Title
Empower saving energy into smart communities using social products with a gamification structure for tailored Human–Machine Interfaces within smart homes

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Empowering Saving Energy at Home through Serious Games on Thermostat Interfaces

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Abstract

The residential Heating Ventilation and Air-Conditioning (HVAC) system use around 3/5 of the total energy consumption. Thermostats optimize the HVAC operation; however, householders have attitudes that lead into behavioral and usability problems toward the thermostat's interface usage. So a serious game applied in the thermostat interface can balance entertainment and education. Therefore, thermostat interfaces must address strategies that reduce energy without losing thermal comfort. This paper proposed an interactive interface type and a predicted interface type based on an HVAC strategy and a Natural Ventilation strategy. These strategies measured the impact of adaptive thermal comfort, energy consumption, and costs. Hence, twelve energy models located at Concord, Riverside, Los Angeles, and San Diego in California were simulated using EnergyPlus through LadybugTools. The first interactive interface included Serious Game elements, so the householder interacted with the date, location, and setpoint. The second interface predicted the energy consumption and thermal comfort during winter and summer in Concord by a two-layer feed-forward Artificial Neural Network structure. The results show that the proposed structure decreases the energy consumption by at least 62% without losing thermal comfort.

Keywords: energy simulation, adaptive thermal comfort, ANN thermostats interfaces, adaptive thermostats interfaces, serious games, user type

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1. Introduction

In 2020, the US electricity consumption was about 3.6 trillion kW; the residential sector contributed 40% to the electricity consumption and 22% to the energy consumption [1]. The Heating Ventilation and Air-Conditioning (HVAC) system is the greatest energy consumer in this sector, with about 40% to 60% [2, 3, 4, 5]. Existing technologies can reduce envelope losses, increase the efficiency of HVAC systems, or control the HVAC operation [6]. Thermostats control the HVAC systems, and more than 86% of the residential buildings have one, representing an opportunity area to optimize HVAC usage [2]. Householders set their thermostats based on their behavioral adaptation, garments, and activities [7, 8, 9] affecting the impact on energy use [2, 3, 4, 5, 10]. Connected thermostats can reduce energy consumption from 10% to 35% of the peak load and 5% of occupant energy efficiency due to behavioral change [11, 12]. In that sense, attractive gamified Human-Machine Interfaces can engage end-users to better interact with the thermostat [13, 14, 15]. Moreover, Ponce et al. [13] suggest using Serious Games (SGs) within the thermostat interfaces as they balance entertainment and education to teach, engage, and motivate householders reduce energy consumption.

SGs focus their efforts on teaching end-users specific topics such as energy reduction to improve their skills, acquire knowledge, and get more experience. Thus, SGs consider experience, multimedia, and entertainment elements. Some of the SGs applied to the energy topic include end-users interacting with household appliances to see how their actions either by a single user or by all the family members, affect the energy consumption [13, 16, 17, 18]. Thus, changing user behavior through real-time feedback, historical feedback, financial information, social influences, gamification, and goal-setting strategies can decrease energy consumption by 18% [19]. However, to succeed in those reductions, it is relevant to focus on the end-users' behavior and usability problems, for instance, when using a thermostat [13, 20, 21, 22, 23, 24, 25]. Hence, Ponce et al. [13, 26] classified the householders based on their personality traits [27], SG user [28] and energy end-user segment [29] when socially connected devices at households are deployed.

Additionally, Ponce et al. [13] described six behavioral problems that avoid energy savings through thermostats: (1) Users operate the thermostat differently than how the engineers intended or the manual establishes [21]. (2) Users do not understand the functions and feel complicated to use the thermostat. (3) Users do not know or care about the benefits of thermostats. (4) Users are not aware of the environmental impact. (5) Users' interests are different from energy saving. (6) Users do not know how to use the HVAC system. Nevertheless, two additional behavioral problems must be added: (6) Users have a psychological, physiological, and behavioral adaptation that affect their thermal comfort [7, 9], preventing the reduction in energy consumption. (7) Users face energy poverty problems [30, 31, 32, 33] and suppress their energy needs to financially meet other basic needs avoiding energy saving behaviors and leading in the misuse of thermostats.

The psychological dimension derives from the perception and reaction to past experiences and expectations. The physiological adaptation relates the body reaction based on genetic adaption and acclimatization with the exposure to thermal factors. The behavioral adjustment considers the personal, technological and cultural responses that an individual perform to adapt in their environment. Hence, comfort is a desirable human condition and a comfortable environment where people require change [8].

The thermal comfort concept gained attention since the 1920s as it became possible to control indoor temperatures [34]; however, it was until the 1970s that Fanger [35] proposed the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) that considers six mandatory parameters [36]: metabolic rate, clothing insulation, air temperature, air speed, and humidity. In 1998, de Dear and Brager [7] proposed the adaptive method based on human behavior through three categories of thermal adaptation: behavior, clothing, and air temperature. In 2002, Nicol and Humphreys [9] included the outdoor temperature to calculate the range of thermal comfort temperatures at indoors. The occupants have a higher degree of freedom to adjust the clothing insulation and wider acceptance of indoor temperatures during swing seasons that fall outside the conventional adaptive comfort zone [37].

Adaptive behavior requires to consider the conditions to which an individual is exposed. The behavior includes adaptive and non-adaptive actions [30]. The adaptive actions occur when the individual opens or closes windows, adjusts thermostat setpoints, uses heaters or coolers, or adapts through a set of actions as a response to warm or cool environments [30, 38]. The non-adaptive actions rely on reporting discomfort, occupant presence or data gathering from sensors [30]. Therefore, Humphreys et al. [39] outlined how householders use strategies to achieve thermal comfort such as selecting areas shaded by trees or sheltered from wind, occupying rooms based on the season, selecting the type of HVAC system, thermostat, ceiling fans or other type of control to increase the air movement inside a room to cool the occupants and become comfortable [40]. Other strategies include selecting the type of garments and activities based on the climate, season, indoor temperature, or fashion style. Thus, they pointed out that householders have attitudes toward the indoor operative temperature because there are users that prefer to save or spend money by accepting wider ranges of indoor temperature.

By considering the outdoor temperature, it is unnecessary to think about other factors such as humidity or air movement because thermal comfort can be achieved by clothing insulation or even by metabolic rates [9]. Besides, adaptive thermal comfort provides opportunities to reduce costs and become energy efficient, and an example is by changing clothes with few to little cost or adjusting setpoints [20, 8]. During cooling periods, increasing the setpoint by 1.8 °F (1 °C) can save 6% of electricity [14]. In [41], they used the adaptive comfort model in Europe, and depending on the location, they found an energy saving of 35% compared with a static setpoint.

It is complex to measure householders' satisfaction because their comfort is related to perception and other context-specific factors, such as age, gender, income, cultural aspects, specific needs or any possible disability or long-term illness beyond climate zones [3, 34, 40, 39, 33, 38]. Unfortunately, income aspect may affect the thermal comfort perception because although users would prefer to be comfortable, a lack of income or inadequate levels of essential energy services in the household lead into domestic energy deprivation or better known as energy poverty condition [30, 31, 32, 33]. Low income homes spend less or around 2/3 of their income on fuel leading on a lack of thermal comfort [32].

Furthermore, the authors of this research had proposed gamified strategies that reduced energy through tailored interfaces [13, 14, 42, 43, 44, 45, 46, 47, 48]. Nevertheless, until this paper, they simulated the thermal comfort and energy consumption in different locations to be added within the thermostats' interfaces.

Existing energy building simulators such as EnergyPlus can predict the overall energy consumption and the two thermal comfort models, the adaptive and the PMV/PDD model [49, 50, 51, 52, 53, 4]. This software bases its features and capabilities on BLAST and DOE-2, two different software tools that were in development in 1996 by the Department of Energy [49]. Honeybee Energy from Ladybug Tools (LT) uses Energy Plus for the simulation. LT from Grasshopper visual programming language is a graphical interface that runs within the Rhinoceros software [54]. Examples of applying these tools include:

- The analysis of thermal mitigation potential of façades in Copenhagen, Madrid, Brindisi, and Abu Dhabi [55];
- the modeling of outdoor thermal comfort to get the UTCI values and energy demand in urban canyons [56];
- an algorithm proposal that finds the optimal skylight design while saving energy by considering the impacts of daylight [57];
- the energy performance analysis of a building that integrates photovoltaic panels on façades for power generation [58, 59, 60].

Figure 1 shows the two types of approaches used for thermal comfort and the thermal scales; Figure 1(a) depicts the building or group approach that considers the six parameters proposed by Fanger [35] and considered in the ASHRAE 55 Standard [36]. Figure 1(b) shows the adaptive thermal comfort, that considers the human-centered approach [8]. This paper focuses on adaptive thermal comfort as it is demonstrated that it fits better in the residential sector [3]. Figure 1(c) shows three types of scales used to measure thermal comfort: the thermal sensation, the thermal preference, and the thermal stress.

The thermal sensation is often known as the predicted mean vote (PMV) index. The ideal scale is the 4 where the individual feels comfortable, or no changes are required in the indoor room [8]. The thermal preference vote is a sensation scale that map the individual's preference when operating HVAC systems or performing activities [61]. Additionally, to avoid local thermal discomfort due to cold feet when the individual prefers warmer temperature or has hot head but prefers cooler temperatures, the body requires to stay in heat balance and adaptive strategies can be addressed as turning on electric fans or put the feet on cold water or cover their feet with warmer socks. The Universal Thermal Climate Index (UTCI) reflects the human physiological reaction to the actual thermal condition and is categorized as thermal stress [62]. Therefore, an individual can have no thermal stress within an air temperature range from 48.2 °F to 78.8 °F (9 °C to 26 °C).

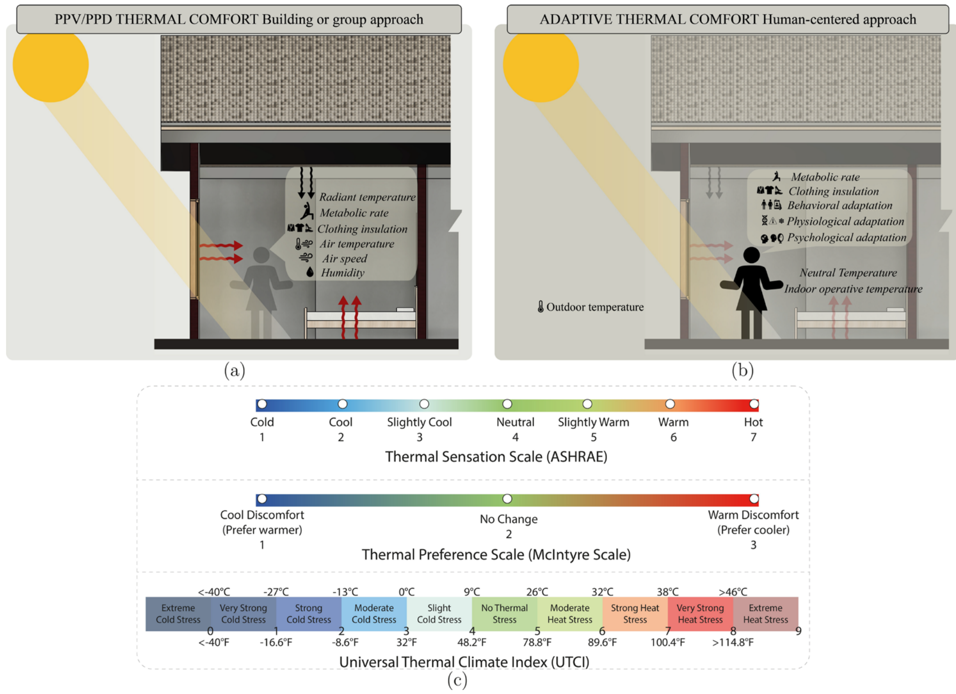


Figure 1: Thermal comfort approaches: (a) Building or group approach, (b) human-centered approach, and (c) thermal scales.

Artificial Intelligence (AI) can classify clothes and predict thermal comfort [20], energy consumption [45], or propose rules to classify the type of end-user and propose game elements that teaches, engages, and motivates householders in reducing energy even if they are not interested [13, 23, 26, 42].

Hong et al. [63] employed the thermal sensation scale to predict energy savings in a fifteen-floors residential apartment. Ngarambe et al. [64] suggested using AI methodologies to predict thermal comfort. Alamin et al. [65] proposed an Artificial Neural Network (ANN) to predict the energy consumption of the fan-coil by considering as the input variables the energy consumption of the fan-coil for one sample delay and two sample delays, the impulse air velocity, and the indoor air temperature. Zhang et al. [66] used the six factors of the PMV/PPD model to predict if the space was comfortable. Another proposal analyzed occupied periods in a residential building to include a temperature control algorithm to predict setback temperature for the cooling system [67]. Other predictions included the use of input variables as outdoor temperature, outdoor relative humidity, Indoor temperature, cooling load, air handling unit supply air temperature, condenser fluid temperature setpoint, and condenser fluid pressure setpoint to predict the total amount of cooling energy consumption for the next hour [68].

