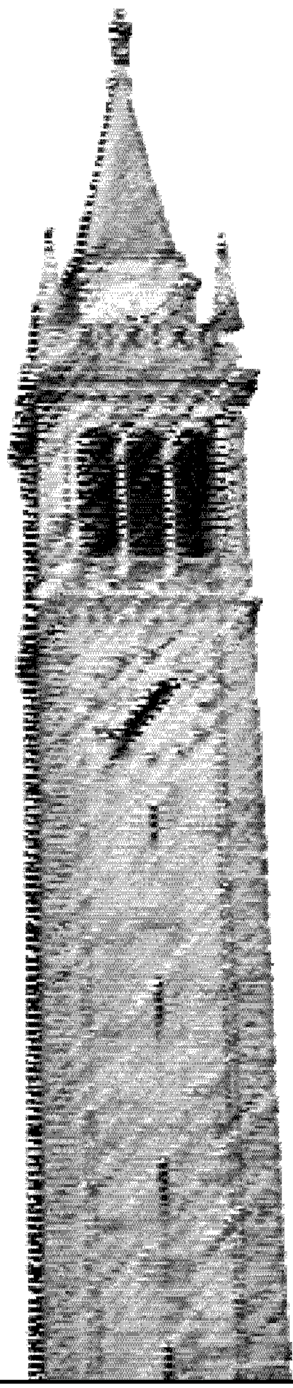
# Developing a Digital Twin for Indoor Environments: A Case Study



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# Developing a Digital Twin for Indoor Environments: A Case Study

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## Research Project

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Approval for the Report and Comprehensive Examination:

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### Abstract

A Digital Twin (DT) refers to a digital replica of a physical entity which holds a dynamic copy of the physical entity's state. With the rise of energy consumption in the built environment, it becomes an urgent matter to improve energy efficiency in buildings. DT has the potential to improve energy efficiency in a building. It can not only aid in optimizing energy usage in a building, but also act as a platform for testing building control systems. Current development of DT mainly focus on the field of smart manufacturing and product design and less on the building level. This paper presents a framework to create a digital twin for indoor environments for the purpose of occupants' satisfaction and energy efficiency. The initial experiment result builds a foundation in future DT development with a digital-physical heat loss comparison. The limitations, challenges, and future direction in creating DTs for the built environment are also addressed.

# Contents

# 1 Introduction

Energy consumption in the information age remains a challenge for industrialized nations worldwide. The world's industrial sector consumes around 54% of total delivered energy[1] worldwide [1]. Furthermore, this energy consumption has only increased in recent years and shows little to no signs of halting. Similar to energy consumption, overall worldwide carbon emissions set a record high in 2019 and the value is still increasing [2]. Since 1997, more than 1200 relevant policies in 164 countries, the countries that account for more than 95% of greenhouse gas emissions, have been recorded in public databases [3]. Countries are faced with constant external scrutiny from other countries and internal scrutiny from citizens to be accountable to their environment. This mounting global pressure and environmental concerns provide ample motivation to further reduce energy consumption worldwide. With this in mind, industrialized nations are scrambling to identify sources of high power consumption and attenuate the consumption from those sources.

Building power consumption in modern countries far outweighs most other forms of energy consumption. In fact, residential and commercial buildings, specifically, account for more than 40% of energy consumption worldwide [4]. With the primary culprit identified, the question remains how best to approach the deceleration and efficiency of energy consumption in building technology. Heating, ventilation, and air conditioning (HVAC) systems, entities that are moving mass through a building, are major sources of high energy consumption in the building [5]. The overall climate change produced by the ordeal of meeting a country's power needs put a severe burden on the local weather of many towns. Rising waters produce damp environments, hotter climates become hotter, and increased variability in the expected weather patterns cause residents to rely on these high-power-consumption HVAC systems increasingly, thereby worsening the power draw on the system as a whole, which then results in more carbon gas emission, and the cycle continues. The extreme temperature results in increased usages of the heating and cooling systems in the building to maintain occupants thermal comfort, which cause knock-on effect on the increment of global energy consumption.

Although these HVAC utilities are high power consumption entities, the total amount of power they consume can be limited and conserved via proper management. There has been significant past research and advancement in previous years regarding reducing energy comsumption of the HVAC systems while maintaining occupants' thermal comfort. For example, Hoyt et al. show that increasing the set point temperature by $1°C$ can reduce the energy consumption by as much as 15% [6]. Other research endeavors have been done to investigate occupants' thermal comfort in dynamic indoor conditions based on human response and circadian rhythm of body core temperature [7]–[10]. Berglund and Gonzalez [11] showed

[1]Delivered energy is the electricity delivered at the site of use but doesn't include the losses between conversions.

that a rise from 25 to 27 degree Celsius at a rate of 0.5 degree Celsius per hour would not be noticed by the occupants. In addition, occupants have a higher temperature tolerance in the afternoon with a 1.5 degree Celsius difference compare to the morning [10]. As a result, the dynamic set point temperature settings throughout the day is one potential method to help reducing energy consumption in buildings.

While Mishra et al. [10] did dynamic temperature control, Zou et al [12]. use occupancy positioning systems to detect the presence of human in the office to ensure that the luminosity and temperature are at an appropriate level in a particular area of the building. In addition, light sensors were deployed to maintain appropriate luminous levels given the lighting conditions from the window throughout the day [13]. Other research groups designed machine learning based HVAC controller to adapt human's behavior in the office and further optimize the energy used in the building [14]. Researchers also implement fault diagnosis to prevent degradation of the system which help reduce up to 30% energy consumption in a building [15].

