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Application of Occupancy-Based Control in Building Energy Saving and Indoor Thermal Comfort

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Abstract: ***Research on smart energy saving is becoming famous globally in different sectors. The current research is anticipated to lower energy demand and consumption in the building industry, which has already reached 49% globally and is projected to rise by 2% yearly, incurring significant monthly costs. One prevalent problem nowadays is striking a balance between energy efficiency and. Most research has concentrated on energy efficiency without taking into account occupant thermal comfort, which might pose health risks to both young and old occupants. The proposed model is capable of setting the ideal temperature set point to achieve healthy comfort. Although our proposal lacked an experimental evaluation a different machine learning technique can be integrated alongside fuzzy logic algorithms to enable significant energy saving as well as maintained thermal satisfaction of occupants.***

Keywords: energy efficiency, machine learning technique, thermal comfort

1.0 Introduction

Today, research on HVAC energy optimization solutions is one of the top famous and trending research in industries and academia. Recent studies show industries, businesses, healthcare, cities education sectors are switching from traditional energy control systems to modern approaches to energy saving. The practice can help to reduce the demand for energy in the building sector which has already reached 49% across the globe with an annual increase of 2% costing a lot of dollars monthly (SAULLES, 2017). Thermal satisfaction is one of the key factors to consider for healthy living at home and greater productivity at work. However, recent solutions focused on providing a general solution to optimize energy consumption in HVAC systems without consideration of thermal satisfaction which varies from region to region, and also from age to age.

Furthermore, the research delves into the latest advancements in state-of-the-art, encompassing binary and fuzzy control algorithms, to present a refined idea or methodology that preserves the lifespan of electrical appliances and allows handling of a greater range of values when determining whether to turn them on or off. These parameters include things like interior and exterior temperatures, humidity, and the requirement for system use by occupants, among other things. This gives the ability to manage vague and confusing information so that decisions may be made as though a human is making them.

The proposed approach is similar to the approach in IoFClime (Meana-Llorián, 2017), however, our method is equipped with tools like an occupancy detection algorithm that can identify if someone is in the room. (occupant needs to use the system) to prevent the HVAC system from working in case the occupant forgets to turn it "OFF" while leaving the room and a machine learning algorithm that tries to learn from occupant behavior toward thermal preference and adapt to it. The interesting thing part of this approach it knows when the occupant leaves and arrives in the house. This will enable the control to turn "ON" HVAC system to stabilize the room at a low temperature and try to maintain his preferred thermal comport before arriving at the room at a low cost. For elderly people who need assistance in maintaining their temperature (when it's low or high) this can be done automatically without any assistance since control can learn from their thermal satisfaction. Although our study did not perform any experimental evaluation to prove the effectiveness of our approach, nevertheless, it offers thorough comprehension and sheds light on topics for industry or academic researchers looking to advance the state of the art in the relevant subject. Therefore, the rest of this research is structured as follows: The study materials and methodology are presented in Section 2, and a review of the state of the art is carried out in Section 3. The case study presented in Section 4 is followed by a conclusion.

2.0 Literature Review

The motivation of this study is to be able to manage and control HVAC systems in smart building structures in the presence of occupants in the room using IoT devices. This objective can be achieved with the help of a Machine learning algorithm to determine the presence of an occupant and understand his thermal satisfaction in a particular season. The fuzzy algorithm would be used in the switching of ON and OFF electric appliances this is because it permits dealing with more values for thermal control in a way similar to a person doing. This can be achieved with the help of data feed to control IoT devices. IoT devices can be seen as any physical object that has the potential to connect to the internet and to be controlled in such a way with the help of IoT platforms. Examples include lights and air conditioners that can be turned on and off using a smartphone app. Hardware and software infrastructure that offers APIs to enable real-time package execution and enhancement for LabView and ThingSpeak are examples of IoT platforms.

