Accurate quantification of HVAC energy savings without a historical baseline

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1 Introduction

HVAC energy consumption plays a significant part in building operating cost due to the high electrical consumption and maintenance costs associated to its operation [1]. On a global scale, buildings contribute 36% of global energy consumption and 39% of energy-related carbon dioxide emissions [2]. To reduce carbon emission and enhance global environmental sustainability, much research has been conducted in energy efficiency to minimize building energy consumption [3]. Research includes a combination of selecting highly efficient equipment, monitoring and fault detection as well as supervisory control [4]. In recent time, with the rapid advancement of integrated circuitry, IOT sensors have been used intensively in HVAC energy optimization [5, 6]. One such solution is provided by SensorFlow who use a combination of IOT occupancy sensors, smart thermostats and smart energy meters to control room air temperature/humidity and optimize energy usage based on occupancy detection, as shown in Figure 1. This optimization may include turning off equipment or increasing/decreasing air-temperature setpoints in cooling mode/heating mode respectively when occupancy sensors detect no presence of humans indoor. The SensorFlow solution has been adopted in many hotels across the South East Asia region, showing a strong performance in reducing a buildings energy consumption.

An important aspect of energy optimization is to quantify the energy savings achieved. This is a significant factor for the clients to decide whether thwy should adpopt the solution. Tuominen et. al. [7] show that low adoption of HVAC energy efficiency solutions is often due to the lack of trusted projected savings information. Benedetto et. al. [8] did an intensive review on quantifying energy savings for retrofitting scenarios in buildings including both deterministic and data-driven methods. For all the methodology mentioned in [8], a baseline model is required to compare with the actual measurement of the retrofitting resulting in energy savings. Baseline models can be constructed through energy simulation software, which requires knowledge of building structure, or data-driven modeling technique which require building historical data prior to the retrofitting.

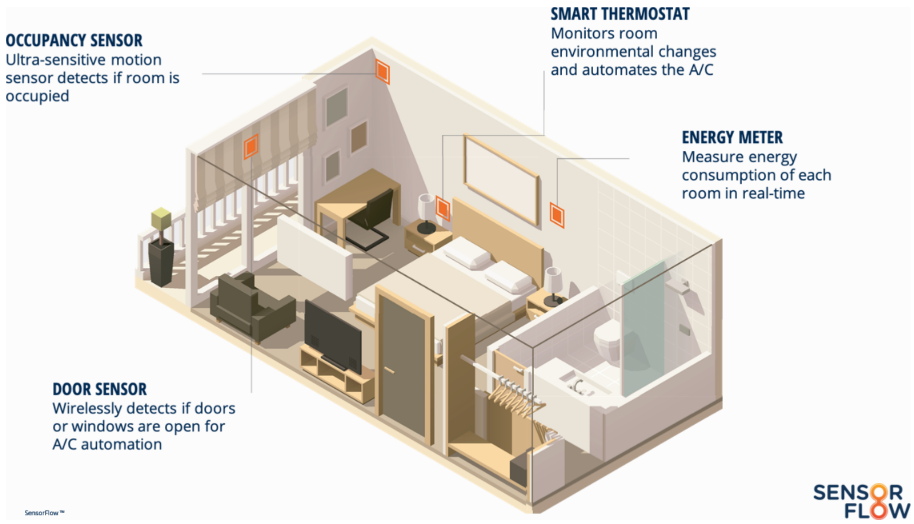

Figure 1: SensorFlow Solution with sensor network, smart thermostats and smart energy monitoring device.

Kissock and Eger [9] suggested to use cooling degree days (CDD), historical energy bills and building occupancy data to build a regression model as a baseline model. Unfortunately this information is usually not available for the majority of buildings in South East Asia. Energy measurement sensors and monitoring are only installed with the retrofit solution, so no detailed data is available on pre retrofit periods. Furthermore past energy bills include more than just HVAC consumption which make it hard to quantify the savings achieved on optimising the hvac system only.

Different from other HVAC energy efficient solutions where optimization is applied by replacing old inefficient equipment or changing operational control algorithm [10, 11, 4, 12], SensorFlow's Solution optimizes energy usage based on occupancy data, i.e. presence of humans indoors. This optimization, hence, only occurs during a certain period of time, e.g. when no human is presents, and with advanced sensors, this period can be precisely recorded. In addition to automating the air-conditioning turn off and turn on based on human presence, SensorFlow's solution also provides a setpoint limitation feature i.e. the setpoint of the HVAC system can be automatically limited to not go below a certain pre-selected setpoint. This paper presents a data-driven approach to quantifying energy savings using SensorFlow's energy efficiency solution by building a baseline model using data recorded during the period after the retrofit installation. The baseline model will then be used to compute the energy saving achived from performing occupancy based changes to the HVAC system load. The baseline model in this paper is constructed using a gradient boosted machine (GBM) model which is proven to be highly accurate in building energy modelling [13]. The accuracy of the baseline model is assessed by 5-fold cross-

