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Detection of occupancy status from internet connectivity for non-intrusive load monitoring

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ABSTRACT

Non-intrusive load monitoring (NILM) methods are widely used for appliance level energy disaggregation in residential buildings. These methods mostly depend on electrical features, and they have not been much successful in applying for commercial buildings. However, recent research has indicated that the accuracy of existing NILM methods can be improved by associating with occupancy data. Therefore, in this paper a novel occupancy detection algorithm is proposed which can detect occupancy status of individuals using the connectivity of their information technology (IT) devices to the local area network of the building. The model is validated using data collected at a university building, with mean errors of 01:23 and 04:02 minutes for the detection of arrival and departure. The occupancy profiles developed by the proposed model can be used to disaggregate energy consumption in a commercial building to appliance and occupant level.

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1. INTRODUCTION

Global energy consumption has increased by more than 50% in the last twenty years, and it is estimated to increase annually by 2% in the next 30 years [1]. Commercial and residential buildings share more than 40% of the global energy consumption [2] and are also responsible for a similar portion of green house gas (GHG) emissions [3]. In Malaysia, contribution of the entire building sector to the total energy consumption is 48% [4]. Out of the total electricity consumption in Malaysia commercial buildings (including universities) have consumed 43,724 GWh (almost 30%) in 2017 [5]. Load monitoring plays a vital role in energy management. Out of the two load monitoring methods; intrusive and non-intrusive, non-intrusive load monitoring (NILM) has become a largely researched topic [6] due to its competitive advantages.

The very first NILM model was introduced by Hart *et al*. [7] in 1986. As opposed to intrusive load monitoring (ILM), the interesting feature of NILM was its ability to disaggregate energy consumption down to the sub-circuit level while having an energy meter installed only at the main circuit breaker of the interested building or section. After the introduction of first model, Hart himself as well as many others have proposed a variety of NILM solutions [6], [8]-[10]. In the literature, classification of NILM approaches has been done in many different manners [9], [11], [12]. Even though NILM approaches have shown a significant success in residential building sector, it has not been successful so far commercial buildings due to various reasons like large number of identical appliances and occupants [11], [13]-[15]. A detailed review of NILM applications in commercial buildings has been done in our previous work [16].

In modern day commercial buildings, plugged in electrical loads (PEL) are becoming higher contributors to the total energy consumption and it is estimated to be 40% in 2035 in United States [17], [18]. Majority of the PEL are networked appliances like computers, printers, scanners and all-in-one devices. Several research have been focused on disaggregation of PEL [17]-[20] but still it is challenging to disaggregate when the number of loads are high and mixed up with many other loads like lighting and heating, ventilation and air-conditioning (HVAC) systems. Pure NILM methods based only on electrical features are not capable to answer this issue [21]. Non-electricity data has been associated in certain studies [22], [23] but additional sensors need be installed. Recent studies [21], [24] reveal that the association of occupancy data is a better alternative. Therefore, a need exists to develop a framework that can disaggregate all kinds of different appliances including PEL using occupancy information of a building.

Even though there is a limited use in NILM, occupancy measurements of a building are widely used in smart energy management systems [25], [26]. Occupancy of a building can be detected from different methods such as; passive infrared sensor (PIR), Bluetooth, CO_2 sensors, cameras, audio sensors, wireless local area network (WiFi) and ultrasonic sensors [26]-[28]. WiFi and Bluetooth are preferred out of these due to the convenience in obtaining information without installation of additional sensors [25], [29]. In addition to WiFi; appliance status (of computers) and personal calendars have also been used in certain studies [25], [30]. However, the capability of energy related occupancy detection and its use in NILM is less explored.

Accordingly, a problem exists in determining the energy related occupancy status of individuals and locations in a building from readily available/easily accessible information. Therefore, we propose an Occupancy detection model which can detect occupancy status of occupants in a commercial building from their internet connectivity and working schedules. Proposed model is explained in section 2 and it is validated by experimental results in section 3.

