Neural Network Based Occupancy Prediction using Patterns detected in WiFi Occupancy

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Abstract:

The role of occupants in building energy management is well established. Occupant information from commercial buildings can function as a metric for the heating, ventilation, and air conditioning (HVAC) loads. Predicting these loads ahead in time could aid in setting up HVAC protocols to minimize wasteful energy demand and improve occupant comfort. To this extent, several frameworks were proposed that use occupancy data collected from commercial office buildings and graduate student offices to predict occupancy. However, the occupancy data collected in these frameworks are controlled and have limited complexity compared to larger commercial spaces such as airports, libraries, lecture halls, and shopping malls. Therefore, this paper presents the results of a study that demonstrates the feasibility of occupancy predictions from a relative dynamic environment using WiFi data and neural networks. The results demonstrate that reliable occupancy predictions are possible using intrinsic variables that have significant correlation with the occupancy profile of a time-segment. Similar conclusions can be extended to extrinsic variables if they are significantly correlated to the occupancy.

Keywords:
Occupancy Prediction, Neural Networks, HVAC, Commercial Buildings, Energy, LAPART

1. Introduction:

Integration of technology into various industrial fields is taking place rapidly. The construction industry and built environment (residential and commercial buildings) have seen their share of technology integration in the name of modernization. The investment into modernization of infrastructure recommended in the ASCE Infrastructure Report card[1] led to the surge of renovations, sensor networks, smart devices to control indoor climate, and WiFi infrastructure in most commercial buildings. With buildings consuming over 20% of total delivered energy globally in 2018 [2], the need for energy efficiency through modernization is a priority. In addition, the global commercial building footprint is projected to increase along with the energy consumption per unit area for the next three decades [2][3][4]. In this context, the modernization of commercial buildings with various technologies provides opportunities to achieve an unrealized energy saving in commercial buildings.

The growth in commercial buildings garnered researchers' interest in their energy consumption and their energy-saving potential[5]. This raised the significance of building energy modeling to identify energy efficient designs. However, the actual energy consumption revealed large discrepancies with modeled energy and the reasons for it were attributed to variable building occupancy [6]. Since this finding, commercial building occupancy became an integral part of energy management strategies. The dynamic nature of occupancy within buildings complicates the modeling process [7]. Modernization of buildings with technology aided studies to obtain occupant information from various sensory infrastructure (e.g., environmental sensors, dedicated occupancy sensors, RFID, bluetooth devices, and WiFi networks) [8]. However, accuracy, complexity, costs associated with dedicated infrastructure and privacy concerns impeded the wide scale implementation of these frameworks.

In commercial buildings, heating, ventilation, and air conditioning (HVAC) accounts for 40% of total energy consumption [9]. A demand-driven HVAC operational strategy can play a significant role in the energy efficiency of commercial buildings [7]. From the results in [10], it is evident that existing WiFi routers can be a source of reliable occupancy estimation without added infrastructure and complex computational resources while preserving occupants' privacy. Additionally, the occupancy-based HVAC schedules and the corresponding energy consumption results published in [11] emphasize that demand-driven HVAC operation can significantly reduce building energy consumption. However, knowing the occupancy profiles of a building in advance can improve energy efficiency furthermore by reducing unnecessary energy demands of the HVAC systems [5],[9]. Additionally, the knowledge of occupant load in advance can be used to pre-condition (heat/cool) the space which can improve occupant thermal comfort levels.

To acquire knowledge of occupancy, prediction frameworks were proposed that frequently employed Markov chains, support vector machine, k-nearest neighbor (kNN), and Artificial Neural Networks (ANN) [12]. Using the data collected from a variety of sensory infrastructure within commercial spaces such as commercial offices, university offices, single, and multi-person offices, occupancy predictions were made at different levels. Some frameworks predicted the state of the occupant ('in' or 'out') [13], others predicted the number of occupants by detecting their state [14],[15], and the rest focused on behavioral aspects (choice of lighting, windows, and blinds) of occupants [16], [17]. While these frameworks provide insight into predicting a fixed number of "long-term" occupants in office spaces, occupancy prediction in a dynamic environment (e.g., airports, shopping malls, gymnasiums) remains a challenge. This paper presents the results of a study that demonstrates the feasibility of making short term occupancy prediction in a relatively dynamic environment using WiFi data and neural networks.

2. Literature

Occupant behavior is considered one of the most complex processes taking place within buildings [18]. The stochastic nature of building occupants complicates the process of indoor microclimate control (heating and cooling) and energy conservation strategies. Researchers attempted to model and predict this complex behavior of occupants to achieve various energy efficiency goals over the past decade. Studies used occupants' behavioral aspects such as windows, blinds, and lighting choices to improve energy efficiency [16]. The comprehensive review conducted by [17] highlights that building occupants tend to override any automated window shading, and lighting protocols to suit their personal preference. However, generalizing such behavior of occupants can be tedious and may not always aid in realizing the maximum possible energy savings in commercial buildings. More importantly, in commercial spaces such as airports and university buildings, occupants may not have control over lighting and shading.

Discrete methods as in case of [15] used 'occupancy matrix' to define spatial distribution of occupancy in an office space. The occupancy matrix is formed by dividing a 2-D space into multiple zones based on the thermal zones and presence of an occupant in each zone. A binary system of zeros and ones was used to represent occupancy and non-occupancy zones. Occupancy data from the test space was obtained using dedicated iBeacon infrastructure. This occupancy data coupled with the thermal zone information defined the dynamic spatial occupancy distribution. Using the spatial occupancy distribution (i.e., occupancy matrix) cooling requirements for unoccupied zones was reduced. However, office spaces are typically occupied by same set of occupants during the occupied state and this approach may not be applicable for larger commercial spaces with new occupants every day.

Environmental sensors such as CO_2 sensors use the correlation between the standard quantity (e.g., CO_2/person) per person to estimate occupancy. In [19], occupancy data from CO_2 sensors were used with hidden Markov model algorithm to predict occupancy. This system utilizes the correlation between occupants and CO_2 concentrations to predict occupancy. Using this approach, the prediction made for an office space achieved an accuracy ranging between 85% - 93%. While the occupancy inferred is non-intrusive in nature, environmental sensors such as CO_2 sensors can be unreliable in occupancy estimation due to the complexity of CO_2 concentrations which could results in inaccurate predictions [5]. Additionally, the results are from tests performed for a maximum of five occupants and the prediction accuracy may differ in dynamic environment with higher number of occupants.

In a different approach, WiFi probe data (i.e., media access control (MAC) address) was used in tandem with Markov based feedback recurrent neural network algorithm to predict occupancy [5]. A graduate student office with 25 'long-term' residents was used to conduct various validation experiments. Each MAC address was assigned to a single occupant and that information was stored as memory. Using the neural network approach, the state of each MAC address ("in" or "out") was predicted and thereby estimated the total occupancy of the office space. Contingent on allowed tolerances, this approached reached accuracy ranging between 80% to 94%. However, in a dynamic occupancy environment (e.g., airports and shopping malls) a MAC address assignment approach is not possible as occupants of such commercial spaces cannot be classified as 'long-term' residents. Additionally, MAC addresses contain occupant identifiers and may raise occupant privacy concerns.

A separate set of studies proposed frameworks for using occupancy data obtained from different sources such as RFID tags [20], cameras [8], and smart meters [21], among others to improve energy efficiency of commercial buildings. In summary, these frameworks achieve their goals with limitations such as privacy concerns, added infrastructure expenses, and limited applicability, among others. These limitations may hinder large scale implementation of these frameworks and when implemented may not realize the full potential in energy savings.

Occupant comfort level data highlight the need for HVAC energy conserving strategies to incorporate occupant comfort parameters [22]. The heat dissipation of occupants inside buildings contribute towards the cooling load in the cooling dominated months and [23][15]. This occupant heat dissipation effect has a profound impact on heating loads in heating dominated months [23]. Additionally, the metabolic rates of occupants vary depending on the type of commercial building. The metabolic rates of occupants in gymnasiums, stores, and terminal buildings are said to be higher at 1.6met (metabolic equivalent unit) followed by schools at 1.2met compared to other types of commercial buildings [24]. The higher metabolic rates induce higher heat loss of occupants due to their homotherm nature [25]. The metabolic rates and the amount of heat dissipated by occupants in both summer and winter months are identical [24], highlighting that occupants' thermal interaction in all types of weathers remain constant. Furthermore, the human body radiates different levels of heat throughout the day, implying that the occupants' thermal interactions within buildings are dynamic throughout the day [26]. Moreover, dynamic variation of indoor spatial temperature that account for thermo-physiological parameters such as occupants' metabolic rate and sweat production can positively impact their comfort and health [25].