With the emergence of Internet of Things (IoT) technologies, it opens greater opportunities for researcher to develop more efficient solution to help reducing energy consumption. IoT sensors can be deployed around the buildings and can provide information about the internal environment of the buildings. However, the collected data through IoT sensors in the building are often being underutilized. In recent years, the term "digital twin" has become popular in designing and manufacturing industry. Digital Twins (DT) refers to a digital replica of a physical entity which holds a dynamic copy of the physical entity's state [16]. DT technology can assist in preventing downtime of the systems by attributing anomalies in the physical/virtual twin system to defects or failing hardware [17]. This not only speeds the detection of faults potentially avoiding dangerous conditions to the internals of HVAC systems, but also is able to locate this failed hardware and have it be replaced in time to maintain system efficiency. Additionally, DTs can analyze and facilitate the manufacturing process to help in decision making [18] and optimize building internal control systems to prevent overshooting which results in energy loss [14]. Furthermore, it creates a better platform for data integration and allow better use for existing data.

DT technology research is still in its infancy and has vast potential to solve a number of modern energy issues. Current implementations of DT largely lie in product planning and manufacturing processes. For research related to DTs of the built environment, or man made living structures, most work addresses the theoretical concepts but lacks actual implementation or real-world experimentation. In contrast, this paper aims to develop a framework and implementation of a real-world digital twin of heat balance model in the built environment. The DT created in this paper utilizes the heat balance model in the built environment for the purpose of satisfying occupants satisfaction and improving energy efficiencies of the built environment's internal HVAC systems. Current challenges and limitations in developing DTs for built environments and the future direction of DT research is addressed.

# 2 Related Work

The "twin" concept of a digital twin originates from NASA, where they kept the *physical* twin on the ground to replicate the situation in space and help dissolve complications that happened during operations [19]. Outside of the actual launch phase, NASA has used digital twins for robust testing of its components during dynamic testing and quality assurance. In this fashion, the digital twin could be configured to account unknown or unforseen circumstances aboard a space-borne vessel. While NASA used DT technology to increase the degree of testing on important components to save time and improve testing quality in ultra-high-fidelity testing suites, DT technology can likewise be used to avoid in-situ building efficiency experiments, where the comfort and time of participants are at stake.

Grieves and Vickers [16] defined DT as a virtual entity that has the complete details of the physical system, meaning that the information retrieved from the physical system should match with that of the virtual twin. Currently, most DT applications lie in the fields of product design, production, and manufacturing. For example, Fang et al [20] develop an architecture for a DT-based job scheduling in the smart manufacturing field. Their DT is based on Demo3D, a modeling software used for prototyping systems and equipment. Their virtual system is able to respond to unexpected events and reschedule the worker in a timely manner. Another example in operations and manufacturing systems is proposed by Leng et al [21]. They develop an architecture of a DT-driven prototype manufacturing cyber-physical system (MCPS) where they integrate data, system network, decision, and control into one place. Both of these examples focus on smart manufacturing and optimizing the decision planning of their resources.

In recent years, several companies including Johnson control [22], Enertiv [23] , and Willow [24] have invested in building a digital twin for built environment in order to reduce maintenance costs and facilitate building management. Their virtual model included spatial information, static information, and real-time sensor data to allow remote operations and monitoring. In addition, several research institutes and enterprises started an EU-funded project, SPHERE [25], which aims to develop a DT by performing vertical integration where they combine design, construction, manufacture, and operation systems into one platform. Their DT is based on the Building Information Modeling (BIM) systems.

BIM is widely used in building projects to assist in management, planning, and maintenance [26]. However, it does not require synchronization with sensor data deployed in the building. As a result, most sensors in the building are underutilized. For example, BIM can maintain occupants' comfortness based on room temperature and $CO_2$ concentration in the air. However, it does not take into account the full factors that may affect occupants' satisfaction such as occupancy and radiant heat from windows. BIM system is usually used in design and construction phases and rarely get update overtime, while the DT model continuously receive information from the physical building and adjust the model to better match the physical entity. In addition, DT can perform background analysis to facilitate in control decisions for the real building. Although BIM is distinct from the DT, it has a high potential in developing into a DT in the built environment. Another work that is built on the BIM system is done by Lu et al. [27]. They propose an architecture of DT in the built environment by integrating data sources from different systems. Similar to the SPHERE project, the research in built environment currently mainly focus on systems integration when developing a DT.

Most research provide framework on building a DT. However, they lack real-world implementation of the concept. Francisco et. al. developed a digital twin of energy management in a smart city where they monitor the smart electricity data to access building energy performance [28]. Though they provide a real-world example, they rely on energy meter data solely to create the energy benchmark for buildings during different period of time. One limited experiment was carried out by Khajavi et al. [29] where they build a DT of building's facade. They explore three environmental parameters: lighting, temperature and humidity and establish a sensor network to create a DT. Bluetooth technology is used for data transmission to reach synchronization between the physical system and the model. This is a preliminary study on DT in the built environment and may provide a basis for building a larger network.

Although the works of the above authors are substantial, we have found our work to be unique among them due to it's real-world implementation and applicability. In addition, while most research relies on systems integration to develop DTs, we focus on low level development where we analyze the model from ground up. The goal of this paper is to tackle the limitations of the current state-of-art DT in smart building and provide a real-world context of developing a DT.

# 3 Case Study

## 3.1 General Introduction

The case study [30] aims to develop a DT in a indoor environment of a building for the purpose of improving energy efficiency and occupants' satisfaction. The experiment was conducted in a well-instrumented lab located in Singapore. Even though in the real world, not every building spaces have comparable amount of sensors mounted compare to the testbed, we aim to use testbed as a foundation to provide a framework and implementation examples.

