

Energy Efficiency Effectiveness of Smart Thermostat Based BEMS

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Abstract: The research details the design and development of a spreadsheet based software system that has been built using the principles of Monte Carlo simulation. The simulation has been applied to a residential building with a certain number of rooms, each with specific characteristics pertaining to volume, occupancy, and thermostat set point. The consideration of variables related to the building envelope and weather, and the HVAC system have provided a realistic view that enables the accurate estimation of annual energy usage and costs. The main findings of the research are reflected in the sensitivity analysis that estimates energy use and cost based on variance in the set point of thermostats that operate based on occupancy levels in various times of the year when the weather pattern could change drastically with respect to time, under the inherent weatherization levels of the building. The most important conclusion is that, upon analyzing the results of the sensitivity analysis, specifically with respect to the operations of the thermostats and occupancy levels under constant building envelope characteristics, decision makers will be able to incorporate energy efficiency measures and infrastructure improvements over time, in order to save energy and cost.

Keywords: HVAC; BEMS; smart thermostat; HVAC zoning

1 Introduction

Global energy consumption continues to increase each day. In the 1970s, the global energy usage was about 3860 Million Tons of Oil Equivalent (MTOE), and within ten years, the numbers are almost doubled and took the global energy usage to 6630 MTOE [1]. The average US energy consumption in the previous decade was around 100 quadrillion BTUs, varying from 94 quadrillion BTUs to 101 quadrillions BTUs [2]. According to the US Department of Energy, buildings account for about 40% of the total energy consumption, of which HVAC systems is 42.5% in the United States [2]. Hence, enhancing the research of the HVAC operation system can result in opportunities to save energy and therefore reduce the operating costs for a residential or industrial area.

People install thermostats at fixed places to sense the temperature of rooms and regulate the operation of the HVAC systems. Room temperature is changed with the occupant's requirements. A typical residence uses a single thermostat in a fixed position, although the temperature profile is not uniform across the thermal space. The insulation and infiltration in individual rooms may not be the same, so they respond differently to the conditioning systems. For the shortcoming of occupancy detection, a single sensor



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control system may unnecessarily cool or heat the thermal environment and thus result in higher energy consumption. New generation control systems along with zoning, could deploy several sensors or thermostats in different rooms to regulate the flow in the unoccupied spaces. Then the system will learn human behavior continuously and control the airflow into the rooms. Though implementing this strategy helps in enhancing the occupant's comfort with a reduction in energy consumption, it still has drawbacks. As these systems have several moving parts, the equipment has a high probability of breaking down. A survey was done by EIA about human behavior shows that 45% of people use central control, and 31% of people use individual control air conditioning units. Thus, it is essential to know the estimated energy savings if the zoning systems with advanced controls are to be installed.

The primary research objectives are:

- To develop a model to determine the HVAC energy consumption. The model will have inputs with varying parameters that are associated with building characteristics and HVAC characteristics.
- The research aims to compare the impact of factors occupancy, weather, the volume of the room, building envelope and thermostat setpoint on energy consumption.

The main findings of the research are reflected in the sensitivity analysis that estimates energy use and cost based on the variance in the set point of thermostats that operate based on occupancy levels in various times of the year when the weather pattern could change drastically with respect to time, under the inherent weatherization levels of the building. Upon analyzing the results of the sensitivity analysis, specifically for the operations of the thermostats and occupancy levels under constant building envelope characteristics, decision-makers will be able to incorporate energy efficiency measures and infrastructure improvements over time, to save energy and cost.

1.1 HVAC Controls

HVAC usually works at part load or is turned off depending on the heating and cooling loads, occupancy, weather and other factors. Controls usually have a couple of sensors or a single sensor that senses the current state and compares it with the desired state. Finally, it turns the equipment on or off based on the desired state. There are several ways to control the temperature. One such method is to control the air volume supplied into the room and the other is to regulate the load factor of the equipment. Without proper controls, there might be overheating or overcooling of the space.

1.1.1 Single Thermostat System

In a single thermostat control system, there is only one thermostat in the whole space governing the operation of the HVAC system. The thermostat senses the temperature of the area around it and regulates the HVAC system accordingly. A research done by EPA shows, in winter, about 42% of them turn the heat down and 2% of them turn their heating systems off [3]. This creates an opportunity to employ programmable thermostats. Programmable thermostats are the thermostats that have the feasibility to adjust the temperature based on the programs. It has been thought that programmable thermostats should reduce up to 30% of the HVAC consumption by altering the heating and conditioning of the building as per the occupant's daily schedule. But the energy wastage factors of the programmable thermostat are: 1) The temperatures are not set back if the occupants leave the house before the schedule, 2) The setback temperatures are higher, which causes the system to run even when the house is vacant, 3) If the occupants return back to the house earlier than the scheduled time they feel uncomfortable. This resulted in people reducing their set back schedules or even stopping the usage of the schedules. This explains why only 12% of the 118 million households program their thermostat though 41% of them own a programmable thermostat [4].

The updated version of the programmable thermostat is the smart thermostat. The only difference between a programmable and smart thermostat is the ability to connect to the internet and allowing the users to adjust the heating or cooling settings from other internet-connected devices like smartphones and computers. Though the smart thermostats were introduced, the energy wastage could not be minimized completely. As a result, Smart Learning Thermostats were announced to the market. Smart Learning Thermostats are those which repeatedly learn the occupancy and the setback schedule of the occupant and act according to the learned behavior. This helps the thermostat to analyze the lifestyle of the occupant and then preheat or cool the building while being energy efficient.

The problem with the single thermostat system without zoning is that the rooms which do not need conditioning are also conditioned. Many people close the vents in the rooms, not in use. The HVAC system and ductwork are designed considering the area of the entire building. If the vents are closed in the rooms that are not in use, the air does not have any chance to move out of the system, resulting in an increase of pressure in the ductwork and thereby developing air leaks in the ductwork. This may also result in overheating the furnace or freezing the air conditioner. Zone controls are an answer to these problems.