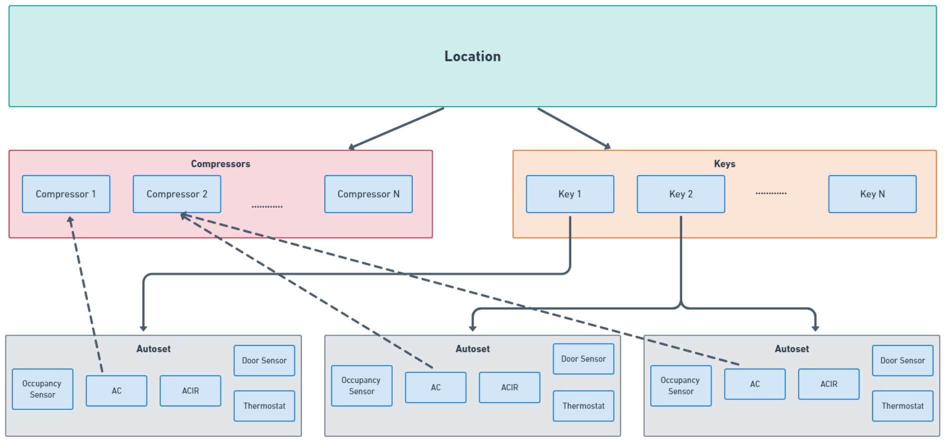

Figure 2: SensorFlow HVAC Sensor System Layout.

validation (CV) R^2 and RMSE criterias. The paper is organized as follows: the next section will describe the data collected by SensorFlow for model training, Section 3 describes a process of modeling baseline model while Section 4 provides a method to accurately quantify the energy savings, Section 5 presents a case study of a hotel using SensorFlow's solution and Section 6 concludes the paper.

2 Data Description

This section describes the data that is recorded and utilized by the SensorFlow system to build the baseline model. Data is organized in a hierarchical manner which mirrors the building layout of a hotel and it's HVAC structure.

The design of our data hierarchy closely mirrors the physical setup of this HVAC system layout depicted in Figure 2. SensorFlow adopts a tree-like data structure where a location represents the concept of a parent that encapsulates all underlying data pertaining to it.

A location (hotel) comprises keys and compressors. A key represents a room or collection of rooms in a hotel, analogous to the space a single physical hotel key would provide access to. It is important to note that a key could contain both a single and multiple number of rooms. As indicated by the green arrows in Figure 2, within each key are contained one or more autosets. To each autoset belong multiple nodes (i.e sensors / devices). An autoset, short for automation set, represents the most basic unit of automation in SensorFlow. It typically comprises a group of nodes that contains an occupancy sensor, optionally a door sensor and a thermostat. From the individual nodes of an autoset, measurements of the room environment and air conditioner operation are collected. These include temperature, humidity, setpoint, chilled water valve state (close or open), fan speed, automation status, occupancy data. Compressors, meanwhile, are represented on a parallel branch of the hotel's tree structure, alongside keys. The compressor is the device responsible for moving the refrigerant between the evaporator and condenser coils, that results in cooling of the indoor room. As depicted by the orange dotted lines in Figure 2, one or more indoor fan coil units (FCUs) are mapped to a compressor, whereby the energy usage of the FCUs is measured via the power consumption of it's mapped compressor(s). The power consumption of the compressor is measured by an energy monitor that is connected to it.

In addition to the measurements collected from SensorFlow installed devices, we gather external environmental data from publicly available sources specific to the location of the property . These external parameters are namely outdoor temperature and outdoor humidity. The external data is gathered and stored in 15 minute intervals and serves as input towards building the features of our model as described in Section 3. A complete overview of measurements are summarized in Table 1.

Measurements from all nodes are recorded at least every 15 minutes or whenever states change, such as rooms becoming occupied/unoccupied, guests interacting with thermostats etc. This results in measurements being recorded at asynchronous timestamps. To enable efficient working with the data the data is subsequently synchronized by interpolating the measurements to a common timeline at intervals of 5 minutes across all parameters. Care is taken to not interpolate over long periods of missing data by setting the maximum interpolation window to 30 minutes. With this data set we define the status of each autoset at any point in time as being the interpolated measurements at the closest 5 minute mark.

3 Modeling Air-Conditioning Power Consumption

To be able to create a simulated baseline it is necessary to understand the relationship between HVAC load and power consumption as present in the building or resort that is to be measured. For HVAC systems, almost all power is consumed by the compressor or chiller system which is providing the cooling while the Fan coil units in the room only regulate the demand, but do not consume significant amounts of energy themselves. As such to be able to simulate the power consumption in different demand scenarios we need to build a model that connects the cooling load as demanded by the Fan coils to power consumed at the compressor or chiller system. This section will describe the features we use to build such a model and how we evaluate the quality of the model generated.

