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Recognition and Analysis of Air-conditioner Operation Based on Basic IAQ-monitoring

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Abstract. Building performance simulations are particularly important for the development of various building energy efficiency strategies. However, the accuracy of these building simulations is often greatly influenced by real occupant behaviour, which leads to deviations between expected and measured performance. The occupant behaviour varies greatly from region to region and even within the same region due to the differences in cultural, climatic and socio-economic contexts and building characteristics. Therefore, typical occupant behaviours and usage patterns in local buildings should be considered to improve the accuracy of the building simulations. To achieve this purpose, sufficient occupant data is needed to derive these typical behaviours. The cost of data collection and analysis as well as privacy concerns, are the main challenges that must be addressed. This study proposed a simple method to recognise the use of individual split-air-conditioning units based on basic environmental parameters (indoor air temperature, humidity and CO_2-concentration) collected by IAQ-sensors in residential buildings. This method was used to analyse the air-conditioning (AC) usage patterns of 98 rooms in 49 residential apartments over one year in Hanoi, Vietnam and validated through comprehensive occupant surveys and on-site measurements. While deriving typical behaviours, deviations from measured room temperature and AC set temperature were observed and discussed in detail. The highlights of the proposed method are as follows: a) The data on AC operation can be determined without labour-intensive manual processing; b) The necessary input data can be collected by using standard IAQ-monitoring instruments, which minimises the cost of data collection and the invasion of occupant privacy; c) Missing information about AC usage can be added to data sets of previous studies for further analysis.

Keywords. Occupant behaviour, Residential building, Air conditioning, Operation recognition, Case study.
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1. Introduction

The use of air conditioners (AC) for space cooling accounts for nearly 20% of the total electricity consumption in buildings worldwide today, which places a huge burden on the grid and increases CO_2 emissions [1]. Meanwhile, the AC's household penetration rate in many emerging countries with hot climate zones is currently low, for example, nearly 50% of urban households and 80% of rural households in Vietnam are not yet equipped with AC [2]. With rising living standards, population growth and more frequent heatwaves, the AC ownership is expected to increase significantly, especially in the Asian region [1] [3]. Therefore, it is important to improve the energy efficiency of the buildings there to reduce the energy consumption and emissions related to air conditioning. Many studies have revealed that occupant behaviour significantly impacts energy consumption and is a major factor in the building performance gap [4]-[7]. Different cooling behaviour can significantly differ in AC-related energy consumption, even in the same building [8]. The effectiveness of building performance improvement actions differs under diverse occupant behaviour, so it is essential to quantify its impact on energy efficiency measures [7]. In order to gain insight into cooling behaviour, a large amount of AC operating data, such as on/off-states (AC events) and cooling setpoints, is required to determine typical AC usage patterns and derive occupant behaviour models. In previous studies, researchers have used different methods to directly or indirectly obtain the data on the AC operation. Measurement parameters such as indoor air temperature (1), AC power consumption (2), AC supply air temperature (3) and infrared (IR) control signals of AC remotes (4) are often used to determine

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the AC operating status as illustrated in. **Fig. 1**. Advantages and disadvantages of these methods are listed in **Tab. 1**.

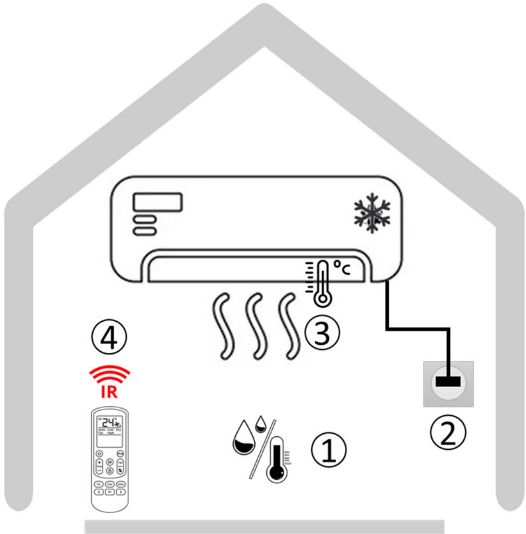

Fig. 1 - Common measurement parameters for monitoring the AC on-off state

Zhang et al. [9] monitored the indoor climate with temperature/humidity data loggers. The AC events were determined by directly observing the change in the room temperature. The indoor air temperature measured after the cooling process has become stable is estimated as the cooling set temperature. Although the parameters required for this method can be obtained with low-cost measuring instruments, the manual processing is labour-intensive. Furthermore, night ventilation or air exchange with adjacent air-conditioned rooms can also lead to changes in indoor climate that may interfere with the results. In contrast, by monitoring the AC power consumption, Ren et al. [10] determined the AC on/off-state more accurately and obtained the actual AC-related energy consumption