1.1.2 Zoning Systems

HVAC zoning system employs dampers in the ductwork to regulate and redirect the airflow into different areas (zones) in the building. Zoning helps in gaining more control over the HVAC system by turning the system off as soon as the desired temperature is met in a particular zone. Zoning does not affect the efficiency of the HVAC system and eliminates the problem of overheating or overcooling of the furnace or air conditioner. It reduces energy consumption while addressing the comfort requirements of the occupants by maintaining the zone at the desired state. The main components required for HVAC zoning include;

- **Central Control System:** It is a control hub for all components such as thermostats, HVAC systems, dampers, etc. The control system is the only source of communication between the system components. It is the only processor for the entire zoning system.
- **Thermostats:** In order to regulate the temperatures, each room should be facilitated with a thermostat. The thermostat in each room sends the signal to the central control system. This helps the control system to control the dampers to vary the airflow into the room to maintain the desired temperature.
- **Zone Dampers:** Damper is a valve or a plate which can be regulated to vary the airflow. These are wired to the control system. They open or close based on the signal from the thermostat present in the room.
- **Bypass Damper:** In a single duct system, if the damper is closed for one of the zones, pressure builds up in the ductwork. Bypass damper acts as a relief valve, which helps in venting out the air.

1.1.3 Building Energy Management System (BEMS)

The main function of the Building Energy Management System is to regulate, monitor and control HVAC systems. BEMS will employ computers to manage the energy consumption of the devices and building technical services. BEMS can integrate the building's HVAC and lighting. However, some expensive state of the art BEMS can incorporate additional building systems such as video surveillance, access control and interfacing with fire and security controls.

This research considers a residential house that has been zoned. It is installed with a BEMS, which takes feedback from the smart thermostats with occupancy detection capability present in each zone. Thus, it regulates the HVAC system's load factor.

2 Literature Review

There are many options to reduce the energy consumption of the buildings sustainably. Because of the numbers, there is more research done on improving the efficiency of HVAC systems. The factors which

influence the HVAC energy consumption are building envelope, HVAC equipment and its efficiency, level of the thermostat, outside temperature, occupancy and controls.

There are many studies done on building envelope design and retrofits. Al-Saadi S and Al-Jabri K believe that thermal characteristics of the building and building envelope such as heat load in the building, indoor temperature, heat transmission and heat storage should be accounted for in the design and construction phase of a building [5]. They developed several building envelopes designs and have done a sensitivity analysis to narrow down several design factors like the amount of insulation for the walls and doors, length of overhang on the windows, external shading, air infiltration, etc. The results showed that minimum energy savings of 18% might be obtained by enhancing the design factors. Another study done by McKay [6] proved that the amount of insulation in the walls and roof would have a significant effect.

Many studies and surveys proved that there is an increase in satisfaction level for the occupants when there is a thermostat in their room that they can control [7]. Guo et al. examined a double corridor classroom building for the setback and set up temperature [8]. Guo et al. in their study created a smart thermostat that acquires information by X10 sensors deployed in several rooms in 8 houses they experimented on [8]. There are many ways to detect the occupancy; some of them require customers to wear a tag [9]. Gao et al. in their study created a smart thermostat that acquires information by X10 sensors deployed in several rooms in 8 houses they experimented on [9]. Gupta et al. proposed an innovative way to estimate the occupancy by calculating the arrival time of the resident [10]. Qela et al. attempted to study on self-learning thermostats [11]. A study was done to evaluate the percentage of savings obtained on heating and cooling in residential houses using Nest thermostats compared to manual and programmable thermostats [12]. Jin et al. [13] proposed energy savings technique for BEMS which is based on occupancy sensors. Existing IT infrastructure is used to collect accurate occupancy data inexpensively for non-energy purpose. This study suggest to incorporate those occupancy information with the current BEMS system where, building electronic devices such as HVAC and lighting usage can be monitored and controlled more effectively. The simulation results showed significant energy reduction while they used occupancy information for controlling building electronic devices.

After realizing the importance of energy savings, which can be achieved by installing programmable thermostats, US Department of Energy's Energy Star program started promoting programmable thermostats as a means of reducing energy usage for residential customers anywhere from 10 to 30% [14]. After such similar studies were done by US EPA and Energy Star [3], realizing that there were no savings or sometimes increased usage from programmable thermostats, Energy Star decided to stop the program in 2009. Two methods were developed by Van der Ham et al. [15] where they trained smart thermostats to gain information about the house characteristics such as heat loss rate and heat capacity over the time in order to ensure that homeowners are knowledgeable about the energy efficiency improvement opportunities present. In another study, Danassis et al. [16] discussed about decision making mechanisms to guide the temperature regulation of existing HVAC installations in a smart building environment. Researchers used Artificial Neural Networks and Fuzzy Logic to train the decision making process for the occupants' thermal comfort at an acceptable level of cost.

A model was developed by Muratori et al. [17] based on the overall thermal resistance theory. The model performs a control volume analysis based on the fundamentals of thermodynamics. The model then estimates the energy required for the HVAC system to raise or drop the ambient temperature of the room. White et al. [18] developed a new model that uses monthly average outside temperature only to calculate total monthly energy consumption. Some researchers have adopted either multiple linear regression methods or artificial neural networks to estimate the energy consumption of HVAC systems. For example, Zhou et al. [19] developed a model for commercial building by using a time series analysis method combined with a

regression model. Olofsson et al. [20] developed a model using neural networks to estimate the energy demand based on a time interval of two to five weeks. Many engineering and statistical models were proposed and developed by the authors for validation purposes.

Currently Building Energy Management (BEMS) is an important technology for energy consumption monitoring and reduction. Cheng et al. [21] studied the published research work about the return on investment of BEMS through the timeline from 1977 to 2017. Researchers have determined that the payback periods for the BEMS reduced from 5.4 to 0.7 years for implementation in commercial buildings. In another study Jones et al. [22] investigated the operational characteristics of energy management systems for reducing the energy consumption. The designed system studied the efficiency benefits of low temperature heating and the prosumer concept using a simple and inexpensive hardware configuration.

3 Methodology

With million residential houses being built every year, it is important to know the effect of various factors on the HVAC energy consumption [23]. Most of the studies overlooked the combined effect of all the factors that affect energy consumption. In the residential sector, the lack of knowledge among the users on the effect of factors such as insulation, thermostat level, zoning, and building envelope, leads to significant investment in HVAC systems, which may not prove to be economically feasible.

The main objective of this research is to develop a simulation model that will allow the users to estimate the total energy consumption of an HVAC system with a smart thermostat based BEMS in a residential house. It provides an opportunity for the user to decide on purchasing the HVAC system and the associated controls. The information flow diagram shown in Fig. 1 details the parameters used in the simulation system.

