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Abstract. Most of the commercial buildings in Malaysia are still equipped with the legacy control for their Heat ventilation and air conditioning system (HVAC), which several studies claimed to have contributed to energy consumption in buildings. A significant amount of this energy is consumed by the building Heat Ventilation and Air Conditioning units. This is mostly due to the lack of smart and remote functionalities in the legacy HVAC systems to control the chillers and the Air handling units. This massive energy consumption is an antithesis to what governments all over the world are aiming for. However, scalability and deployment of low-cost resource-limited hardware embedded with control algorithms used to save energy in commercial building's Heat Ventilation and Air Conditioning (HVAC) units is a difficult engineering task. But the unprecedented advancement and perverseness of information technology services over the past two decades has led to an ever more connected world. This project will leverage the concept of the Internet of Energy to make the systems smarter and more decentralized for flexible energy usage. Modern-day devices are increasingly linked to the internet, creating what is now referred to as the internet of things (IoT). The IoT paradigm has provided technologists with the ability to remotely control devices, and with the recent progress in Machine learning (ML) and Artificial Intelligence (AI), devices are trained to make smart decisions that can independently influence human to machine interactions.

Keywords: Artificial Intelligence, Energy Consumption, Internet of Energy, Internet of Things, Machine Learning, Heat Ventilation and Air Conditioning.

1 Introduction

The estimated global energy consumption by the building sector both commercial and residential buildings is about 20%[1]. Couple this with accelerated population and economic growth, and we have a projected 1.3% increment in building's energy consumption from 2018 to 2050[2]. In addition to the massive energy consumption, the building sector accounts for two-thirds of halo-carbon, one-third of greenhouse gases, and 25-33% of black carbon emissions[3]. The energy consumption of commercial buildings in Malaysia rose from 91,539 GWH to 108,732 GWH in 2011; while the overall energy consumption of the country is estimated at 116 Million tons of oil equivalent in 2020[4]. Buildings in the United States alone account for 40% of the energy consumption, of which half of this is used up by Heat Ventilation and Air Conditioning (HVAC) systems[5]. Also, the growing energy costs, increase in restrictive environmental regulations, and request by consumers for better green and sustainable services are factors driving the calls for efficient energy management[6].

In light of this need for better energy management, a wide variety of Building Energy Analysis(BEA) modelling approaches have been developed by different scholars since the early 1990s[7]. Curram and Mingers [8] hypothesized that researchers can leverage current technologies to reduce electricity consumption in buildings by as much as 30 to 80%. This is a promising estimate but to achieve the energy reduction goal, an efficient and cost-effective system is needed. This research focuses on the following problem statements:

1. Legacy HVAC systems lack communication and smart functions needed for efficient energy-saving operations
2. The relationship between several factors affecting the efficient operation of HVAC systems is complex and non-linear

The rest of the paper is organized as follows: Section II presents a research background. Section III introduces the research methodology details on the project description, challenges, and concerns, and the preliminary simulations are described in the subsequent sections; finally, conclusion and future work in section IV.

2 Research Background

Many approaches proposed in the literature to improve the energy efficiency of the HVAC system use a simplified thermal dynamics model to predict the temperature evolution of buildings[9-13]. In Barrett and Linder [14] the authors designed and developed a nonlinear model of the building's HVAC system including the chillers, air handling units, and different temperature zones: the solution to this problem is a token-based Model Predictive Control (MPC) scheme to improve energy efficiency in the building.

Li and Xia [15] used the equivalent thermal parameter model to simulate air conditioners for Demand Response Programs (DR). And Jagarajan, et al. [16] proposed a simplified thermal model in the stochastic state-space and performance maps for predicting the coupled thermal response of a cooling unit. While Husin, et al. [17] implemented an aggregated model of a house cooling unit to establish the relationship between the external environment, indoor temperature, and the power consumption of the cooling system.

Borowski, et al. [18] proposed a dynamic control strategy to participate in demand response schemes by using a simple model of an air conditioning unit which was then further scaled to include many such units. The accuracy and performance of these models rely heavily on the thermal dynamic models and mathematics behind it. However, the occupant's comfort level and the temperature of the building are affected by several random variables that are very difficult to model accurately. Therefore, "it is often intractable to develop a building dynamics model that is both accurate and efficient enough for effective run time of HVAC control"[19]. This nonlinear and highly complex relationship between the environment and energy consumption of the HVAC system has encouraged researchers to actively explore the use of real-time data-driven methods with the use of Reinforcement machine learning models to approach this problem[20].