In summary, a constant heating or cooling setpoint temperature may not improve occupants' thermal comfort inside buildings. A new setpoint that is a function of number of occupants in a space may contribute towards improving occupant comfort inside buildings. Additionally, knowing the occupant count for a space ahead in time can allow for pre-conditioning the space to that specific number of people can result in increased occupant comfort and avoid HVAC wasteful demand. With emphasis on the need for such HVAC strategies [27], [28], an occupancy prediction approach that addresses the identified limitations is essential.

To this extent, predicting occupancy from a dynamic environment such as airports, public libraries, institutional buildings, and gymnasiums among others can be used to create HVAC operational schedules to improve occupants' thermal comfort and reduce energy consumption. In this study, using patterns detected in WiFi measured occupancy [29] and the LAPART neural network [30], occupancy predictions were made for a university lecture hall that has relatively complex occupancy patterns.

3. Methodology

The methodology for this study consists of three parts: 1) Occupancy pattern detection: Using a Fuzzy ART Neural Network to learn patterns in WiFi measured occupancy data, 2) Occupancy prediction: Using a LAPART neural network to make short term occupancy profile predictions, and 3) Energy Calculations: HVAC energy consumption was estimated using predicted occupancy profiles. **Figure 1** graphically illustrates the components of the methodology.

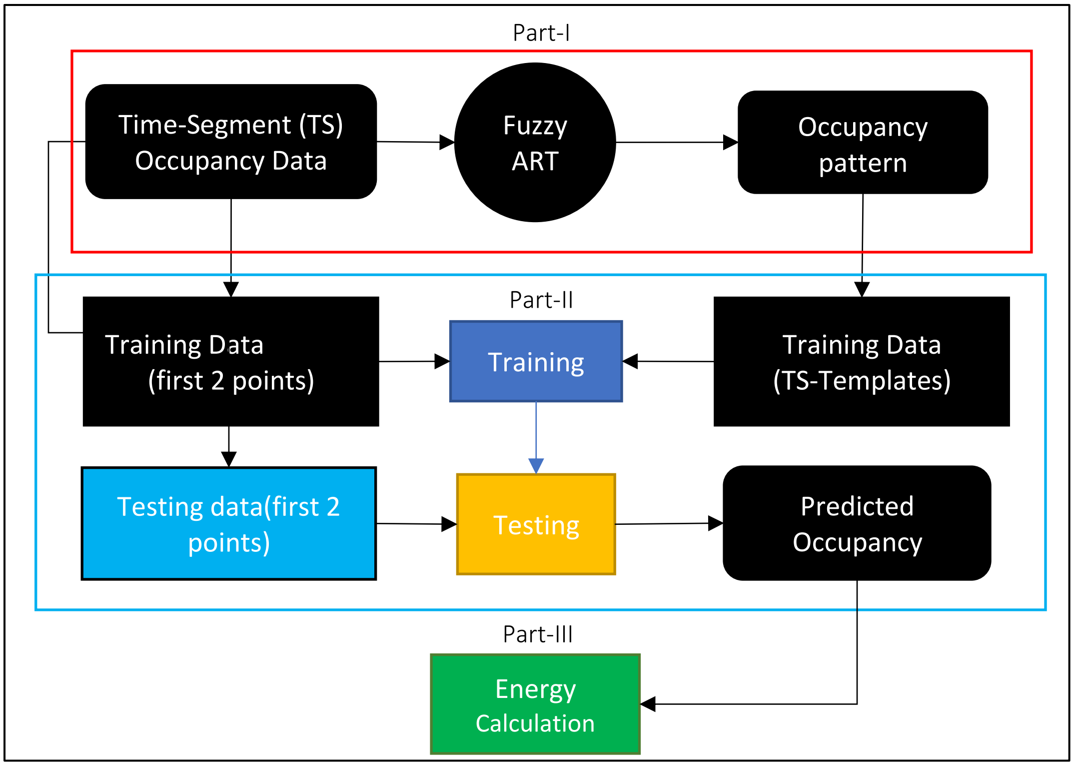

Figure 1: Methodology

3.1. Part-I: Occupancy pattern detection

Sixteen weeks of occupancy data were collected from existing WiFi routers in a lecture hall at University of New Mexico between August 18, 2019, and December 07, 2019. The structure of patterns in the WiFi measured occupancy need to be studied to learn the statistical variability in the data. This allows for learning rules by which occupancy profiles represented by input patterns can be classified into various categories [31]. Patterns in the occupancy data were learned using the Fuzzy ART Neural Network [32]. This self-organizing neural network segments data into unlabeled categories, the granularity (i.e., size of the hyperbox) of which is determined by a single vigilance parameter, ρ. The effect of ρ on number of categories learned is visualized in **Figure 2**.

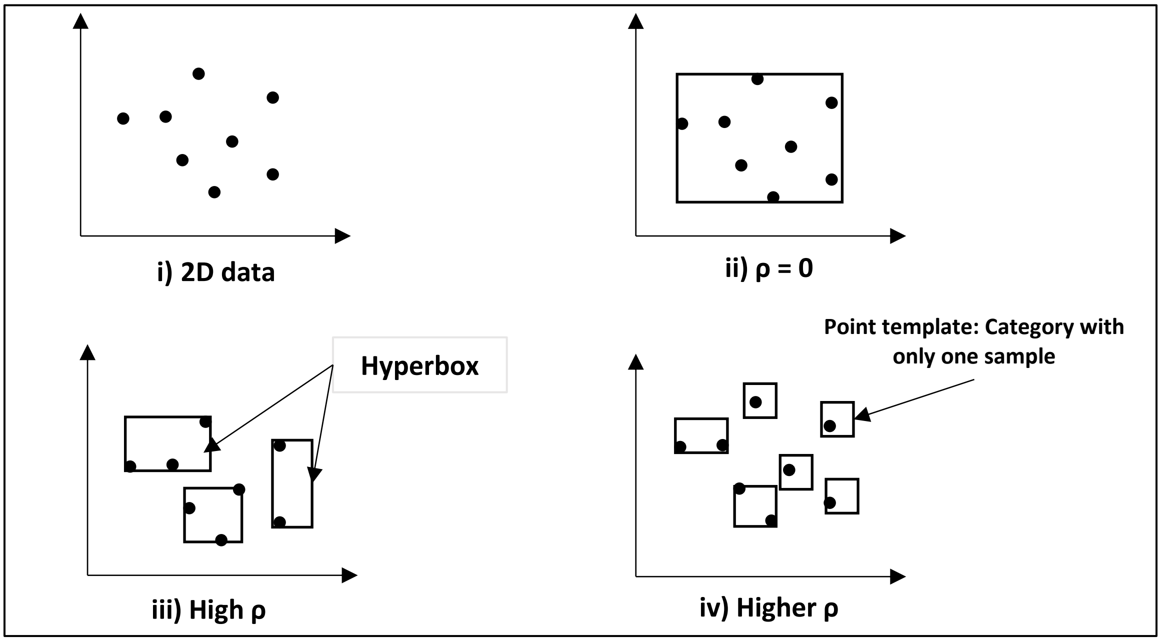

Figure 2: Fuzzy ART, effect of ρ on hyperboxes. i) synthetic 2D data, ii) hyperbox at ρ = 0, iii) hyperboxes at a high ρ (e.g., 0.8), and iv) hyperboxes at a higher ρ value (e.g., 0.95)

In this study, each category represents a collection of 'similar' occupancy profiles. Fuzzy ART executes an unsupervised learning process and for every input profile (examples shown in **Figure 3**, **i) and ii**), the neural network searches for a category that it matches [33]. Figure-3 Plots are in a 9D space where, the timestep axis represents the orthogonal axes of 2D space plots shown in figure 2. The learned categories are visually represented by a fuzzy template shown in **Figure 3**, **(iii)** (i.e., n-dimensional hyperbox) and the template selected by the neural network that best matches the input profiles is referred to as the matching template. The fuzzy templates are defined by the minimum and maximum of member profiles. Essentially, each fuzzy template is an envelope of member profiles.

Various experiments were performed to learn patterns in the occupancy data and the results were presented in [34]. The results in [34] emphasize that significant patterns can be learned from WiFi measured occupancy data by dividing a 24-hour profile into smaller time-segments bound by external schedules. The time-segments in this study were defined by the duration of lectures scheduled. The scheduled lectures repeat twice or thrice in a week. For examples, lectures that are scheduled for 50 minutes repeat three times in a week and lectures that are scheduled for 75 minutes repeat twice in a week. The occupancy profiles for 50-minute and 75-minute time-segments are represented by a 9-D and 12-D vectors, respectively. Ten different time-segments were identified throughout the data collected. Occupancy profiles of individual time-segments are clustered into various categories by the Fuzzy ART neural network algorithm. The hyperbox learned to enclose the data points of a category will be referred to as a template for the remainder of this paper.