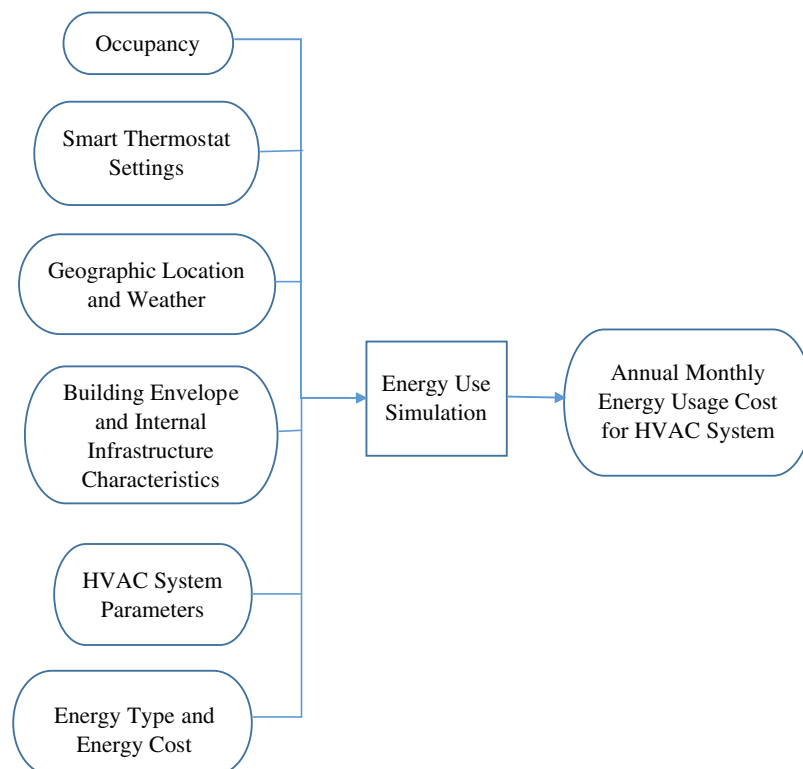


Figure 1: Flow Diagram of the simulation system

3.1 Description

The simulation is done in Microsoft Excel[®] based on the discrete event Monte Carlo Simulation methodology. The randomness of the variables is generated using the heuristic approach. HVAC units are usually measured often in terms of BTUH or Tons of HVAC. A ton of air conditioning can remove 12,000 BTUs per hour of heat energy from a space. The energy consumption by the system can be calculated using the formula;

$$\text{Energy consumption} = R \times LF \times UF \times OH$$

where, R = Rating of the System (Btu/hr); LF = Load Factor (%); UF = Utilization Factor (%); OH = Operating hours (hours).

The simulation is done with a frequency of 30 minutes for a whole year, specifying the utilization factor and the annual operating hours. One of the main goals of the model is to determine the load factor of the HVAC system at various intervals of time. As mentioned earlier, the load factor of the HVAC system is adjusted based on five factors. The simulation model was created with a user-friendly interface while maintaining a high degree of detail.

3.2 Monte Carlo Simulation

Monte Carlo Simulation is a method that is used to find solutions to mathematical and statistical problems through statistical sampling. The results are computed based on random sampling and statistical analysis. The main purpose of the Monte Carlo simulation is to understand the impact of the risk and uncertainty of a particular system. The behavior of the systems can be observed by the experimental process of drawing many samples and then analyzing their behavior. Though we have ample information about the factors affecting the outcome, it is difficult to predict the future with minimum error. Monte Carlo Simulation generates a possible outcome of a decision, thereby helping us to make a better decision under uncertainty. The simulations help to build a model by substituting various values for any factor that has uncertainty based on probability distribution. It records the results and continues to perform the same calculations repeatedly. It uses a different set of random numbers from the distribution every time. To generate different sets of random numbers continuously, it requires programming of a software system. This study utilizes Microsoft Excel[®] VBA[®] (Visual Basic for Applications) to perform the simulation.

3.3 Heuristic Approach

Heuristics are simple and efficient guidelines that people often use to make conclusions. It is a method of problem-solving, learning, or discovery that employs a practical method, which may or may not provide optimal solutions but is sufficient for immediate goals to achieve the necessary levels of satisfaction.

3.4 Simulation Software

Visual Basic Application (VBA)[®] is a programming language for Excel[®] and other Microsoft Office[®] programs has been used for developing the simulation. It enables building user-defined functions and automating processes. VBA allows users to automate by writing code or by creating macros. Excel VBA[®] is employed to code the excel model, to perform the calculations and run the simulation model. The visual basic code was used in this study. The model was developed using Visual Basic Applications (VBA)[®] in Microsoft Excel[®]. The model was created with a user-friendly interface while maintaining high degree of detail.

3.4.1 User Inputs and Model Outputs

One of the inputs which the user needs to provide is the configuration of the house, mainly the number of bedrooms. The simulation considers one kitchen and a living room along with the bedrooms. The model also requests the user if there are any plans for building envelope improvements and asks for the month in which

improvements are made if any. The model also asks for the number of times the thermostat settings are changed. The user also has the privilege to input the volume, building envelope and thermostat levels. If the user fails to input these values, the model generates a random level of all three factors. The model also checks if there are any power outages in the area. If yes, the user needs to provide the maximum number of power outages and the maximum time one power outage may last. The model also considers the location where the user's house is located as the weather varies all over the United States. The user is guided with a map and region number for information, which can be helpful to determine the appropriate region where the house is located.

This is a user interactive simulation. All the probability values for the occupancy, weather and room volume (from [Tabs. 1–5](#)) are predetermined number for running the simulation. Then users can change all these values according to their requirements. The simulation model allows the user to input the capacity of the HVAC system and rates associated with the cost of electricity and natural gas. This allows the model to calculate the energy consumption and the associated costs to run the HVAC systems. As many residential areas are not subjected to electrical demand costs, this study does not consider any peak demand or any costs associated with demand. After the user provides all the inputs, the simulation model is executed. The completed simulation then provides an estimate of the annual energy consumption and the energy costs that are generated based on the inputs provided by the user.