Feng, et al. [21] used classical Q-learning to optimize the reward function to control the HVAC system but this is not suitable for cases with large state space. The heat transfer process was modelled in Ascione, et al. [22] but the authors only evaluated the solution with a single-zone building. However, in 2015 a Deep Reinforcement Learning (DRL) algorithm defeated the world champion in the game of Go. This model shows great versatility in solving complex and nonlinear problems.

Importance of Internet of things and Machine learning 1- Internet of things can be used to transform legacy BAS into a more smart and efficient system. 2- Machine learning algorithms are effective in solving non-linear, complex problems. 3- The low power consumption, versatile, and open network architecture of the IoT devices can transform traditional BAS control architecture to a more decentralized and smart system to conserve energy in buildings.

3 Methodology

The solutions proposed in the literature are classified into three; white box, black box, and grey box[23-27]. The white box approach involves the design of the physics model of buildings. The model helps to form the problem, understand the improvements needed, and monitor the performance of the solution. The downside to this approach is that the relationship between the thermal variables of a building is complex and non-linear. Furthermore, this solution cannot be scaled because buildings have different characteristics[28-31].

The black box approach investigates the building-energy-related model without understanding its internal relationships. While the grey box approach or hybrid approach incorporates the properties of both the white and black box approach. These models were designed to eliminate the limitations that exist in either of them. Fazenda, et al. [32] created the model of a building using Energy Plus and fed the variables affecting the comfort and energy consumption of the building into a Reinforcement machine learning model. The model interacts with these variables to learn the relationships between them to create the best energy-saving policies. However, the centralized nature of HVAC systems is the main obstruction to accurate monitoring and control. This is mostly due to the lack of smart and remote functionalities in the legacy HVAC systems to control the chillers and the Air handling units[33]; Which usually leads to massive leakage in electricity consumption. But the advances in the field of information technology and engineering has brought about the paradigm shift to the Internet of Things(IoT).

The integration of the Internet for electrical energy transactions has contributed positively to the global energy market in many ways. Internet of Energy (IoE) seeks to build a self-managed smart electrical infrastructure that minimizes energy waste through the use of Building Automation Systems (BAS)[34]. IoE has brought about a revolution in power generation, storage, and transmission through the incorporation of sensors, the Cloud, smart grids, clean energy infrastructure, and Advanced Metering Infrastructure(AMI) (see figure 1). Furthermore, the massive but recent proliferation of distributed renewable energy sources is shifting the focus from the traditional top to bottom generation and distribution of electricity to a more decentralized system. However, with new technology comes new challenges. The most prevalent issues facing the IoE include Demand-side management, P2P sharing, Big data, scalability and security.

Accumulation of large energy data leads to the challenge of how to manage these data to get meaningful and actionable information. This presents a huge opportunity for data-driven approaches over traditional physics-based methods. This project will leverage the concept of the Internet of Energy and Machine learning to make the systems smarter and more decentralized for flexible energy usage. The projected outcome of this study is to produce:

1) Multi-zone control devices for data collection and actuation: To enable decentralized control of the HVAC system, the building is compartmentalized into zones depending on its weather condition. These data are collected by the sensors, processed and acted upon by the actuators retrofitted into the rooms.
2) Machine learning algorithms for data processing and prediction: The Machine learning algorithms are used to analyze the big data, predict the energy consumption, and the suitable temperature set-points for the zones.