The two main questions that needed to be addressed are:

1. How many sensors needed to be deployed in order to create a DT for indoor environment?
2. How to evaluate whether the virtual model matches the physical space?

Instead of building the virtual model from ground up, we utilize the existing building model, EnergyPlus, to facilitate the realization of the DT. EnergyPlus is a widely known open source building model simulation software [31]. The main purpose of EnergyPlus is to model the energy consumption of a building including heating, cooling, ventilation, lighting, water usages, and plug load. However, the model can also output the temperatures and air mass flow rates between equipments in a sub-hourly time step. We make use of this output function to create a digital twin for a heat balance model of testbed rooms. Our DT of indoor environment doesn't focus on the spatial information (e.g. 3D architecture) of the test bed, but the environmental measurements, such as temperature, air flow rates, and humidity. The purpose of our experiment is to synchronize the data between the physical sensor measurements and the model output.

## 3.2 Design Framework

We propose a framework of a live connection between the physical entity and the virtual model as shown in Figure 3.1.

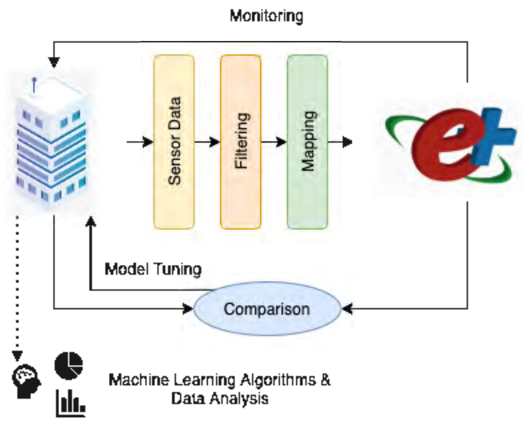


Figure 3.1: The framework for the connections between the physical system and the EnergyPlus model.

### 3.2.1 Data Collection

There are more than 300 hundred sensors placed throughout the laboratory. The measurements include but are not limited to temperatures, humidities, flow rates, pressure, valve openings, and heating/cooling powers. They are placed at several locations in the testbeds. Although these sensors are all used in the testbed, this experiment specifically focuses on the air sensors. Additional details are covered in the implementation section. All the collected data are stored in the PI System, which is a data management platform developed by OSIsoft. The data is collected in 15-minute intervals. This is set to be equal to the internal timestep of EnergyPlus.

### 3.2.2 Filtering

After successfully retrieving the data, essential filtering is needed to eliminate the noise of the data. Undesired noise may result in diminished model accuracy, especially for longer experiments. The filtering techniques used are based on human knowledge of the sensors and historical data of the measurements. Two methods are applied in this step:

1. Upper and Lower bounds
2. Moving Average Filtering

Upper and lower bounds are set by existing knowledge of the domain of the signal coming from the sensors and the human knowledge of the settings of the environment. Moving average filtering is then applied to help smooth the time series data by replacing each data point with the average of neighboring data points.

### 3.2.3 Mapping

The sensor measurements from the physical buildings are often not the direct inputs or outputs for the EnergyPlus model. First, we would like to different two terms used in this paper: *user input settings* and *EnergyPlus inputs and outputs parameters*. User input settings are environmental controls that are available to occupants. EnergyPlus inputs parameters are measurements from sensors or inferred information from the sensors that are not directly controlled by occupants. Table 3.1 shows a list of parameters for each term. These terms are selected based on the experimental design for this paper. More details will be described in section 3.3.

Table 3.1: List of user input settings and EnergyPlus input parameters.

| User Input Settings | EnergyPlus Input Parameters | EnergyPlus Output Parameters |
|---|---|---|
| Set Point Temperature | Material Properties | Temeperature |
| Supply Air Temperature | Chilled Water Supply Temperature | Air Mass Flow Rate |
| Equipment Load | Outdoor Temperature | |

In addition, the measurement units taken from each system may not coincide. Necessary unit conversion needs to be done for correct mapping. In the mapping phase, one crucial decision that needs to be made is the number of signals that are essential to pass into the model. Having refined parameters can not only save computational power, but also provide a higher potential to extend to other similar model.

### 3.2.4 Comparison and Model Tuning

After successfully linking the sensor data to the model, we need to tune the model to match the physical entity by comparing outputs. Having a meaningful comparison of outputs between the physical system and the virtual model are important. Comparing all the parameters are computationally expensive and there might not be a corresponding sensor in the physical system with respect to that of the model. The purpose of our experiment is to match indoor environment parameters. As a result, one of the comparison metrics we use is to compare the amount of heat removed in the indoor space between the actual space and the virtual twin. Although just matching the heat removal parameter may not be sufficient to conclude that the physical and virtual system are identical, we can say that they behave in a similar way given the user input settings. Further metrics need to be developed to guarantee that the model matches closely with the physical system. However, this metric development will not be the focus of this paper.

Model tuning is needed if there exists deviation between the output comparisons of the physical and virtual systems. To approach the issue, we searched the parameters that are sensitive to the output changes. If applicable, we estimate those parameters based on the physical system's sensor measurements and apply to the model. Lastly, trial and error method is used to improved the matches between the two systems, physical and virtual.

### 3.2.5 Monitoring

One requisite backbone of the DT is the cross-talk between the the physical entity and the virtual twin. This is the key differentiation between DTs and other simulation models. Once the virtual model matches closely to the physical system, it can provide real-time feedback to the physical system. The DT can identify abnormal data or large discrepancies that may be caused by machine failure. One application is in fault detection and diagnosis for the building systems, which prevent unexpected machine failure and reduces maintenance cost. In addition, the response time for system failure can be massively reduced. The DT can not only send out warning signals, but also allows technicians to inspect the system virtually and address the problem in the most efficient manner.

