264.10	$\bar{EI}_{Bc}$	223.80	$\bar{EI}_{Bd}$	244.85	$\bar{EI}_{Cd}$	257.63
$\bar{EI}_{aB}$	220.90	$\bar{EI}_{aC}$	233.83	$\bar{EI}_{aD}$	215.80	$\bar{EI}_{bC}$	249.75	$\bar{EI}_{bD}$	228.13	$\bar{EI}_{cD}$	214.95
$Eff_{ab}$	-0.006	$Eff_{ac}$	-0.002	$Eff_{ad}$	-0.058	$Eff_{bc}$	-0.004	$Eff_{bd}$	0.001	$Eff_{cd}$	0.004
Dorm Building Results											
$\bar{EI}$	379.89	$\bar{EI}$	379.89	$\bar{EI}$	379.89	$\bar{EI}$	379.89	$\bar{EI}$	379.89	$\bar{EI}$	379.89
$\bar{EI}_{ab}$	375.18	$\bar{EI}_{ac}$	370.30	$\bar{EI}_{ad}$	379.10	$\bar{EI}_{bc}$	364.90	$\bar{EI}_{bd}$	373.88	$\bar{EI}_{cd}$	368.93
$\bar{EI}_{AB}$	384.60	$\bar{EI}_{AC}$	389.48	$\bar{EI}_{AD}$	379.75	$\bar{EI}_{BC}$	395.25	$\bar{EI}_{BD}$	385.70	$\bar{EI}_{CD}$	390.5
$\bar{EI}_{Ab}$	374.30	$\bar{EI}_{Ac}$	369.43	$\bar{EI}_{Ad}$	379.15	$\bar{EI}_{Bc}$	374.83	$\bar{EI}_{Bd}$	384.38	$\bar{EI}_{Cd}$	389.33
$\bar{EI}_{aB}$	385.48	$\bar{EI}_{aC}$	390.35	$\bar{EI}_{aD}$	381.55	$\bar{EI}_{bC}$	384.58	$\bar{EI}_{bD}$	375.60	$\bar{EI}_{cD}$	370.80
$Eff_{ab}$	0.000	$Eff_{ac}$	0.000	$Eff_{ad}$	-0.005	$Eff_{bc}$	0.002	$Eff_{bd}$	-0.001	$Eff_{cd}$	-0.002

### 3.3. Monte Carlo Analysis Results

The results of the 60 runs of Monte Carlo analysis are shown in Figure 4. The upper part of the figure illustrates the spread of the results for the three types of buildings. Each dot indicates the energy intensity obtained from one of the 60 runs. Box-and-whisker plots are also overlaid showing the average, first, and third quartiles, as well as the minimum and maximum values observed. In general, significant levels of variations are observed between the runs, with the highest difference for the classroom building and the lowest difference for the dorm building. As shown in Figure 4, the classroom building baseline average is 212.3 KWh/m<sup>2</sup>/year, with a possible minimum and

maximum of 157.6 KWh/m<sup>2</sup>/year and 265.6 KWh/m<sup>2</sup>/year, respectively. This is equivalent to a variation exceeding ±25% from the average energy intensity. The office building, on the other hand, shows a variation of ±19%, while the dorm building a variation of ±7%. Results confirm that uncertainty in the chosen human-related parameters can lead to significantly different energy intensity levels. These results are in accordance with those of the differential analysis, confirming the particularly high sensitivity of the building energy use levels, particularly the classroom building, to the studied parameters.