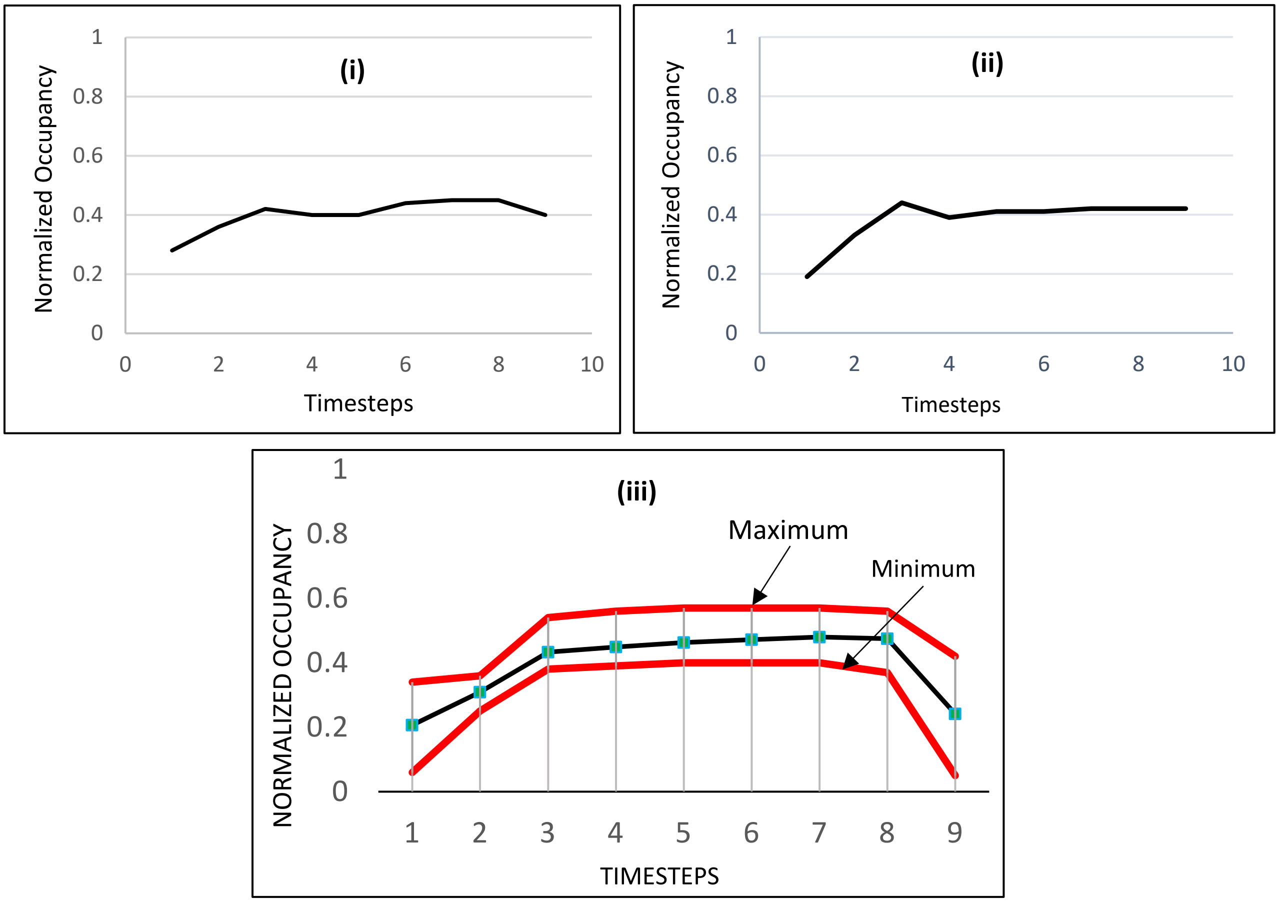

Figure 3: i) sample input profile-1, ii) sample input profile-2, iii) A sample fuzzy template representing category of similar profiles

From the templates learned for each time-segment, the one that occurred most frequently was identified. The fuzzy template representing this frequently repeating template is termed as *Most Likely Template* (MLT). The time-segments identified in the data take place on multiple days. For example, time-segment #1 is a 50-minute time-segment that was scheduled on Mondays, Wednesdays, and Fridays from 10:00 am to 10:50am. The MLT for a time-segment can be different on each scheduled day (i.e., for time-segment #1, the MLT on Mondays and Wednesdays is Template #1 but for Fridays, it is Template #2). Similarly, the MLTs for each time-segment were identified on all scheduled days. Additionally, each time-segment has a template with zero occupancy profiles (i.e., occupancy remained zero throughout the time-segment) and it is termed as *Holiday Template* (HT). HT profiles represent holidays, lecture cancellations, and relocations, among others.

Furthermore, HVAC energy consumption for a 5-day week was estimated for four different occupancy schedules: 1) MLT Schedule: a composite profile for each day of the week was created by concatenating the MLT average profiles (i.e., average of measured member occupancy profiles) for all the time-segments in a day, 2) WiFi Schedule: occupancy profile with actual WiFi measured samples for each time-segment, 3) Registered Schedule: occupancy profile with registered number of students for each lecture (i.e., time-segments) scheduled in a day, and

4) Fixed Schedule: a fixed schedule that assumes maximum occupancy during working hours (from the beginning of the first time-segment to the end of last time-segment in a day). These energy simulations were performed in EnergyPlus using a dual-duct energy model. Detailed steps for dual-duct energy simulation setup are explained in Section 3.3. The HVAC energy consumption results can corroborate the potential use of MLTs as expected occupancy for a time-segment.

3.2. Part-II: Occupancy prediction

The MLTs identified for each time-segment may be used as expected occupancy. As explained in section 3.1, multiple templates were learned for each time-segment as shown in **Figure 4**. Each profile shown in **Figure 4** gives an example of the average occupancy profiles (i.e., average of measured member occupancy profiles) of the six templates learned for time-segment #4. Out of the six occupancy profiles shown in **Figure 4**, Template #1 (shown in blue dashed line) was identified as the time-segment's MLT, and Template #2 (shown in red) was identified as the HT. Hypothetically, when MLT profile is used as expected occupancy for time-segment #4 and the actual occupancy matches the HT profile, the occupancy is overestimated.

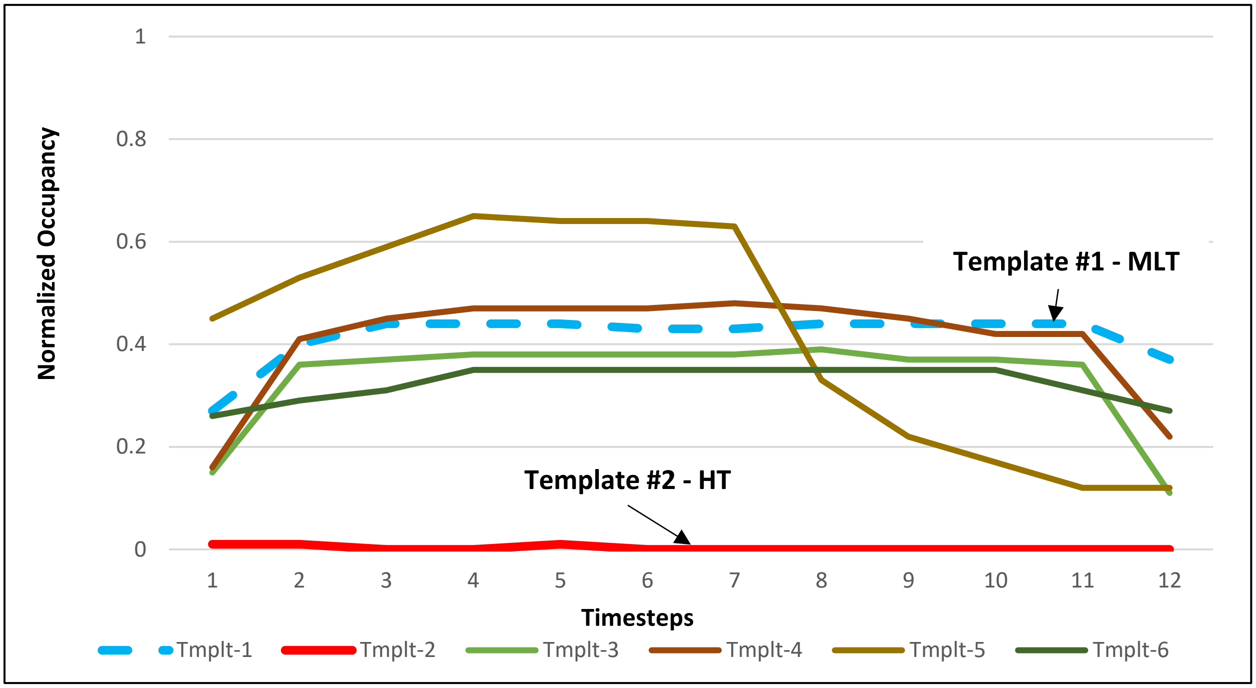

Figure 4: Learned template profiles (average profiles) for time-segment #4.