data. However, indoor climate, such as air temperature and humidity, as well as the cooling setpoints must be measured separately. In addition, the power measuring instruments also increase the costs and are not suitable for some scenarios, e.g., in some households investigated in this study, the AC power supply cable is enclosed in the wall and cannot be connected to an external power meter. Song et al. [11] also determined the air conditioning events by observing temperature changes, but the difference is that they used the temperature measured at the AC supply air vent. When the AC state changes, the change in the air supply air temperature is more noticeable than the change in room temperature, thereby avoiding false recognition caused by other cold/heat sources. However, the AC events were still manually recognised and the indoor climate needs to be measured by other instruments. Mun et.al. [12] adopted a more direct method to determine the AC operating status by collecting and analysing the infrared control signals from the AC remote. In this way, the on/off-state and the AC operating mode (incl. the cooling setpoint and the fan speed) can be obtained accurately. During the pre-processing of the signals collected by the IR receiver, signals from other home appliances must be excluded. Moreover, due to the different protocols, the AC control signals for each AC unit must be analysed individually.

A common disadvantage of these methods mentioned above is the labour-intensive manual processing. In addition, the data collection in residential buildings is very challenging, not only due to the cost of the measuring instruments but also because of the intrusion of long-term measurements on the occupants. Therefore, the data collection and processing process must be improved to make it more implementable in practice.

Tab. 1 - AC event recognition methods used in previous studies

	Measuring instruments/ key parameters/sample size	**Pros & Cons**
Zhang et al. (2013) [9]	• T/RH data logger • Indoor air temperature • 10 dormitories (bedroom) in Guangzhou, China (January 2009 – January 2010)	(+): Low-cost and low-complexity (-): Manual recognition is labour-intensive. (-): Recognition may be affected by night ventilation or air exchange with adjacent rooms.
Ren et al. (2014) [10]	• Power meters • Power of AC • 34 households (living room and bedroom) in 8 different cities in China, (mid-July – mid-September 2013)	(+): AC energy consumption can also be measured (-): Additional costs for power meters and possible limitations on installation (-): Indoor climate must be measured separately.
Song et al. (2018) [11]	• Temperature logger • Supply air temperature of AC • 43 households (living room and bedroom) in Tianjin, China (May – November 2016)	(+): The change in the air supply temperature can indicate the AC on/off state more obviously. (-): Manual recognition is labour-intensive. (-): Indoor climate must be measured separately.
Mun et al. (2019) [12]	• Infrared receiver • Control signal of AC remote • 4 households (living room) in Seoul, South Korea (late July – early September 2017)	(+): AC settings can be accurately obtained (-): Pre-processing procedure is labour-intensive (-): Indoor climate must be measured separately

With the development of sensor technology and the growing concern for comfort and health, measuring instruments for indoor environment monitoring are becoming more popular in people's daily life. Key parameters in the indoor environment such as air temperature, humidity and carbon dioxide (CO_2) concentration can be long-term measured with an integrated IAQ sensor. Thanks to IoT technology, measurement data can be uploaded to cloud servers and accessed remotely. Considering these advantages, this study proposes a simplified method for determining the operating status of split-AC using cloud-based IAQ data loggers. To improve the efficiency of data analysis, automatic recognition algorithms have been developed based on a long-term investigation of 49 households in Hanoi, Vietnam.

2. Methodology

2.1 Direct observation (DO)

The use of AC is accompanied by significant changes in indoor climate. By directly observing the rate of change of the relevant parameters, e.g. temperature gradients, it is possible to manually recognise the space cooling events and determine the AC on/off moments as adopted by Zhang et al. (2013) [9] in their study. However, rapid drops in outdoor temperature (e.g. due to rainfall) or in adjacent rooms (e.g. due to space cooling) can also cause similar changes in room temperature with air exchange. Determining the AC on/off-state with room temperature alone is unreliable in some cases. Long-term observations of indoor climate data have shown that when the AC is turned on the humidity in a room usually drops significantly, sometimes even more sensitively than the temperature (especially under hot and humid conditions). In addition, most occupants only use AC in the rooms they occupy and close the windows during the cooling process, which leads to an increase of the CO_2-concentration in these rooms. Therefore, the humidity change rate and CO_2-concentration in the indoor air were introduced as additional parameters to manually determine the AC operating status in this study. **Fig. 2** illustrates the working principle of the DO-method with an example of a bedroom. Since rapid simultaneous drops and rises of room temperature (red curve) and absolute humidity (blue curve) may indicate that the AC is on and off respectively, the AC on/off moments can be first determined by observing the sudden changes in the time series (black dashed lines). The occupancy status of this room can be estimated from the CO_2-concentration (yellow curve). When the CO_2-concentration continuously exceeds 500 ppm it can be considered as evidence that the room is occupied. The estimated occupancy profile (green dotted step curve) indicates on the one hand that the room is poorly ventilated when the AC is in use (blue zone), and on the other hand confirms that the change in indoor climate is not caused by airflow from other rooms or from outdoor.