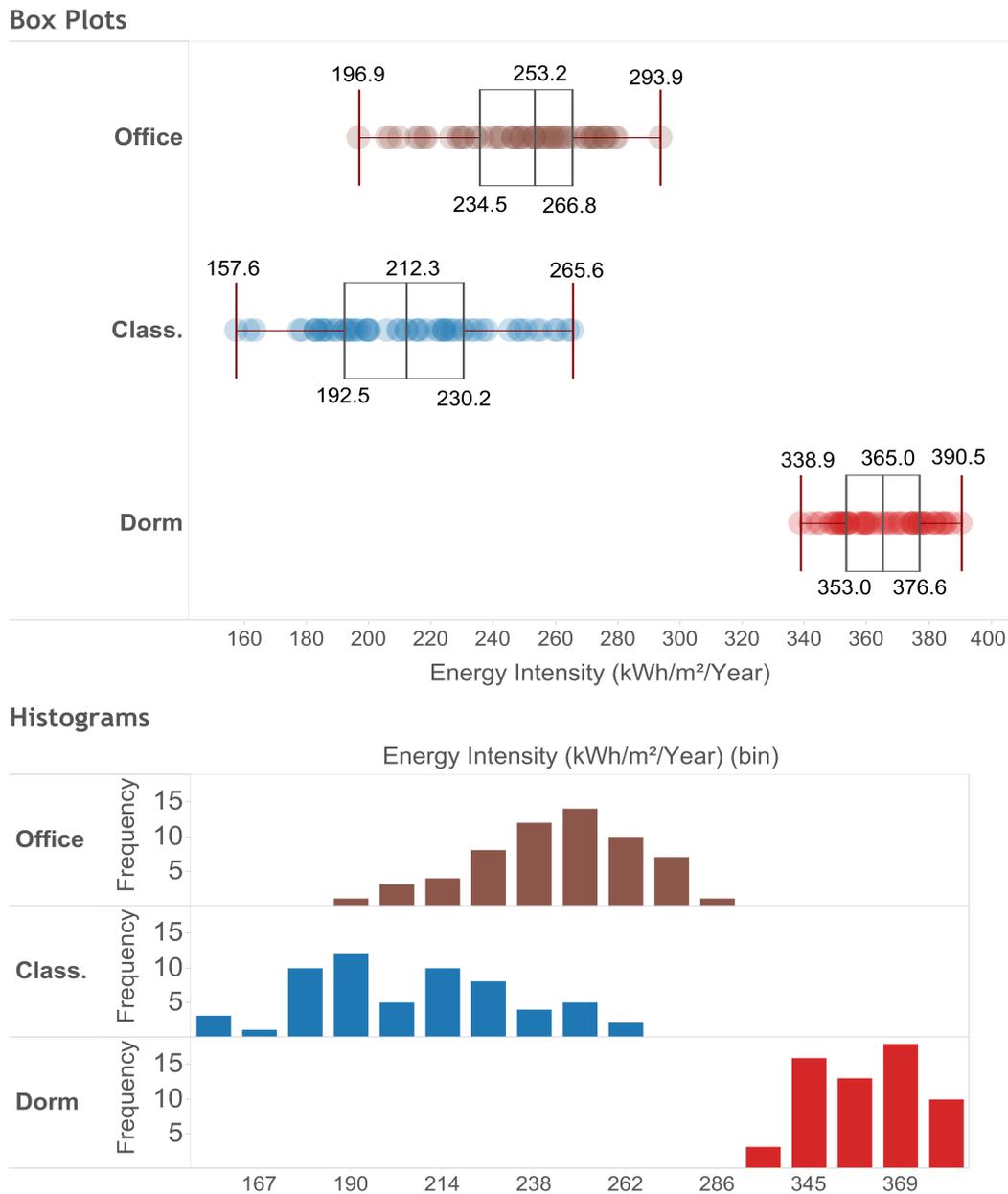


Figure 4. Monte Carlo analysis results.

The lower part of Figure 4 shows the same data, but in a histogram format in order to better visualize the variability within the runs. The X-axis represents energy intensity bins of 12 KWh/m<sup>2</sup>/year, while the Y-axis shows the frequency distribution of the 60 runs. In general, the results of the runs for the three buildings are relatively well distributed around their means. The symmetry is best illustrated in the office building case, where the results of the runs form a bell-shaped

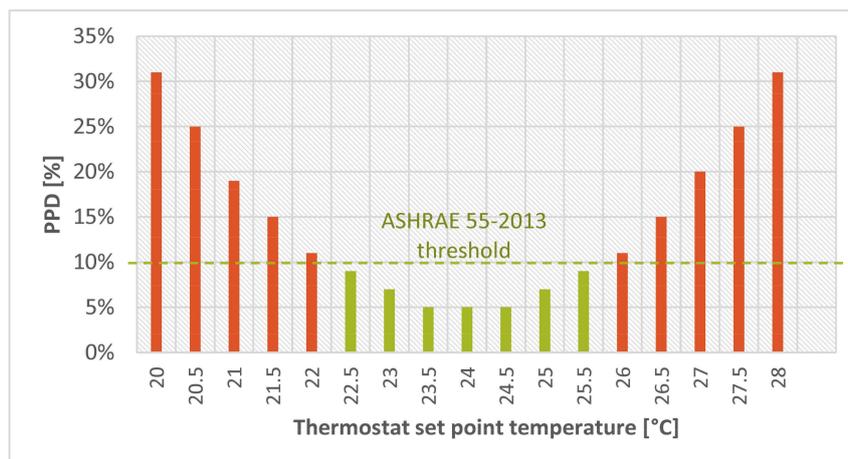
distribution. It is important to mention that the choice of the bin size influences these shapes to some degree. While other bin sizes can better illustrate the symmetry in the results of the classroom and dorm building, one bin size was chosen for all of the buildings for consistency when analyzing the results.