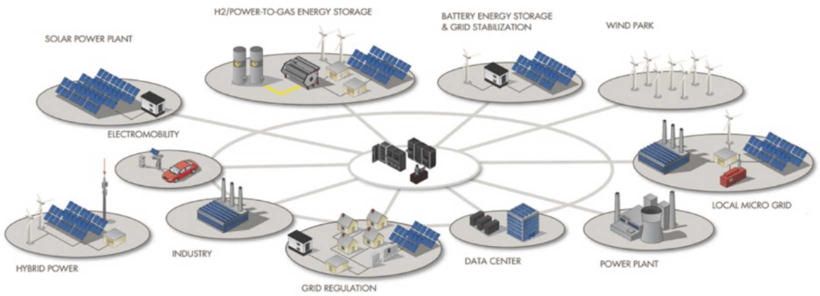

Fig. 1. Internet of Energy

3.1 Relevance to Government policies

This project is aligned with the Government's policy to focus on Research and Development in the Energy sector. It has become paramount for countries to be proactive in tackling the problems of global warming with efficient energy policies. Amongst the commitment made by the Malaysian Government to the 2015 Paris agreement was the voluntary reduction of up to 40% reduction of her Carbon emission intensity of GDP (Gross domestic product) with regards to the 2005 level[35]. Also, the country is aiming to reduce its green gas emissions for each unit of economic growth by 35% from 2005 levels by 2030; With international support, that could increase to 45%. Furthermore, part of the 11th Malaysian plan for encouraging sustainable energy use to support growth was improving the sustainability, reliability, and efficiency of the electricity sub-sector. The efficient management of electrical energy regulation of 2008 addresses the issue of energy efficiency by requiring more accountability from the big energy users of the industry. Some of the key points from the regulation require constant auditing of electrical energy management and proper in house policies to encourage efficient use of electrical energy such as the use of demand-side management[36]. Finally, the National Energy Efficiency Action Plan (2016-2020) encompasses all the other policies identified earlier. The action plan provides a detailed framework for how the country plans to reduce its energy consumption to meet international standards by 2025. And pivotal to this plan is the proper integration of demand-side management schemes to essentially help buildings monitor and effectively manage their energy consumption[37].

3.2 Proposed deliverable

The IoT architecture has three levels; the control, cloud, and field level. The field level comprises of the old BAS and IoT layer. Various sensor modules are set in each room of a zone (three rooms constitute a zone) and they total estimations on temperature, humidity, and CO2. The measurements are transmitted through a wireless network, powered using ESP32. Created by Espress if Systems, ESP32 is a low-cost, low-power chip (SoC) device with Wi-Fi & dual-mode Bluetooth capabilities. The ESP32 was chosen because of its versatile communication modules (Bluetooth and Wi-Fi) and very low energy consumption.

These parameters are transmitted into the Zone Module in each region that in turn uses weather forecasts from Web servers or clouds together with measurements to predict the minimum cooling energy needed in each field. The Zone Module solves a problem of optimization using Machine learning. The measurement results are the cooling levels from which mass flow rates are predicted and transmitted via Wi-Fi to the IoT Gateway. Furthermore, an IoT layer provides the use of Ethernet-based communications at the application level, such as the Message Queue Telemetry Transport (MQTT) and Advanced Messaging and Queuing Protocol AMQP. They take the IP extensions of the IoT layer into account. Network extension services for interfacing IoT and BAS components with the network via IoT Gateway are supported by the IoT Layer (see figure 2 for the overall architecture of the proposed solution).

The sensor module has the purpose of sensing the temperature, CO2, and relative humidity, and then transmitting measurements from several areas of a zone with wireless communication. In Figure 2 you can see the sensor assembly. The main processor is an ESP32 with interfaces between the sensors. The ESP32 is chosen due to its low power consumption and its well-designed power management system is fairly stable.

The temperature and humidity are measured using a DHT22 sensor. Similarly, the occupancy is detected using CO2 sensor MH-Z19.

1) Controller: The controller module consists of the latest Raspberry Pi Zero, an Arduino ESP32, a DHT22 (temperature and humidity sensor), and a CO2 sensor MH-Z19. The Raspberry Pi Zero is used due to its ability to perform complex computations using Python or other programming languages and the Linux Operation System. More importantly, and ESP32 has wife capability that is used for logging data into the central repository through the IoT gateways with the cloud.

2) Software architecture: The IoT has numerous software components that function in different layers. The Raspberry pi at the field level is programmed using Python. The prediction of the occupant's comfort and the energy consumption is also done with Python with aid of open source libraries such as Scikit learn and Tensor flow. The IoT services are implemented on web-based applications (e.g., Node JS) for implementing MQTT clients. The BAS application that transfers data from BACnet and Lonworks is readily available from the vendors and no conversion is made.