Moreover, occupants' comfortness can be accounted for with DT. There remain possibilities for the DT to learn individual's preference of temperature and lighting based on past data, which in turn optimize the settings of the environment. DT can address the change of the environment immediately and provide recommended updates of settings for the physical system. For example, if the radiation from the sun is larger, the DT can recommend the physical system to lower an automated window curtain instead of increasing the cooling power of the HVAC system, thereby saving substantial power in the long run.

DT can provide constant screening checks of the physical system and optimize its settings while improving energy efficiencies and occupants' comfort in an indoor environment.

### 3.2.6 Machine Learning Algorithms and Data Analysis

DT integrates all the data from the physical entity and provide complete information of the building. This opens wide opportunities in machine learning and data analysis fields. Research related to buildings are often data hungry and it may takes months to conduct a single experiment. With DT, researchers will be able to use it as a platform to obtain real building data and run experiments without interrupting or disturbing the actual physical spaces and their occupants. The virtual model can be used to predict future data of the building which can not only anticipate system failure but also provides feedback for unknown or unforeseen scenarios. In addition, if DT perfectly replicates the physical building, it can be used to test machine learning based control systems. In recent years, deep reinforcement learning has been used extensively in designing building control system in order to adapt to the human-in-the-loop environments. However, the main challenges for reinforcement learning to adapt to actual buildings are the length of the training time required and the inability to explore the entire search space due to the impact on occupants' comfort. With DT, reinforcement learning algorithms can be trained in the virtual representation of the actual building and apply the the actual system after the training is complete.

Furthermore, it may be cost-ineffective or impractical to place a new sensor in the actual building. However, this can be easily done in DT, where virtual sensors can be placed anywhere. DT has the potential to provide more complex information that is normally hard to obtain in the physical system. The additional information may be useful to further optimize the energy efficiencies and occupants comfort in the built environment.

### 3.2.7 Real Time Synchronization

In the previous mapping section, we differentiate the user inputs and EnergyPlus inputs/outputs parameters. The goal is that we want to match the EnergyPlus output parameters with the physical system's output parameters when given the same user settings to both systems. Figure 3.2 shows the data flow of the system to achieve real time synchronization. Ideally, the model is continuously comparing itself with the physical entity and calibrate if needed to stay up-to-date to the current physical system.

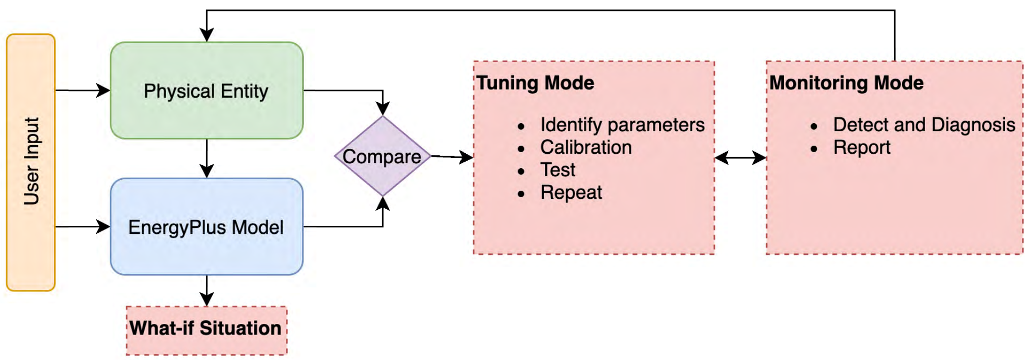


Figure 3.2: Data flow of the physical and virtual systems.

## 3.3 Implementation

### 3.3.1 Physical Testbed

The digital twin was created using a well-instrumented testbed located in Singapore as shown in Figure 3.3. There are a total of four testbed rooms, each with an area of 25 $m^2$ and a height of 2.6$m$. The testbed supports remote operations and offers well-regulated inddor environment. In addition, the testbed is insulated from the outdoor weather. As a result, it won't be affected outdoor temperature and solar radiance. However, there exists daylight emulator to emulate outdoor weather if it's needed for the experiment.

For the experiment, we will be focusing on creating a DT for heat balance model of Room 3 indicated in Figure 3.3. The indoor space of the testbed is shown in Figure 3.4. There are measurement equipments, table, chairs, personal fan, computer, and heater in the room.

The HVAC system of the room is decoupled into four parts: Room Water Loop, Air Handling Unit (AHU) Water Loop, Air System, and Outdoor Air Emulator. Talbe 3.2 shows a list of measurements in the testbed. This is not an exhaustive list. The measurements are taken at several locations throughout the entire system. We aim to develop the heat balance model of the room, where we try to match the heat removal rate between the physical room and the virtual model based on EnergyPlus. Consequently, we'll be focus on the air system of the testbed.