#### 4. Discussion

The findings of this study confirm that human actions can have major effects on building performance. In addition to equipment, lighting, and window operation patterns, a simple action such as adjusting HVAC set point temperatures by  $\pm 2$  °C can lead to a 26.5% change in the energy consumption of the classroom building, while the office and dorm buildings have shown changes of 16.6% and 8.5%, respectively. Assuming an electricity tariff of 0.087 \$/kWh, which is the unsubsidized cost of electricity generation in Abu Dhabi [32], the estimated savings in utility costs amount to \$88.1 K/year, \$18.5 K/year, and \$8.4 K/year for the classroom, office, and dorm buildings, respectively. The results are in line with the work of Afshari et al. [3], who varied HVAC set points for a commercial office building in the UAE. While the building type and experimental settings are different than the ones used in the current study, the authors in [3] estimated that a 4 °C increase in set point temperatures could lead to a reduction of 29% in cooling loads, which is equivalent to a change of 17.6% in the total building energy consumption. The findings are very comparable to the ones observed in the current study, further confirming the validity of the results.

In practice, despite the highlighted energy monetary savings from a  $\pm 2$  °C change in thermostat settings, such measure might not be realistic given its potential negative impact on the thermal comfort levels of occupants. To shed light on this matter, we calculate and show in Figure 5 the predicted impact of various thermostat set point values on the comfort levels of occupants according to ASHRAE 55-2013 standard [50], which was calculated using the University of California Berkeley Center for the Built Environment CBE thermal comfort tool [51]. The calculations are made assuming an indoor relative humidity of 50% [52], an indoor air speed of 0.1 m/s [50], a “light wearing” average clothing level for occupants (i.e., clo value of 0.61), and an average metabolic rate of 1.2 METS, corresponding to a relaxing or standing activity level [50,51]. The thermal comfort metric used is the percentage of people dissatisfied (PPD), which is calculated for thermostat values ranging from 20 °C to 28 °C at a 0.5 °C increment. According to ASHRAE 55-2013 standard [50], only PPD values lower than 10% are considered acceptable. As shown in Figure 5, the acceptable range of set point values is between 22.5 °C and 25.5 °C, inclusive. This indicates that starting from the current base case value of 22 °C, a maximum increase of 3.5 °C (i.e., reaching up to 25.5 °C) can be considered realistic, beyond which the PPD drops below the maximum recommended value of 10%.

Another interesting observation in the results of Figure 5 is that the base case value of 22 °C, which is very common in the UAE and other countries in the Gulf region [3,32,33], results in sub-optimal conditions for the building occupants (i.e., PPD = 11%). This observation leads us to question whether it is adequate to apply standards developed in Western countries (e.g., ASHRAE 55-2013) to other regions such as the Arabian Gulf, or not, where a temperature of 22 °C might be considered comfortable by building occupants. It also motivates the need to study and better understand the link between occupants’ characteristics and the way they perceive the indoor conditions of their building spaces. Important research efforts have been deployed on this topic linking the comfort levels of building occupants to their gender [53], age [54], nationality [55], and economic class [56], among other factors. We believe that more research efforts are needed that originate from Gulf countries and assess the applicability of Western standards to the region.



**Figure 5.** Impact of thermostat set points on thermal comfort, expressed in percentage of people dissatisfied (PPD).

This paper also provided an overall understanding of the human role and responsibility in energy conservation. In the Monte Carlo analysis, all of the buildings have shown important variations in their energy intensity when uncertainty was applied to their human-related parameters. A  $\pm 25\%$  variation in energy intensity was observed for the classroom building, followed by  $\pm 16\%$  and  $\pm 9\%$  for the office and dorm buildings. The results for the classroom and office buildings are in line with the work of Azar and Menassa [26], who estimated the potential energy savings from human actions in US commercial office buildings located in hot weather zones to be in the range of 21–27%. Here again, while the building type and location are different than the ones used in this study, the comparability of the results help validate the findings of the current work. To sum up, it can be concluded that if building designers and engineers do not properly account for uncertainty in operation parameters during the design phase, they run the risk of generating energy estimates that deviate from actual levels by as much as 25%.

## 5. Conclusions

Prior to concluding, it is important to highlight some of the limitations of this study, which can guide future research on the topic. One such limitation is the lack of publically available building energy data in the UAE, which resulted in the partial reliance on data from international sources. Future research can involve local data collection efforts to overcome this barrier. Another limitation is the lack of distinction between the levels of building systems' control of occupants and facility managers. Nonetheless, the main goal of this paper was to quantify the potential impact of changes in existing energy use patterns independently of the controlling stakeholder, a goal that was successfully achieved. Along the same lines, the current work did not focus on the probabilities of occupants taking specific actions, such as adjusting thermostat set points. Assumptions were therefore made in the parametric variation phases, such as occupants opening windows in a pre-defined pattern. Future data collection efforts can help overcome such assumptions by monitoring the actual energy use behaviors of educational building occupants in the UAE. Finally, while studying the water consumption patterns of occupants is beyond the scope of this paper, it can be included in future extensions of this work.