3.1 Feature Engineering

The first step in model building is to extract the right features from the data. In our case, our features need to describe the total load that is currently put on

	Measurement Type	Description
Indoor environment measurements	temperature ambient	Temperature of the room in degree C measured by the thermostat
	humidity ambient	Relative humidity in %RH of the room measured by the thermostat
AC measurements	guest setpoint	Setpoint temperature for the Air-Conditioner chosen by the guest
	temperature setpoint	Actual setpoint temperature for the air-conditioner set by the SensorFlow system (by default, same as the guest_setpoint value unless the hotel chooses to implement a limit on the minimum setpoint using SensorFlow's solution in order reduce energy consumption)
	valve openness	The status of the cooling valve. The cooling valve controls the inflow of chilled water into the fan coil in chiller based HVAC systems.
	power status	Status representing if the Fan coil is switched on or not
	automation status	Status representing if the AC is in automated state or not, i.e. did SensorFlow change the parameters in any way.
Occupancy measurements	occupancy status	Status representing if the room is occupied or not, as measured by the occupancy sensor
	door open status	Status representing if a door to the outside in the room is open or not as measured by the door sensors
Energy measurements	Power	Power consumption of the compressor in Watt as measured by the energy meter
	Energy	Energy consumption of the compressor in kWh based on power measurements recorded by the energy meter
External measurements	outside temperature	outdoor temperature at the location based on time series weather data from public online sources
	outside humidity	outdoor relative humidity at the location based on time series weather data from public online sources

Table 1: Data Definition and Description.

a compressor. The following 4 features are extracted from the data collected by SensorFlow sensor network:

1. Outdoor wet bulb temperature (outdoor_wetbulb)
2. Outdoor dry bulb temperature (outdoor_temperature)
3. Total number of air-con cooling (total_cooling)
4. Total cooling degree demand hours (total_cddh)

A compressor or chiller system can supply one or more rooms, hence features 3 and 4 are the total of the values of the respective features in each room.

3.1.1 Outdoor wet and dry bulb temperature

The outdoor environment is the same for all compressors and affects them equally. We obtain the outdoor dry bulb temperature directly from external public weather data portals as is, collected from the nearest weather station. The outdoor_wetbulb temperature in a given location is computed from outdoor dry bulb temperature and relative humidity values collected from the nearest weather station. The outdoor_wetbulb is computed by using the following equations which appear as (17-19) in [14].

$$T_{wb} = f^{-1}(0.01 R_H e_s(T_{DB}) + \gamma P_a T_{db})$$

where R_H is the outdoor relative humidity (%), T_{db} is the outdoor dry-bulb temperature (^oC), $\gamma = 6.46e^{-4}(^oC^{-1})$ is the psychrometrics coefficient and $P_a = 1013.25$ (hPa) is the atmospheric pressure at sea level.

$$\begin{aligned} f^{-1}(x) &= 7.438995 \times 10^{-10}x^5 - 4.063282 \times 10^{-7}x^4 + 9.16616 \times 10^{-5}x^3 \\ &\quad -1.15133 \times 10^{-2}x^2 + 1.02533x - 5.585331 \\ e_s(T) &= 2.796413 \times 10^{-8}T^5 + 2.671942 \times 10^{-6}T^4 + 2.73199 \times 10^{-4}T^3 \\ &\quad +1.41951 \times 10^{-2}T^2 + 0.444226T + 6.1078 \end{aligned}$$

Higher outdoor temperature and relative humidity levels typically lead to higher power consumption.

3.1.2 Total number of air-con cooling

The air conditioning system has an outdoor compressor unit and 1 or more indoor fan coil units. The outdoor compressor unit typically consumes power anywhere between 1kW for smaller split units to 20kW for bigger VRV units whereas the indoor fan coil unit consumes less than 150 W, mainly from operating the fan motor. As the cooling is provided by the compressor unit, the FCU power on/off indicator does not account for the change in power consumption levels over time in a reliable way, especially when the compressor is maintaining a constant indoor temperature. For example the FCU would not demand cooling from the compressor if the indoor temperature has reached or sunk below the setpoint, even though it is still switched on. To model this behavior accurately we need to know if the FCU is actually cooling the room or not at any given point in time. In Chiller systems, this is directly captured by the open/close status of the cooling valves which is captured by our sensors. For split and VRV systems however we only control the setpoint and the system decides the best way to reach or maintain it. We can therefore not directly measure the cooling demand activity of the FCU. In these cases, we compute the cooling activity by using the indoor relative humidity data in the rooms. Besides cooling the room FCUs also work as a strong dehumidifier in the rooms, actively sucking moisture out of the environment when the coil is cold. As such we can observe the cooling activity of an FCU by observing the relative humidity in the room which will be on a downward trend when the FCU is actively cooling the room and then starts on an upward trend when it is not cooling the room. We have observed relative humidity to be more sensitive to cooling changes than indoor temperature, hence we use the indoor relative humidity to infer whether the room is currently cooling or not. The higher the number of rooms that are cooling (indicated by total_cooling), the higher will be the compressor unit power consumption. The valve_open, which indicates whether room is in cooling or not, is computed using the following formula where rh is the indoor relative humidity of the room.

$$\text{valve\_open} = \begin{cases} 1 & \text{if } \frac{d(rh)}{dt} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Figure 3 shows a sample trace of indoor ambient temperature and relative humidity while an FCU is active in the room, cooling to varying setpoints. The green trace represents the relative humidity and it is very visible how the humidity behaves very differently with respect to whether the FCU is cooling or not, indicated for example by the prominent zig-zag pattern during times where the FCU is maintaining temperature.