Additionally, for time-segment #1, the MLT on Fridays is Template #2 as explained in section 3.1. However, Template #2 is also the HT for time-segment #1. Therefore, when Template #2 profile is used as expected occupancy, the occupancy maybe underestimated relative to the actual occupancy. **Figure 5** shows the MLT and HT profiles along with the rest of the learned profiles for time-segment#1.

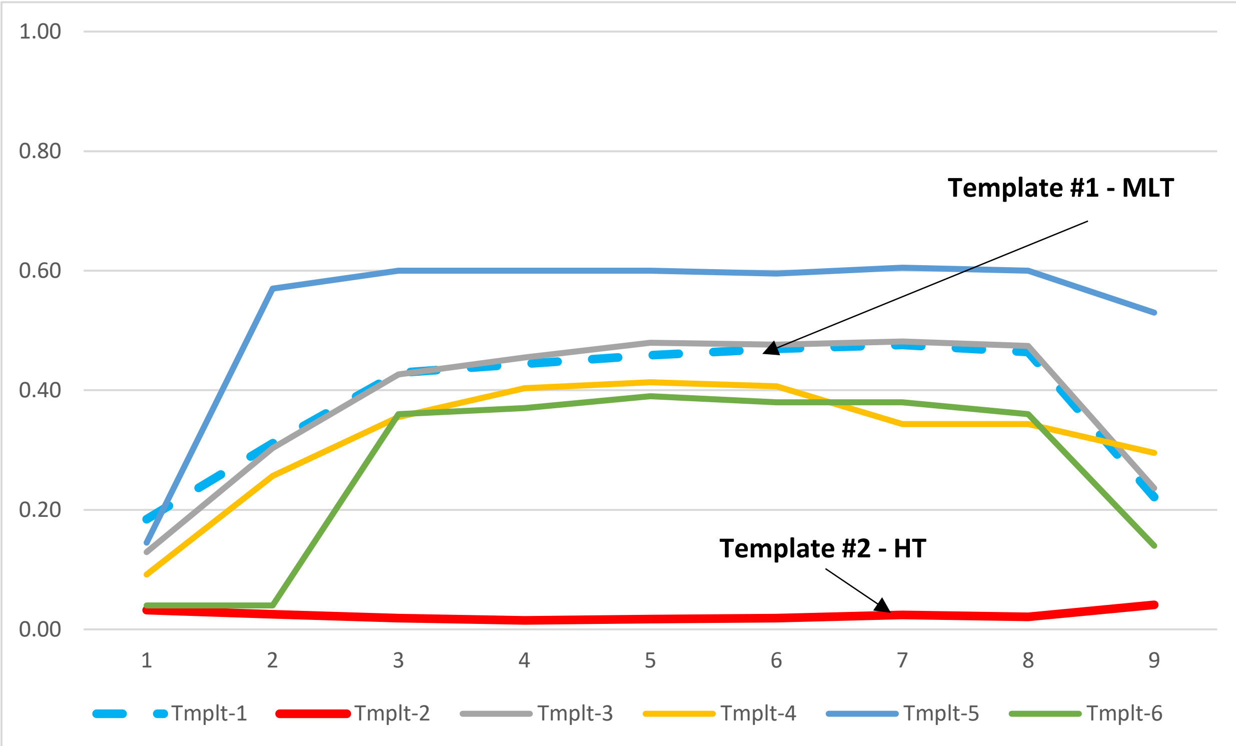

Figure 5: Template Profiles (average profiles) for Time-Segment #1

Therefore, operating HVAC systems based on a fixed MLT profile as expected occupancy may result in wasteful HVAC demand when occupancy is overestimated and occupants' discomfort when occupancy is underestimated. A mechanism is needed to able to detect a better suited template for a time-segment when MLT is incorrect. Intrinsic and extrinsic parameters available can be used to detect a more suited template profile. Some of the extrinsic variables that can be used are day of week, time of the day, occupancy schedules, and other parameters that are unique to a specific type of commercial building. Extrinsic variables such as day of the week and occupancy schedules were used to select the MLT profiles for a time-segment. Intrinsic variables may hold sufficient information to be able to find a better matching template. For this study, the first two samples of real-time WiFi measured occupancy at the start of each time-segment may be used to find a better matching template for the reminder of the time-segment. Therefore, the feasibility of using the first two real-time WiFi measured occupancy need to be verified. To this extent, using the first two time-samples of a time-segment, the 2D Euclidean distance between the first two points of its resonant template and the MLT were compared with the Euclidean distance of the full resonant template with the MLT distance. If these distances are highly correlated then, it is possible that the initial time-segment will be predictive of the full-time segment. The data used to test the correlations were calculated using **Equation 1**.

Equation 1: Equation to calculate the multidimensional distance. For a 2-D point (n = 2); 9-D point (n = 9); 12-D point (n = 12); x_i = n-dimensional MLT profile; a_i = n-dimensional template profile

$$\text{Multidimension distance per template w.r.t MLT} = \sqrt{\sum_{i=1}^{n}(x_i - a_i)^2}$$

For 50-min time-segments, distances in 2D and 9D spaces were computed and for 75-min time-segments, distances in 2D and 12D spaces were computed. A total of *n-1* pairs of distances were calculated for each time-segment where *n* is the number of templates learned for that time-segment. The calculated points were plotted against each other and the R^2 values were calculated. The R^2 value represents the part of the variance of a dependent variable (i.e., full template) explained by an independent variable (i.e., the first two template samples). Here a high R^2 value implies the possibility of distinguishing the templates using the first two template time-samples. Therefore, a high correlation between the distances calculated in different spaces lends evidence that it may be possible to learn to associate the 2D points with 9D points. Based on this hypothesis, using Neural Networks and the first two measured occupancy-samples of a time-segment a matching template was predicted for that time-segment. The template predictions were made using Laterally Primed Adaptive Resonance Theory (LAPART) neural network [30].

LAPART adopts a neural inferencing mechanism to make predictions from learned patterns [30], [35]. LAPART architecture consist of two pattern classifier subnetworks (i.e., Fuzzy ART subnetworks referred to as the A-side and B-side) laterally connected with adaptive connections. The graphical illustration in **Figure 6** shows LAPART architecture with Fuzzy ART subnetworks [33]. This architecture implements a dual system of inference rules. Recognizing a member of a familiar category by one subnetwork prompts a rule which infers that a member of a familiar category will be recognized by the other subnetwork [30]. The second rule enables the other network to reject the prediction inconsistent with the input data. **Figure 7** illustrates the prediction rule in LAPART system. For example, if an input sample *x'* is found in '*category-a*', then the corresponding value *y'* should be in '*category-b*' if the inference is correct. The granularity (i.e., size of the hyperbox) of these categories in subnetwork-A and subnetwork-B are determined by vigilance parameters ρ_a and ρ_b respectively.