Table 1: Rules for occupancy of spaces

Bedroom			
Start Time	End Time	Weekday	Weekend
11.00 PM	9.00 AM	85%	85%
9.00 AM	5.00 PM	15%	50%
5.00 PM	11.00 PM	50%	50%
Kitchen			
Start Time	End Time	Weekday	Weekend
11.00 PM	6.00 AM	10%	10%
6.00 AM	2.00 PM	65%	65%
2.00 PM	5.00 PM	40%	40%
5.00 PM	11.00 PM	75%	75%
Living Room			
Start Time	End Time	Weekday	Weekend
11.00 PM	9.00 AM	20%	20%
9.00 AM	5.00 PM	40%	70%
5.00 PM	11.00 PM	60%	60%
Bathroom			
Start Time	End Time	Weekday	Weekend
12.00 AM	12.00 AM	15%	15%

3.5 Factors

3.5.1 Occupancy

This study calculates the energy consumption with an assumption that each room has a smart thermostat with occupancy detecting capability. These can sense if the room is occupied or not and set back the thermostat when the room is unoccupied. The occupant's schedule and some heuristic rules are used to sense the occupancy of a person in the room. If the user of the model feels that the schedule does not match the base schedule used for the simulation, he or she can change the schedule accordingly. The model has the capability to differentiate between a weekday and a weekend and change the heuristic rules accordingly. As the frequency of the model is for 30 minutes, for each step, i.e., for every 30 minutes, occupancy is sensed for all the rooms and occupancy level is established. The model estimates the time of sleep and sleeping time of the user and retains the occupancy level until he or she sleeps and then the occupancy level continues to update. The model is flexible; hence, if the user's activity is varied or if the user opines to alter the probability matrices, this can easily be done in any of the following Tables, starting with [Tab. 1](#).

3.5.2 Weather

In this study, the weather is assumed to be at three levels—level 1 as mild, level 2 as moderate and level 3 as extreme weather conditions. The weather factor is updated every eight hours and is assumed to be the same for the next eight hours. To determine the weather factor, the year is split into four seasons and the rules are shown below.

It should be noted that the climate conditions vary as per the location. The United States is divided into nine regions, as shown in [Fig. 2](#).

The model uses heating and cooling degree days to determine if heating or cooling is required. [Tab. 2](#) shows the probability chart for the three different weather levels throughout the year.

Table 2: Rules to determine weather factor

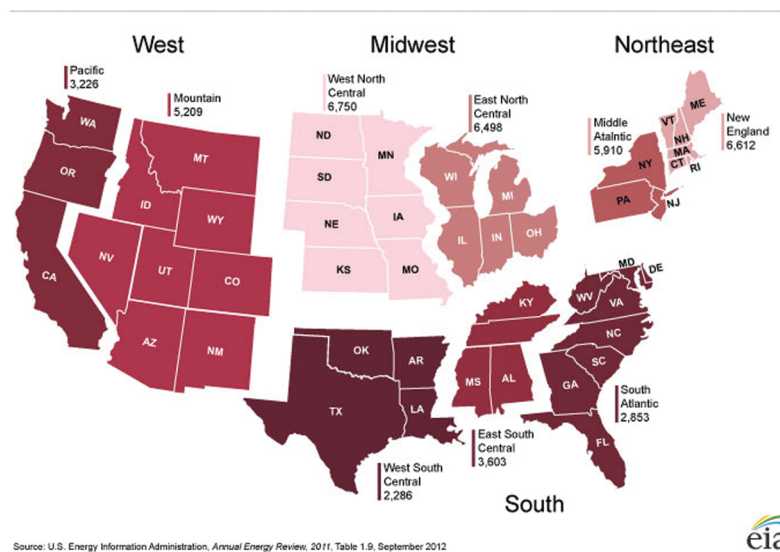
Months	Season	level 1	level 2	level 3
March 1st–May 31st	Spring	40%	40%	20%
June 1st–August 31st	Summer	40%	35%	25%
September 1st–November 1st	Fall	40%	40%	20%
December 1st–February 28th	Winter	10%	30%	60%

3.5.3 Volume of the Room

To lower or increase the room temperature, the HVAC should either add or remove heat from the area. The amount of heat or cold air added to the room is directly proportional to the volume of the room. Three levels are considered for the volume of the room—level 1 as small, level 2 as medium and level 3 as large. The level is randomly generated if the user does not provide input. The randomness is generated, assuming that all three levels have an equal probability of 33%. [Tab. 4](#) below shows the standard floor area of different rooms in residential buildings.

3.5.4 Building Envelope

The building envelope is considered as one of the critical factors to determine the load factor. The building envelope includes walls, fenestration, roofs and doors. Two levels—level 1 as good and level 2 as bad are considered for the building envelope. The level for the building envelope is an input given by

**Figure 2:** Census region [24]**Table 3:** Rules to determine weather factor

Months	Season	Level 1	Level 2	Level 3
March 1st–May 31st	Spring	40%	40%	20%
June 1st–August 31st	Summer	40%	35%	25%
September 1st–November 1st	Fall	40%	40%	20%
December 1st–February 28th	Winter	10%	30%	60%

Table 4: Standard sizes of rooms in residential building

Floor Area (Sq.ft)				
Level	Bedrooms	Bathroom	Living Room	Kitchen
1	144	54	216	50
2	250	70	320	104
3	384	96	616	120

the user. If the user fails to input the level for the building envelope, it is generated randomly. For the study, two levels are considered for the building envelope and are distributed at 50% each.

3.5.5 Thermostat Setpoint

People prefer their comfort levels, i.e., one might prefer their room at a higher temperature and the others might prefer their room at lower temperatures. As mentioned, the thermostat setpoint can affect energy consumption. This is also another input from the user. Like the volume and building envelope, if the user does not want to enter the level, it is randomly generated. There are two levels of thermostat factor—level 1 for lower setpoint and level 2 for the higher set point. The tables below help the user and the model to determine the thermostat level, respectively.

Table 5: User guidelines to determine the level for the thermostat

	Level 1	Level 2
Summer	70–80°F (68%)	60–70°F (32%)
Winter	60–70°F (37%)	70–80°F (63%)

The model also considers the number of times the thermostat settings are changed yearly. Then it updates the thermostat level with the updated frequency (365/number of changes per year). If there are no changes to the thermostat, the initial input from the user will be used for the calculations.

3.6 Load Factor Determination

Load factor is a function of the five factors—occupancy, outside weather, thermostat set point, building envelope and volume of the room. Thus, assigning levels for all the five factors is a pre-requisite to determining load factor. The level for the five factors is occupancy-2, weather-3, volume of the room-3, building envelope-2 and thermostat set point-2. Thus, the maximum number of possible combinations are considering all these levels and factors are 72 sets ($2 \times 3 \times 3 \times 2 \times 2$). Load factor is assigned to each possible set (pre-determined). To determine the load factors, worst conditions are considered where HVAC system is assumed to be running at full load. Then the load factors are assigned to the remaining 71 sets. At 30 minutes interval, new generated sets (5 factors) is compared to the pre-determined set and a load factor is assigned to that set. An example of the determination of load factor for six sets is shown below in [Tab. 6](#).