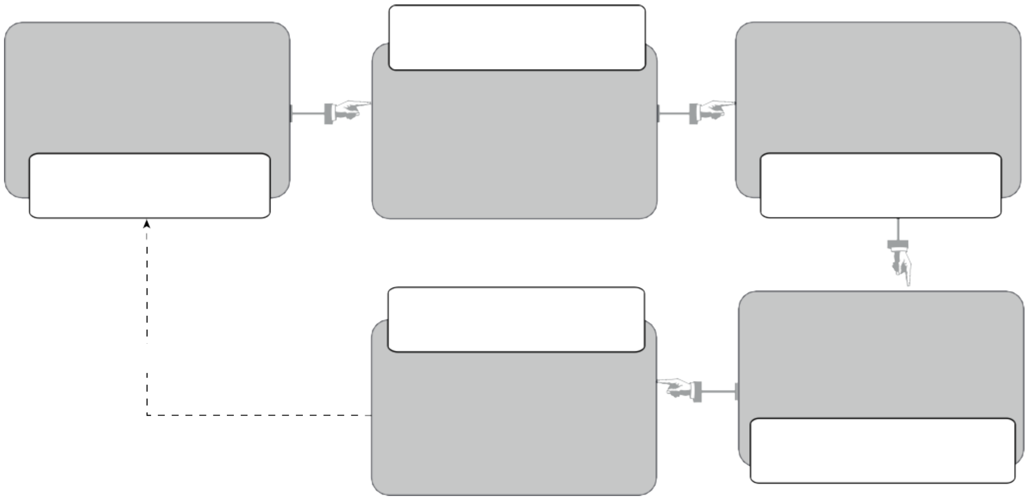
However, none of these proposals included the adaptive theory comfort applied on the thermostat usage as setpoint, date, and location to link those parameters into an SG interface. Thus, the end-user could learn in a ludic manner without being intrusive about the implications of changing those parameters with the thermal comfort, energy usage, and bill costs. Hence, the research question that this paper focuses on addressing is as follows:

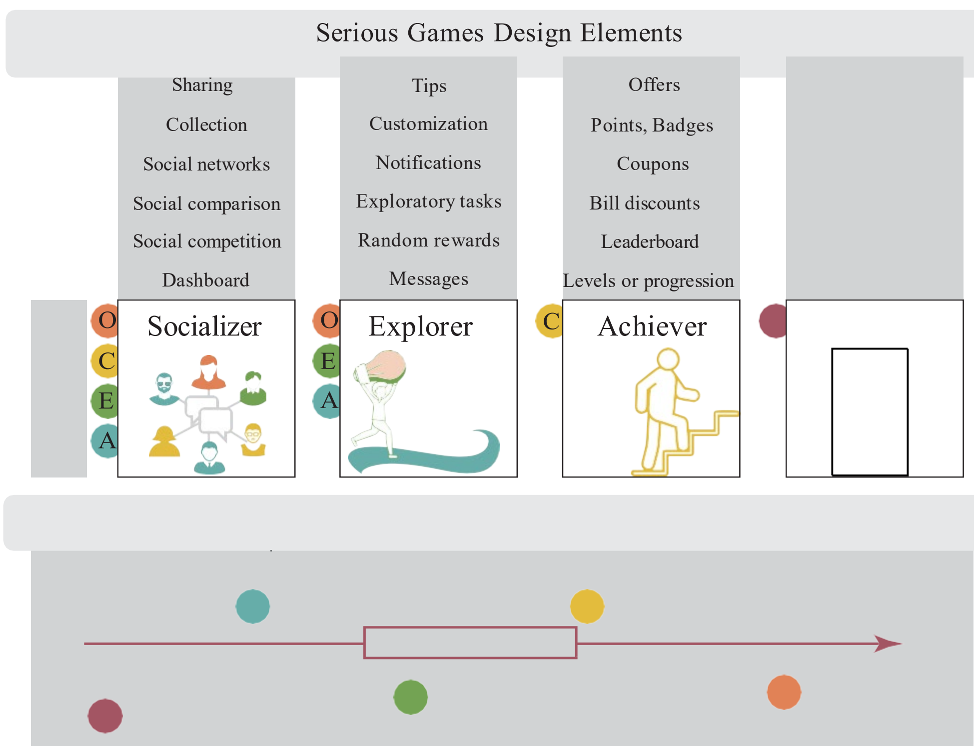
- What requirements does a Serious Game interface need to teach the end user the benefits of using an adaptive strategy to promote energy and money savings without losing thermal comfort?

The remainder of this paper is as follows. Section 2 provides a five-step framework for tailoring SGs interfaces. Section 3 describes the methodology used in each step of the framework to simulate the energy models and strategies for predicting thermal comfort and energy usage. Therefore, two interactive interfaces were proposed within a serious game context to teach, engage, and motivate end-users to become energy-aware connected thermostat integration into a device. Section 4 presents the results of the methodology used and the results of the two interactive interfaces applied into Bedroom 2. Section 5 describes the scope of the research and discusses the advantages and disadvantages of the study. Finally, conclusions and suggestions for future work are presented in Section 6.

2. Proposed Framework

Figure 2 describes the five required steps to propose a tailored SG interface. This framework considers a continuous adjustment and feedback environment to analyze if the end-user is engaged and is saving energy or money. Besides, if it is required, the SG design elements displayed on the platform could be updated. Fanghella and Della Valle [31] suggested that end-user behavioral factors explain up to 50% of the variance of overall cooling and heating consumption. Ponce et al. [13] indicated that householders must take an active role in energy platforms to give them the desire to control their energy behavior.




Serious Games Design Elements
Sharing
Collection
Social networks
Social comparison
Social competition
Dashboard
Tips
Customization
Notifications
Exploratory tasks
Random rewards
Messages
Offers
Points, Badges
Coupons
Bill discounts
Leaderboard
Levels or progression
O
C
E
A
Socializer
O
E
A
Explorer
C
Achiever

1. User and product type identification: During the first step the type of user and SGs design elements for energy-saving platforms are identified (see Figure 3). The type of product is identified and the type of user is obtained by surveying them through accepted surveys [46, 43, 13].

    - The openness personality trait appreciates divergent thinking and novel ideas with a curious and imaginative attitude. The conscientiousness trait is a rule-follower with clear goals in life. This user type is self-discipline, competitive, and responsible. The openness and conscientiousness traits are positive to learn new things through internet while saving energy. The extraversion trait prefers social interactions, exciting and diverse activities with an assertive and optimistic attitude. Higher levels of extraversion lead in saving energy attitudes. The agreeableness trait has a modest, cooperative, and altruistic nature with a sympathetic and tolerant attitude to others and with inclinations to save energy. The neuroticism trait experiences negative emotions leading in an impulsive, stressful, and bad-tempered attitude. Higher neuroticism's levels have positive energy saving attitude.
    - The achiever SGs user type focuses on earning points and levels. The explorer type finds and gathers all the information available on the game and about the players. The main purpose for the socializer user type is the interaction with other players. On the contrary, the killer type imposes on others to control them.
    - The green advocate energy end-user segment prefers new technologies to continue be energy aware. The traditionalist cost-focused segment has few to no interest in new technologies and cost-saving is their motivation with an extensive overall energy-saving behavior. The home-focused segment looks for household improvements while saving energy and money. The non-green selective segment is a not energy aware type and selects energy savings though set-and-forget inventions. The disengaged energy waster segment's motivation relies on saving money through energy savings
    - The social product bullet refers to household appliance that will communicate between the householder and the product and between products to propose a tailored service; for instance, the connected thermostat [15, 45, 13].

- This step may be omitted if there is no information available or consider a generic end-user.

2. Household characteristics identification: This step collects the household characteristics (building materials, occupancy hours, location), the energy usage patterns, the thermostat setpoints, the outdoor and indoor temperature, the adaptive and non-adaptive behaviors and the occupant behavior.
3. Simulation analysis: This step builds a persona, a calibrated energy model and perform the thermal comfort analysis and statistical analysis.
   - Ponce et al. [26] describes a persona as a fictitious individual that represent the characteristics of a consumer group. For instance, this persona can consider the general characteristics of a group that contain the majority of the personality traits like the socializer or explorer SG type and the killer type.
4. Build an AI algorithm: Once collected the information from the previous step, during the third step is proposed the AI algorithm depending on the target. An example is by employing a multilayer ANN to predict energy consumption, cost, thermal comfort and SGs design elements.
   - AI acknowledges three big areas: Fuzzy logic (FL) [69, 70, 71, 72], Artificial Neural Networks (ANN)[73], and Genetic Algorithms (GA) [74]. Moreover, the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [75, 76] combine the ANN with FL. Therefore, this step can be changed for another type of decision system.
5. Propose tailored SGs interfaces: the fourth step analyzes the results and plot them into a tailored SG interface or platform. The interface considers the SGs design element depicted in Figure 3.
   - A generic interface can be used in case of not knowing the user type. This generic interface must consider the majority of the personality traits (for instance, the socializer SG tupe) and the killer SG type. Another consideration is that the display should display the saving money and saving energy element as the type of energy end-user segment is not known.

3. Methodology

This section presents the five steps of the proposed Framework and the required tools to propose SGs interactive interfaces.

3.1. Step 1 and Step 2: Householder and Home Characteristics

This research considers a generic persona that gathers the five personality traits, the SGs player type and do not know if they prefer to save energy or money. The social product considered is the connected thermostats. Figure 4(a) shows the east façade of the home and Figure 4(b) the 3D Energy Model that was created and simulated in Rhinoceros + Grasshopper and LT. Figure 4(c) depicts the floor plan; its distribution had three bedrooms, one bathroom, one kitchen, dining and living room, dining, and a one-level home with an attic. Bedroom 2 and the Dining and Living Room have two room air conditioners and two wall furnaces. For this paper, all the units were in kWh to better dimension the energy savings impacts.

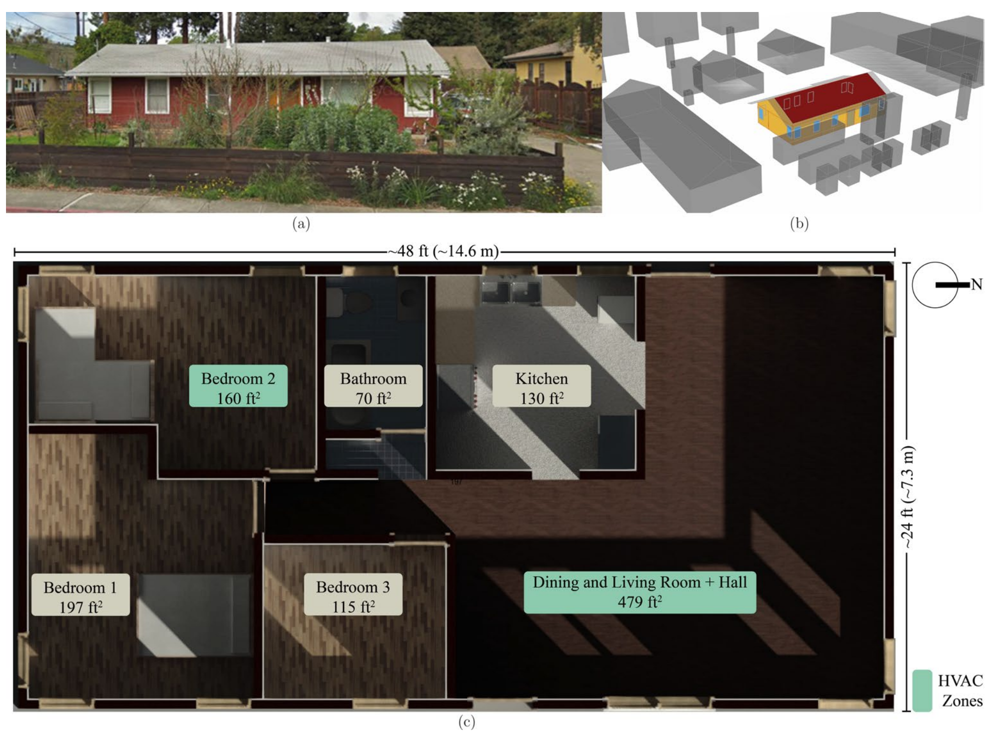


Figure 4: (a) East Fa¸cade, (b) 3D Energy Model, and (c) Home Zones (Floor plan distribution).

The software used during this research were:

- Rhinoceros Version 7 SR10 and Grasshopper 3D version 1.0.0007
- Ladybug Tools Version 1.2.1.
- Excel from Microsoft 365
- RStudio Version 1.4.1106 and RPubs
- Neural Network toolbox from MATLAB Version R2021a
- MATLAB /Simulink Model Version 1.36 and Simulink Version R2021a

The adaptive thermal comfort considers the metabolic rate and the clothing insulation as they are related to the occupant. An acceptable range of clothing insulation is 0.5 clo for typical summer season and 1.0 clo for winter season [77]. The metabolic rates considered for the simulation [78] were:

- Activity: Sleeping
  - Activity level: 72 W/person
  - Metabolic rate = 0.7 met
- Activity: Seated or writing
  - Activity level: 108 W/person
  - Metabolic rate = 1 met
- Activity: Standing
  - Activity level: 126 W/person
  - Metabolic rate = 1.2 met
- Activity: Typing
  - Activity level: 117 W/person
  - Metabolic rate = 1.1 met
- Activity: Cooking
  - Activity level: 190 W/person

– Metabolic rate = 1.8 met

The energy model required of the weather file in EnergyPlus Weather Format (EPW). Thus, the climate data were from the Climate One Building repository; this meteorological database derived weather data hourly from 2004 to 2018.