2.1 Internet of Things

The term "Internet of Things," or "IoT," describes networks of intelligent items that can transmit and receive data, connect to the Internet, and communicate with other objects and people (Matsui, 2018). Examples include internet-connected cameras that enable you to upload pictures to the internet with just a click, automatic home automation systems that switch on your front porch light as soon as you get home from work, and wristbands that let your friends know how far you've jogged or ridden your bike during the day.

Recent developments show billion people are benefitting from IoTs and it increasing dependency of industries, businesses, healthcare, cities, and networking activities on automation of various physical entities (Matsui, 2018; M Victoria Moreno, Santa, Zamora, & Skarmeta, 2014; Park & Rhee, 2018).

IoT systems save billions of money and provide consumers with new experiences globally (Whitmore, Agarwal, & Da Xu, 2014). Examples include self-driving cars, smarter medical equipment, robotic manufacturing, smart grids, and many industrial control systems. These systems are usually distributed publically via wireless connections and cloud computing.

Any gadget that has an ON/OFF switch has the potential to be connected through the Internet of Things. With this potential, buildings and residences may be made more energy-conscious, resulting in safe, cost-effective, and healthy living conditions without sacrificing occupant comfort (Meana-Llorián, González García, Pelayo G-Bustelo, Cueva Lovelle, & Garcia-Fernandez, 2017). To lower energy use, several studies have been conducted by academic institutions, businesses, and the International Energy Agency. According to current research, a household's yearly energy usage may be reduced by 15–23% when they deploy IoT devices (Grid, 2016).

2.2 Occupancy detection

Detecting intruding objects is very essential in many areas such as homes, malls, hospitals schools, and banks (Mansur, Carreira, & Arsenio, 2014). There are different approaches by which intruding objects can be detected inside the room, the approaches include background subtraction, Deployment of the static camera is the common approach to observe an intruding object in the room (Akkaya, Guvenc, Aygun, Pala, & Kadri, 2015). The most common method is scene analysis, which is based on the assumption that an image of the room without an intruding object reflects or exhibits certain properties that can be presented in the form of a statistical model(M. V. Moreno, Ubeda, Skarmeta, & Zamora, 2014). This enables to detection of intruding objects in the room when spotting parts of the image deviating from the model.

Research by Akkaya et al. (2015) uses machine learning to identify occupancy in smart buildings to conserve energy. Their approach considers the number of occupants presently in the building to increase or reduce the temperature in the building. Thermal imaging was used for occupancy detection, pyroelectric infrared sensors, together with RGB cameras (Mansur et al., 2014). For headcount and Gaussian processes and background subtraction approach implemented with the OpenCV library was used.

2.2.1 Decision control system

To create an explicit controller for the system and execute an effective energy control management scheme that is comparable to what humans do, the system must first be modeled. To create a controller that satisfies the specified design criteria, this type of control is often modeled by estimating parameter approaches (decision algorithm) in system identification or by explicitly modeling the system dynamics (Haider, See, & Elmenreich, 2016). Relay for predictive control of an external alarm signal that is sent in advance by a smart grid or timetable. Predictive control data, such as cost, thermal demand, or PV generation, are often required by the current prediction algorithm in conjunction with a scheduling system to satisfy demand at the lowest possible cost. According to Tsui and Chan (2012), this suggests that controllers must be aware of the proper input and process it to determine when it is ideal to use energy. Since the process cannot be altered in this stage, the control system must use the input data to produce the optimal output from the process. A PID controller is a more advanced type of controller, although a simple one can be a summation point to determine the difference between input and output for processing. Table 1 below provides an overview of various decision control algorithms:

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Table 1 summary of different decision control algorithms