Table 6: Load factor assignment

Category	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Load Factor	100%	40%	80%	70%	20%	0
Occupancy	1	0	1	1	1	0
Weather	3	3	3	3	1	1
Volume of the Room	3	3	2	2	1	1
Building Envelope	2	2	2	1	1	1
Thermostat Set Point	2	2	2	2	1	1

3.7 Energy Costs Calculations

The capacity of the heater, tonnage and COP of the air conditioner, type of fuel and the rate structure is the inputs given by the user. The heater and the air conditioner capacity are used while calculating the energy required to heat and cool the building, respectively. kW of the air conditioner is calculated using the COP and tonnage of the air conditioner.

The model has the capability of identifying if cooling or heating is required. The model uses degree days of the respective region selected by the user. It then establishes a probability of cooling using the degree heating days and degree cooling days. [Tab. 7](#) below shows the heating degree days and cooling degree days of the region 8—South Atlantic.

Table 7: Probability of air conditioning [24]

Name	HDD	CDD	Cooling
January	569	29	5%
February	460	30	7%
March	322	53	15%
April	129	84	40%
May	39	189	83%
June	2	338	100%
July	1	412	100%
August	1	392	100%
September	11	264	96%
October	118	123	52%
November	315	47	13%
December	445	44	9%

Energy is calculated for the heater and air conditioner using the formula shown below.

$$\text{kWh} = \text{kW} \times 0.5 \times \text{LF}$$

$$\text{MMBtu} = \text{MMBtu/hr} \times 0.5 \times \text{LF}$$

$$\text{kWh Cost} = \text{kWh} \times \$/\text{kWh}$$

$$\text{MMBtu Cost} = \text{MMBtu} \times \$/\text{MMBtu}$$

where, kW = kiloWatt of Air Conditioner or Heater, MMBtu/hr = Capacity of the heater, LF = Load factor of the system. The formula contains 0.5, as the energy consumption and energy costs are calculated on a 30-minute interval. Once the energy is calculated for all the 30-minute intervals, the energy for the heater and air conditioner are summed up on a monthly basis and on an annual basis.

3.8 Assumptions and Limitations

The following assumptions are made in this study: the frequency of the simulation is 30 minutes, determined load factor would be the average load factors in that 30 minutes interval, building envelope improvement starts at the beginning of the month, natural disasters were ignored, a smart thermostat is used with occupancy sensor, zoning with variable air volume (VAV) control systems are available, restrooms are tied with the respective bedrooms, ventilation and exhaust air effects are ignored, weather factor updates only after 8 hours, no demand cost for residential area.

The limitations are that the system is not able to handle more than five bedrooms, only two energy sources are considered, namely natural gas and electricity.

4 System Execution and Results

A two bedroom house as an example will be discussed here to explain how the model works. All the inputs will be entered into the program.

4.1 Example Input

The HVAC systems employ a natural gas furnace with 30,000 Btu/hr and 2 Tons air conditioner with COP of 3 for heating and cooling, respectively. The user plans to upgrade the building envelope in June. The user updates the thermostat two times a year. The user expects a maximum of 2 power outages in the Morgantown, WV area; each power outage may last for 6 hours. It is assumed that the user's house is in Morgantown (Region 8—South Atlantic). The cost of natural gas and electricity considered are \$7/MMBtu and \$0.1/kWh.

The monthly energy consumption and the energy costs associated with the simulation performed are shown in [Tab. 8](#) below.

Table 8: Energy consumption

Month	Electricity Consumption (kWh/month)	Natural Gas Consumption (MMBtu/month)	Electric Costs (\$)	Natural Gas Costs (\$)
January	9	12	1	84
February	68	11	7	77
March	35	8	4	56
April	242	5	25	35
May	491	1	50	7
June	470	0	47	0
July	485	0	49	0
August	487	0	49	0
September	483	0	49	0
October	261	2	27	14
November	56	5	6	35
December	54	10	6	70

It can be observed that there is no natural gas consumption in the months of “June, July, August and September” as the user's location does not have any requirement for heating in these months according to the past ten years data. Thus, the possibility of heating in these months is very low. It can be observed that there is a possibility for cooling in months “December and January” although they are winter months.

4.2 Sensitivity Analysis

To study the effect of different levels of each factor on energy consumption, simulation is performed using varying combinations of pertinent variables. The results from the simulation software executions are plotted. Though the levels for the factors change for each simulation run, some inputs are considered to be the same for each run and they are; region, zero power outages, region 8, heater capacity 50,000 Btu/hr, and using a 3 ton air conditioner.

The total energy consumption for a residential house with regular controls are about 50% higher compared to the house employed with a smart thermostat with occupancy sensor-based BEMS. To observe the effect of energy consumption with and without occupancy detection, a graph is plotted between the monthly energy consumption of HVAC system (Electricity and NG) vs. the occupancy detection capability as shown in [Figs. 3 and 4](#).

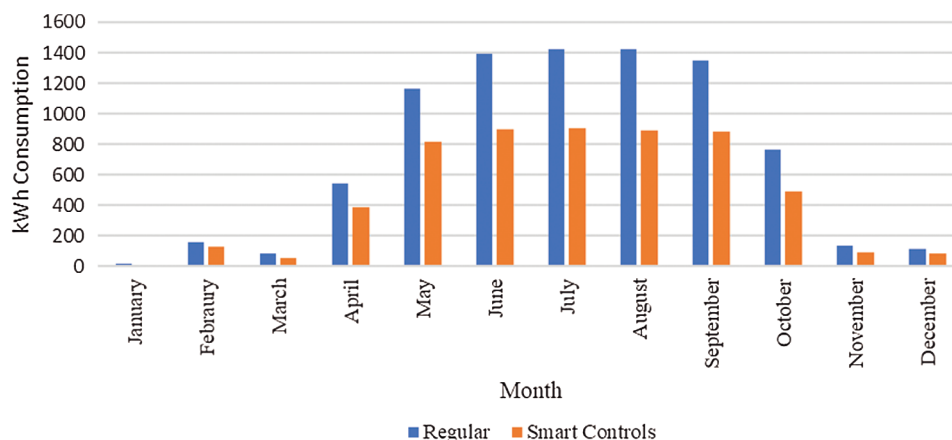


Figure 3: Electricity and natural gas consumption for regular controls vs. smart controls