Five Californian locations were selected: Concord [79], Riverside [80], Los Angeles [81], and San Diego [82]. All the locations belonged to the IECC Climate Code 3B (warm, marine). Moreover, whereas the IECC Climate Zone 3B covers the four locations, the California Climate Zone (CaCtZ) considers three different zones. Hence, the selection of these places relied on considering the north part and the south part of Zone 3B to measure the HVAC kWh consumption compared to the three different CaCTz.

The kWh costs were calculated using the current Electricity time-of-use C (E-TOU-C) [83] rate from the Pacific Gas and Electric Company (PGE) for all the locations to uniform the results and value the costs' impacts.

3.2. Step 3: Simulation analysis

This subsection describes the energy model characteristics and the parameters needed to perform and analyze the energy simulations.

3.2.1. Energy Model Calibration

The ASHRAE Guideline 14 was followed to calibrate the building model and achieve Normalized Mean Bias Error (NMBE) values within $\pm$5% and Cumulative Variation of Root Mean Square Error (CV(RMSE)) values below 15% [84, 85, 86]. The NMBE and CV(RMSE) were calculated using Equations (1) and (2).

$$NMBE = \frac{1}{\bar{m}} \cdot \frac{\sum_{i=1}^{n} (m_i - s_i)}{n - p} \tag{1}$$

Where $\bar{m}$ is the mean of measured values, p is the number of adjustable model parameters and is suggested to be one for calibration purposes. m_i is the measured values and s_i is the simulated values, n is the number of sample.

$$CV(RMSE) = \frac{1}{\bar{m}} \sqrt{\frac{\sum_{i=1}^{n} (m_i - s_i)^2}{n - p}} \tag{2}$$

The measured data came from the PGE utility bill and consumed 2,113.7 kWh. The calibrated model had an annual energy consumption of 2,052.1 kWh. The NMBE was 3.18%, and the CV(RMSE) was 10.55%. After this calibration, six cases were analyzed.

3.2.2. Energy Model Cases

The energy model required the HVAC setpoints; thus, in addition to the owner HVAC schedule, two additional HVAC schedules were included. Figure 5 (a) displays the HVAC setpoints from the owner's home; during heating periods, the setpoint was set to 68°F at 7 a.m. as it was the hour where all the householders were awake, interacting, for instance, at the dining and living room zone. Woods [10] collected, from 96 houses with a total of 783,459 observations, the monthly cooling and heating setpoints; hence, Figure 5 (b) displays the monthly cooling and heating setpoints proposed by Woods [10]. The 2019 Residential Appliance Saturation Study (RASS) metered 69,682 householders and 303 households to provide information on appliances, equipment, and general consumption [87]. Figure 5 (c) displays the cooling and heating setpoint based on the utility that belonged to Concord, Riverside, Los Angeles, and San Diego were used to feed the energy model.

Therefore, twelve energy models were developed to compare the differences between HVAC strategy and natural ventilation strategy. These models gave as a result the indoor temperatures, electrical consumption, billing costs, and thermal scales (thermal sensation, thermal preference, and UTCI). The selection of these locations relied on the importance that each location belongs to the ASHRAE Climate Zone 3B; however the California Climate Zone is different, Concord belongs to the California Climate Zone 12, Riverside to the California Climate Zone 10, Los Angeles to the California Climate Zone 9, and San Diego to the California Climate Zone 10. Therefore, the selection of the thermostat setpoints were based on Figure 5. The twelve models were divided into six cases:

- Case 1: Owner's heating and cooling setpoint (See Figure 5 (a)). Energy model 1 was the HVAC simulation and Energy model 2 was the Natural Ventilation simulation.

- Case 2: James Wood's heating and cooling setpoint (See Figure 5 (b)). Energy model 3 was the HVAC simulation and Energy model 4 was the Natural Ventilation simulation.

- Case 3: RASS's heating and cooling setpoint from Concord, CA (See Figure 5 (c)). Energy model 5 was the HVAC simulation and Energy model 6 was the Natural Ventilation simulation.

- Case 4: RASS's heating and cooling setpoint from Riverside, CA (See Figure 5 (c)). Energy model 7 was the HVAC simulation and Energy model 8 was the Natural Ventilation simulation.

- Case 5: RASS's heating and cooling setpoint from Los Angeles, CA (See Figure 5 (c)). Energy model 9 was the HVAC simulation and Energy model 10 was the Natural Ventilation simulation.

- Case 6: RASS's heating and cooling setpoint from San Diego, CA (See Figure 5 (c)). Energy model 11 was the HVAC simulation and Energy model 12 was the Natural Ventilation simulation.

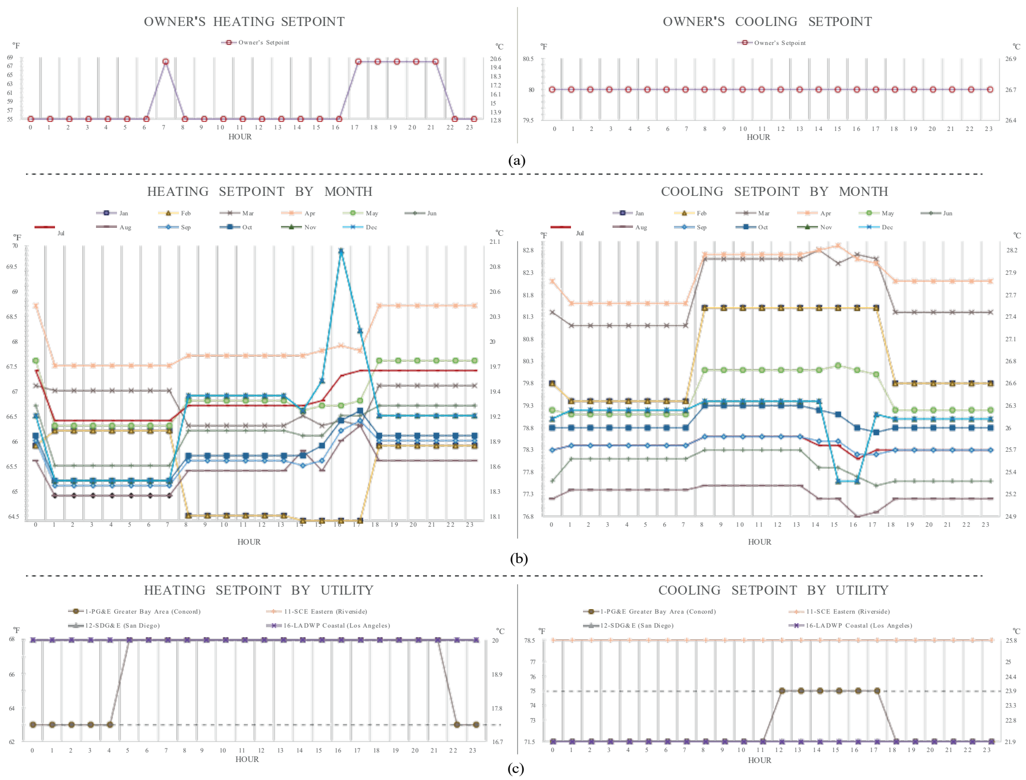


Figure 5: Heating and Cooling Setpoint by month: (a) Current heating and cooling set-point; (b) Thermostat setpoints analyzed by Woods [10]; (c) RASS setpoints by Utility [87];

Table 1 describes the location, occupancy hours, HVAC schedules, number of family members, equipment, and shows the building materials characteristics used to feed the 3D energy model simulator. The 1000 square foot household is located at in Concord, CA. Besides, for the cost calculation the rate was considering using the electricity time-of-use C (E-TOU-C) [83] with these characteristics:

- Summer: From June 01 to September 30
  - Peak: 0.34229 $/kWh
  - Off-peak: 0.27885 $/kWh
- Winter: From October 01 to May 31
  - Peak: 0.2452 $/kWh
  - Off-peak: 0.22788 $/kWh

An adaptive strategy was added by first considering opening the windows to ventilate the indoors and then closing the window when the indoor temperature was higher than the HVAC setpoints to turn on the system. Therefore, this research analyzed twenty-four strategies; twelve were for HVAC usage, and the other twelve were for Natural Ventilation (NV).

Figure 6 depicts the nine steps used to build and run the energy model simulations and the block generated using the LT.

3.2.3. Adaptive Thermal Comfort Analysis

The mean outdoor temperature estimated the exponentially weighted running mean outdoor temperature with an α= 0.7 (Equation (3)). Research indicates that mid-latitude climates have alpha values lower than 0.9, such as 0.7 because people are used to weather variability [88]. This formula means that today's prevailing mean outdoor temperature would be 30% of yesterday's mean daily outdoor temperature in addition to 70% of yesterday's running mean outdoor value. This equation advances the value of the running mean from one day to the next and is convenient for computer algorithms and manual calculations. However, a value for running mean temperature has to be assumed for day one to seed the sequence. Besides, the running mean needs to be initiated seven days before the start of the period of interest. Therefore, the first day of January seeded the sequence, and the last week of December initiated the period.

Table 1: Characteristics fed into the residential energy simulator.

Characteristics	Description
Location Case 1 to 3	Concord (IECC 3B; CaCtZ 12 [79]). *Utility: PGE.*
Location Case 4	Riverside (IECC 3B; CaCtZ 10 [80]). *Utility: SCE.*
Location Case 5	Los Angeles (IECC 3B; CaCtZ 9 [81]). *Utility: LADWP.*
Location Case 6	San Diego (IECC 3B; CaCtZ 10 [82]). *Utility: SDG&E.*
Non occupied	8 am to 3 pm (Monday to Friday)
HVAC schedules	Heating: November to March Cooling: April to October
Occupants	4 family members (mother, father, two children)
Equipment	Appliances: gas water heater, stove, oven, and two wall-furnaces. Electric: refrigerator (100 W), microwave (500 W), instant pot (900 W), electric kettle (1000 W), toaster (600 W), two room air conditioners (840 W, 1100 W), computer/monitor (120 W), laptops (60 W), LED lights (10 W).
Construction set	
External wood wall (R11): 2x4 @ 16" (40.6 cm) O.C.	Wood Siding, Wall insulation R10, 1/2" (1.27cm) Gypsum Board
External window: Single pane wood framed windows.	U 0.20, SHGC 0.22, Simple Glazing
Ceiling (R22)	Wood Siding, 5/8"(1.6 cm) Plywood, Insulation R20, 5/8"(1.6 cm) Plywood
Exterior Roof (R25)2x6 @ 24"(61 cm) O.C.	Asphalt Shingles, Insulation R24, 5/8" (1.6 cm) Plywood.
Floor (R22): Under floor crawl spaces; 2x8 @ 24"(61 cm) O.C.	5/8"(1.6 cm) Plywood, Insulation R20, 5/8" (1.6 cm) Plywood, Wood Siding

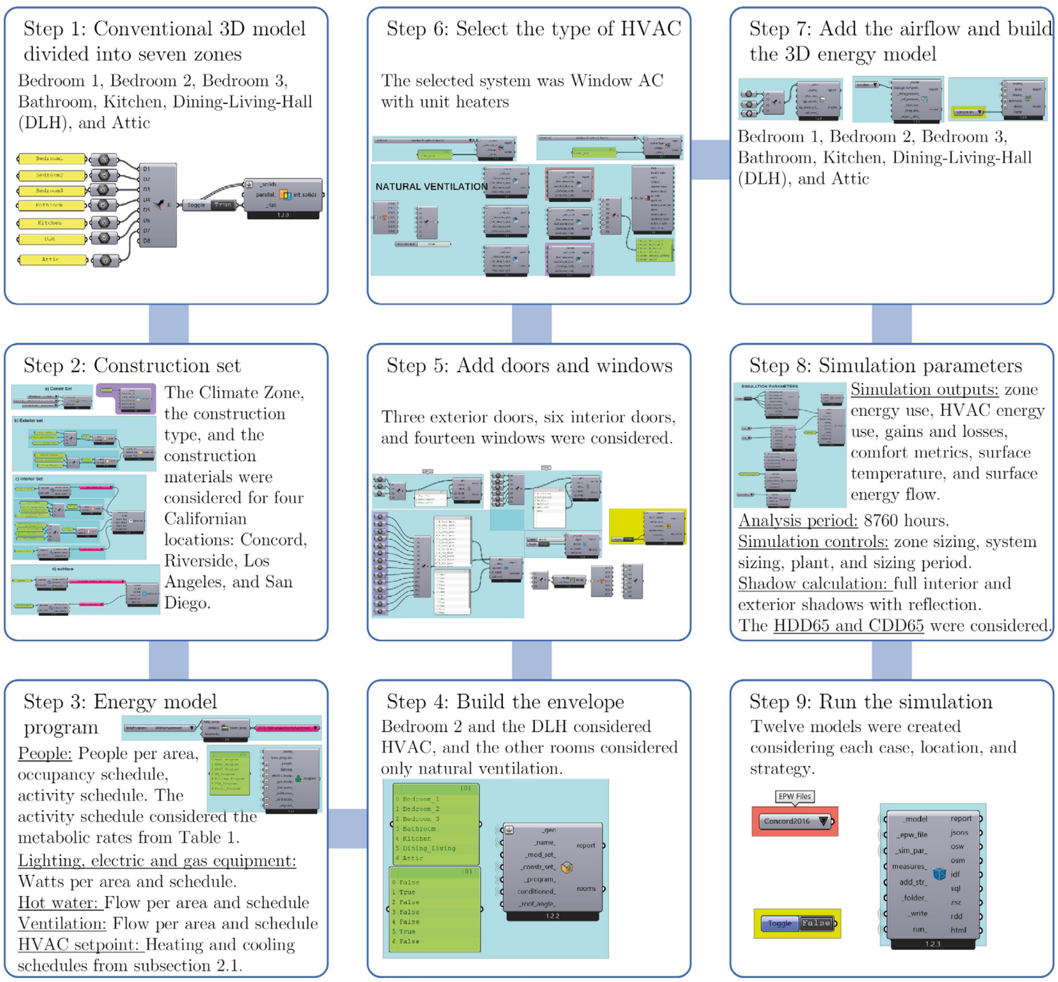


Figure 6: Energy model diagram of each step of the simulation.