3.1.3 Cooling Degree Demand Hours

A well-known concept in energy modeling for assessing the cooling load of a building is "Cooling degree days" as reported in The International Performance Measurement and Verification Protocol (IPMVP®) [15]. This measure quantifies the cooling demand based on how much time in a day was spent above a certain outdoor threshold temperature, beyond which cooling is required. Researchers have used modified cooling degree days method that also incorporates other features like the wet-bulb temperature to take into account the latent heat and improve on the air-conditioning power prediction [16, 17, 18]. Although cooling degree days are usually used on a monthly basis for historical base-lining purposes, the fine-grained data we collect on individual room setpoints allows us to create a much more powerful feature. Inspired by the cooling

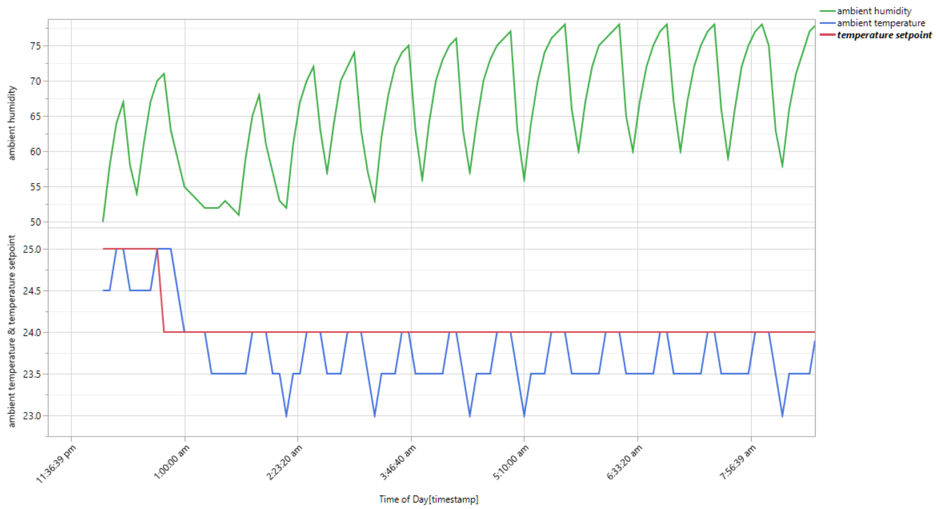

Figure 3: Trace of indoor humidity (green line), indoor temperature (blue line) and temperature setpoint (red line).

degree days, we refine the feature to also take the setpoints set by the guests into account i.e. long hours of operating at low setpoints will lead to a higher cooling demand. Since the SensorFlow system measures the setpoint selected by the guests on every FCU we compute a new feature which we call "Cooling Degree Demand hours" (CDDH) as

$$\text{cddh} = \text{time} \times \text{powered} \times (\text{outdoor\_temperature - setpoint})$$

where *powered* is a binary variable indicating whether the FCU is switched on (1) or off (0), setpoint is the thermostat setpoint and time represents the time spent at the specific settings. For example, if a FCU runs for 1 hour at a setpoint of 24C while the outdoors temperature is 30C it would have consumed $1 \times 1 \times (30^o C - 24^o C) = 6$ cooling degree demand hours.

We then calculate the total_cddh as the sum of cddh of all rooms supplied by a compressor.

3.2 Model training and validation

The model used is ML.net [19] implementation of a Gradient Tree-Boosting Algorithm with Tweedie Loss Function [20, 21]. This model is in the family of classification and regression tree-based machine learning methods [9]. The implementation uses an ensemble of trees with gradient boosting - this technique is found to have best performance for prediction of building energy consumption data [22, 23, 24, 25].

To assess the model, five fold cross validation is used i.e the data-set is divided into 5 sets of training and test data. The average metrics R^2 and RMSEP, i.e. the percentage of RMSE over the range of measurement, of these 5

Compressor type	outdoor wetbulb	outdoor temperature	total_cooling	total_cddh
Chiller	6.13	15.07	12.29	3.35
VRV	0.33	0.72	0.46	0.8
Split	0.04	0.03	0.06	0.21

Table 2: Feature Importance Scores by Permutation Feature Importance analysis.

test data-set is then considered for the model pass criteria. We use the recommended criteria as in [5] i.e $R^2 > 0.6$ and RMSEP $< 10\%$. The model is then trained on the whole month data-set which is later used to make predictions. SensorFlow only claims savings on automation from compressors that pass a stringent modeling accuracy criteria. This stems from the principle that in order to claim savings in a non-SensorFlow setting, we should have a degree of confidence in the compressor behavior under a SensorFlow setting. Thus, savings ought to only be claimed on compressors where there is high degree of confidence that it's consumption patterns have been well understood and it's behavior in a non-SensorFlow scenario can be predicted with confidence. As a result, any savings resulting from failed compressors are trimmed to 0 and do not count towards total savings, even if the system was operational and likely did save energy on these machines by reducing demand.