2. PROPOSED MODEL

The objective of this model is to determine the occupancy status of an individual energy consumer within a building. The main input are the connection/disconnections events of an individual occupant with the local area network (LAN). In addition, regular working schedules of an individual are also used. As shown in Figure 1, the output (occupancy status of individuals) are determined using an occupancy detection algorithm and will be used as an input for energy disaggregation in our future research. Nature of the input data, extraction of useful information, expected output and the occupancy detection algorithm are described in detail under the following subsections. Since this model is experimented at a university building, terms related to the university environment have been used as examples for the convenience of explanation.

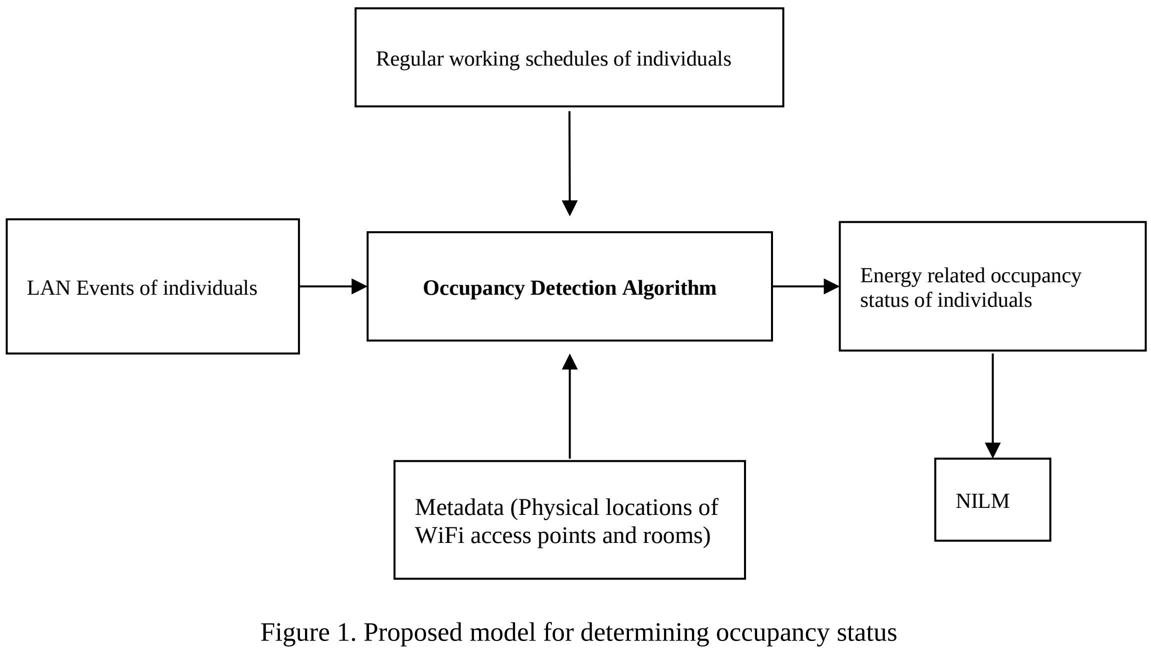

Figure 1. Proposed model for determining occupancy status

2.1. Input data

Main source of input for this model are the events associated with devices connected to the local area network (LAN) of the building. In addition, the regular working schedules of individuals as well as some location related metadata are required. The nature of the 3 types of data collected are described in the following subsections.

2.1.1. LAN events

Mobile information technology (IT) devices of employees such as smartphones, tablet and laptop computers are usually connected to the wireless local area network (WiFi) of the organization and their events of connection. Disconnection and roaming (moving from one access point to another) are collected by the network administrator who logs them using a WiFi analyzer software. A sample WiFi event log is shown in Table 1.