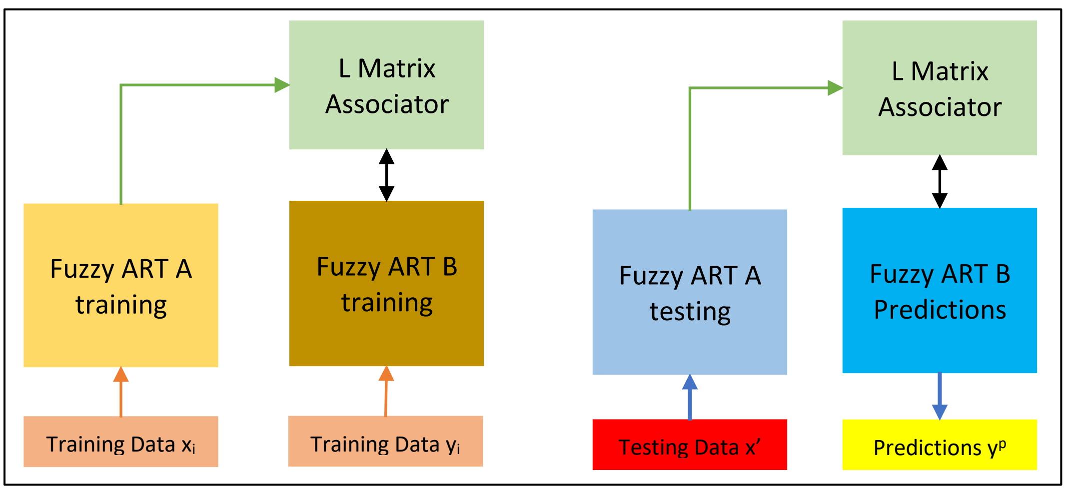

Figure 6: Graphical illustration of LAPART architecture

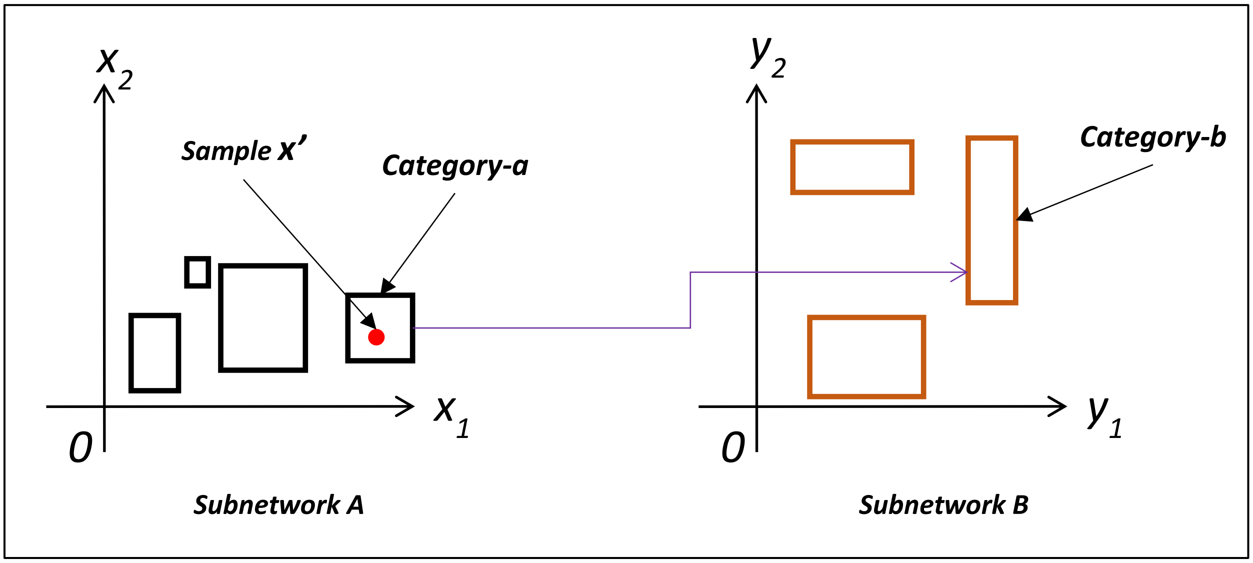

Figure 7: Associations between stimuli in LAPART

In this study, the training set for LAPART consists of N pairs of input patterns (i.e., N= 3x16 for lectures scheduled thrice a week and N=2x16 for lectures scheduled twice a week). The first member of the pair is for the A side input (from the 2D space) while the second member of the pair is for the B-side input (from the 9D space as shown in **Table 1**. The A-side input patterns consists of the first two measured occupancy samples of time-segments with dimensionality two and the B-side input patterns consists of the corresponding matching template profiles with dimensionality nine or twelve. The testing set has similar structure and dimensionality as the training set shown in **Table 1**. Here, LAPART system uses the A-side input patterns and the relations inferred during training to predict B-side template profiles. The B-side training set it then used to verify the predictions. The sample input data shown in **Table 1** corresponds to time-segment-1 scheduled from 10:00 am to 10:50am on Mondays, Wednesdays, and Fridays. Therefore, it has 48 patterns and **Table 1** shows the first 16 samples (i.e., 16 Mondays). Similar input datasets were formed for all the time-segments.

Table 1: Sample of LAPART Training Input

	A-Side Input		Template # for B-side inputs	B-side Input								
	A - 1	A - 2		B - 1	B -2	B -3	B -4	B -5	B -6	B -7	B -8	B -9
1	0.28	0.36	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
2	0.19	0.33	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
3	0.01	0.00	t2	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.06
4	0.19	0.30	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
5	0.27	0.34	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
6	0.06	0.26	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
7	0.16	0.31	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
8	0.12	0.29	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
9	0.34	0.34	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21

10	0.09	0.41	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25
11	0.03	0.25	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25
12	0.25	0.25	t1	0.21	0.31	0.43	0.45	0.47	0.47	0.47	0.46	0.21
13	0.02	0.27	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25
14	0.03	0.25	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25
15	0.19	0.19	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25
16	0.06	0.22	t3	0.11	0.3	0.41	0.43	0.45	0.45	0.46	0.46	0.25

Since feasibility of occupancy profile prediction is being tested in this study, all the A-side samples from training were used in testing. LAPART system predicts a matching midpoint (average of template upper bound and lower bound) profile for every A-side input. These results provide evidence that occupancy profiles of a time-segment can statistically be distinguished by the first two measured occupancy samples of that time-segment.

3.3. Part-III: HVAC energy estimation

A comprehensive HVAC energy analysis was performed using the predicted occupancy (i.e., midpoint template profiles) for a 14-week period starting from August 18, 2019 to November 24, 2019. The energy simulations were performed in EnergyPlus, version 9.0. The simulations were performed on four different occupancy schedules: 1) fixed schedule, 2) registered schedule, 3) WiFi schedule, and 4) predicted schedule. The fixed/static schedule assumes maximum occupancy for the lecture hall and the HVAC system runs from the beginning of the first time-segment in the day to the end of last time-segment in the day. The registered schedule runs the HVAC systems only during the time-segments (i.e., scheduled lectures) assuming registered students per lecture as its occupancy. The WiFi schedule runs the HVAC systems using the actual measured occupancy during the time-segments. Additionally, the occupancy measured outside the durations of time-segments were omitted from the WiFi schedule. The predicted schedule runs the HVAC systems using predicted composite profiles (i.e., concatenating the midpoint profiles predicted for individual time-segments in Section 3.2).

The lecture hall is served by a dual-duct HVAC unit and hence, a dual-duct model was built in EnergyPlus for all the energy consumption estimates in this study. The dual-duct model was designed using the instructions provided in EnergyPlus ‘Input Output Reference’. The modules that are essential for a dual-duct model as listed in EnergyPlus – Input Output Reference manual are: 1) HVAC Template: Thermostat, 2) HVAC Template Zone: Dual Duct, 3) HVAC Template: Plant – Chilled water loop, 4) HVAC Template: Plant - Chiller, 5) HVAC Template Plant: Tower, 6) HVAC Template: Plant Hot water loop, and 7) HVAC Template: Plant – Boiler. **Figure 8** shows the list of modules created for the dual-duct HVAC system in EnergyPlus model.

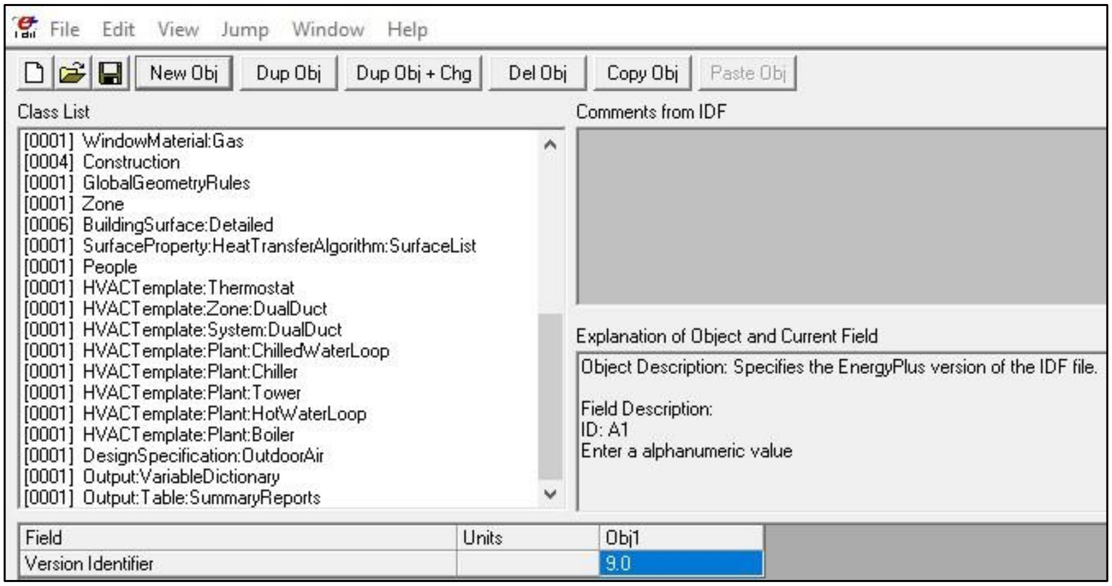

Figure 8: EnergyPlus Dual-Duct model's module list

In addition to the list of modules shown in **Figure 8**, the occupancy schedules were added to 'Schedule Compact' module. Additionally, thermostat schedules for setpoint temperature were created for corresponding occupancy schedules. These EnergyPlus schedules were built for a 14-week period starting from August 18, 2019, to November 24, 2019. The limitations within EnergyPlus Schedule Compact module restricted the entries for occupancy schedule to a 14-week period. However, a 14-week period should be adequate enough to draw conclusions on energy consumption for different occupancy schedules.