3.3 Feature Importance Analysis

To assess the impact of each feature on the modeling, a Permutation Feature Importance analysis is performed. Permutation feature importance works by randomly mutating the value order of each feature column, one column at a time, and then evaluating the model. Permutation feature importance does not measure the association between a feature and a target value, but instead captures how much influence each feature has on predictions from the model. Below table shows the permutation feature importance measure of each feature computed for a typical compressor of Chiller, VRV and split type - the higher the value, the more important ithe feature is. It can be noted that total_cddh is the most important feature for VRV and split type compressors whereas outdoor_temperature along with total_cooling are the important features for Chiller type. This is an encouraging result as both total_cddh and cooling are specific new features enabled by the SensorFlow system through its detailed observation of the HVAC system.

4 Energy Savings Quantification

This section describes the process of quantifying the energy saving using SensorFlow's solution. Unlike other solutions where energy savings are achieved by replacing old equipment with more efficient equipment or optimising control algorithms, SensorFlow's solution aims to reduce wastage by perfomring demand side optimisation. This results in SensorFlow only optimizing the energy consumption during a certain period of time (automation period), e.g. when the hotel room is unoccupied. Hence, it is necessary to quantify the energy savings during this period only. Conventional methodology based on historical monthly bill, occupancy rate and cooling degree days data still can be used to calculate the energy savings, however, those data are often limited due to the availability in different hotels. Furthermore, the fine-grain data from the SensorFlow sensors enables a more accurate calculation of the energy savings. This can be done by simulating the automation period as if the SensorFlow Solution was not installed, this simulation scenario is called Non-SensorFlow world. The simulation result is then compared with the actual measurements to achieve the energy savings.

4.1 Simulation Process

To calculate the savings using SensorFlow's solution, a simulation is pertformed to create a scenario in which SensorFlow is assumed not to be deployed at the property, this scenario is called Non-SensorFlow world. The following points are assumed for the Non-SensorFlow world

- If the AC is automated by SensorFlow, e.g. AC is automatically turned off by SensorFlow or the setpoints was changed, then the AC would have remained the same status, e.g. AC remained ON and the temperature setpoint remained unchanged while the guest was not in the room.
- In addition, in case of any setpoint limitation, the original guest selected setpoint is used for simulation of the Non-SensorFlow world instead of the setpoint limited by SensorFlow, e.g. if setpoint limitation in the room is selected to be 23^oC, and the guest set the setpoint as 19^oC then 19^oC is the AC setpoint in the Non-SensorFlow world.

Due to the non-existence of the Non-SensorFlow world, simulation is conducted to evaluate power consumption in the Non-SensorFlow world. Simulation includes simulating all the features mentioned in Section 3. All the simulated features will be then fed into the model obtained from the Section 3 to simulate the power consumption of the Non-SensorFlow world. The energy savings of using SensorFlow solution can be then calculated.

4.2 Simulation of Features

Out of four features in Section 3, only the "total cooling" feature cannot be measured, the other three can either be measured or easily simulated:

- "outdoor_wetbulb" and "outdoor_temperature" are measured by external instruments and they are independent of the SensorFlow system.

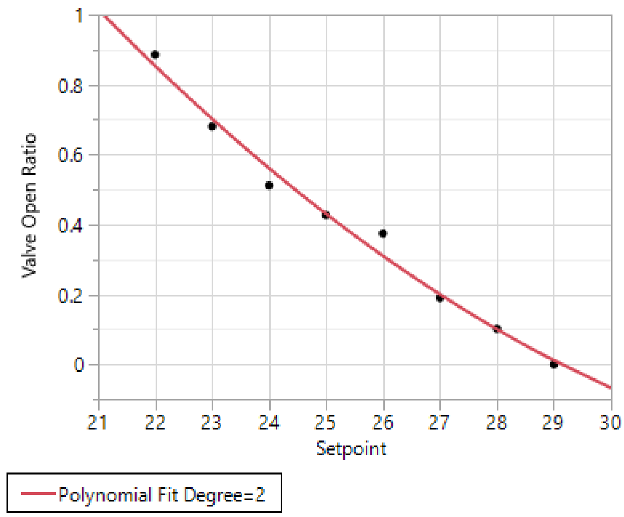

Figure 4: Relationship between temperature setpoint and valve open ratio λ.

- "total_cddh" is calculated by assuming the AC was ON and the temperature setpoint remained in the Non-SensorFlow world as if the AC was not automated.
- Simulation of "total_cooling" requires data gathered from the smart thermostat. This data includes humidity data for the case of infrared remote thermostat or valve open/close data of FCU controlled by the wall-mounted thermostat.