Table 1. Sample WiFi event log of mobile IT devices

Date and Time	Bindings
12.10.2021 23:58:57	SNMPv2-SMI::enterprises.25053.2.2.2.8=AP[164-@1c:b9:c4:2d:11:e0] radio [11g/n] detects User[19NT681@64:dd:e9:76:f1:d3] in WLAN[ITUM_Wireless] roams from AP[164-@1c:b9:c4:2d:11:e0]
12.10.2021 23:58:53	SNMPv2-SMI::enterprises.25053.2.2.2.8=AP[164-@1c:b9:c4:2d:11:e0] radio [11a/n/ac] detects User[19NT681@64:dd:e9:76:f1:d3] in WLAN[ITUM_Wireless] roams out to AP[164-@1c:b9:c4:2d:11:e0]
12.10.2021 23:58:48	SNMPv2-SMI::enterprises.25053.2.2.2.8=User[19NT681@64:dd:e9:76:f1:d3] joins WLAN[ITUM_Wireless] from AP[164-@1c:b9:c4:2d:11:e0]
12.10.2021 23:56:53	SNMPv2-SMI::enterprises.25053.2.2.2.8=User[19NT673@d8:bb:2c:72:e8:91] disconnects from WLAN[ITUM_Wireless] at AP[103-@1c:b9:c4:2d:02:b0]

Desktop computers which are physically connected to the local area network via ethernet cable are not detected by the above software, so the system events of those desktop computers were separately collected from the network administrator. System events of a personal computer (PC) can be simply collected using the event viewer app (an in-built app in Microsoft Windows) from the PC itself or from the network administrator. A sample system event log is shown in Table 2.

Table 2. Sample system event log of a PC

Date and Time	Source	Event ID	Task category
10/07/2022 1:02	Microsoft-Windows-Kernel-Boot	20	-31
10/07/2022 1:02	Microsoft-Windows-Kernel-Boot	153	-62
10/07/2022 1:02	Microsoft-Windows-Kernel-General	12	-1
09/07/2022 17:40	Microsoft-Windows-WindowsUpdateClient	19	Windows Update Agent
09/07/2022 17:40	Microsoft-Windows-WindowsUpdateClient	43	Windows Update Agent
09/07/2022 17:40	Microsoft-Windows-WindowsUpdateClient	44	Windows Update Agent
09/07/2022 17:09	Service Control Manager	7040	None

2.1.2. Regular working schedules

Any permanent occupant of a building (employee of the organization) should have at least one permanent location (e.g. room/cubicle) to stay during office hours. When there is a possibility of one person staying at two or more different rooms (e.g. a lecturer teaching at different auditoriums, and a demonstrator being at different laboratories) the possible duration of stay at each location are obtained from his/her personal time table. Further if there are any allocated regular time slots for common gatherings (e.g. lunch hour, weekly/monthly meetings) such information are also used along with personal time tables in order to derive a regular working schedule for each occupant. A sample working schedule is shown in Table 3.

Table 3. A sample working schedule (weekly) of an occupant

Location	Duration of stay	Frequency
Cubicle/default location	8.30 am – 4.30 pm	
Auditorium/Lab 1 (if any)	10.30 am – 12.30 pm	Once a week (e.g. Tuesday only)
Lunch room	12.30 pm – 1.30 pm	Every day
Auditorium/Lab 2 (if any)	2.00 pm – 4.00 pm	Twice a week (e.g. Thursday/Friday)
Meeting room	9.30 am – 11.30 am	Once a month (e.g. 3rd Wednesday)

2.1.3. Meta data

In addition to the information extracted from LAN events and personal timetables, the model should be provided with the physical locations of all rooms and WiFi access points. In case if many rooms are served by a single access point, rooms connected to each point should be separately listed. If one room is connected to several points, the point with highest probability is selecte. Such information will be useful in deciding the room occupied by an individual from his recent connection to the wireless LAN.