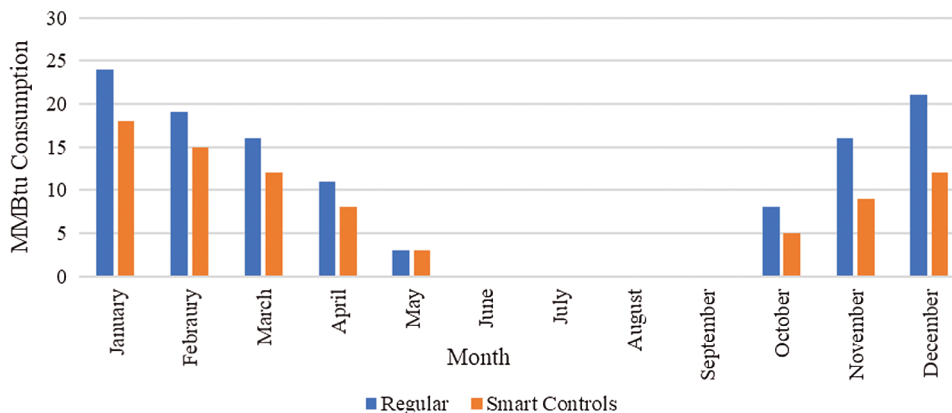


Figure 4: Natural gas consumption for regular controls vs. smart controls

The simulation results for the different volume level shows that energy consumption, both natural gas and electricity increase as the volume level increase. The effect of the volume of room on energy consumption is shown in the [Figs. 5 and 6](#).

To inspect the effect of thermostat level, two simulation runs are performed; case 1 (level 1—low comfort levels) and case 2 (level 2—high comfort levels). The energy consumed by the HVAC system is higher in case 2, compared to the energy consumption in case 1. A bar graph is plotted between thermostat comfort levels vs. the energy consumption as shown in [Figs. 7 and 8](#) to study the effect of thermostat set points on the energy consumption.

The model also considers how many times the thermostat comfort levels are changed, and three different simulation runs are completed. It can be observed that the energy consumption does not have any relationship with the number of times the thermostat setpoints are changed. The [Figs. 9 and 10](#) showcases bar graphs showing the outputs from the three simulation runs.

The HVAC energy consumption depends on the building envelope and observed that the energy consumed in the case 2 (level 2), is same as the energy consumed in case 3 (level 2 and will be upgraded in July) for the first six months and case 1 (level 1) in the last six months, as the building envelope is at level 2 till June 30th and at level 1 for rest of the year. To study the effect of building envelope on energy consumption a graph is plotted as shown in [Figs. 11 and 12](#).