4. Results

The HVAC energy consumption values for four different occupancy conditions listed in Section 3.1 are provided in

Table 2.

Table 2: HVAC energy consumption for a 5-day week

Occupancy Type	Energy Consumed [GJ]
Fixed Schedule	2.44
Registered Schedule	1.28
WiFi Schedule	1.04
MLT- Schedule	0.84

The pairs multi-dimensional points (i.e., 2-D, and 9-D or 12-D) calculated per template w.r.t the MLT of each time-segment were plotted as shown in **Figure 9**. The example correlation plots provided in **Figure 9** are for time-segments #1, #2, #3, and #4 where time-segments #1, #2, and #3 are 2-D vs 9-D plots and time-segment #4 is a 2-D vs 12-D plot. The r^2 values for each time-segment ranged between 0.76 to 0.98.

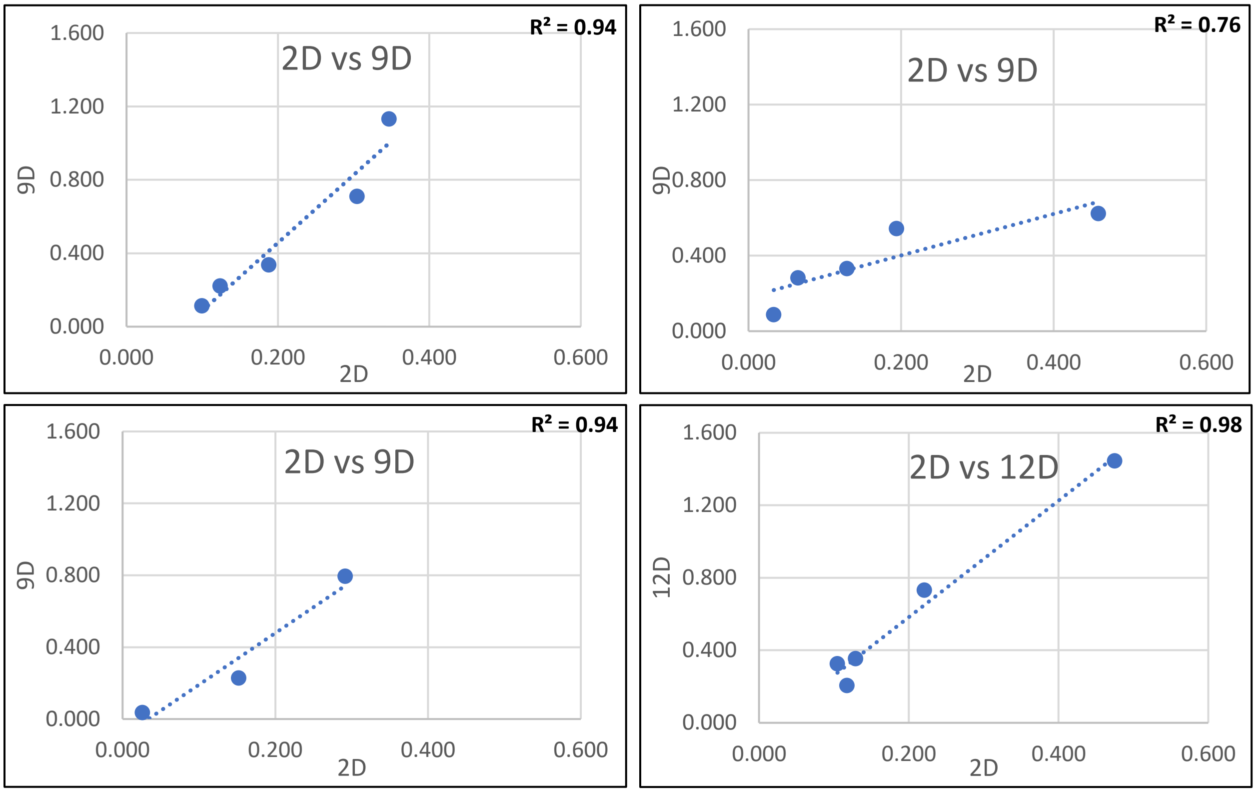

Figure 9: Correlation between A-side and B-side inputs for different time-segments. Top row: time-segment #1 & #2, bottom row: time-segment #3 & #4.

Figure 10 shows LAPART predicted midpoint occupancy profile (shown in green) at $\rho_a = 0.90$ and $\rho_b = 0.90$. **Figure 10** includes the A-side input of two measured occupancy samples (shown in black), and the corresponding B-side input of average template profile (shown in red) for time-segment #1. The R^2 value for predicted midpoint profile and input average template profile in **Figure 10** is 0.955.

Figure 11 shows four predicted midpoint occupancy profiles that matched with the 48 A-side inputs for time-segment #1 at $\rho_a = 0.90$ and $\rho_b = 0.90$. Similarly, midpoint profiles for the given A-side inputs were predicted for all the ten time-segments at $\rho_a = 0.90$ and $\rho_b = 0.90$.

Table *3* provides the training error for LAPART algorithm estimated for all time-segments.

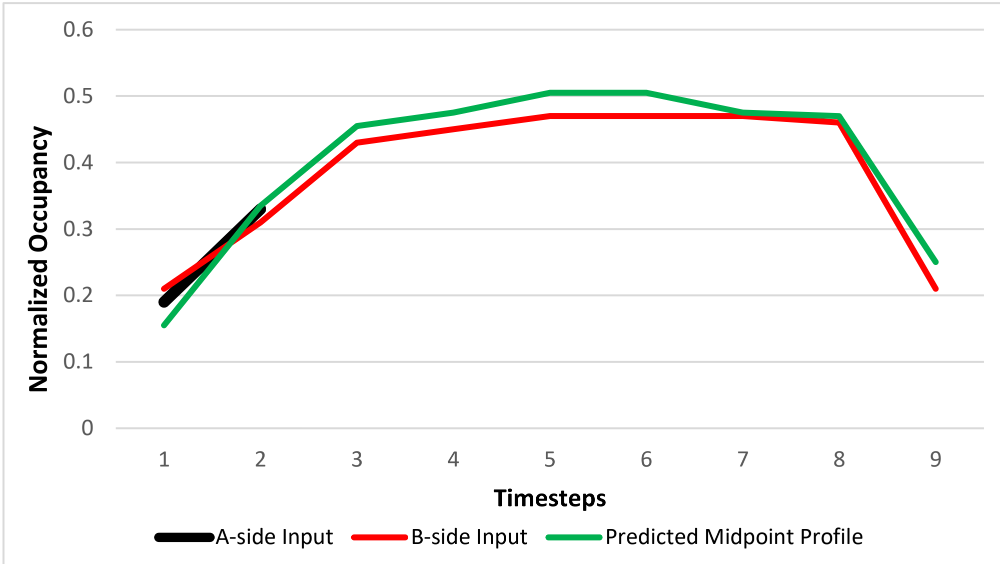

Figure 10: LAPART predicted occupancy profile for a given A-side input.