2.2. Occupancy detection algorithm

Collected WiFi events and system events of desktop computers are further analyzed in the steps described in the subsections below in order to derive the occupancy status of users. Movements are detected from mobile devices as explained in 2.2.3 and the start/shutdown events of computers are detected as explained in 2.2.5 and 2.2.6. After detecting, all movements/events are synchronized to one table per person (as shown in 2.2.7) and that table will be the occupancy profile of that person.

2.2.1. Pre processing of WiFi events

Occupancy related information contained in WiFi events are extracted and tabulated for each occupant in the building on a daily basis as shown in Table 4. Laptops need to be distinguished from other mobile devices such as smartphones and tablets. Since the Mac address doesn't indicate the type of device, laptops are recognized from their association with limited number of access points as they are not used while walking throughout the building. It can also be verified from the manufacturer details obtained from the user since the first six digits of Mac address indicate the manufacturer.

Table 4. Extract from the daily event list of a single occupant

Time (hh:mm:ss)	User ID	User Mac Address	Roaming from AP No:	Roaming to AP No
14:07:11	manjulad	aa:f7:1d:e4:55:da	44-ADM1	115-ADM1
14:08:55	manjulad	aa:f7:1d:e4:55:da	115-ADM1	44-ADM1
14:32:26	manjulad	9a:cb:8c:17:a5:59	0-None	44-ADM1
14:34:41	manjulad	9a:cb:8c:17:a5:59	44-ADM1	34-

For a selected device, a random event E(i) is defined as E(i)=[T(i), APF(i), APT(i)] where i ϵ [1:m] so that;

- T(i)=Time at which the ith event occurred
- APF(i)=ID of the Access point which the device roams from at T(i)
- APT(i)=ID of the Access point which the device roams to at T(i)

In the event of a device being joined to the WiFi network at any access point (not roamed from another point) APF(i) is marked as '0-None'. Similarly, in the event of a disconnection APT(i) is marked as '0-None'. In all other events (roaming from one point to another) both APF(i) and APT(i) will have values.

2.2.2. Filtering and reordering of events

There is a possibility of an occupant being connected (by a mobile device) to a WiFi access point in the considered building during an odd time while he is walking nearby the building for some other purpose. To avoid such connection being identified as an entry to the building, a maximum period of office hours is defined (T_{min}<T(i)<T_{max}) and all the events which do not lie within that duration are filtered out. In case of multiple events being taken place at the very same time [T(i)=T(i+1)=T(i+2)], there is a possibility of them being logged in an incorrect order which may create confusions. So all sets of simultaneous events are re-ordered to match with preceding and succeeding events [APT(i-1)=APF(i) and APT(i)=APF(i+1)]. If two or more consecutive events are found to be the similar [APF(i)=APF(i+1) and APT(i)=APT(i+1)] the duplicate event/s are filtered out as they do not provide any additional information.

2.2.3. Preliminary identification of occupancy status

After reordering and filtering out unnecessary events, occupancy status of all events are determined considering the fact whether the associated access points are inside or outside the building of concern, as shown in Table 5. The set of access points inside the considered building (local APs) is defined as AP_LOC. Preliminary occupancy events (occupancy status and the corresponding time) are further processed to derive actual occupancy events as described in subsequent sections. Events associated with mobile phones and those of laptop computers are processed as described in 2.2.4 and 2.2.5 respectively.

Table 5. Identification of occupancy status

Condition	Occupancy status, OST(i)	Description
APF(i), APT(i) ∈ AP_LOC	In	Continue to remain inside the building
APF(i), APT(i) ∈ (AP_LOC)’	Out	Continue to remain outside the building
APT(i) ∈ AP_LOC APF(i) ∈ (AP_LOC)’	Entry	Enters the building from outside
APF(i) ∈ AP_LOC APT(i) ∈ (AP_LOC)’	Exit	Exit from the building
APF(i) = ‘0-None’ & APT(i) ∈ AP_LOC	On	Connects to WiFi network inside the building
APF(i) ∈ AP_LOC APT(i)=‘0-None’	Off	Disconnects from WiFi network inside the building
APF(i) = ‘0-None’ & APT(i) ∈ (AP_LOC)’	On out	Connects to WiFi network outside the building
APF(i) ∈ (AP_LOC) APT(i)=‘0-None’	Off out	Disconnects from WiFi network outside the building