Equation (4) describes the adaptive thermal comfort formula for the acceptable operative temperature used in this paper for a time-interval of seven days.

$$\overline{tpma(out)} = (1-\alpha)[t_{e(d-1)} + \alpha t_{e(d-2)} + \alpha^2 t_{e(d-3)} + \alpha^3 t_{e(d-4)} + \alpha^4 t_{e(d-5)} \ldots] \quad (3)$$

Where $\overline{tpma(out)}$ is the prevailing mean outdoor temperature, the α is equal to 0.7, and $t_{e(d-n)}$ is the mean daily outdoor temperature for the day before the day in question.

$$80\%\ Acceptability\ \ limit = (0.31 * \overline{tpma(out)}) + (54.2F \pm 6.3F) \quad (4)$$

In °C the Equation (4) should be changed from 54.2 $\pm$6.3 to 17.8 $\pm$3.5. The operative temperatures for the HVAC Zones (Bedroom 2 and Dining and Living Room) considering the upper and lower 80% acceptability limits of Equation 4 were plotted to visualize the adaptive thermal comfort from each case using the HVAC and the NV strategy.

Table 2 shows the thermal sensation values considered for each case. The shaded row means the Neutral thermal sensation scale and the No Change thermal preference scale.

3.2.4. Statistical Analysis

As a result of the energy model, a new database was created with thirty-two variables for the thermal comfort and the statistical analysis. Table 3 depicts those variables.The statistical analysis data was performed using RStudio Version 1.4.1106.

The descriptive analysis was conducted for the outdoor temperatures and indoor variables of subsection 3.2.2:

- For the outdoor temperatures, the boxplot summarized Concord, Riverside, Los Angeles, and San Diego's monthly mean temperatures; and the bar chart depicted the frequencies of the heating degree days (HDD65) and cooling degree days (CDD65) with a baseline of 65 °F (18.3 °C).
- For the indoor variables, the shape statistics, the histogram, and the Kolmogorov-Smirnov test determined the kWh and costs' normality. The objective was to decide the appropriate central tendency and dispersion measures to describe the variables, select which test best fit

Table 2: Thermal Sensation Scale values considered for each case (See Figure 1(c)).

Cases		1		2	3	4	5 and 6
		Summer	Winter	Summer and Winter			
ASHRAE Scale (°F)	1	[35,46]	[32,41]	[32,41]	[32,41]	[32,41]	[32,41]
	2	(46,55]	(41,50]	(41,50]	(41,50]	(41,50]	(41,50]
	3	(55,64.4)	(50,55)	(50, Htg.Stpt-3)	(50,60)	(50,65)	(50,65)
	4	*[64.4,80]*	*[55,78]*	*[Htg.Stpt-3, Clg.Stpt+3]*	*[60,78]*	*[65,80]*	*[65,74.5]*
	5	(80,90]	(78,85]	(Clg.Stpt+3, 90]	(78,90]	(80,90]	(74.5,90]
	6	(90,114]	(85,114]	(90,114]	(90,114]	(90,114]	(90,114]
	7	(114,inf)	(114,inf)	(114,inf)	(114,inf)	(114,inf)	(114,inf)
ASHRAE Scale °C)	1	[1.7,7.8]	[0,5]	[0,5]	[0,5]	[0,5]	[0,5]
	2	(7.8,12.8]	(5,10]	(5,10]	(5,10]	(5,10]	(5,10]
	3	(12.8,18)	(10,12.8)	(10, Htg.Stpt-1.7)	(10,15.6)	(10,18.3)	(10,18.3)
	4	*[18,26.7]*	*[12.8,25.6]*	*[Htg.Stpt-1.7, Clg.Stpt+1.7]*	*[15.6,25.6]*	*[18.3,26.7]*	*[18.3,23.6]*
	5	(26.7,32.2]	(25.6,29.4]	(Clg.Stpt+1.7, 32.2]	(25.6,32.2]	(26.7,32.2]	(23.6,32.2]
	6	(32.2,45.6]	(29.4,45.6]	(32.2,45.6]	(32.2,45.6]	(32.2,45.6]	(32.2,45.6]
	7	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)

both strategies' comparison, and analyze if there was a statistically significant change. Furthermore, a table summarized the characteristics of operative temperature and thermal sensation scales.

Table 3: Variables created from the energy model to analyze the HVAC usage in Bedroom 2 and the Dining and Living Room zones.

Outdoor variables	Indoor variables	Indoor variables by HVAC zone (Bedroom 2 & DLH)
Outdoor Temperature	Heating Setpoint	Operative Temperature
$\alpha = 0.7$	Cooling Setpoint	UTCI
Upper limit (80%)	HDD65	Thermal sensation
Lower limit (80%)	CDD65	Thermal Preference
Month	Total Heating kWh	Heating kWh
Day	Total Cooling kWh	Cooling kWh
Hour	Total Heating Cost	Heating Cost
Date (mm.dd.hr)	Total Cooling Cost	Cooling Cost

The comparative analysis for the kWh and the costs between the HVAC strategy and the NV strategy of each case were performed using the Wilcoxon signed-rank test; this test is a non-parametric alternative to paired t-test.

- The null hypothesis was that the differences of medians of the kWh and costs between both strategies are equal.
  - *H0: Median* $kWh_{Natural\ Ventilation}$ *- Median* $kWh_{HVAC} = 0$

The paired samples were dependent and continuous variables; the 8760 observations yielded the annual data. Consequently, the pair had those hours for each strategy. Besides, both groups were pairs as they were measured for two occasions, for the HVAC strategy (before) and the NV strategy (after).

3.3. Step 4: AI Decision system

Four ANN models were developed, two for the summer and winter period of the HVAC strategy and two for both seasons of the NV strategy. Summer periods were from June to September and Winter periods were from October to May. Each ANN model considered a two-layer feed-forward network with

100 neurons in the hidden layer and a hyperbolic tangent sigmoid transfer function [89].

The Neural Network Tool (nntool) is a graphical user interface that opens the Network/Data Manager window to create an ANN [89]. The network type used in this paper was the Feed-forward backpropagation, with a network training function that uses the Levenberg-Marquardt optimization method to update the weight and bias values. In addition, it employed the gradient descent with momentum weight and bias learning function and a mean squared error performance function.

Once obtained the database from the energy model, the Concord strategies were selected (Case 1 to 3), due to they had more information to feed the ANN model in terms of a broader range of heating and cooling setpoints leading into a wider range of energy consumption. Hence, eight matrices considering Bedroom 2 divided into winter and summer periods were created in MATLAB to feed the ANN models.

3.4. Step 5: Thermostat Interactive Dashboards

Two types of interfaces were proposed using the premise of teaching the end-users how to save energy and money through a set of SGs design elements. The first interface based their displayed information using the database variables described at the beginning of subsection 3.2.4. Thus Figure 7(a) displays the interface layout of the Dining and Living Room and Figure 7(b) for Bedroom 2. The numbering represents the input variables that the end-user needs to select. In contrast, the letters display the third column values of Table: Indoor variables by HVAC zone (Bedroom & DLH).

- Input variables: (1) Month, (2) day, (3) hour, (4) strategy.
- Output variables: (A) Outdoor temperature, (B) HVAC setpoint, (C) Operative temperature, (D) kWh, (E) Cost, (F) thermal sensation.

This interface aims to teach the end-user the differences in cost, energy, and thermal sensation between strategies and the impact benefits of the NV strategy.

The second type of interface were divided into summer (Figure 7(c)) and winter period (Figure 7(d)). These interfaces were the result of the ANN models generated in the previous subsection 3.3. The numbering represents the input variables that the end-user needs to select, whereas the letters display the result.

- Input variables: (1) Month, (2) day, (3) hour, (4) setpoint, (5) Strategy, (6) Outdoor temperature.

- Output variables: (A) Indoor temperature, (B) kWh, (C) thermal sensation.

Furthermore, the number six is blue because the outdoor temperature is an input value needed to predict the output values; however, the temperature was linked into a matrix with the dry-bulb temperature values from the EPW file. Thus, the end-user did not need to plug hypothetical outdoor temperatures. As a result, it was easier for the end-user to test each strategy to analyze the changes depending on the selected strategy without worrying about outdoor temperatures. In both types of interfaces, the thermal sensation scale was shown using the values in Table 2 so that people could visualize in which comfort range they could find themselves.

3.4.1. SG design elements

Therefore, the SGs design elements that appears in the interface consider all the personality trait and energy end-user segment behavior by displaying the electricity and money consumption with the following SG player type:

- Socializer: Dashboard

- Explorer: Tips, notifications, messages, voting mechanisms

- Achiever: Levels or progression

- Killer: Voting mechanisms and degree of control through the thermostat setpoint.

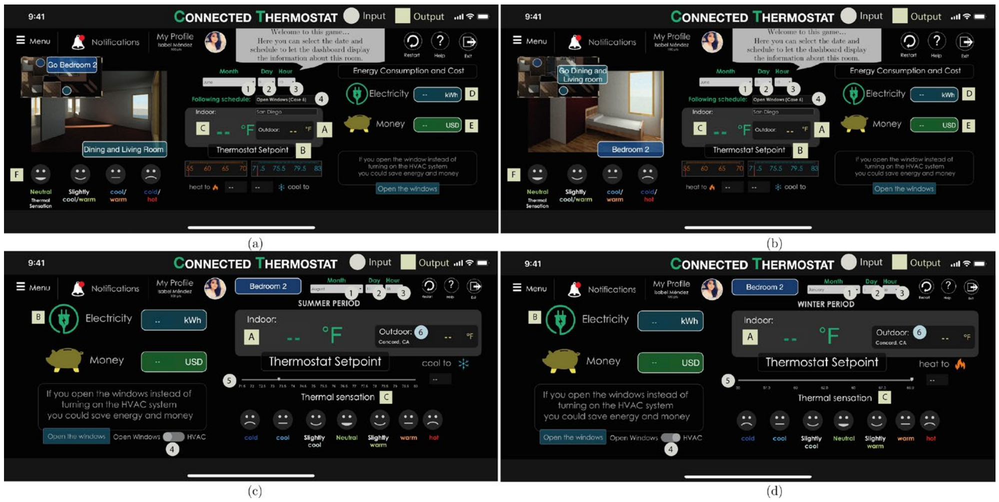


Figure 7: Interactive Dashboard Elements for a Thermostat within a Serious Game context: (a) Dining, Living room, and hall zone; and (b) Bedroom 2 zone. ANN Interactive Dashboard Elements: (c) Summer period; and (d) Winter period.

4. Results

Figure 8(a) shows the boxplot for the monthly outdoor temperature for Concord, Riverside, Los Angeles, and San Diego and their statistics. Figures 8(b) and (c) represent the heating and cooling degree-days of those locations considering 65 °F (18.3 °C) as a baseline.

During the summer periods, Riverside required more cooling than other places. Furthermore, Los Angeles and San Diego required lesser cooling compared to the other places. During winter periods, Concord needed more heating than the other locations. Los Angeles required the least heat of all the places. Another relevant aspect to consider was that Riverside and Concord had the highest standard deviation compared to the other locations; for example, those broader ranges were noticeable from June to September.