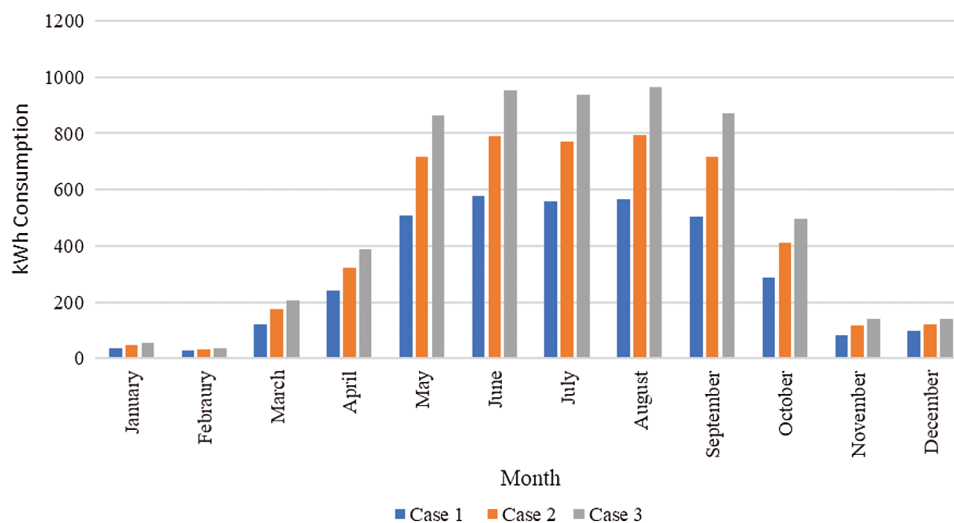


Figure 5: Electricity consumption for varying volume levels

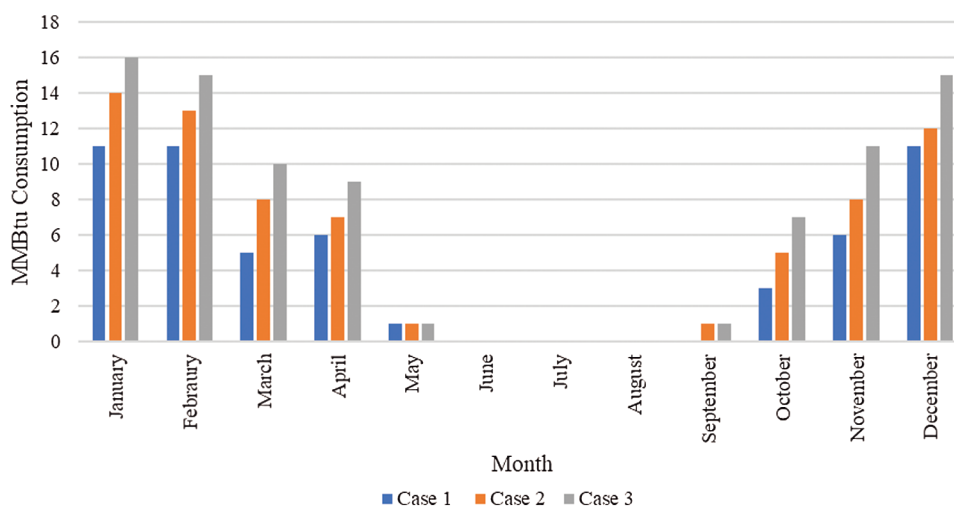


Figure 6: Natural gas consumption for varying volume levels

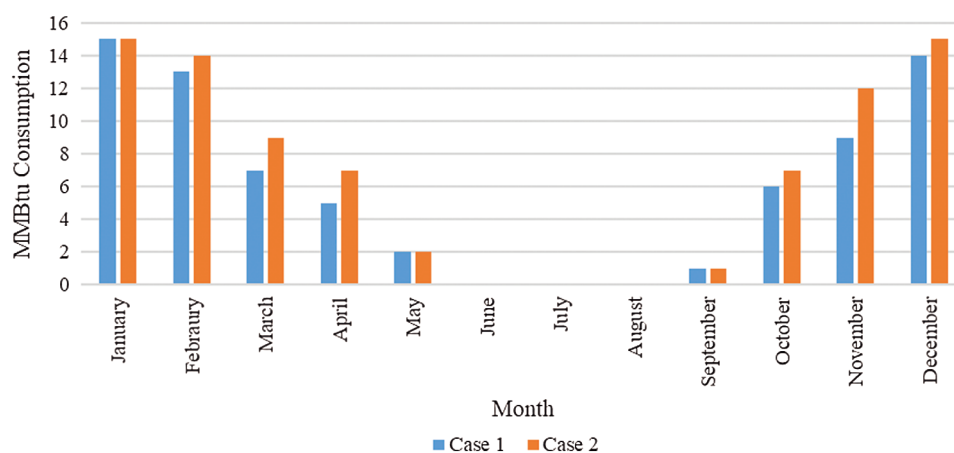


Figure 7: Natural Gas consumption for different thermostat comfort levels

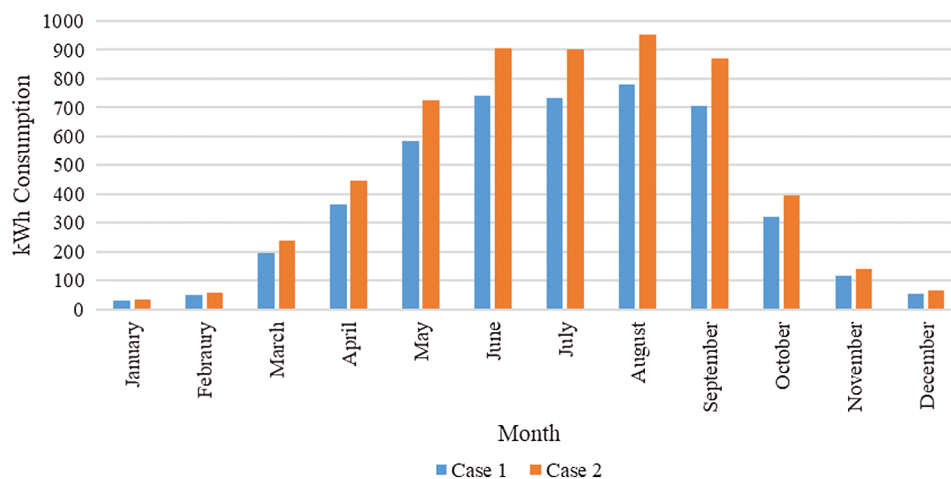


Figure 8: Electricity consumption for different thermostat comfort levels

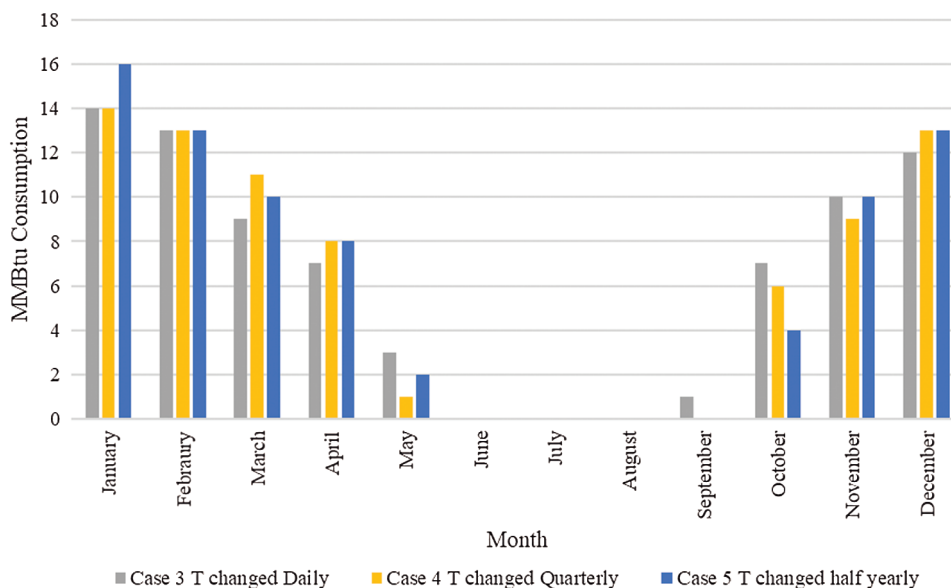


Figure 9: Natural gas consumption vs. # of times thermostat set points changed

To understand the importance of the user's location while calculating the energy consumption, eight simulation runs, one run for each location are performed. It can be observed that the costs associated with heating (natural gas) is higher compared to costs associated with cooling (Electricity) in all the regions except for South Atlantic and West South Central. Fig. 13 gives us information regarding energy costs associated with a residential house with a similar configuration and thermal comfort levels in different census regions throughout the United States.

4.3 Validation

The model has been applied to simulate the HVAC system for a typical household located in the area of Morgantown, WV (i.e., South Atlantic region). The user has a heater with a capacity of 85,000 Btu/hr. The user's house has five bedrooms, living room and a kitchen. However, there is only one regular thermostat in the living area. The occupancy of the house is very minimal, and the user prefers energy-efficient thermostat