2.2.4. Revision of mobile phone events

If all connection, disconnection and roaming events of an occupant are accurately logged, the derived occupancy status of the i^{th} event, OST(i) should always match with those of adjoining events. For example; if OST(i)=‘On’, OST(i-1) should be either ‘Off’ or ‘Off Out’and if OST(i)=‘Off’, OST(i+1) should be either ‘On’ or ‘On Out’. However, there can be missing events of any event log in practice so the proper combination of occupancy status in adjoining events, OST(i-1:i:i+1) might not be available. Therefore, all odd combinations of events are corrected according to the criteria given in Table 6.

Table 6. Criteria for correction of odd combinations in occupancy status

Existing odd combination		Proposed correction	
OST(i)	OST(i+1)	OST(i)	OST(i+1)
Off	In		On
Off	Out	Exit	
Exit/Out	On/In		Entry
Exit/Out	Exit		Out
Out	Off	Entry	
Exit	Off	In	
Off Out	Entry/Out/Off Out	Out	
Off Out	Exit/In/Off	Entry	
On Out	On Out		Out
On Out	In	Entry	
On Out	On	Out	Entry
Entry/On/In	Entry/On		In
Entry/On/In	Off Out/Out/On Out		Exit

An occupant’s mobile phone may be temporarily disconnected from the WiFi due to one of the following events while he/she is staying inside the building or while moving outside the building: i) phone is switched off during lecture/meeting; ii) phone battery dead and put into charge; iii) stationed at a location with low signal strength; iv) WiFi network is temporarily down; and v) purposely switched to mobile data (for the use of restricted apps).

In case of both disconnection and re-connection being taken place in the same region (either inside building or outside building) it is assumed that the user has neither entered nor exit the building even though there is a possibility for such entry/exit.When disconnection and reconnection occurs in different regions it is more difficult to assume the movement but the best possibility is assumed as shown in Table 7. If there are any isolated ‘On Out’/‘Off Out’ events even after this correction (probably the first and last events of the day) they are also simply revised as ‘Out’.

Table 7. Revision of temporary disconnection events

Existing combination		Revised combination	
OST(i)	OST(i+1)	OST(i)	OST(i+1)
Off	On	In	In
Off	On Out	In	Exit
Off Out	On	Entry	In
Off Out	On Out	Out	Out

As mentioned in Table 5, an ‘Exit’ event is identified when the mobile device of the occupant roams from a local (located inside the considered building) access point to another. However, there is a possibility of an occupant being connected to an outside access point while he/she is staying inside the building. Such false

'Exit' events are detected and corrected as 'In'. Detection criteria is explained in Figure 2. Similarly, there can be false 'Entry' events which are detected in a similar manner and corrected as 'Out'.