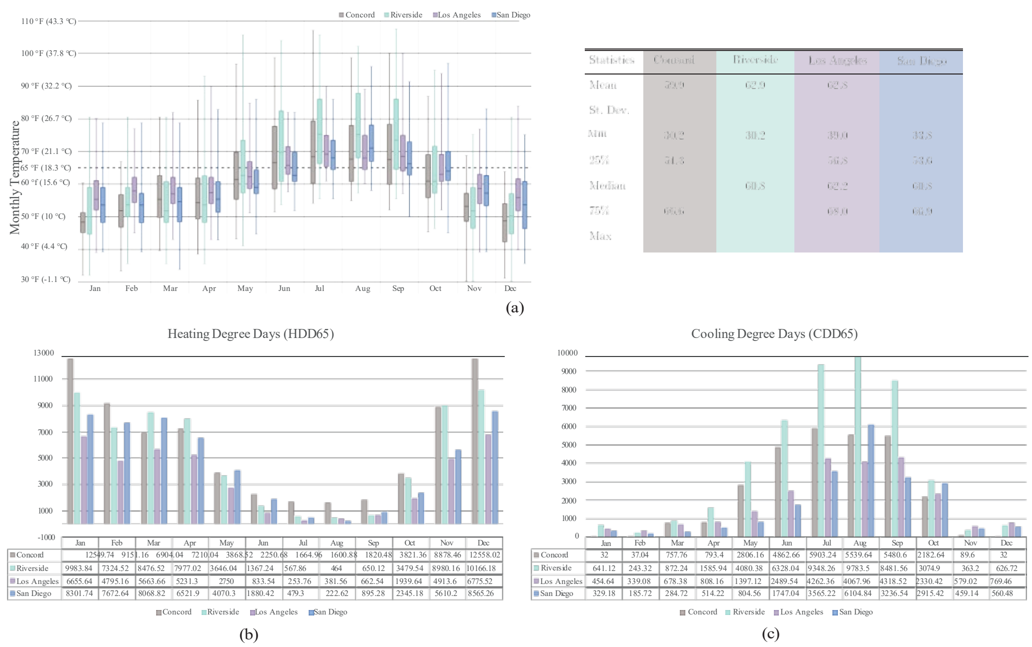


Figure 8: Concord, Riverside, Los Angeles, and San Diego: (a) Monthly Outdoor Temperature; (b) Heating Degree Days considering 65 °F (18.3 °C) as a baseline; (c) Cooling Degree Days considering 65 °F (18.3 °C) as a baseline.

Moreover, according to the UTCI scale, there was no thermal stress up to 78.8 °F (26 °C), and the neutral thermal sensation scale limits were up to 80 °F (26.7 °C) for Cases 1 and 4 (See Table 2). Therefore, it was possible to infer that there was a chance of reducing energy consumption by initially opening windows before turning on the HVAC system.

4.1. Operative Temperatures and Thermal Sensation Scales by Case and Strategy

Figure 9(a) depicts the monthly boxplot for Bedroom 2 and Figure 9(b) for the Dining and Living Room Zone. Furthermore, each image displays the summary statistics of each strategy by case. The maximum temperature decreased when the windows were open; the minimum temperature increased for the NV strategy. From the boxplot, it was interesting that the temperatures varied due to the cooling and heating setpoint for the Concord location (Cases 1 to 3). In contrast, Riverside, Los Angeles, and San Diego remained with similar temperatures. The drastic changes between seasons were presented in the first case, due to during heating periods, the thermostat setpoint is 55 °F to 68 °F (12.8 °C to 20 °C). The summer season did not present dramatic changes between cases as the cooling setpoint was under 80 °F (26.7 °C).

Cases 5 and 6 for the Bedroom presented changes in the thermal sensation scales. For the NV strategy, the maximum values were a neutral thermal sensation for the ASHRAE scale and no change for the thermal preference scale. For the DLH, the maximum values decreased with the NV strategy from Cases 3 to 6 for the ASHRAE scale and thermal preference. In general, the thermal scales were within the slightly cool to slightly warm spectrum in all the strategies. Case 1 presented wider sensation scales because the householders were habituated to that thermal sensation, although their thermal sensation falls out of the common thermal sensation. In the case of the UTCI scale, most of the cases had no thermal stress, and cases 1, 2, and 4 presented moderate heat stress.

4.2. Adaptive Thermal Comfort Results

The full plotted interactive graphs of each case and strategy were uploaded to the RPubs webpage [90, 91, 92, 93, 94, 95]. Thus, the reader can interact with each case and view the hours of occupancy, not occupancy, and sleeping activity and the 80% acceptability limits to review if, in that specific time or hour, the individual was comfortable. The relevance of presenting the graphs with references is because it was complicated to show the differences between strategies in a single picture.

Figure 10 displays the annual operative temperature and with the 80% acceptability limits for the first case. This figure shows the strategies with the occupied, not occupied, and sleeping activities. Then, the next graphs show the information filtered by occupied activity to indicate that the end-user is within the adaptive thermal comfort range during the occupancy. For the specific case of bedroom 2, the sleeping activity fell below the acceptability limit; however, a blanket covers the householder, then there is an acceptance of those ranges.

Although by following the Equation (4), Case 1 had no thermal comfort during half the year, the actual occupied hours fell within the acceptability range making the place comfortable for the inhabitants. Moreover, if the natural ventilation strategy was added, the thermal comfort increased and continued relying on the acceptability range, and the costs savings increased by 78%.

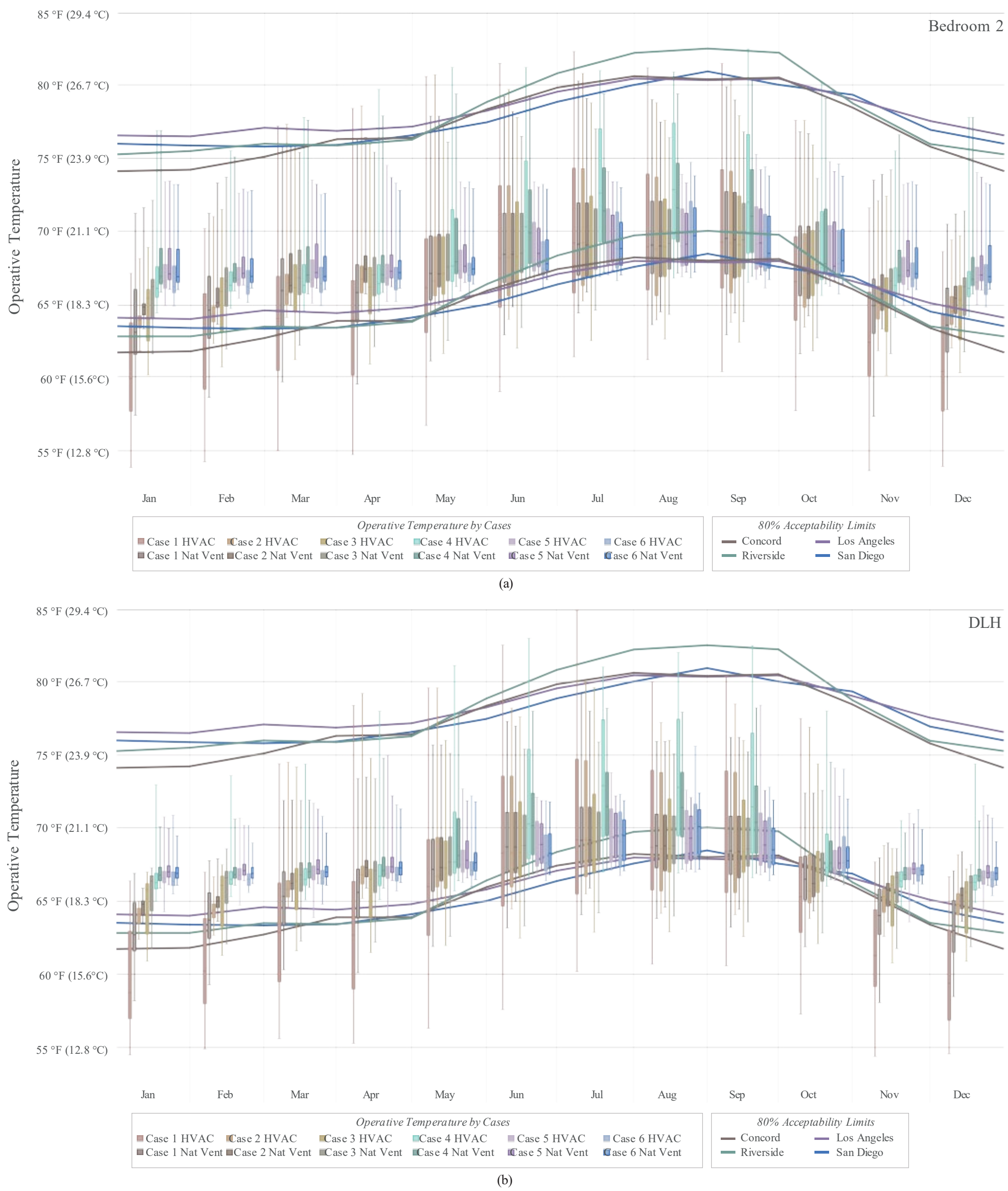


Figure 9: Monthly Operative Temperature boxplots and their summary statistics for each case: (a) Bedroom 2 and (b) Dining and Living Room.

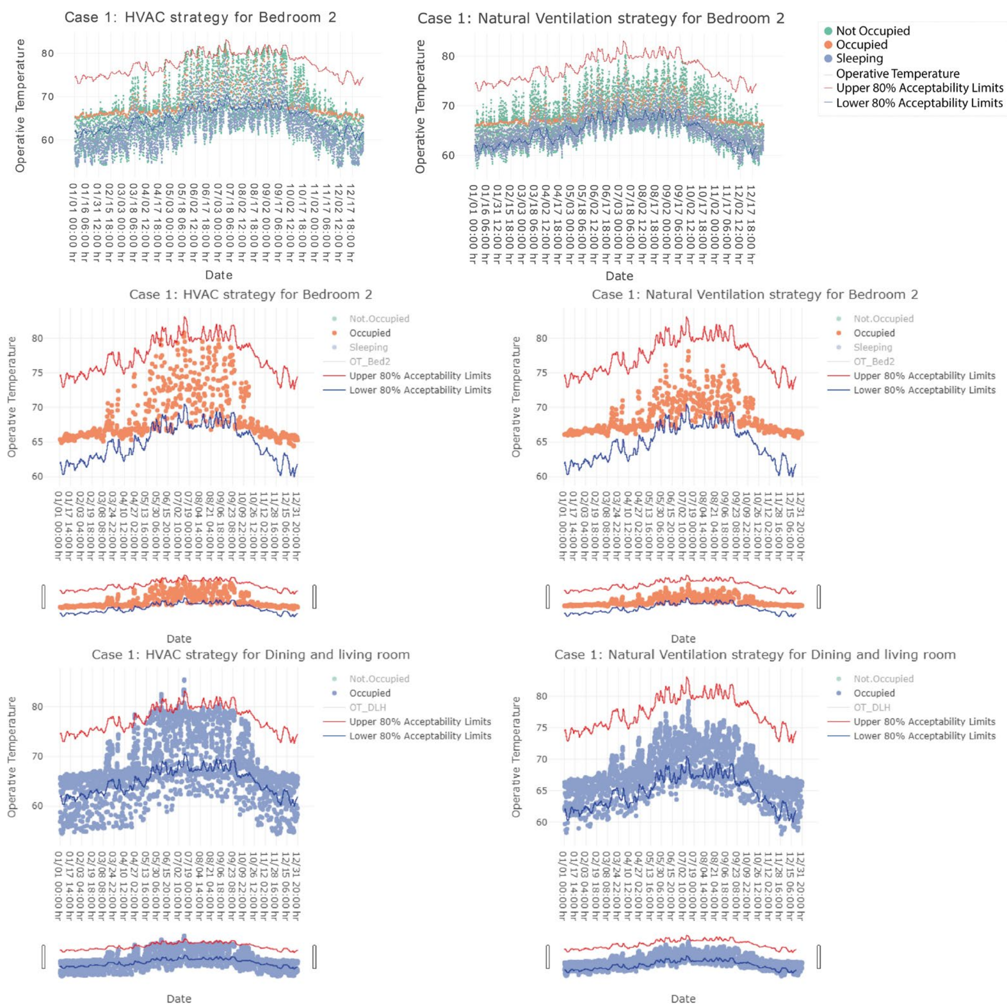


Figure 10: Case 1: Annual operative temperature with occupancy hours of both strategies.

For instance, in Case 1 Bedroom, the NV strategy raised the thermal comfort within the range; for the case of the DLH zone, it also improved; moreover, there were hours in which the occupied activities in the HVAC case were outside the upper limits of acceptability. Case 2 had an hour in which both cases were outside the comfort range; however, for the NV, this hour increased the comfort. The hour was 08/20 21:00 hours from 65.2 °F to 66.4 °F (18.4 °C to 19.1 °C).

Regarding the DLH zone, cases two and four had hours during summer when the temperature range went below the acceptability limit; however, the temperature increased due to activities and equipment usage.

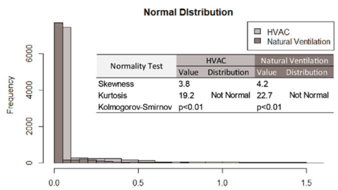
In both strategies for the bedroom zone, from cases 3 to 6, the thermal comfort ranges were within the range most of the time. However, by opening the windows, there was more energy reduction, and the thermal comfort increased. For the case of the DLH, the thermal comfort increased and remained within the range of the acceptability limits. Case 5 and 6 in the DLH zone were within the acceptability limits of thermal comfort.

4.3. Statistical Analysis

The six cases succeeded in terms of thermal comfort; however, the major differences were in kWh usage and their costs. Thus, satistical analysis was performed to analyze if there were significant changes between strategies; the first step was to evaluate the normality of the data. Therefore, Figures 11 and 12 exhibit the shape statistics, histogram, and Kolmogorov-Smirnov tests for each case; none of the cases were normal. Besides, below each histogram, the summary statistics of kWh and costs of each zone were displayed.