In summary, this paper fills an existing gap in the literature by studying the impact of human operation and actions on the energy consumption of typical UAE educational buildings. Three different building types were modeled, namely: office, classroom, and dorms. Several sensitivity analysis methods including differential, fractional factorial, and Monte Carlo analyses, were then applied to test the influence of human actions on building energy use. Based on the findings of this study, the following conclusions are made.

First, there is an urgent need for programs and initiatives to educate occupants and facility managers on the significant influence of thermostat control on building performance. Programmable thermostats are recommended for office and classroom buildings to ensure that an efficient HVAC strategy for occupied and unoccupied periods is implemented. Facility managers have a key role to frequently test and update this strategy, ensuring low energy consumption levels coupled with acceptable thermal comfort levels for occupants. In dorm buildings, smart thermostats can also be employed to learn from the schedules and thermal preference of occupants in an effort to optimize and customize the thermostat settings for different rooms.

Another finding from the current work is that different building types respond differently to changes in human-related parameters. In general, the classroom building has shown the highest sensitivity, followed by the office and dorm buildings, respectively. Consequently, the authors recommend that interventions targeting educational buildings (e.g., in a campus) should start with classroom buildings, which can result in significant and fast energy savings. Furthermore, given the low after-hours levels of occupancy in these buildings, aggressive energy saving strategies can be implemented without compromising the thermal comfort and well-being of occupants.

Finally, the findings of this paper motivate the need to further investigate user-centric solutions that aim to diffuse energy conservation practices among building occupants (e.g., energy education and feedback, financial or social incentives, and gamified energy conservation programs) [26,57–59]. More specifically, future research can build on the results of the current work to develop interventions that specifically target the actions of occupants with the highest influence on building performance. Such a customized individual-level approach to energy conservation can help promote sustainable behaviors and reduce the energy intensity and carbon footprint of the building sector.

**Author Contributions:** Ahmed Al Amoodi conceived the experiments, conducted the analysis, and wrote the first draft of the paper. Elie Azar coordinated and reviewed the work, he also prepared the final version of this paper.

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## Appendix A

Table A1 presents the building schedules used in the base case models, expressed in terms of diversity factors for the different hours of the day. A value of 0 represents 0% occupancy while a value of 1 represents 100% occupancy.

**Table A1.** Building schedules for the base case energy models, obtained from ASHRAE (2013a).

	Office Building			Classroom Building			Dorm Building		
	Week-Days	Week-End Day 1	Week-End Day 2	Week-Days	Week-End Day 1	Week-End Day 2	Week-Days	Week-End Day 1	Week-End Day 2
1 h	0	0	0	0	0	0	1	1	1
2 h	0	0	0	0	0	0	1	1	1
3 h	0	0	0	0	0	0	1	1	1
4 h	0	0	0	0	0	0	1	1	1
5 h	0	0	0	0	0	0	1	1	1
6 h	0	0	0	0	0	0	1	1	1
7 h	0.1	0.1	0.05	0	0	0	1	1	1
8 h	0.2	0.1	0.05	0.05	0	0	0.9	0.9	0.9
9 h	0.95	0.3	0.05	0.75	0.1	0	0.4	0.4	0.4
10 h	0.95	0.3	0.05	0.9	0.1	0	0.25	0.25	0.25
11 h	0.95	0.3	0.05	0.9	0.1	0	0.25	0.25	0.25
12 h	0.95	0.3	0.05	0.8	0.1	0	0.25	0.25	0.25
13 h	0.5	0.1	0.05	0.8	0.1	0	0.25	0.25	0.25
14 h	0.95	0.1	0.05	0.8	0	0	0.25	0.25	0.25
15 h	0.95	0.1	0.05	0.8	0	0	0.25	0.25	0.25
16 h	0.95	0.1	0.05	0.45	0	0	0.25	0.25	0.25
17 h	0.95	0.1	0.05	0.15	0	0	0.3	0.3	0.3
18 h	0.3	0.05	0.05	0.05	0	0	0.5	0.5	0.5
19 h	0.1	0.05	0	0.15	0	0	0.9	0.9	0.9
20 h	0.1	0	0	0.2	0	0	0.9	0.9	0.9
21 h	0.1	0	0	0.2	0	0	0.9	0.9	0.9
22 h	0.1	0	0	0.1	0	0	1	1	1
23 h	0.05	0	0	0	0	0	1	1	1
24 h	0.05	0	0	0	0	0	1	1	1

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