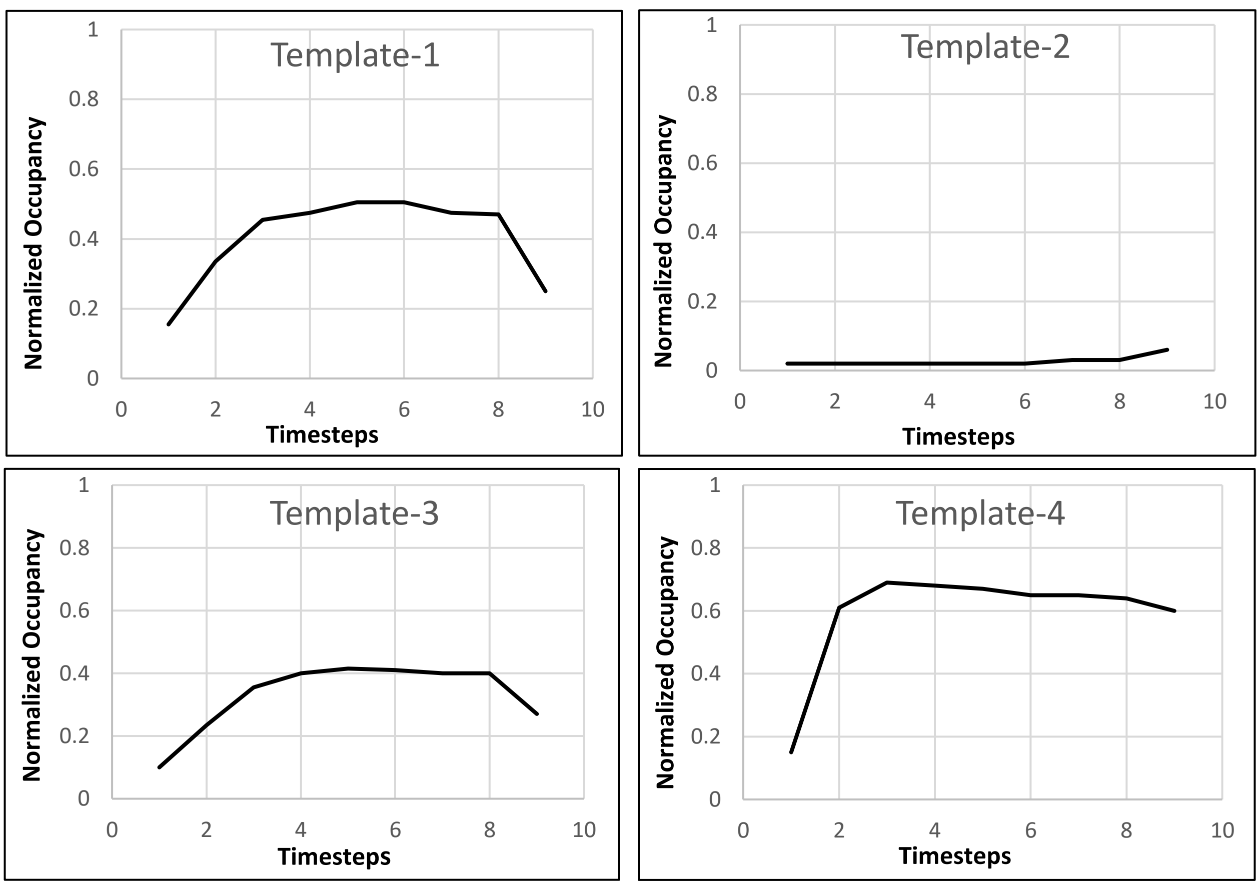

Figure 11: LAPART predicted midpoint template profiles for time-segment #1 at A-ρ = 0.90 and B-ρ = 0.90

Table 3: Training Error for LAPART

Training Error	
Time-Segment	**Error Fraction**
Time-Segment -1	0.063
Time-Segment -2	0.021
Time-Segment -3	0.000
Time-Segment -4	0.000
Time-Segment -5	0.000
Time-Segment -6	0.000
Time-Segment -7	0.000
Time-Segment -8	0.000
Time-Segment -9	0.000
Time-Segment -10	0.000

Figure 12 shows an example 24hr. composite profile formed for Monday (week-1) using the predicted midpoint profiles for time-segments 1 to 4. Similar composite profiles were created for each weekday for all 16-weeks. These composite profiles were used as occupancy for the 'predicted schedule' in EnergyPlus HVAC model as explained in Section 3.3. EnergyPlus simulations were performed for four different occupancy schedules listed in Section 3.3. The energy consumption was estimated for a 14-week period from August 18, 2019, to November 24, 2019. The 14-week energy consumption for all the four occupancy schedules listed in Section 3.3 are presented in **Table 4**.

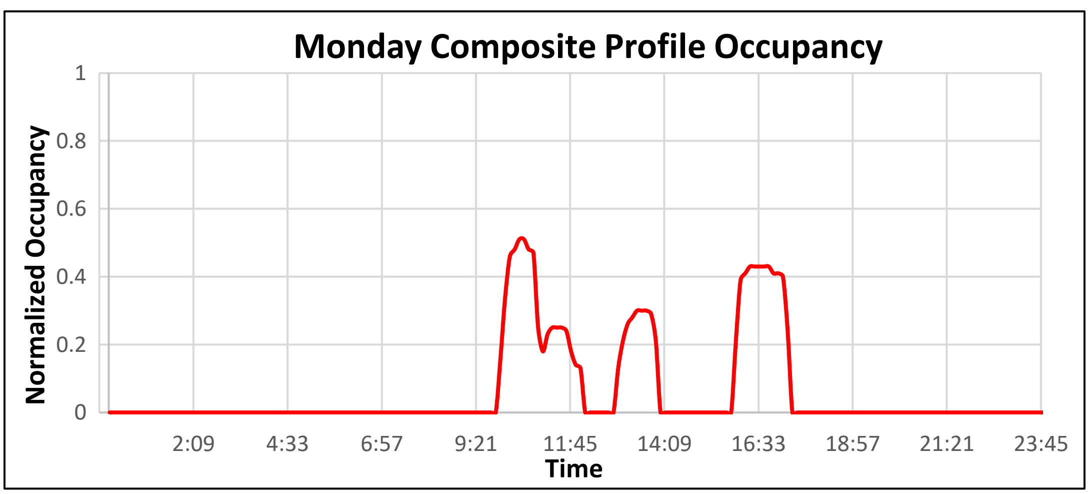

Figure 12: A 24hr composite profile created from predicted midpoint profiles for time-segments 1 to 4.

Table 4: HVAC energy consumption for a 14-week period

Occupancy Schedule Type	Total Energy [GJ]
Fixed occupancy	43.92
Registered occupancy	18.30
WiFi occupancy	14.51
Predicted occupancy	14.27

5. Discussion

This section discusses the implications, potential benefits, and limitations of this study. The proposed methodology has the following implications.

The current occupancy prediction strategies use complex occupancy data and unique IDs to make predictions. Though these methods are successful, their applicability is limited to buildings that have occupants who can be categorized as 'long-term' occupants. In this study, the patterns learned from WiFi measured occupancy data provide an alternative way to forecast occupancy in buildings with occupants that cannot be classified as 'long-term' occupants. From the patterns learned, the MLT pattern identified for each time-segment can serve as an occupancy forecast for that time-segment. The HVAC energy consumption results for different occupancy schedules presented in **Table 2** justify the use of MLT patterns as a baseline for expected occupancy. As explained in Section 3.2, MLTs may not always match with the actual occupancy of a time-segment.

To address this, a variable that has sufficient information to predict a better matching template is needed. The variable examined in this study was the pair of time-samples at the beginning of each time-segment. The correlation analysis and the results presented in **Figure 9** suggests that the first two measured occupancy samples of a time-segment can possibly be used to predict a better matching template for that time-segment. Based on this premise, occupancy template predictions were made for a time-segment using the first two measured occupancy samples. The predicted profiles are shown in
Figure *11* and it can be observed that the first two measured samples contain sufficient information to predict templates with statistical variability. For example, Template -2 and Template-4 illustrate statistical variability compared to Template-1 and Template-3. A visual comparison between the predicted profile and the input profiles shown in **Figure 10** highlight the prediction accuracy. Additionally, the low training error presented in **Table *3*** further strengthens the prediction accuracy.

The modeled HVAC energy consumption results are provided in **Table 4**. As expected, the 14-week energy consumption for the fixed occupancy schedule is the highest. The energy consumption for registered occupancy suggests that when other source of occupancy data is available, a registered schedule can be used to realize significant energy reduction compared to a fixed occupancy schedule. Furthermore, the energy consumption of WiFi occupancy highlights that the actual occupancy is typically lower than registered occupancy emphasizing the importance of collecting occupancy data. The energy consumption of Predicted Occupancy is within 2% of WiFi occupancy's energy consumption that further validates the prediction occupancy.

The proposed methodology for occupancy forecast uses existing infrastructure that eliminates additional investments and occupant privacy concerns. More importantly, this approach can be implemented in commercial buildings such as shopping centers, airports, and gymnasiums where the occupants cannot be designated as 'long-term' occupants. The MLT patterns identified from the set of patterns learned for a time-segment can be used as a baseline for occupancy forecast of that time-segment. Additionally, the results lend evidence to the possibility of using variables that are significantly correlated to the occupancy, a better matching template can be predicted for a time-segment.

Knowing the occupancy count can be used to precondition a space/zone ahead in time to increase occupant thermal comfort during a time-segment. As the impact of occupants' metabolic rates and the associated heat loss is evident in the literature, the temperature setpoints can be made a function of expected number of occupants. This temperature setpoint schema accounts for the total heat loss from n number of occupants and estimates a new setpoint T_n that is lower/higher (i.e., lower for summer months and higher for winter months) than the standard temperature setpoints. For example, different temperature setpoints can be employed for different occupant counts. This particular practice not only ensures the occupant thermal comfort but also reduces the HVAC demand (in case of low occupancy). Additionally, as the metabolic rates vary throughout the day, different setpoint can be used for different time-segments with similar occupancy. For examples, T_{n1} can be the setpoint for time-segment#1 with 40 occupants that takes place at 9am and T_{n4} can be the setpoint for time-segment#4 with 40 occupants that takes place at 1:00pm. This temperature setpoint schema can positively impact occupants' thermal comfort and their health.