Algorithm	Pros	Cons	Study	Strength	Weakness	Recommendation
Rule-based algorithm	-Easy to design and simple to simulate - no external parameters needed -cheaper to implement -flexible	-Extensive knowledge of rules is required -do not allow rules to be adjusted on a similar use-case with different parameters	(Drungilas & Bielskis, 2012; Revel et al., 2015; Risteska Stojkoska, Trivodaliev, & Davcev, 2017), (Salamone, Danza, Meroni, & Pollastro, 2017) S50	-The techniques show fascinating results on simulated building -effective automatic control	A high false flag is observed -Many of these studies were simulated in an office building -can reduce the life span of electric appliances due to frequent off/on	-fuzzy logic would produce more promising results compared to the classical binary approach -Machine learning needs to be introduced to learn from previous activities and be able to model new rules when necessary -other classes of build environment need to be considered
Model-free algorithm	-Easy to design and simulate --- required data from prediction output -Cheaper to implement -Good performance compared to rule based.	-Extensive knowledge of rules is required -complexity in the design model -do not allow rules to be adjusted on a similar use-case with different parameters	(AlFaris, Juaidi, & Manzano-Agugliaro, 2017; Tila & Kim, 2015)	-Provide optimal control	- false flag is observed -Many of these studies were simulated in an office building -can reduce the life span of electric appliances due to frequent off/on	-fuzzy logic would produce more promising results compared to the classical binary approach -other classes of build environment need to be considered
Model-based algorithm	Easy to design and simulate required data from prediction output -Flexible to future changes -optimal result expected compared to model free	-complexity in design - tedious modeling effort -require more computational power -prone to modeling and prediction errors	(Aswani, Master, Taneja, Culler, & Tomlin, 2012; Gateau & Rykowski, 2015)	-technique can be suitable with similar use cases -It allows the policy to be changed when necessary at any point of the prototype lifecycle	Lack of studies in building environments Most of the studies are implemented in the office -can reduce the life span of electric appliances due to frequent off/on	-fuzzy logic would produce more promising results compared to the classical binary approach -Machine learning needs to be introduced to learn from previous activities and be able to model new rules when necessary -other classes of build environment need to be considered
Internal prediction	-high performance -can be applied only on similar use cases	-Robustness Required third-party service	(AlFaris et al., 2017; Huang, Yang, & Newman, 2015; Mansur et al., 2014)		-requires third-party application -Lack of studies in building environments -can reduce the life span of electric appliances due to frequent off/on	-fuzzy logic would produce more promising results compared to the classical binary approach -Machine learning needs to be introduced to learn from previous activities and be able to model new rules when necessary -other classes of built environment need to be considered
External prediction	-Flexible to different use cases on the same model -Optimal result expected	-Robustness -Required third-party service -Required many computational resources	(Sehar, Pipattanasomporn, & Rahman, 2017), (M. V. Moreno et al., 2014), (Rabbani & Keshav, 2016), (Wei et al., 2018), (Singh et al., 2017), (Shakeri et al., 2017)		Lack of studies in building environments Most of the studies are implemented in the office	-fuzzy logic would produce more promising results compared to the classical binary approach -other classes of build environment need to be considered
Schedule based algorithm	-Flexible for future changes -better result is expected	-Expensive to maintain - Extensive knowledge of rules is required Complex to design	(Tsui & Chan, 2012), (Asif et al., 2018; Bari et al., 2015; Serra, Pubill, Antonopoulos, & Verikoukis, 2014),(Chen, Wei, & Hu, 2013), (Walker, Brown, & Neven, 2016), (Ejaz, Naeem, Shahid, Anpalagan, & Jo, 2017), (Lu, Zhou, Chan, & Yang, 2017)		This may result in expensive energy purchase Lack of studies in building environments	-fuzzy logic would produce more promising results compared to a classical binary approach -Machine learning needs to be introduced to learn from previous activities and be able to model new rules when necessary -other classes of build environment need to be considered

2.3 Mode free algorithm

Model-free algorithms are used in studies (Langevin, Wen, & Gurian, 2013) to eliminate modeling complexity and offer the best control solution. This may be done by creating rules or heuristics to establish a control trajectory about projected demand and price estimates. These control decisions have a classical foundation and need expert knowledge before rule creation. The successful implantation of this approach suggests that, with proper design, these rules might represent a reasonable balance between MPC and non-predictive methods, being computationally cheap while still using predictions and existing data. One of the drawbacks of this method is that designed rules might not produce optimal solutions or not be flexible in other possible use cases of different parameters.