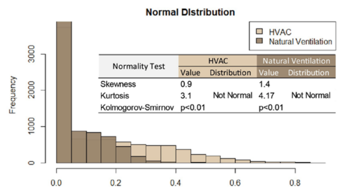
Thus, the next step was to deploy the comparative analysis between cases and strategies using the Wilcoxon signed-rank test. Table 4 showed the paired sample Wilcoxon test based on the positive ranks. In all of the cases, the null hypothesis were rejected as the medians were not equal. Moreover, the p-values were statistically significant and were based on positive ranks, meaning that there were changes between the NV with the HVAC strategy.

The statistical analysis demonstrated that there were statistically significant changes by allowing NV. Thus, major savings were achieved. Furthermore, the plotted thermal comfort charts available on the RPubs [90, 91, 92, 93, 94, 95] and exemplified on Figure 10 showed that the thermal comfort increased or remained within the acceptability ranges of comfort in all the cases. Hence, by just doing minor changes in routines and activities as opening the windows instead of turning on the HVAC, money savings were achieved without losing thermal comfort.



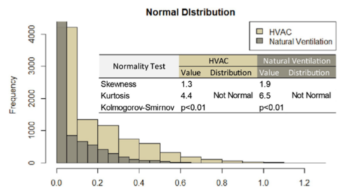
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.069	0.197	0	0	0	0	1.57
Nat. Vent.	0.032	0.103	0	0	0	0	0.9

Total kWh for Case 1: Bedroom 2



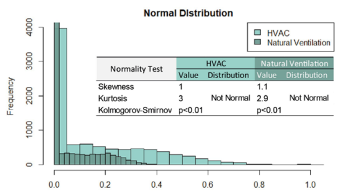
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.159	0.177	0	0	0.098	0.281	0.88
Nat. Vent.	0.057	0.081	0	0	0.0006	0.105	0.502

Total kWh for Case 2: Bedroom 2



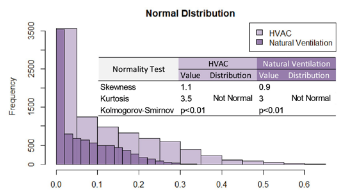
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.177	0.201	0	0	0.113	0.286	1.206
Nat. Vent.	0.073	0.113	0	0	0.007	0.115	0.676

Total kWh for Case 3: Bedroom 2



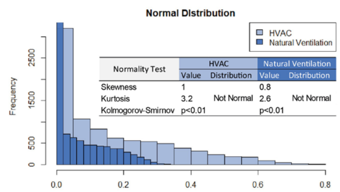
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.166	0.194	0	0	0.086	0.304	1.024
Nat. Vent.	0.075	0.098	0	0	0.008	0.148	0.417

Total kWh for Case 4: Bedroom 2



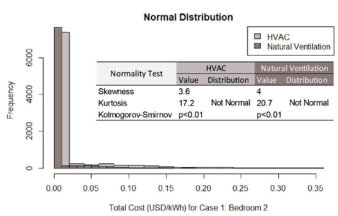
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.119	0.124	0	0.006	0.081	0.198	0.606
Nat. Vent.	0.066	0.071	0	0	0.042	0.115	0.330

Total kWh for Case 5: Bedroom 2



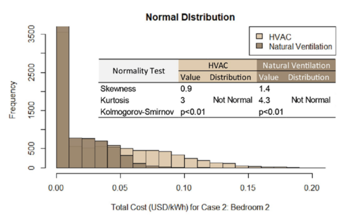
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.165	0.173	0	0.012	0.105	0.277	0.796
Nat. Vent.	0.076	0.081	0	0	0.048	0.135	0.332

Total kWh for Case 6: Bedroom 2



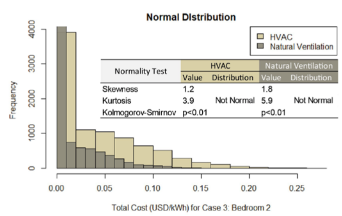
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.017	0.047	0	0	0	0	0.36
Nat. Vent.	0.008	0.024	0	0	0	0	0.21

Total Cost for Case 1: Bedroom 2



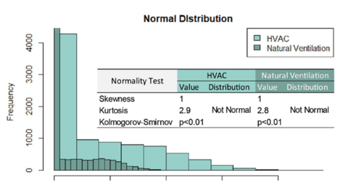
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.037	0.041	0	0	0.025	0.066	0.21
Nat. Vent.	0.013	0.019	0	0	0.0002	0.025	0.123

Total Cost for Case 2: Bedroom 2



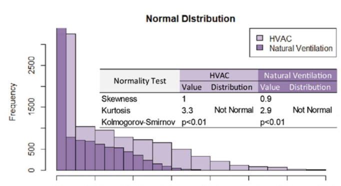
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.043	0.047	0	0	0.029	0.071	0.275
Nat. Vent.	0.018	0.026	0	0	0.002	0.029	0.154

Total Cost for Case 3: Bedroom 2



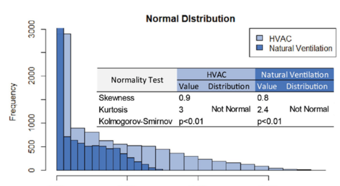
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.039	0.044	0	0	0.022	0.071	0.233
Nat. Vent.	0.013	0.019	0	0	0.002	0.034	0.095

Total Cost for Case 4: Bedroom 2



Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.028	0.029	0	0.002	0.021	0.047	0.138
Nat. Vent.	0.016	0.017	0	0	0.011	0.027	0.090

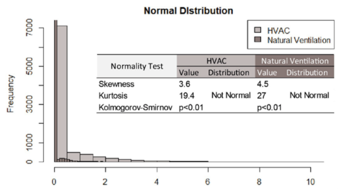
Total Cost for Case 5: Bedroom 2



Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.039	0.040	0	0.003	0.027	0.065	0.181
Nat. Vent.	0.018	0.019	0	0	0.012	0.032	0.076

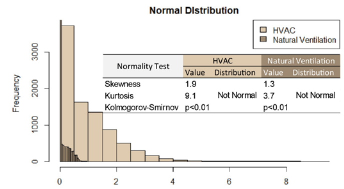
Total Cost for Case 6: Bedroom 2

Figure 11: Normality Tests for Bedroom 2.



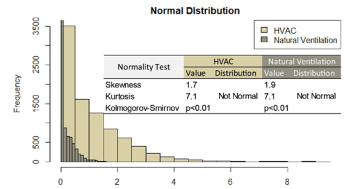
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.359	0.893	0	0	0	0.072	10.154
Nat. Vent.	0.064	0.217	0	0	0	0	2.034

Total kWh for Case 1: DLH



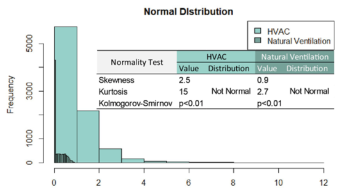
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.931	1.030	0	0.016	0.688	1.426	9.227
Nat. Vent.	0.140	0.189	0	0	0.014	0.258	1.045

Total kWh for Case 2: DLH



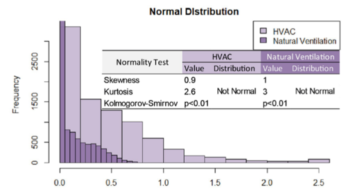
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	1.047	1.101	0	0.126	0.76	1.595	9.057
Nat. Vent.	0.175	0.261	0	0	0	0.285	1.609

Total kWh for Case 3: DLH



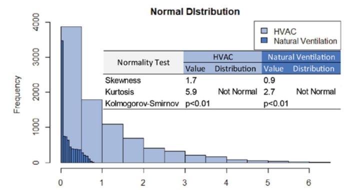
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.841	1.024	0	0	0.578	1.297	11.070
Nat. Vent.	0.188	0.230	0	0	0.061	0.364	0.957

Total kWh for Case 4: DLH



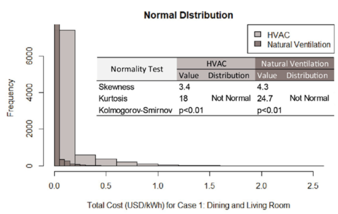
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.446	0.477	0	0.068	0.321	0.663	2.580
Nat. Vent.	0.150	0.017	0	0	0.086	0.265	0.746

Total kWh for Case 5: DLH



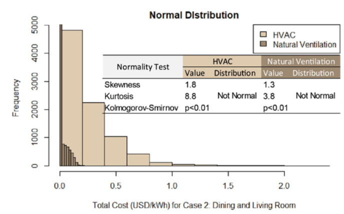
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.978	1.096	0	0.161	0.622	1.396	6.131
Nat. Vent.	0.180	0.197	0	0	0.111	0.319	0.774

Total kWh for Case 6: DLH



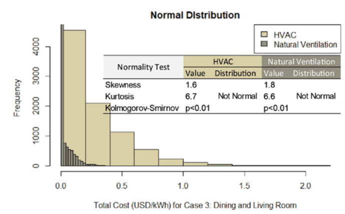
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.090	0.219	0	0	0	0.018	2.490
Nat. Vent.	0.015	0.051	0	0	0	0	0.464

Total Cost for Case 1: DLH



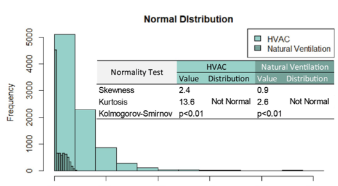
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.225	0.247	0	0.004	0.168	0.343	2.262
Nat. Vent.	0.032	0.044	0	0	0.003	0.060	0.256

Total Cost for Case 2: DLH



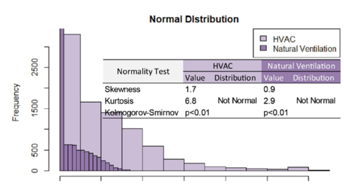
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.258	0.272	0	0.034	0.187	0.390	2.176
Nat. Vent.	0.042	0.061	0	0	0.008	0.069	0.367

Total Cost for Case 3: DLH



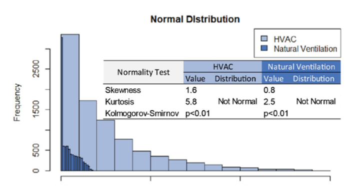
Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.201	0.239	0	0	0.143	0.311	2.523
Nat. Vent.	0.044	0.053	0	0	0.015	0.084	0.218

Total Cost for Case 4t: DLH



Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.106	0.110	0	0.018	0.081	0.158	0.633
Nat. Vent.	0.035	0.039	0	0	0.023	0.062	0.170

Total Cost for Case 5: DLH



Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.232	0.251	0	0.044	0.154	0.328	1.452
Nat. Vent.	0.042	0.045	0	0	0.029	0.075	0.176

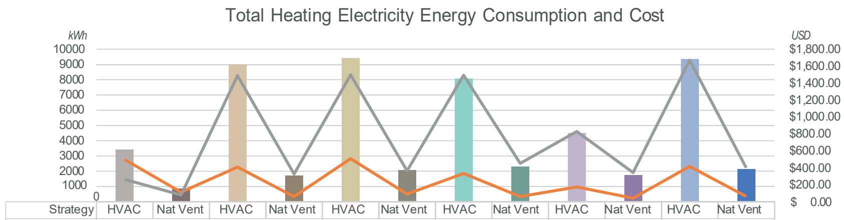
Total Cost for Case 6: DLH

Figure 12: Normality Tests for Dining and Living Room.

Table 4: The Paired Samples Wilcoxon Test for Bedroom 2 and DLH.