The valve used in the Fan Coil Unit (FCU) wall thermostats is either in Open or Close state where Open indicates the cooling is being provided to the room and Close indicates otherwise. This state can be digitized as 0 (CLOSE) or 1 (OPEN) as described in the Section 3.1.2. SensorFlow system can capture the ratio of the valve open period over the total AC ON time for each setpoint. This valve open ratio, λ, depends on many factors such as temperature setpoint, AC types and weather conditions. Figure 4 shows the relationship between the temperature setpoint and λ. This valve open ratio information can be used to simulate the valve open state in the Non-SensorFlow world. Because $0 \leq \lambda \leq 1$, simulation can be done by assuming this valve open state is a random variable of which value is drawn from a Bernoulli learned from λ. The simulated valve open state can then be used to compute the simulated total_cooling feature.

For the case of infrared remote thermostat that does not contain valve open data, Eq.(1) is used to approximate the valve open state, hence λ, from the humidity data. The above process is then used to compute the simulated tool_cooling feature.

After all the features for the Non-SensorFlow world are simulated, the power consumption in the Non-SensorFlow world can be obtained using the model in the Modeling Section. The energy savings using SensorFlow solution can then be determined as

$$\text{energy\_savings} = \text{simulated\_power\_consumption} - \text{actual\_power\_measurement}$$

4.3 Simulation Verification

Section 4.1 describes a process to simulate the power consumption in the Non-SensorFlow world, i.e. the scenario where SensorFlow solution was not deployed. This section is to verify the correctness of that process. To verify the simulation of Non-SensorFlow world, the simulation process in Section 4.1 is applied on the actual data when the hotel room is not automated, e.g. when the hotel room is occupied. This is done by assuming the data does not contain the "total_cooling" feature and this feature is simulated using the method in Section 4.2. After obtaining the simulated power consumption, the same criteria used in Section 3 is used to validate the simulation process.

4.4 Energy savings adjustment based on rented information

The existence of the SensorFlow system introduces a change in behavior by reducing the need for housekeeping staff to monitor the air-conditioner powered status of individual vacant rooms. In a Non- SensorFlow world, if a guest checks out of a room with the air-conditioner left on, the housekeeping staff would switch it off. In order to replicate the same behavior in non SensorFlow world, we determine if a room is rented or not by using the occupancy sensor data and only claim automation and savings in a room that is rented or booked for a given day. To determine whether a room is rented on a given day, the following definition is assumed: "*A room is considered 'rented' if the room is occupied for more than 90 minutes between 4pm and 11am next day (as picked up by our occupancy sensor); else, unrented*". This is reasonable as hotel guests usually check-in and stay during the time frame in the assumption. After trimming any automation in unrented rooms to zero, the energy savings is calculated by simulating the Non-SensorFlow world as in Section 4.1.

In case of a split air-conditioning system, the fan coil unit or the indoor unit power consumption is also measured by the energy meter installed at the compressor side. This is typically not the case for VRV or chiller type systems where the compressor side energy meter only measures the compressor energy consumption. As SensorFlow saves on the fan coil unit (FCU) power consumption as well when the air-con unit is switched off, this is added to the claimed total savings. The total FCU in kWh is computed by multiplying the number of automation hours by FCU power consumption in kW when the air-con is on. The FCU power consumption is taken as 50 W or 0.05 kW which is the typical for standard hotel rooms . For example, if we automate 1000 hours in the month

Tariff type (SGD per kWh)	Tariff hours Savings (kWh)	Tariff Savings (SGD)		
Peak	7 am - 11 pm	0.2085	17405.6	3629.07
Off peak	11 pm - 7 am	0.1271	2697.3	342.83
Total Claimed Savings			20102.9	3971.9

Table 3: Computation of claimed savings in dollars according to electricity tariff.

for a VRV or chiller system hotel, we add $1000 \times 0.05 = 50$ kWh to the total FCU energy savings.

Furthermore the SensorFlow does not claim any savings if the guests switch off the AC themselves, either through using the thermostat or an existing key card system. The SensorFlow system precisely records when it automates VS when changes are made by external agents, preventing unfair overclaiming of savings not generated by teh system.

5 Case Study

This section presents a case study of one hotel, called hotel A, of our client hotels, which has 154 guest rooms (with 246 automated rooms or autosets) supplied by 21 Mitsubishi VRV compressors. The SensorFlow system is installed in this property with occupancy sensors and smart thermostats in every guest room. Energy meters are measuring the power consumption of each compressor as shown in Figure 1. The models are developed for each compressor and the savings claimed for the whole property is the total of the savings claimed for each compressor. As the SensorFlow system automates the room by switching off the air-con when a guest leaves the room, the overall power consumption of the property reduces with the increase in the number of automated rooms as observed in Figure 5 for the time period 26th-29th November 2019. Note how in this property the total energy consumption drops throughout the middle of the day when tempeartures rise to their highst points. This is a direct effect of the SensorFlow system which reduces demand during this time which is the primary time when guests are out of their rooms and oftne leave FCUs running. In most cases without demand reduction systems installed a building would show increased HVA consumtpion during the middle of the day. As such SensorFlow enables the client to save energy during highest demand times where energy costs are also at their peak.