2.4 Non-predictive

Conversely, non-predictive algorithms address how control action is determined from the existing state of the system (Steyerberg & Harrell, 2016). Conversely, a predictive algorithm may be categorised based on expected values and how the scheduling process is managed. Since no prediction is flawless, handling uncertainties might be crucial, and non-predictive control is now used for the majority of energy optimization for household appliances (Barata & Silva, 2013). Real-time sensor data, including temperature sensors, voltage or frequency in the electric grid, photovoltaic power output, and cost data, may be utilized to predict control decisions for energy optimization control. This method is generally employed in situations where forecasts are either unreliable or unable to provide more insightful data. On occasion, the predictive approach's costs may outweigh the benefits of improved controls. To estimate the control signal, three methods are used: rule-based approach, classical control, and predetermined program and timetable. Fast service for grid voltage or frequency stabilisation is an excellent illustration of non-predictive model-based control. According to Aswani et al. (2012), internal prediction control ensures the integrity control flow through user-implemented rules and processes that are akin to model-based control. While some non-predictive control systems rely on data that flows from the outside to the inside, cloud IoT solutions like IoTfy are the primary source of this type of data, which is then used by the application as control information for prediction. Demand response is one instance of this kind of control (Sikora, 2017).

2.5 Scheduling control algorithm

In the residential domain, an energy consumption scheduling strategy is one way to prevent excessive electricity costs during peak demand. With the help of this technology, tenants can reschedule or delay power consumption to specific times of the day when there will likely be little power demand. Studies in (Asif et al., 2018; Brundu et al., 2017; Bujdei & Moraru, 2011; Ciabattoni, Ferracuti, Ippoliti, Longhi, & Turri, 2016; Drungilas & Bielskis, 2012; Lu et al., 2017; M. V. Moreno et al., 2014; Pan et al., 2015; Shakeri et al., 2017) employs a schedule-based strategy to save energy costs and prevent appliances from using electricity during periods of high demand. To let other household appliances use the power that this equipment stores, an accessible standby appliance, for instance, may be programmed to consume energy when the cost of energy is lower. Examining environmental elements such as weather and occupant choice for thermal comfort might help achieve this. Either a static approach or runtime control can be used to accomplish this.

The guidelines for the occupant thermal comfort profile in a static method would be modeled using the weather and the user's indoor activities. These methods allow for intelligent energy management anytime energy reaches a certain level where it may be sold for less, lowering the energy use price. Similar to this, these methods typically result in a decrease in localised power generation by taking into account the energy needs of households. Static scheduling is therefore the best choice for residents of single buildings. While the runtime technique creates occupant profiles for energy usage based on weather forecasts and the energy consumption history of the previous day.

3.0 Case study

Many of the rules in the model-based approach controller employ inference rules to determine the appropriate process input, while the predecessors and helpful resource restrictions are used in the scheduling method to anticipate the start and finish times of tasks. Similar to this, these controllers make decisions using a conventional binary technique, which makes electrical appliances often turn on and off. Since many of the current approaches employ binary algorithms, this practice tends to shorten the lifespan of electrical equipment (Brundu et al., 2017; Tsai et al., 2016).

As a result, our work uses predictive control to augment binary decision algorithms with sets of values other than zeros and ones by utilising fuzzy decision-making algorithms. This adds context and allows the control to handle a wider range of values. These variables include characteristics such as "Size," which

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might have values of "Small," "Massive," "Very big," and so on. This control facilitates the management of vague and ambiguous information to enable decision-making akin to that of a human.

The proposed model can be split into f (3) modules a) occupancy detection of object entrance and exits in the room environment. b) Smart control is composed of a fuzzy control system (smart object) and c) Cloud server (see figure 4). Since devices communicate, share, and store information, the server is required and this research chooses a Google cloud server for communication between devices and appliances.