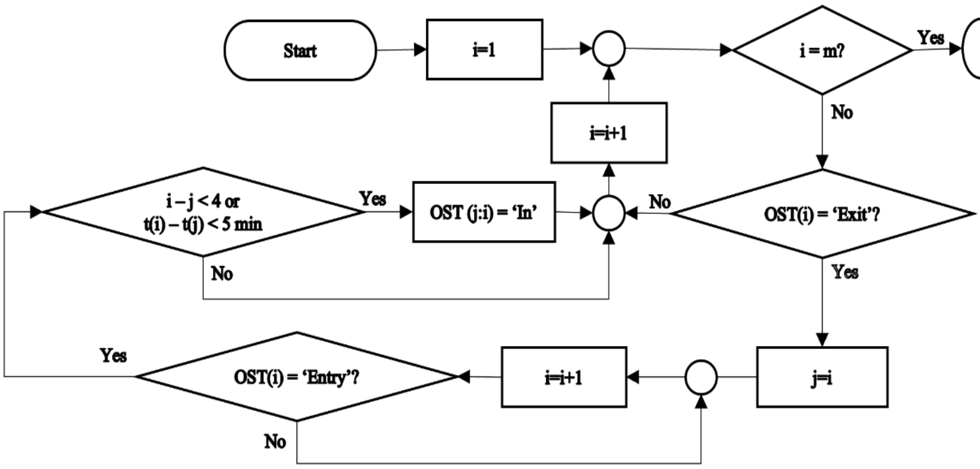

Figure 2. Revision of false 'Exit' events

2.2.5. Revision of laptop events

In case of events associated with laptop computers, the revision of occupancy status is done in a comparatively simple but different manner as shown in Table 8. Temporary 'Exit-Entry' pairs are filtered out just like in the case of mobile phone events but instead of 5 minute maximum, a one hour period is considered for laptops. If the 'Entry' event is found one hour after the 'Exit' event, the respective 'Exit' and 'Entry' events are considered as 'Laptop Shutdown' and 'Laptop Started' respectively. The isolated 'Entry'/'Exit' events are treated in the same manner unconditionally. The isolated 'On' events and 'Off' events are also recognized as 'Laptop Started' and 'Laptop Shutdown' respectively.

Table 8. Revision of occupancy status of laptop computers

If OST(i) = '…'	& OST(i+1) = '…'	Revised OST(i+1)
"Off"	"In"	"On"
"Out"	"On"/"In"	"Entry"
"Entry"/"On"/"In"	"On"	"In"
"Entry"/"On"/"In"	"Out"	"Exit"

2.2.6. Identification of desktop events

For the detection of desktop computer operation, selected rows of the first two columns (Time and Source) are extracted from the system event log (Table 2) and the row selection is done based on the criteria; S(i) ϵ ['Microsoft-Windows-Kernel-Boot', 'Microsoft-Windows-Winlogon']. Table 9 shows a sample extract. Occupancy status, OST(i) at a given time, t(i) of a given day is determined from S(i) for each desktop computer as shown in Figure 3. It should be noted that OST(i)='Shutdown' when i=1 (opening event of the day is a shutdown) implies that the desktop computer has not been shutdown on the previous day.

Table 9. Extracted information from system event log

Time, t(i)	Source, S(i)
9.24 am	'Microsoft-Windows-Kernel-Boot'
9.25 am	'Microsoft-Windows-Winlogon'
11.43 am	'Microsoft-Windows-Winlogon'
12.15 pm	'Microsoft-Windows-Kernel-Boot'
12.16 pm	'Microsoft-Windows-Winlogon'
4.18 pm	'Microsoft-Windows-Winlogon'

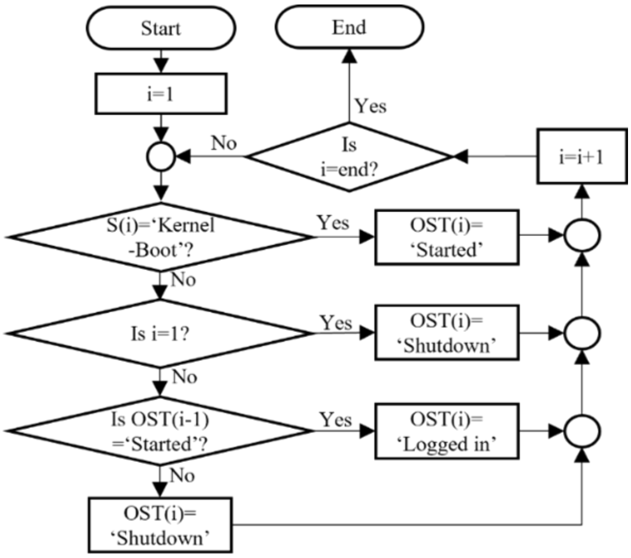

Figure 3. Detection of occupancy in desktop computers

2.2.7. Synchronizing of occupancy events

Once the occupancy status are determined for all devices (mobile, laptop and desktop) of a single occupant, they are synchronized to build up the occupancy profile as shown in Table 10. It should be noted that every occupant is not necessarily using all kinds of devices. However, the higher the number of devices, the better the accuracy of occupancy.