The preconditioning can be advantageous in a scenario where the time-lag to bring the space temperature to the setpoint is high. If the time-lag is smaller, real-time occupant information is sufficient to regulate the temperature of the space.

6. Summary and Conclusion

The feasibility test conducted in this study highlights that the intrinsic variables with significant correlation with occupancy can be used as a predictor for occupancy pattern (via learned templates) of a time-segment. This conclusion can be extended to extrinsic variables that significantly impact occupancy of a time-segment.

In summary, significant patterns can be learned from WiFi data that does not contain any form of occupant identifiers. Occupancy predictions are possible from the learned patterns for a relative dynamic environment such as airports, libraries, institutional buildings, and shopping malls. As occupants in such commercial spaces cannot be classified as 'long-term' residents, the current framework provides a novel occupancy prediction strategy. Additionally, the current approach of using the first two measured samples as predictors for the matching occupancy profile can aid in minimizing wasteful HVAC demand and avoiding occupant thermal discomfort. In future, the current methodology and lessons learned can be implemented for different types of commercial buildings that do not have a registered occupancy and external schedule (e.g., shopping malls, airports, and gymnasiums). External variables such as deals offered at a warehouse (e.g., Costco), flights scheduled at an airport, weather related flight schedule changes/cancellations, and gymnasium memberships can have significant correlation with the occupancy. These variables can be examined to find their potential in forecasting occupancy count. Furthermore, a detailed occupancy comfort study can be conducted to quantify the impact of the proposed variable temperature setpoint schema.

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References

[1] ASCE, “Infrastructure Report Card,” no. March, pp. 1–74, 2013.
[2] EIA and B. Hojjati, “Global energy consumption driven by more electricity in residential, commercial buildings,” *U.S. Energy Inf. Assoc.*, vol. 2019, pp. 2019–2020, 2019.
[3] C. Basu, G. Ghatikar, and P. Bansal, “Enabling Efficient, Responsive, and Resilient Buildings: A Collaboration Between the United States and India,” no. March, 2014.
[4] Y. Jiang, D. Yan, S. Guo, and S. Hu, “China Building Energy Use 2018,” no. December 2016, 2019.
[5] W. Wang, J. Chen, T. Hong, and N. Zhu, “Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology,” *Build. Environ.*, vol. 138, no. March, pp. 160–170, 2018.
[6] E. Azar and C. C. Menassa, “A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings,” *Energy Build.*, vol. 55, pp. 841–853, 2012.
[7] J. Dong, C. Winstead, J. Nutaro, and T. Kuruganti, “Occupancy-based HVAC control with short-term occupancy prediction algorithms for energy-efficient buildings,” *Energies*, vol. 11, no. 9, pp. 1–20, 2018.
[8] Z. Chen, C. Jiang, and L. Xie, “Building occupancy estimation and detection: A review,” *Energy Build.*, vol. 169, pp. 260–270, 2018.
[9] Y. Peng, A. Rysanek, Z. Nagy, and A. Schlüter, “Using machine learning techniques for occupancy-prediction-based cooling control in office buildings,” *Appl. Energy*, vol. 211, no. November 2017, pp. 1343–1358, 2018.
[10] K. C. J. Simma, S. M. Bogus, and A. Mammoli, “WI-FI ROUTER NETWORK-BASED OCCUPANCY ESTIMATION TO OPTIMIZE HVAC ENERGY CONSUMPTION,” vol. 2015, no. Saic 2011, pp. 1–10, 2019.
[11] K. C. J. Simma, A. Mammoli, and S. M. Bogus, “Real time occupancy estimation using WiFi network to optimize HVAC operation,” vol. 00, no. 2018, 2019.
[12] W. Wang, J. Chen, and T. Hong, “Occupancy prediction through machine learning and data fusion of environmental sensing and Wi-Fi sensing in buildings,” *Autom. Constr.*,

vol. 94, no. July, pp. 233–243, 2018.
[13] Y. Ding, W. Chen, S. Wei, and F. Yang, "An occupancy prediction model for campus buildings based on the diversity of occupancy patterns," *Sustain. Cities Soc.*, vol. 64, no. October 2020, 2021.
[14] J. Wang, N. C. F. Tse, and J. Y. C. Chan, "Wi-Fi based occupancy detection in a complex indoor space under discontinuous wireless communication: A robust filtering based on event-triggered updating," *Build. Environ.*, vol. 151, no. November 2018, pp. 228–239, 2019.
[15] W. Wang, J. Chen, G. Huang, and Y. Lu, "Energy efficient HVAC control for an IPS-enabled large space in commercial buildings through dynamic spatial occupancy distribution," *Appl. Energy*, vol. 207, pp. 305–323, 2017.
[16] W. Parys, D. Saelens, and H. Hens, "Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices - a review-based integrated methodology," *J. Build. Perform. Simul.*, vol. 4, no. 4, pp. 339–358, 2011.
[17] H. B. Gunay, W. O'Brien, and I. Beausoleil-Morrison, "A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices," *Build. Environ.*, vol. 70, pp. 31–47, 2013.
[18] S. S. K. Kwok, "A study of the importance of occupancy to building cooling load in prediction by intelligent approach," *Energy Convers. Manag.*, vol. 52, no. 7, pp. 2555–2564, 2011.
[19] S. H. Ryu and H. J. Moon, "Development of an occupancy prediction model using indoor environmental data based on machine learning techniques," *Build. Environ.*, vol. 107, pp. 1–9, 2016.
[20] N. Li, G. Calis, and B. Becerik-Gerber, "Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations," *Autom. Constr.*, 2012.
[21] M. S. Zuraimi, A. Pantazaras, K. A. Chaturvedi, J. J. Yang, K. W. Tham, and S. E. Lee, "Predicting occupancy counts using physical and statistical Co2-based modeling methodologies," *Build. Environ.*, 2017.
[22] D. Li, C. C. Menassa, and V. R. Kamat, "Personalized human comfort in indoor building environments under diverse conditioning modes," *Build. Environ.*, vol. 126, no. September, pp. 304–317, 2017.
[23] Q. Wang, G. Augenbroe, J. H. Kim, and L. Gu, "Meta-modeling of occupancy variables and analysis of their impact on energy outcomes of office buildings," *Appl. Energy*, vol. 174, pp. 166–180, 2016.
[24] K. Ahmed, J. Kurnitski, and B. Olesen, "Data for occupancy internal heat gain calculation in main building categories," *Data Br.*, vol. 15, pp. 1030–1034, 2017.
[25] W. D. Van Marken Lichtenbelt and B. R. Kingma, "Building and occupant energetics: A physiological hypothesis," *Archit. Sci. Rev.*, vol. 56, no. 1, pp. 48–53, 2013.
[26] J. Mege, "Variations , and the Immune System," 2021.
[27] L. Klein *et al.*, "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," *Autom. Constr.*, vol. 22, pp. 525–536, 2012.
[28] C. Liao and P. Barooah, "An Integrated Approach to Occupancy Modeling and Estimation in Commercial Buildings," pp. 3130–3135, 2010.
[29] G. A. Carpenter, S. Grossberg, and D. B. Rosen, "Fuzzy ART: Fast stable learning and categorization of analog patterns by an adaptive resonance system," *Neural Networks*, vol. 4, no. 6, pp. 759–771, 1991.

[30] M. J. Healy, T. P. Caudell, and S. D. G. Smith, “A neural architecture for pattern sequence verification through inferencing,” *IEEE Trans. Neural Networks*, vol. 4, no. 1, pp. 9–20, 1993.
[31] M. J. Healy and T. P. Caudell, “Acquiring rule sets as a product of learning in a logical neural architecture,” *IEEE Trans. Neural Networks*, vol. 8, no. 3, pp. 461–474, 1997.
[32] G. A. Carpenter, S. Grossberg, and D. B. Rosen, “Fuzzy ART: An adaptive resonance algorithm for rapid, stable classification of analog patterns,” *Proceedings. IJCNN - Int. Jt. Conf. Neural Networks*, no. August 1991, pp. 411–416, 1992.
[33] C. B. Jones, “Fault detection and diagnostics of an HVAC sub-system using adaptive resonance theory neural networks,” 2015.
[34] K. C. J. Simma, T. P. Caudell, S. M. Bogus, and A. Mammoli, “FUZZY ART : PATTERN RECOGNITION OF WIFI DETECTED OCCUPANCY IN COMMERCIAL BUILDINGS,” *Springer, Nat.*, no. May, 2021.
[35] T. P. Caudell and M. J. Healy, “Lateral priming adaptive resonance theory (LAPART)-2: innovation in ART,” in *Recent Advances in Artificial Neural Networks*, CRC Press, 2018, pp. 187–211.