The study adopt a similar approach used in (Meana-Llorián, González García, Pelayo G-Bustelo, Cueva Lovelle, & Garcia-Fernandez, 2017) to manage a system that regulates the temperature in the building automatically. While considering outdoor temperature, humidity, and indoor temperature parameters, the study includes the presence of the occupant in the building. This will automate the switching On/Off of the control system whenever the occupant enters or leaves the building. The design fuzzy logic control system collects data from installed sensors and IoT platforms. The LEDs that serve as actuators were also attached to microcontrollers to indicate the state of the control on HVAC. These LEDs come in five different colors each representing a particular state of temperature to simulate temperature control in the building.

3.1 Proposed architecture of the system

To detect the presence of an occupant in the room we choose to use a smart IP Camera Canon product (Canon VB-S30D). The camera is connected to Audino via an Ethernet connection that enables the camera to turn ON/OFF control without the occupant's intervention. To reduce false alarms, we carefully design each rule with a certain frequency flag for five (5) classification scenarios on the scene of action. This indicates two different detections on the scene that the smart IP camera offers (see Figure 1). The first scenario is where after door opens which involves detecting movement/activity in the room and the second is the detection of the occupant leaving the room and losing frequency of movement indicating disappearing from the scene. Alongside this, we used the Open CV library to model the occupant detection for image evaluation together with the Numpy library. This involves a series of workflow, including loading a captured image, transforming it to an array of bytes, converting it to and greyscale, and detecting of occupant using the OpenCV library in the captured image. If there is an occupant present our module returns a 'True' Boolean value else, the 'False' module returns the Boolean value 'False'.

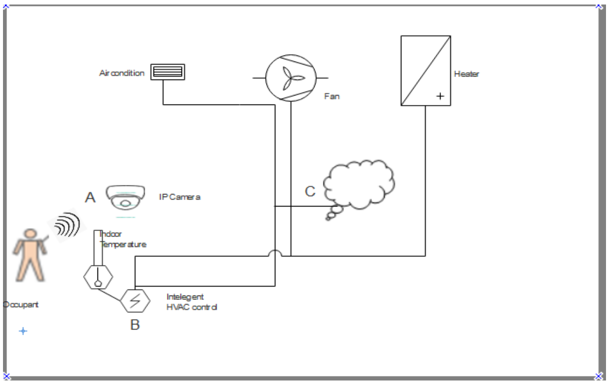

Figure 1: component of proposed approach

The Boolean value received would then be used as input to our second module in the Fuzzy rules sets to choose from available options depending on the condition of indoor and outdoor climate parameters and switch ON/OFF the electric appliance. However, there is a need to set up and modify a few variables that indicate image scaling to have an algorithm to load images, minimum closed detections to compose a single image, and minimum size of each detection. To have much more accurate and better detection we considered having three classifiers capturing the front face, head and shoulder, and upper bodies. For further clarification, we apply the same fuzzy rules with identical temperatures and humidity values that are established using fuzzy sets and linguistic variables (Meana-Llorián et al., 2017). These rules may be applied to outside temperature and humidity values that represent previously acquired fuzzy values. The control can decide the course of action to take to stabilize the room's temperature with the assistance of these data and the interior temperature.

4.0 Conclusion

Building occupancy prediction is an essential parameter in modeling thermal comfort control but it is often ignored or applied inappropriately. To attain higher energy saving and satisfactory comfort, occupancy number and desired comfort parameters are essential. This study added occupancy and desired comfort parameters to the existing. Research suggests that user experience on energy usage can contribute to the design of the rules for HVAC controllers to control how energy is utilized under various scenarios. The research provides a conceptual framework for HVAC energy control using occupancy parameters and in the future, we are looking to investigate adding other input parameters to the proposed approach to account for real-world scenarios to determine the estimated energy consumption during peak hours' period and provide the occupant with an option to decide on energy consumption. Because the proposed system only allows an occupant to specify the comfort preference level without presenting the current electricity tariff. Occupancy prediction can also be improved through the machine learning technique. Because using carbon dioxide to predict the occupants' number before the ventilation process and during the ventilation process is quite subjective. Another possible improvement in this study is an early temperature which will significantly improve energy consumption and thermal comfort by predicting occupant arrival and departure.

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