Table 10. Overall occupancy profile of an individual occupant

Time	Occupancy Status
'21-Oct-2021 08:32:26'	"Entry"
'21-Oct-2021 08:36:32'	"Laptop Started"
'21-Oct-2021 11:23:49'	"Laptop Shutdown"
'21-Oct-2021 11:37:12'	"Desktop Started"
'21-Oct-2021 12:29:50'	"Exit"
'21-Oct-2021 12:41:13'	"Entry"
'21-Oct-2021 15:34:30'	"Desktop Shutdown"
'21-Oct-2021 15:40:24'	"Exit"

In addition to the initial arrival and final departure of an occupant, the above reveals temporary departures/arrivals (if any) as well as the durations worked on computers (if any). Any time gap between the initial arrival and computer start (and also the gap between computer shut down and final departure) is the prospective time period for switching lights/air-conditioning (AC) and use of elevators. Exact location where the occupant stays inside the building during the particular period can be selected from his/her regular working schedule and it can be verified from the associated access points within that period.

2.3. Data collection

A four-storey academic building of a university in Sri Lanka was selected for this study. The building is occupied by 25 employees (academics and support staff). In addition to the employees, students also come to the building to attend lectures, practical classes and sometimes occupy the students' common room. However, during the period of data collection no students were present since the classes were conducted online due to covid-19. Types and number of rooms available in the building are given in Table 11. Two elevators and two staircases are there for the movement between the floors. Also 10 WiFi access points are located within the building.

Data collection started on 11th October 2021 and continued until 13th January 2022. 20 out of 25 employees were actively present during the 3-month period of data collection and all of them provided consent to be part of this study. Accordingly, the 20 user IDs were given to the network administrator and the associated Wifi events during the 3 months were collected. System events of the desktop computers were collected separately from individual machines. These data could have also been been collected from the network administrators. For the verification of entry/exit events derived from the model, the occupants were asked to record their actual entry and exit by scanning a quick response (QR) code pasted on the door of their respective room/lab. For further verification, their digital attendance registers (fingerprint records) of available occupants were also collected.

Table 11. Details of various spaces in the building

Type of building	No
Office (academics lounge)	1
Laboratories	10
Auditoriums/Tutorial rooms	4
Common (lunch) rooms	3
Computer lab	1
Other	2

3. RESULTS AND DISCUSSION

It was observed that all 20 occupants who took part in this study, have been connected to the internet via at least one device enabling to derive occupancy status of all of them but only 10 of them have recorded their entry/exit via QR scan. However, fingerprints were available for 9 occupants (including two who had not scanned QR). Accordingly ground truth was available for 12 occupants. Usage of devices and availability of ground truth for all 20 occupants are summarized in Table 12.

Table 12. Use of devices and availability of ground truth

User index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Mobile	√			√	√		√	√		√	√	√	√	√		√	√	√	√	
Laptop	√	√			√	√			√	√					√	√			√	
Desktop			√	√							√					√		√		√
QR scan	√			√		√		√		√	√					√	√	√		√
Fingerprint	√		√	√				√			√		√				√	√		√

For the verification of the proposed algorithm, entry and exit times derived from the connectivity via mobile phones and computers were compared with actual arrival and departure times recorded by QR scan. The difference between the derived time and actual time (error of detection) in each case are plotted in Figure 4. Mean error for each case is given in Table 13.