The models are trained for each compressor, Figure 6 shows the modeled power consumption predicted by the model against the actual power consumption measured by the energy meter for one compressor named CU-15. The same models are then used to predict the Non SensorFlow world power consumption and the savings are computed. Figure 7 illustrates the predicted Non Sensor-

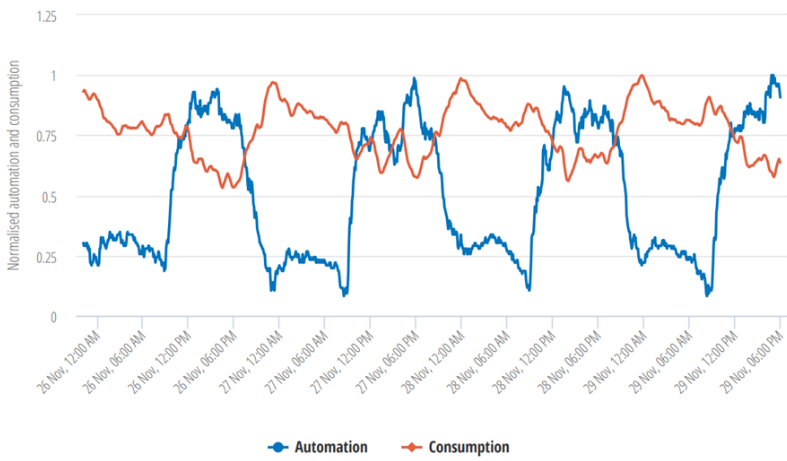

Figure 5: SensorFlow Automation and HVAC Power Consumption.

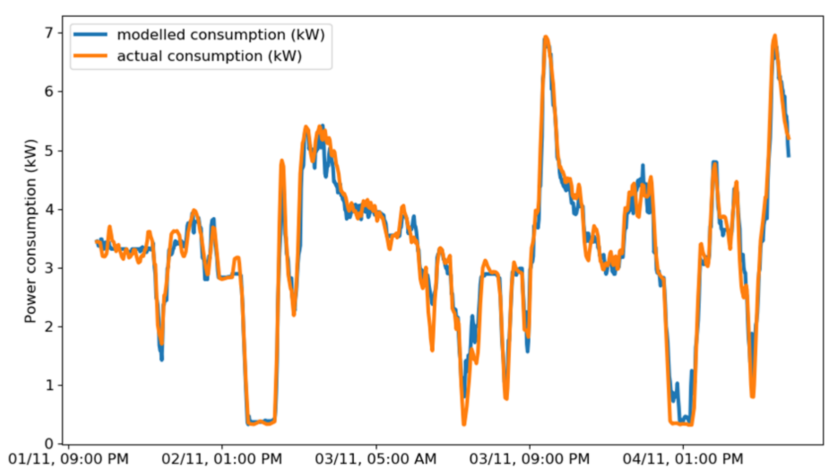

Figure 6: Actual consumption and modeled consumption for Compressor CU-15.

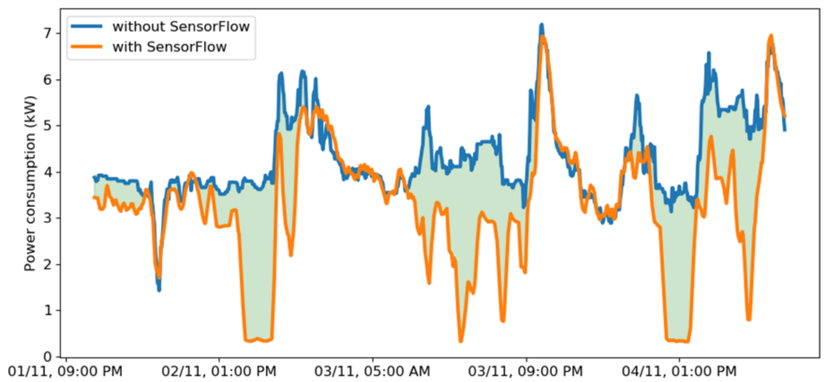

Figure 7: Power consumption with and without SensorFlow solution along with shaded savings for CU-15.

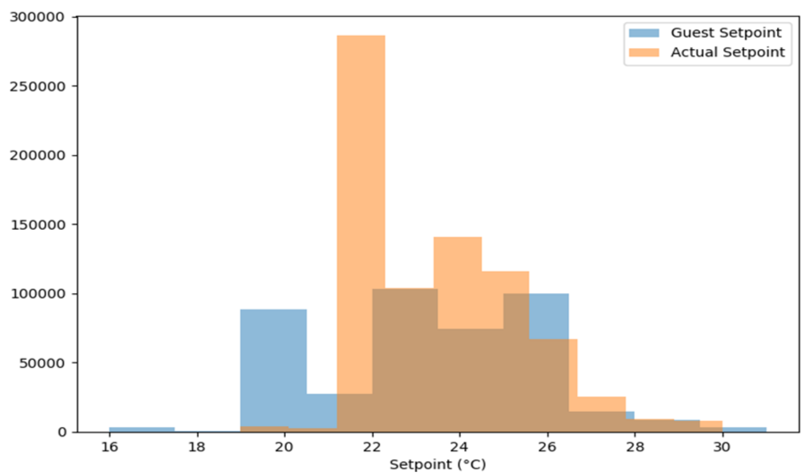

Figure 8: Distribution of guest setpoint and actual setpoint set by SensorFlow solution.