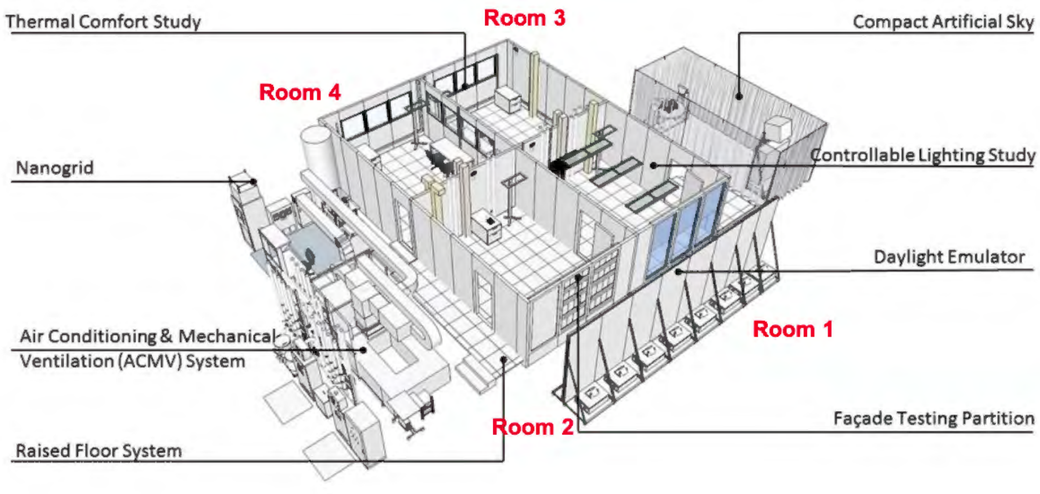


Figure 3.3: Well-instrumented testbed located in Singapore.


Figure 3.4: Indoor space of Room 3.

Table 3.2: Available sensor measurements for the testbed.

| Category | Parameters |
|---|---|
| Room Water Loop | Water Flow Rate<br>Bypass Valve Opening<br>Chilled Water Supply Temperature<br>Chilled Water Return Temperature |
| AHU Water Loop | Water Pressure<br>Water Flow Rate<br>Bypass Valve Opening<br>Chilled Water Supply Temperature<br>Chilled Water Return Temperature |
| Air System | Temperature<br>Relative Humidity<br>$CO_2$ Concentration<br>Air Flow Rate<br>Air Damper Opening<br>Static Air Pressure |
| OAE | Temperature<br>Relative Humidity<br>Air Flow Rate<br>Static Air Pressure |

There are a total of two Air Handling Units (AHU), where two rooms share one. However, each room has its own heater and Variable Air Volume (VAV) in its duct for individual control. The air system connection is shown in Fig 3.5.

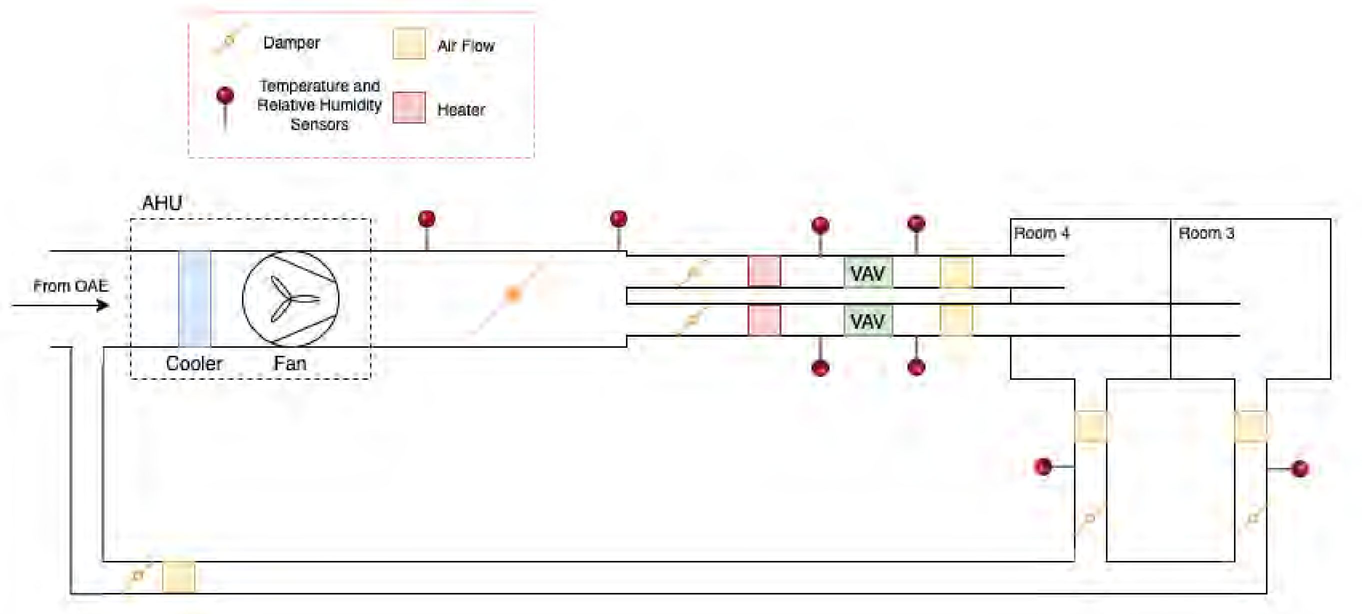


Figure 3.5: The air system connection of the physical building.

There are sensors that measured temperature and humidity locate between each system shown as red pin point on the graph. In addition, air flow rates are also measured in the supply and the return duct.

### 3.3.2 EnergyPlus based Digital Twin model

The EnergyPlus model was original created when the testbed was first built, and it wasn't updated since then. The model was used for estimating energy consumption of the testbed. The DT for the testbed was built based on the existing EnergyPlus model in addition with python script to assist with input and output tracking.