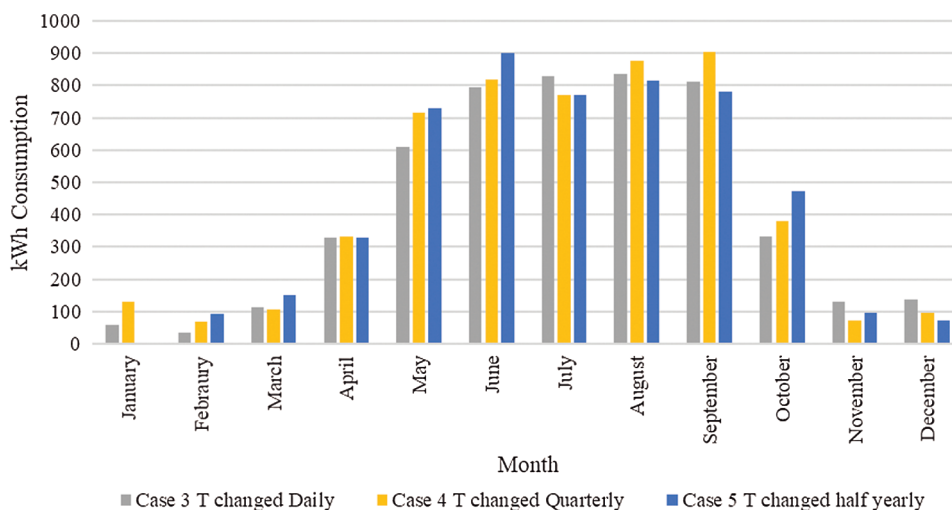


Figure 10: Electricity consumption vs. # of times thermostat set points changed

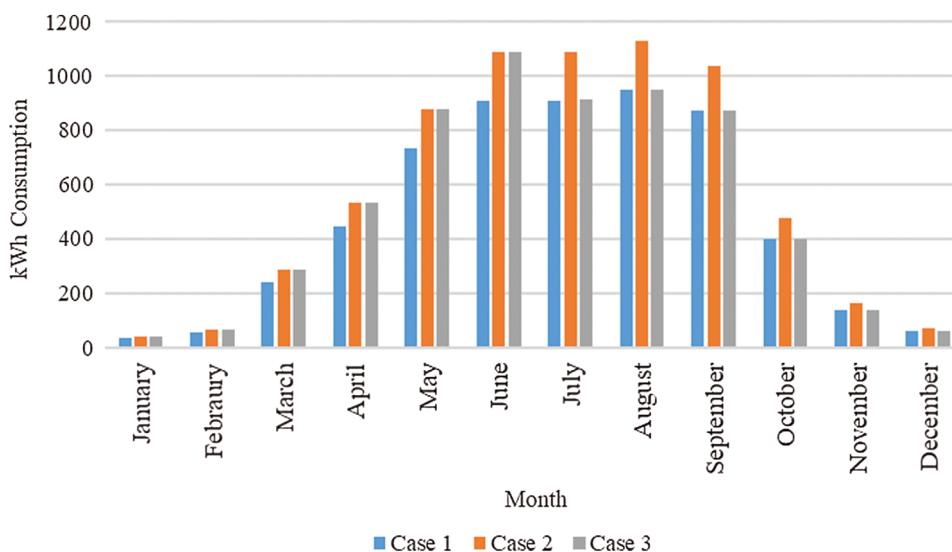


Figure 11: Electric consumption vs. building envelope levels

setpoints (i.e., 60 degrees Fahrenheit in winter and 80 degrees Fahrenheit in summer). The building envelope is tight with good insulation and very minimal insulation. The natural gas bills are obtained from the user and heater energy consumption is estimated after considering the energy consumption for cooking and the water heater. Heater energy consumption was observed to be 32 MMBtu per year. The simulation is performed considering three bedrooms in order to mimic the configuration, as the user's house is not zoned and has only one regular thermostat. The occupancy pattern in the reference sheet is changed to meet the user's occupancy pattern. The model is run to simulate the energy consumption of the heater. The total energy consumed by the heater turned out to be 37 MMBtu per year. The difference between the simulated and the actual energy consumed is 5 MMBtu per year.

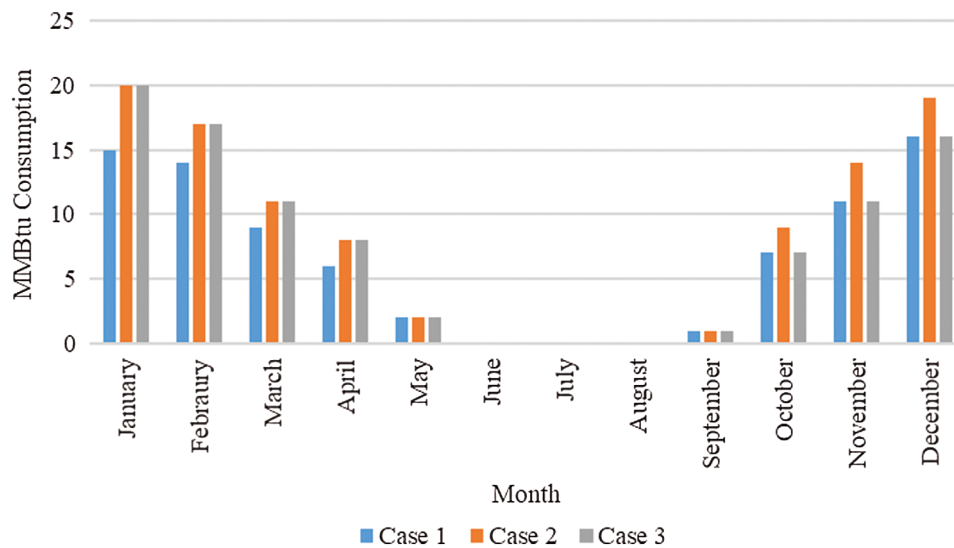


Figure 12: Natural gas consumption vs. building envelope levels

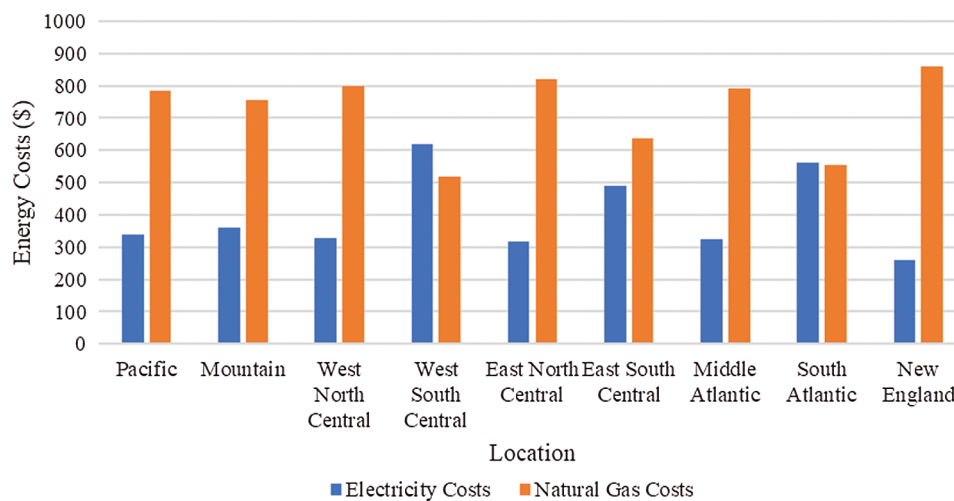


Figure 13: Total energy costs vs. location of user

5 Conclusion

A simulation tool to estimate the energy consumption of a residential HVAC system with smart thermostat BEMS was developed. The tool was implemented in Microsoft Excel[®] with Visual Basic[®]. The technical features of the model include: 1) Compatibility with Windows operating system 2) Capability of handling up to five bedrooms with a living room and a kitchen 3) Provides the user an option to select from nine different locations where his residential area is located. The results of the model include the total monthly and annual energy consumption and associated cost.

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