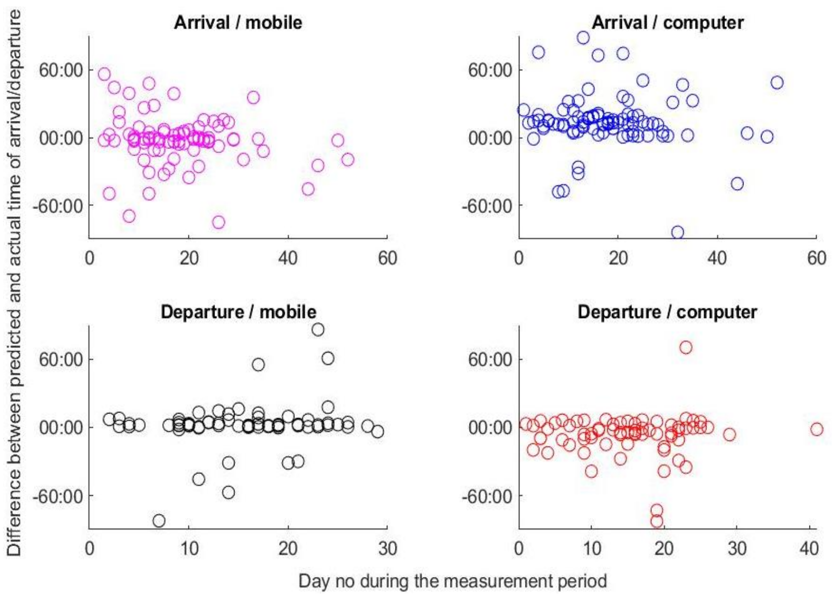

Figure 4. Error of detecting arrival/departure times from mobile devices/computers

Table 13. Mean error of arrival and departure detection

Feature	Detecting device	Mean error (minutes)
Arrival time	Mobile phone	-08:31
Arrival time	Computer	15:28
Departure time	Mobile phone	04:20
Departure time	Computer	-06:29

According to Figure 4, ability of detection differs with the type of the connecting device too. Again, in case of arrivals, the times detected by computers have less difference with actual arrival compared to that of mobile phones. The reason is the tendency of signing into WiFi via computer as soon as it is turned on, unlike a mobile phone which can also be used with mobile data. However, during departure the mobile phone detects better than the computer since computer might be shutdown in advance, but the mobile phone starts roaming exactly at departure time. According to Table 12, there are certain occupants who connect to WiFi only via computer, but it was observed that they use smartphones with mobile data since the organizational WiFi has restrictions on use of certain apps. Accordingly there are disadvantages of using only one type of device to detect arrival and departure time which can be overcome by changing the criteria of detection as described in Table 14.

Table 14. Detection of arrival/departure using both mobile phone and computer events

Internet device of occupant	Time of arrival	Time of departure
Mobile only	Entry time of mobile	Exit time of mobile
Computer only	Start time of computer	Shutdown time of computer
Both mobile and computer	Any of the above events occurs first	Any of the above events occurs last

Once the detection criteria is changed as above a slight improvement was observed in error statistics of arrival/departure detection as shown in Table 15. Also, it was observed that the total number of detected arrivals and departures has also increased from 168 to 256. So, the revised criteria of detection can be considered as more accurate.

Table 15. Mean error of detection after criteria revision

Feature	Mean error (minutes)
Arrival time	01:23
Departure time	04:02

Even though occupancy profile reveals all departures and arrivals of an occupant, only the initial arrival and final departure could be verified from ground truth data since they have not recorded other departures and arrivals in between. However, the accuracy of such events can be verified when they are used for energy disaggregation in the next stage of the research. Therefore, the accuracy of the algorithm is expressed with respect to the initial arrival and final departure.

4. CONCLUSION

This paper presented a model that uses the internet connectivity of occupants of a commercial building and determines their occupancy profiles within the building. The two main features of the developed occupancy profile; arrival and departure times of an average occupant were successfully validated with mean errors 01:23 minutes and 04:02 minutes respectively. However, the other features could have also been validated if more ground truth data like cctv footages were available. These occupancy profiles along with total power measurement of the building can be used to disaggregate energy consumption of the building using non-intrusive load monitoring methods which will be the next stage of this research.

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