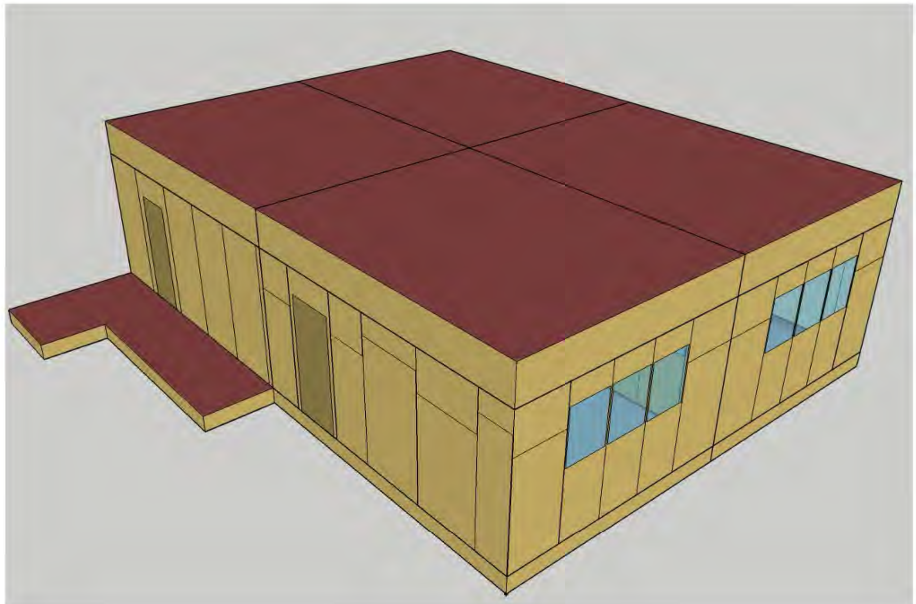

Figure 3.6: EnergyPlus 3D spatial model.

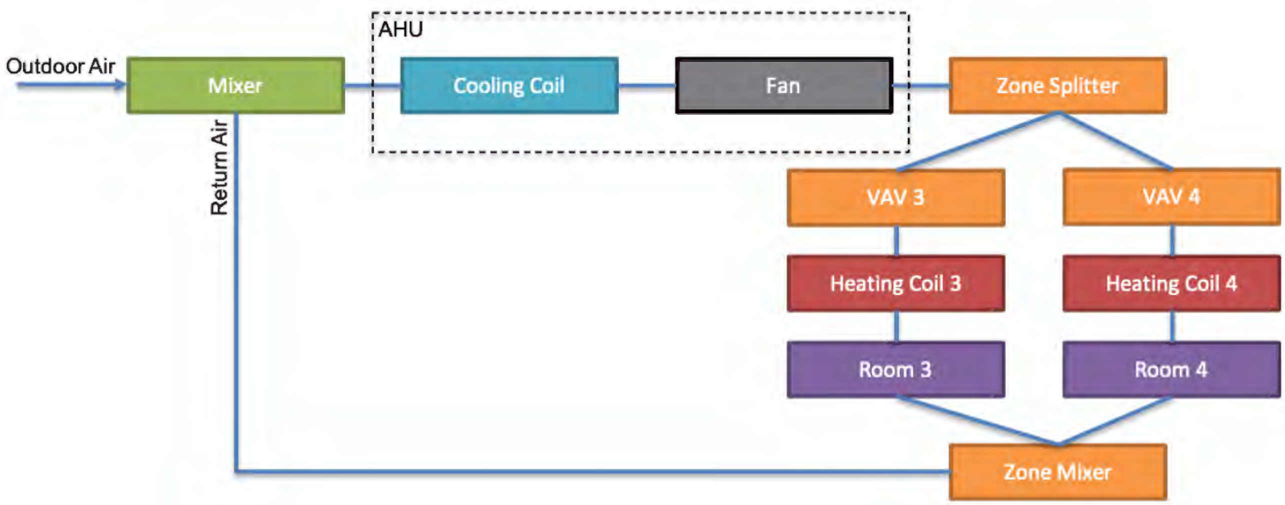


Figure 3.7: EnergyPlus node model for the airsystem of AHU2 which connects to Room 3 and Room 4.

Fig 3.6 shows the EnergyPlus 3D spatial model of the testbed and Fig 3.7 shows the EnergyPlus node model which describes the connection of the equipments in the air system. First, outdoor air is mixed with the return air from room 3 and room 4. Then, the air will go through the AHU system which contains the cooling coil and fan. Here, the air is modulated to reach the desired supply air temperature which supply to both rooms. Each room has its own Variable Air Volume (VAV) which regulates the volume of the air that is sent to the room. Subsequently, the air pass through the heater to adjust the temperature to desire temperature before sending to into the room.

There are hundreds of parameters in the EnergyPlus model. We group them into four different categories: structure, material properties, operation parameters, and output parameters. They are shown in Table 3.3. This is not an exhaustive list. We mainly focus on the parameters that are used for the experiment. The structure describes the location, geometry, and the zone sizing of the testbed. The materials of the testbed include the ones that are used for ceilings, walls, floors, windows, and doors. Parameters for the materials consist of the material's thickness, conductivity, density, and specific heat. Next, there are operation parameters, which can be scheduled and customized based on the experimental design. Lastly, the output parameters are chosen for the purpose of our experiments, which are temperatures and air flow rates. Both values are measured between each node in Figure 3.7.

Table 3.3: EnerguPlus Parameters

| **Category** | **Parameters** |
|---|---|
| Structure | Location<br>Geometry<br>Sizing |
| Material Properties | Thickness<br>Conductivity<br>Density<br>Specific Heat |
| Operation Parameters | Chilled Water Supply Temperature<br>Air Supply Temperature<br>HVAC ON/OFF<br>Set Point Temperature<br>Equipment<br>Light |
| Output Parameters | Temperature<br>Air Flow Rate |

### 3.3.3 Experimental Design

Factorial experiment was designed to perform initial tuning of the EnergyPlus model. There are a total of three independent variables: set point temperature, air supply temperature, and thermal load. Factorial experiment allows us to study the relationship between the independent variables and the effect on the response variables, heat removal rate.