Flow world power consumption against the actual power consumption with the shaded portion indicating the savings for compressor CU-15.

Table 4 in Appendix shows the cross-validated metrics for each of the compressors. As per the metrics criteria described earlier, all the compressor models pass the metrics criteria and hence the total savings will be claimed by adding the savings from each compressor. Table 5 in Appendix shows the number of automated hours clocked in rooms supplied by the compressor, fan coil unit savings since this is a VRV based system, automation savings i.e. savings achieved through turning off the air-con when no human is present in room and setpoint limitation savings i.e. additional savings achieved from limiting the setpoint.

Figure 8 shows the distribution of guest selected setpoint and the actual setpoint (after limiting the setpoint to pre-selected setpoints as desired by the client). It can be seen that the guests selected lower setpoints which is contributing to the savings achieved by setpoint limitation.

In order to compute the savings in dollars, the electricity tariff rates are applied to the savings in kWh as per the tariff structure (peak, off peak or standard). As the savings are calculated at a 5 minute interval, exact tariffs can be applied to achieve more accurate savings number. The calculation results are tabulated in Table 3.

6 Conclusion

This paper presents a novel energy savings solution, named SensorFlow, for hotel properties using an IOT sensor network, comprising of smart thermostats and smart energy monitoring equipment. The energy savings quantification is discussed to justify the performance of SensorFlow solution. This includes the HVAC power consumption modeling process using fine-grained data from the sensor network, the simulation process for the Non-SensorFlow world to calculate the energy savings, and the rented room detection methodology to better claim accurate energy savings. A case study from one of the hotel clients demonstrate the high energy savings performance of SensorFlow's solution as well as the high accuracy of the proposed process to justify the energy savings.

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Appendix

Compressor	No. of rooms	Cross-validated R^2	Cross-validated RMSEP
CU-01	10	0.7442	0.0682
CU-02	12	0.889	0.055
CU-03	16	0.8495	0.0589
CU-04	12	0.8131	0.0683
CU-05	10	0.8386	0.0581
CU-06	6	0.8566	0.0767
CU-07	16	0.907	0.0531
CU-08	12	0.838	0.0652
CU-09	16	0.759	0.062
CU-10	12	0.8459	0.0557
CU-11	13	0.7688	0.0583
CU-12	12	0.8433	0.0608
CU-13	10	0.8236	0.0703
CU-14	3	0.9149	0.0666
CU-15	4	0.8708	0.0611
CU-16	12	0.8898	0.061
CU-17	16	0.8933	0.0504
CU-18	14	0.7684	0.0627
CU-19	15	0.7934	0.0732
CU-20	10	0.7948	0.0565
CU-21	15	0.7209	0.0676

Table 4: Metrics for the 21 compressors in Hotel A in the month of November 2019

Compressor	Total automation hours	Total energy consumption (kWh)	Total claimed savings (kWh)	Automation savings (kWh)	Setpoint limitation savings (kWh)	Fan coil unit savings (kWh)
CU-01	1057.25	3392.91	482.27	397.77	31.64	52.86
CU-02	1655.58	2682.08	878.17	717.97	77.42	82.78
CU-03	2206.83	5216.23	1351.02	1121.85	118.83	110.34
CU-04	1244.83	3143.77	982.29	707.98	212.07	62.24
CU-05	1320.25	2583.13	839.44	716.18	57.25	66.01
CU-06	629.33	1487.05	427.21	390.34	5.4	31.47
CU-07	2096.17	5003.01	1672.86	1421.35	146.71	104.81
CU-08	1687.83	2962.07	978.39	824.86	69.14	84.39
CU-09	1851.67	4279.06	1130.46	934.4	103.47	92.58
CU-10	1295	2790.96	721.8	603.72	53.33	64.75
CU-11	1121.83	4791.35	971.18	777.1	137.99	56.09
CU-12	1853.33	2807.31	1072.54	917.2	62.67	92.67
CU-13	1394	4636.83	1448.22	1268.08	110.44	69.7
CU-14	344	1545.07	353.96	319.69	17.07	17.2
CU-15	367.17	1928.53	423.66	348.73	56.57	18.36
CU-16	1569	4758.42	1405.32	1151.32	175.55	78.45
CU-17	1898.25	5727.51	1490.75	1370.44	25.4	94.91
CU-18	1511	3478.62	898.54	769.02	53.97	75.55
CU-19	1061.25	4549.97	881.67	716.02	112.59	53.06
CU-20	1111.75	2921.89	723.55	584.95	83.02	55.59
CU-21	1483.5	5652.31	969.6	774.15	121.27	74.18

Table 5: Total claimed savings for each compressor with breakdown of automation related, setpoint limitation related and fan coil unit savings.