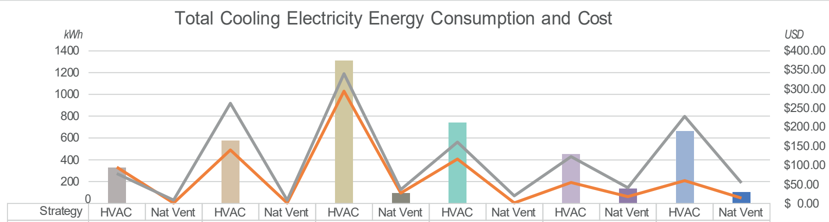
	Positive ranks			Test statistics		
	n	Mean rank	Sum of ranks	Ties	Z	p
		Bedroom 2 ($kWh_{Natural\ Ventilation}$ - kWh_{HVAC})				
Case 1	*2*	103.50	207	6959	-36.740	*<.001**
Case 2	*0*	0	0	2777	-66.990	*<.001**
Case 3	*43*	242.69	10,436	2178	-70.195	*<.001**
Case 4	*4*	115.75	3,007	3007	-65.686	*<.001**
Case 5	*628*	1,425.61	895,285	1510	-68.719	*<.001**
Case 6	*531*	1,160.12	616,026	1343	-71.246	*<.001**
		DLH ($kWh_{Natural\ Ventilation}$ - kWh_{HVAC})				
Case 1	*1*	132.00	132	6303	-42.928	*<.001**
Case 2	*5*	50.80	254	2030	-71.047	*<.001**
Case 3	*16*	161.19	2,579.0	1410	-74.235	*<.001**
Case 4	*59*	165.81	9,783	2217	-69.990	*<.001**
Case 5	*101*	385.45	38,931	1267	-74.760	*<.001**
Case 6	*219*	392.56	85,972	896	-76.374	*<.001**
		Bedroom 2 ($Cost_{Natural\ Ventilation}$ - $Cost_{HVAC}$)				
Case 1	*2*	103.50	207	6959	-36.746	*<.001**
Case 2	*0*	0.00	0	2777	-66.990	*<.001**
Case 3	*43*	235.43	10,436	2178	-70.197	*<.001**
Case 4	*4*	111.25	3,007	3007	-65.686	*<.001**
Case 5	*628*	1,297.41	895,285	1510	-69.170	*<.001**
Case 6	*531*	1,051.11	616,026	1343	-71.560	*<.001**
		DLH ($Cost_{Natural\ Ventilation}$ - $Cost_{HVAC}$)				
Case 1	*1*	129.00	129	6303	-42.928	*<.001**
Case 2	*5*	45.00	225	2030	-71.047	*<.001**
Case 3	*16*	159.19	2,547.0	1410	-74.235	*<.001**
Case 4	*59*	160.47	9,468	2217	-69.992	*<.001**
Case 5	*101*	406.33	41,040	1267	-74.748	*<.001**
Case 6	*219*	399.57	87,506	896	-76.366	*<.001**

* Indicates statistically significant change



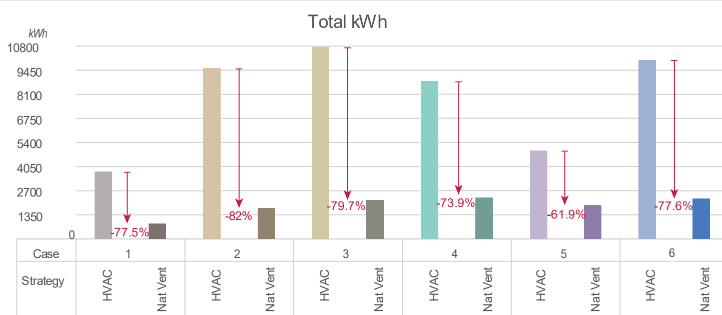
Strategy	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent
Case	1		2		3		4		5		6	
Heating	3417.7	843.5	8977.3	1718.2	9414	2082.5	8081	2300.1	4494.4	1751.6	9351.9	2137.3
$ Peak	$497.60	$111.90	$408.60	$60.30	$507.30	$89.70	$331.00	$60.60	$174.30	$41.80	$414.70	$61.50
$ Off-peak	$264.30	$80.30	$1,488.	$328.50	$1,498.	$365.00	$1,493.	$452.10	$828.30	$345.20	$1,670.	$400.30

(a)

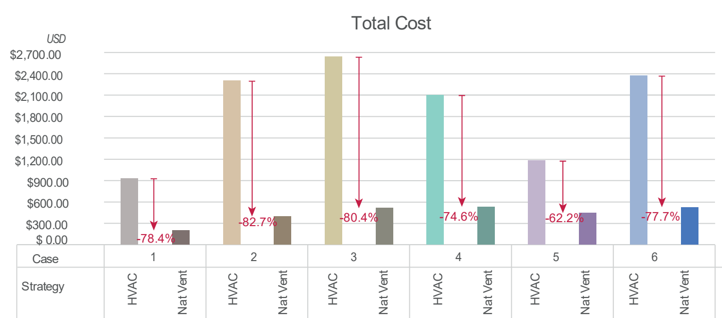


Strategy	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent	HVAC	Nat Vent
Case	1		2		3		4		5		6	
Cooling	329.9	0.3	574.2	3.2	1308.1	95	740.8	6.8	453.3	134.3	661.5	104.6
$ Peak	$95.00	$1.00	$140.00	$1.00	$294.30	$27.00	$116.30	$1.30	$54.90	$17.50	$59.60	$13.90
Off-peak	$78.40	$9.00	$262.90	$8.60	$340.00	$36.50	$161.00	$20.10	$123.20	$41.70	$228.50	$54.10

(b)



(c)



(d)

Figure 13: (a) Total heating electricity energy consumption and cost. (b) Total cooling electricity energy consumption and cost. (c) Total HVAC electricity energy consumption and savings. (d) Total HVAC electricity cost and savings.

Therefore, Figures 13(a) and (b) display the total heating and cooling electricity energy consumption and electricity cost for each case. By choosing the opening windows strategy reflected in changes in energy consumption or potential money savings. Besides, Figure 13(c) shows the total HVAC energy consumption by case and strategy and the percentage of reduction by first opening the windows. Figure 13(d) shows the electricity cost and the percentage of reductions. Case 2 was the strategy that had more drastic changes than Case 5. Those variations involved the setpoint ranges described in Figure 5.

4.4. Simulink Models

Figure 14(a) shows the Simulink code for the first type of interactive interface. The input values required were the month, day, hour, strategy, and case. Thus, 105,120 observations were needed. Each group of observations contained 8760 variables. As a result, the MATLAB function depicted 17 variables. The dashboard enabled the end-user to interact with possible scenarios to value the differences and rate the variations between using HVAC or opening the windows. Besides, this dashboard reflected that either the thermal comfort could be achieved by opening the windows or negatively affecting the thermal sensation scale.

Figure 14(b) shows the Simulink diagram for the second type of interactive interface and the regression plot of each ANN model during the summer period and Figure 14(c) for the winter period. The diagrams also showed the calculations performed to get the costs based on the energy consumption. These costs were calculated with the E-TOU-C rates PGE [83].

4.5. Thermostat HMIs: Interactive Dashboards

Figure 15 shows twelve interfaces considering SGs environment; the left side shows six cases for the HVAC strategy, and the right side compares the differences if the NV strategy is selected. These interfaces belonged to the Bedroom 2 zone.

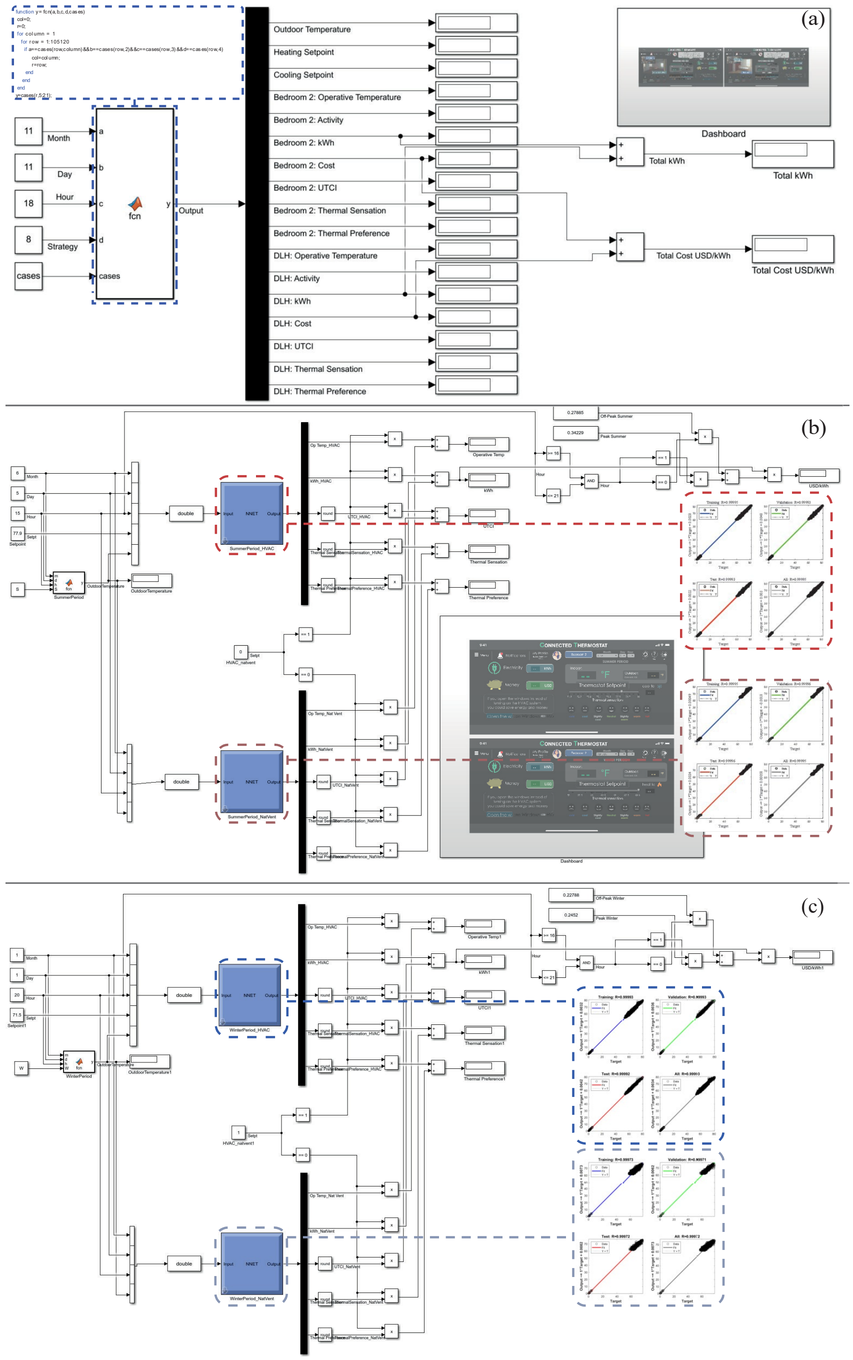


Figure 14: Simulink diagram for the second type of the interactive interface. (a) shows the diagram for the summer period, and (b) for the winter period.

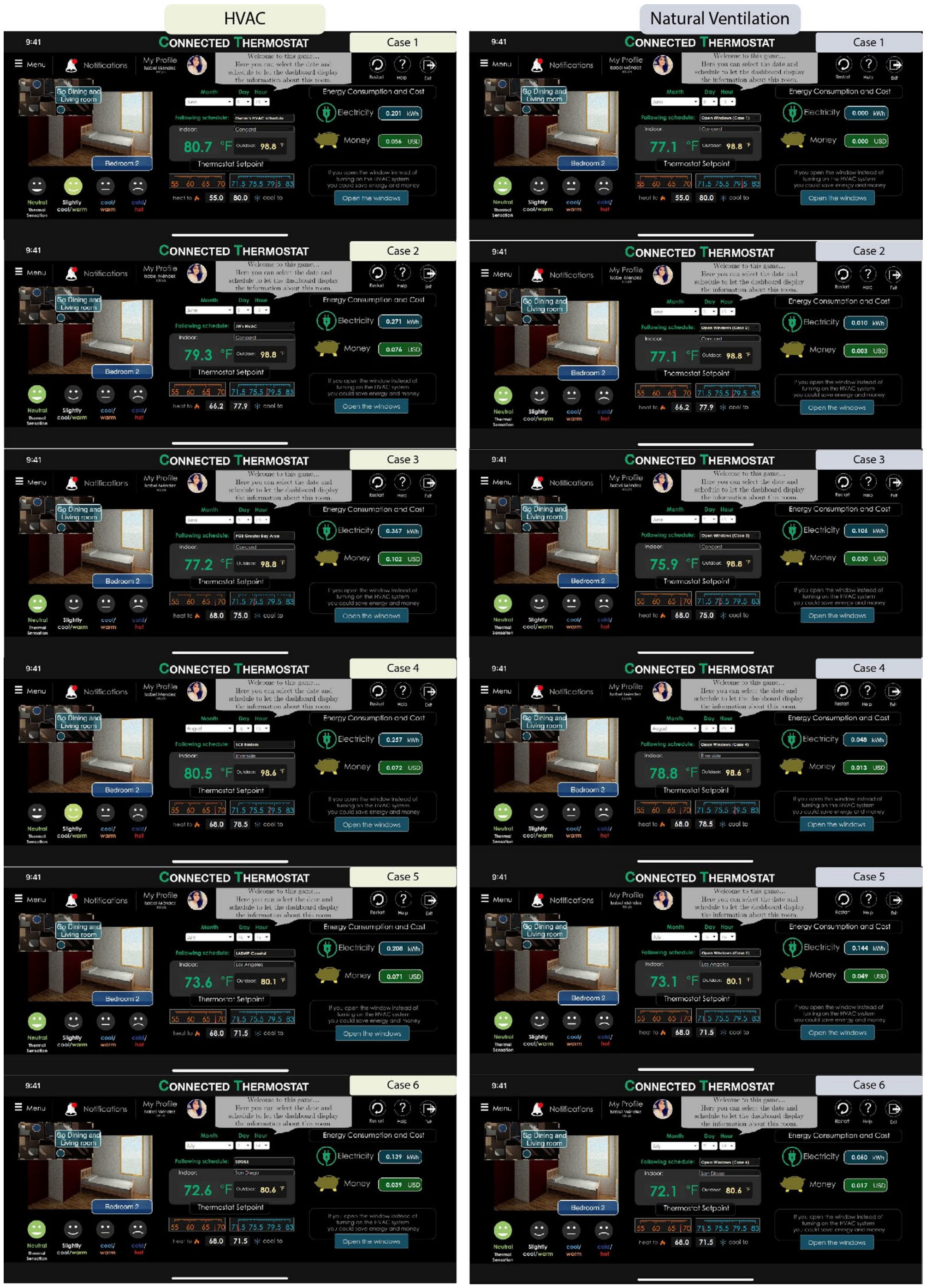
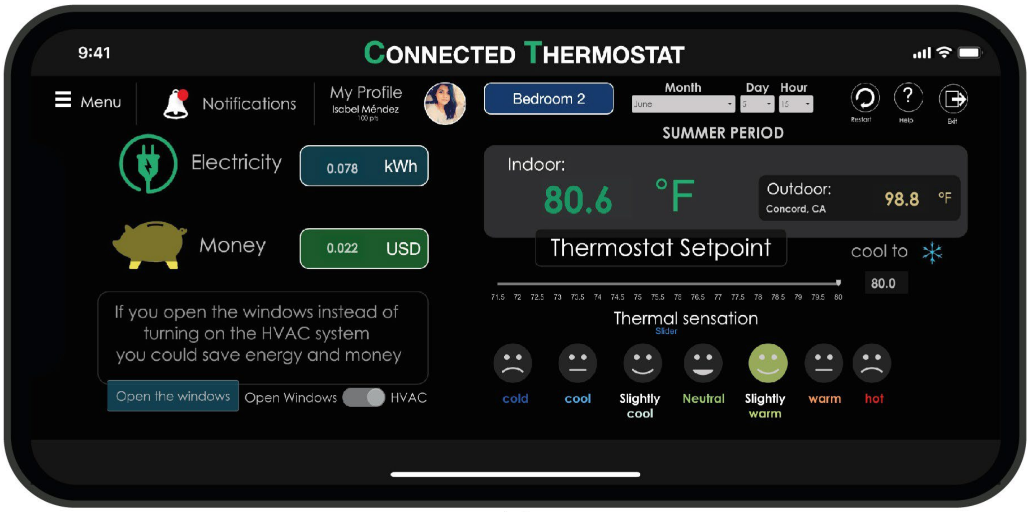


Figure 15: Interactive Dashboard Results.