The conditions of the independent variables are set to normal building operation values and are distinctive enough for analysis. Set point temperatures are set to 24 $°C$ and 26 $°C$. Thermal load of the room is achieved by using heaters, which are set to deliver 500W, 750W, and 1000W. Lastly, air supply temperatures are set to 13 $°C$ and 15 $°C$. It is a $3 \times 2 \times 2$ factorial design with 12 conditions as shown in Table 3.4.

Table 3.4: Factorial Experiment Design with three independent variables: Set Point Temperature (A), Thermal Load (B), and Supply Air Temperature (C).

| | $A_1(24°C)$ | $A_2(26°C)$ | $A_1(24°C)$ | $A_2(26°C)$ | $A_1(24°C)$ | $A_2(26°C)$ |
|---|---|---|---|---|---|---|
| | $B_1(500W)$ | | $B_2(750W)$ | | $B_2(1000W)$ | |
| $C_1(13°C)$ | Group 1 | Group 3 | Group 5 | Group 7 | Group 9 | Group 11 |
| $C_2(15°C)$ | Group 2 | Group 4 | Group 6 | Group 8 | Group 10 | Group 12 |

The 12 combinations of settings are carried out twice with 2 hour duration in testbed 3 and 4. As a result there are a total of 24 experiments. The experiment timeline for a day is shown in Figure 3.8.


Figure 3.8: The timeline for a day of experiments.

Experiments start at 9 am and end at 9 pm with 2 hour duration for each experiment. Six experiments were run in a day and the experiments were done in 4 consecutive days in August 2020. In the next section we will discuss the experimental results and analysis.

# 4 Analysis and Results

To analyze the experiment, we run EnergyPlus with the same input settings as given in the experiment, which include set point temperature, thermal load, and supply air temperature. Then, we continuously update EnergyPlus Input Parameters as listed in Table 3.1 in 15-minute intervals. Lastly, We compare the heat removal rate of experimental results and EnergyPlus output.

We focus on the steady state analysis since EnergyPlus doesn't model the transient state well. Out of the 24 experiments, about half of the experiments did not converge to the corresponding set point temperatures within the 2-hour experiment time frame. As a result, only 13 experiments were analyzed. The reason that the experiments did not converge may be due to high thermal load and high supply temperature that exceeded the cooling capacity of the testbed. Though about have of the experiments did not converge to set point temperature, our purpose for the experiment was to perform an initial calibration. Therefore, 13 experiments are sufficient for our analysis.

To verify that the EnergyPlus DT model matches fairly closely to the physical system, we developed a metric by comparing the heat loss between the physical and virtual systems. Comparing all the parameters that are not inputs to EnergyPlus is another way to verify that the virtual system matches the physical testbed. However, it is not computationally effective and the parameters may scale exponentially for larger physical spaces. Heat loss from a room is calculated by using equation 4.1.

$$h = c_p \rho q \Delta t \tag{4.1}$$

where $c_p$ is the specific heat of the air, $\rho$ is the air density, $q$ is the air flow rate, and $\Delta t$ is the difference between the return air temperature and the supply air temperature.

Figure 4.1 shows the heat loss comparison between the experiment and EnergyPlus model before the calibration. The amount of heat loss is calculated at steady state using equation 4.1. The red line indicates the heat loss from the experiment and the green line shows the heat loss in the model. As seen in the figure, the heat loss between the experiment and the virtual model deviate severely. Next, we'll discuss how we calibrate the EnergyPlus model to better match the physical system.

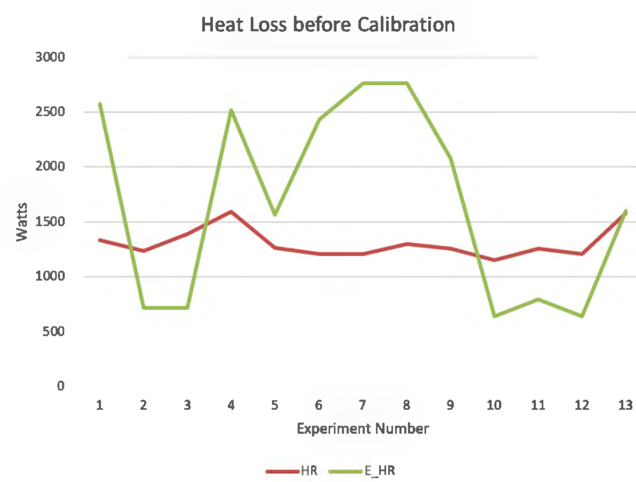


Figure 4.1: Heat loss comparison between the experiments (red) and EnergyPlus model (green) before calibration. The x-axis is the 13 experiments for analysis and y-axis is the amount of heat loss for the room in steady state.

To calibrate the EnergyPlus model, we create a simple thermal circuit model of the room to better understand the heat transfer that occurs in the room. Figure 4.2 describes the thermal circuit model. There are two heat sources in the room: thermal load that is placed in the room during the experiment and the parasitic load that is caused by other equipment in the room. Then, the heat can either be removed from the HVAC cooling system or through the walls.