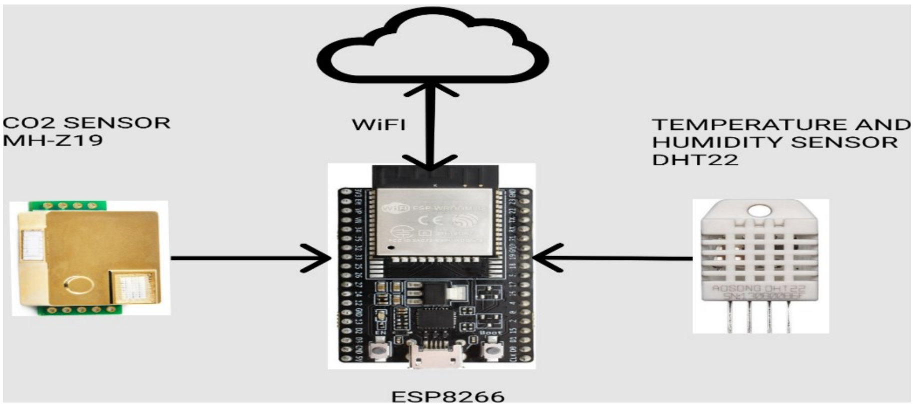

Fig. 2. Technical Architecture

The IoT gateway has interfaces to the different protocols using python and open-source software. The sensor node measurements implemented on an Arduino are transmitted using NRF24L01 to the RPi which aggregates it using python libraries (and AdafruitDHT) Then the RPi uses these measurements to compute the optimal cooling energy and transmits it to the central scheduler via Ethernet which is stored in a database using MySQL (See figure 3 for the overall architecture of the proposed solution).

4 Conclusion

This project aims to reduce the electrical energy consumption of HVACs in commercial buildings. Albeit recent government policies have made occupants and builders energy conscious, most of the existing buildings in Malaysia are not energy efficient. For economic and cultural reasons, the best solution is to retrofit these buildings with energy monitoring and saving devices instead of demolition and reconstruction. We will leverage bi-directional communication provided by IoT to connect the network of

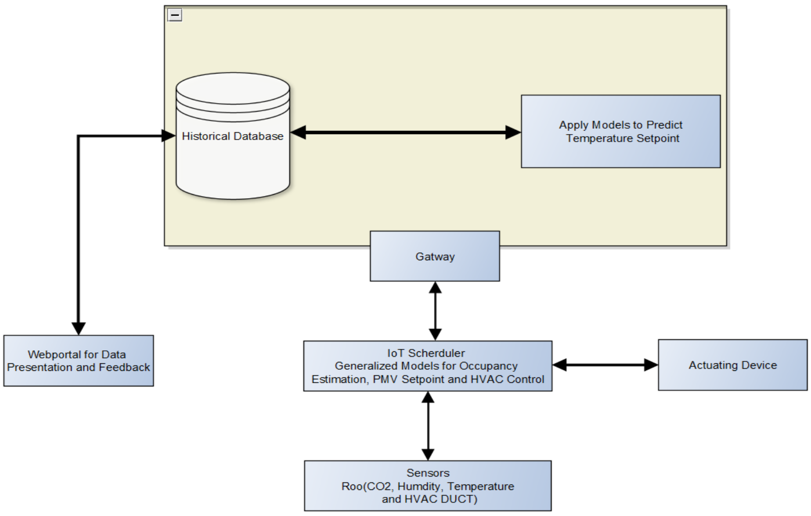

Fig. 3. The overall architecture of the proposed solution

HVAC in the building, and the subsequent big data is processed using powerful machine learning algorithms. The major reason for the huge energy consumption of centralized HVAC systems is the lack of proper monitoring. Primarily, the systems were not designed to provide feedback to building managers or operators. So a situation where a particular zone is over cooled will go unnoticed to the managers, leading to serious energy drain. Proper communication and actuation can eliminate this oversight. Energy consumption in buildings is dynamic, affected by different random variables. It is pure folly to simplify the energy consumption in buildings to binary problems or hardcoded into operational manuals. There is a direct correlation between building energy consumption and the random behavior of the occupants. Therefore, an effective BAS is smart and autonomous to reduce the energy consumption of a building while considering random occupant behaviors.

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