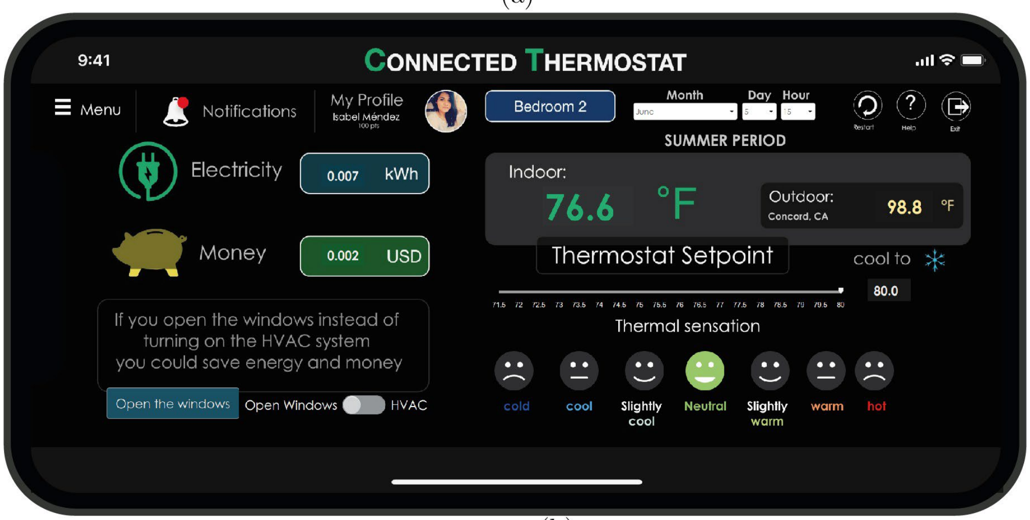
The interface revealed a message indicating to the end-users how they can interact with the interface by selecting the date and the schedule to see how their decisions affect the consumption and the thermal sensation scale. There were cases where the end-user could feel slightly warm with the HVAC strategy, and when the windows were open, the ventilation allowed the end-user to feel neutral. Cases as 4 show that although the outside temperature is warmer than the inside, the indoor temperature decreases by opening windows. This happened because NV allows airflow and removes indoor heat. On the other hand, during these hours this room was not occupied. Thus, strategies as opening windows can be selected. This repository's file titled *InteractiveDashboardDB_ComplementaryData.mat* located the database used to build this interactive dashboard [96].

Figure 16 shows the second type of interactive dashboard. This dashboard used a two-layer feed-forward ANN to predict energy consumption, indoor temperature, and thermal sensation at Concord, California. Although the energy consumption values displayed in this type of dashboard were lower than the energy model results, the differences between opening windows versus using HVAC existed and impacted the indoor temperature, energy consumption, and thermal sensation. For instance, Figure 16(a) displays the interface with more energy consumption than Figure 16(b). This interactive dashboard aims to teach the end-user how interacting directly with the setpoint affects the energy consumption and the thermal sensation scale. In this interface type, the end-user needed to select the month, day, hour, and setpoint to predict the energy consumption, indoor temperatures, and thermal scales for the Bedroom 2 zone. This repository's file titled *InteractiveANNDashboardDB_ComplementaryData.mat* locateed the databases' matrix used to build this interactive dashboard [96].

In both cases, SGs were created to teach the end-user how to manage their thermostat and how their actions directly affected the energy consumption, indoor temperature, and thermal sensation. In addition, the thermal sensation offered an interesting manner to show the end-user how the setpoint and daily occupancy were affected by their usual ranges of thermostat setpoints. Full occupancy hours can be found at this repository's file titled *EnergyModelResults_ComplementaryData.csv* [96].



(a)



(b)

Figure 16: ANN Dashboard results.

5. Discussion

A five-step framework was proposed. This framework integrates the user type, the SGs design element and the thermal comfort within a connected thermostat interface was proposed to include connected thermostat interfaces. The user type was a persona with all the personality traits and their relationship with the energy-end user segment and SG player type (Figure 3.

Four locations in California were analyzed to gather information regarding thermal comfort and four locations in California to analyze six cases. Thermal comfort is directly related to the thermostat setpoint and the adaptive strategy used. Woods [10] analyzed householders' thermostat setpoint usages to understand end-user behavior and, hence, he suggested that energy models and policies should consider different ranges of setpoints. Besides, Figure 13 supported that energy reductions were achieved by providing different ranges of setpoints even by just considering the HVAC strategy. Case 3 considered the Greater Bay Area setpoints collected by the RASS survey, whereas Case 2 considered Woods [10]'s setpoints. Although Case 2 had wider setpoints values, Case 3 had more energy and money usage than Case 2. This means that Case 2 strategy was more appropriate for savings.

Moreover, Case 1 had less energy consumption of all the cases; however, this is atypical. It can be considered a non-typical user and a green-advocate end-user as these household members are aware of the environmental impact of their actions. On the other hand, case 2 can be considered a traditionalist home-focused end-user type [45], and Case 3 was another type of user that does not change the values from default or a disengaged energy waser end-user. The kWh for cooling and heating was consistent with the HDD65 and CDD65 depicted in Figure 8. For instance, Los Angeles' cases were the strategies that had less consumption compared with cases 2, 3, 5, and 6. Case 1, in this case, was out of this analysis as the owners were aware that their consumption was lower than the local metrics.

Furthermore, although the first case showed that theoretically, there was no thermal comfort at some hours, as Fergus Nicol and Humphreys [40] indicated, some of the measures of not losing thermal comfort during low temperatures were taking a nap or going to sleep, in this case, during the hours in which Bedroom 2 was uncomfortable, the individuals were sleeping. Thus, for the case of the DLH zone, there were unmet hours of thermal comfort. However, the individual felt comfortable as they were habituated to these temperatures; moreover, different strategies can be addressed to suggest that the end-user use warmer clothes or possibly perform activities that increase the heating body.

Besides, energy model simulators like the LB Tools [54] allow personalized schedules, activities, or clothes for a year simulation. However, this simulator lacked real-time feedback or usage; thus, the schedules remained constant, while real-time activities were dynamic. Nevertheless, as an approach to energy usage and thermal comfort, these models were ideal for framing out the general framework of energy consumption.

During the decision system process, two types of interfaces were depicted. The first interface added the energy model results into an SG context, and the second interface included a two-layer feed-forward ANN model. Regarding thermal comfort, using the NV strategy in bedroom 2, cases 5 and six showed a reduction for the maximum values of the thermal sensation scale. Cases 3 to 6 show that the NV strategy changed from a slightly warm sensation to a neutral one for the dining and living room zone. Figure 14(a) displayed 17 variables; the activity and the other thermal scales were not displayed in the interfaces to avoid any overcharged dashboard. This research aimed to display the thermal sensation while saving energy and money.

Finally, two types of interaction were promoted. First, the householder interacted with an SGs interface by selecting only the date and the schedule to watch the thermostat setpoint used for that specific scenario and the energy consumption. The idea was to open the individual's mind to the energy impacts of each setpoint case and how that setpoint and location affected the energy usage, money consumption, and thermal sensation. For instance, it was not the same consumption in Riverside as in Los Angeles. Second, the individuals interacted with the ANN interface to teach their energy consumption and thermal sensation by selecting higher setpoints during summer periods or lower setpoints during winter. In addition, the end-user interacted directly with the thermostat setpoint to visualize the immediate effects of changing the setpoint or opening the windows.

On the other hand, there are low-income families that suffer of energy poverty [30, 31, 32, 33]. Thus, the interface can be proposed considering Ponce et al. [26] low-income thermostats proposal. Nevertheless, some householders may not engage or even use an interface due to energy poverty conditions [31]. Therefore, further steps should address this topic.

6. Conclusion

Following, the research question addressed on this paper is answered:

- *What requirements does a Serious Game interface need to teach the end user the benefits of using an adaptive strategy to promote energy and money savings without losing thermal comfort?*

The interface needs to consider the community and not just the single home. This interface should consider the other homes, their electrical or energy consumption, and validate that opening the windows before turning on the air conditioning is suitable for this type of people because thermal comfort is mandatory to be considered beyond just looking for the reduction of energy or electricity billing.

Additionally, the interface must use different scenarios with contextual information to stimulate the user about the strategies adopted to reduce energy or cost savings, depending on their interest. In addition, the purpose of serious games is to motivate and teach the users without making them feel compromised to learn specific activities in a fun way. The interfaces proposed in this research were conceptualized under these concepts.

Hence, knowing the home consumption in detail and the day-to-day activities carried out in the home allows generating interfaces that provide feedback to the user. Therefore, managing a digital environment where the householders are in direct contact with their real electrical consumption allows them to interact with the interface and analyze the real implications of taking or not taking the decision regarding, for example, opening a window or decreasing or decreasing increasing the setpoint. All this, taking into account the primary interest of providing thermal comfort.

Two types of interfaces were proposed for a Serious Games context using a five-step framework. The first interface took the energy model results into an interactive context. Thus, the end-user primarily interacted with the six scenarios to teach them the differences between strategies in an SG environment. The second interface predicted the energy consumption and thermal comfort based on the thermostat setpoint manipulation. Thus, the end-user visualized the differences between opening or using only HVAC during summer or winter.

During these scenarios and depending on the selected case, there was more consumption during off-peak than during peak periods during winter (Figure 13(a)). During summer, cases like 1, 2, and 4 had lower consumption during peak periods (Figure 13(b)). Furthermore, there were energy reductions up to 82% (Figure 13(c)) and cost reductions from 62.2% to 82.7% (Figure 13(d)).

Alternatively, interfaces, as proposed, gather information about end-users preferences. For instance, the thermal sensation component can collect end-user votes to better understand their thermal preferences and adjust techniques to engage them in activities to reduce consumption or money without losing thermal comfort.

Hence, future work includes measuring how this gamified and SGs application affects or benefits the initial conditions selected in the energy model and the future implications of selecting other game techniques. For instance, LT provides a component to select a passive strategy and immediately visualize how these changes affect thermal comfort and energy reduction. Therefore, future research can include but are not limited to these topics:

- In terms of energy simulation impacts, optimization methods suggest a range of minimum or maximum setpoints needed to ventilate or heat the space without losing thermal comfort. Thus, future research should include GA or other optimization methods that can analyze those impacts.
- Use a FL decision system based on the thermal sensation to propose an adaptive strategy that reduces energy consumption and saves money.
- Use of ANFIS systems to connect multi-sensory systems to analyze the clothing insulation or activities to understand end-user behavior and therefore promote strategies that help in reducing energy without losing thermal comfort in real-time.
- Consider a decision system that includes the energy poverty topic and its impact on householder behavior, thermal comfort, and energy savings.

This framework helps build the energy model simulation and proposes the two types of interfaces to analyze the difference of using adaptive strategies; thus, the end-user behavior became energy aware. Besides, employing other adaptive strategies such as garments or metabolic rate to predict thermal comfort or even propose personal thermal comfort models can help better understand the end-user attitudes and behaviors toward saving energy.

Modeling and simulating energy cases require further knowledge of end-users' patterns and environments, such as their behavior during occupied spaces and their location. Besides, these simulations provide insights regarding thermal home and end-users characteristics. Thus, a novel approach analyzed in this research was using SG elements with educational purposes within the thermostat interface and included the impact of thermal sensation on energy and money savings.

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