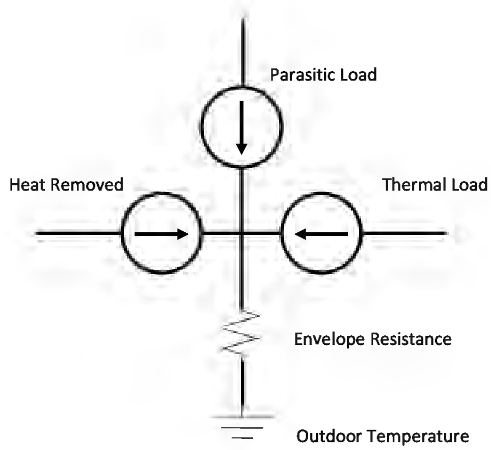


Figure 4.2: Thermal circuit model

The equation for the thermal circuit model is shown in equation 4.2:

$$T - T_{\text{out}} = (h + TL + PL) \times R \tag{4.2}$$

where T is indoor temperature, $T_{\text{out}}$ is outdoor temperature, $h$ is heat loss of the room, $TL$ is thermal load that's placed in the room, $PL$ is parasitic load, and $R$ is the envelope thermal resistance of the wall. Here the unknown values are the parasitic load ($PL$) and the envelope thermal resistance of the wall ($R$). We aim to estimate those values and incorporate them into the EnergyPlus model. There are a total of 13 equations and 2 unknowns. We estimate the parasitic load and the envelop thermal resistance of the wall by using the least square method, where we minimize the square error for the thermal circuit model. The objective is shown in Equation 4.3.

$$\min \sum_{i=1}^{n} \left(\frac{T_i - T_{out,i}}{R} - h_i - TL_i - PL\right)^2 \tag{4.3}$$

The estimated values are then used for calibrating the EnergyPlus model. Then we plot the heat loss comparison again in Figure 4.3.

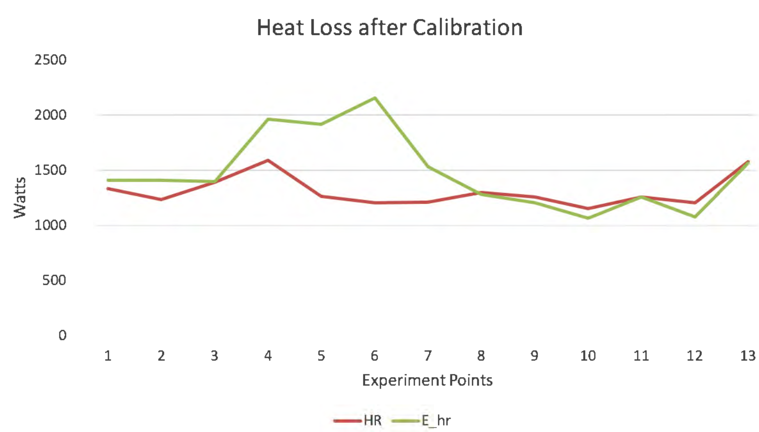


Figure 4.3: The comparison of the heat loss between the EnergyPlus model and the physical entity. The red line represents heat loss from the physical entity for each expeirment and the green line represents the heat loss from EnergyPlus.

# 5 Discussion

As shown in Fig 4.3, after incorporating the parasitic load and envelop resistance of the wall, the heat loss between the physical and virtual entities matches better than before. The deviation for experiments 4, 5, 6, and 7 may be due to the model overestimating the cooling needed for these experiments. They all have higher load and higher supply temperature than input settings. However, there are several other factors that may cause the deviations and it is hard to determine the main cause.

For the purpose of our experiment, there are 7 sensors needed in the physical systems: supply air temperature, room temperature, return air temperature, chilled water supply temperature, outdoor temperature, supply air flow rate, and return air flow rate. Two other variables, parasitic load and envelop wall resistance, are inferred based on the sensor measurements. The model was evaluated using heat balance model where we compare the heat loss between the physical and virtual systems. Although the result is still far from the DT definition, it can act as a stepping stone for future development. Next, we will discuss some challenges with EnergyPlus.

The main challenge for using EnergyPlus as a base for creating a DT is that EnergyPlus requires intensive manual effort to create and tune the model. In addition, to achieve more sophisticate controls, new custom program need to be written using its Energy Management System (EMS). Furthermore, EnergyPlus lacks generalizability and scalability. Each new space or building will require a new EnergyPlus model and building the model from ground up is time consuming.

Next, the experimental limitations will be addressed. Conducting the experiments in a well-instrumented testbed is not comparable to the real life office space or building, where the number of sensor deployment is not highly dense. In addition, real office spaces are often not well regulated compare to the testbed and may experience more noise in sensor measurements. Furthermore, there are more factors that need to be considered other than the three independent variables in the experiment. To realize DTs in the built environment, these factors need to be considered. The testbed was used as a starting point to facilitate in creating a DT because of the existing EnergyPlus model and the large amount of sensors already deployed in the space. Using the well-instrument testbed can not only simplify the experiment, but also help creating the foundation of building a DT. For example, essential parameters can be identified beforehand and we can limit the number of sensors that is needed to be deployed in the real office building. Moreover, we want to examine whether EnergyPlus is a viable option to act as a base to realize a DT.

# 6 Conclusions

The experiment shows the comparison of the heat loss between the physical testbed and virtual model. Though the simulated result matches fairly closely in most of the experiments, it is not sufficient to conclude that they are identical to each other. More experiments need to be done to validate the model. One key challenge in creating DTs is that even extremely well instrumented space can rarely provide enough information to match the very detailed level of abstraction that is available in physics-based models such as EnergyPlus. In addition, to realize the DT, we need to develop systematic metrics that can act as a benchmark for comparing the physical system and its DT. On top of that, the model needs to be generalized so that it is applicable to all buildings.

From this experiment, we learn that EnergyPlus may not be an ideal platform in creating the DT. In future work, we plan to create DTs for indoor environments by architecting its physics-based model exactly at the level of abstraction that can be supported directly by either the available sensors streams, known material properties, and the physical dimension of the space we are modeling. Furthermore, alongside the physics-based model, a "black-box" model using modern machine learning techniques can also be a great value in realizing a DT.

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