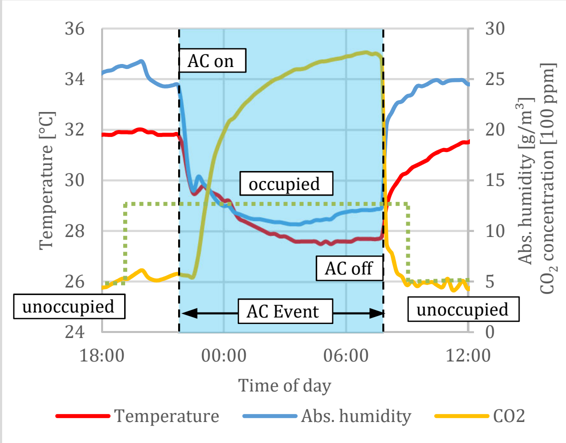

Fig. 2 - Principle of the direct observation method

Manual processing can ensure accurate recognition of AC events, especially under complex conditions (e.g. when indoor environment fluctuates greatly), but it is very labour-intensive and inefficient. Three representative households in this study were analysed using this method to validate and compare the following two automatic recognition algorithms.

2.2 Local extrema analysis (LEA)

The first algorithm for automatic recognition of AC events is also based on finding sudden changes (local extremes) in the time series of room temperature and absolute humidity. Although **Fig.** 2 demonstrates that CO_2-concentration is also correlated with AC use, it cannot be used as a criterion for the automatic determination of AC on/off moments, as changes in occupant CO_2 generation rate and the operation of doors and windows may interfere with the results. However, the estimated room occupancy status can be used to correct the recognition result under certain conditions, e. g. according to the occupant survey, the AC is always turned off when the room is unoccupied.

In order to introduce the rate of change (ROC) of room temperature and absolute humidity as criteria in the recognition process, they are first normalised by their maximum ROC over the period in question and then combined according to **equation (1)**.

$$nROC_{indoor} = \frac{\frac{d}{dt}\rho_V}{max\left(\frac{d}{dt}\rho_V\right)} + \frac{\frac{d}{dt}\vartheta}{max\left(\frac{d}{dt}\vartheta\right)} \qquad (1)$$

Where,

$nROC_{sum}$:	Sum of normalised ROC
ρ_V:	Absolute humidity
ϑ:	Room temperature

Fig. 3 illustrates the working principle of the LEA-method using the same indoor climate data as in **Section 2.1**. The sum of the normalised rates of change of room temperature and absolute humidity ($nROC_{sum}$) deviates significantly at the moment when the AC operating status is changed. The AC on/off state recognition is therefore equivalent to finding

local minima and maxima (valleys and peaks) in the nROC$_{sum}$ time series. In this study, this task was performed with the "Find Local Extrema" function available in the software MATLAB R2020b [13]. The parameter "prominence", which measures how the valley/peak at the AC on/off moment stands out with respect to its depth/height and location relative to other valleys/ peaks, has to be set to a reasonable value. A high parameter value can improve the recognition accuracy but will reduce the sensitivity, resulting in some AC events cannot be recognised, especially those events with short duration (2 – 3 h). A low parameter value, on the other hand, will increase the number of misrecognised AC events. Since there is no universal parameter value that can be applied in all cases, it is necessary to manually select a relatively reasonable values and to fine-tune it in some special cases. In order to correct misrecognised events, an automatic checking procedure is needed to remove frequent AC on/off events (fluctuation) that occur in a very short period of time. In addition, typical room temperature and humidity values observed during the use of AC are used as reference values to check each AC event.

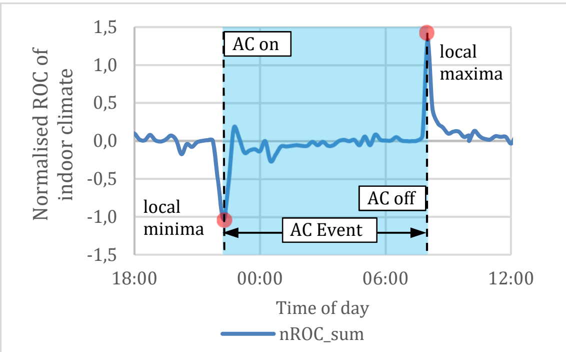

Fig. 3 - Principle of the local extrema analysis

2.3 Deviation monitoring (DM)

As the method presented in **section 2.2** requires manual parameter adjustment and its recognition performance is not very stable, another method "DEM" has been developed to improve efficiency, robustness and accuracy in the recognition processing. It is based on dynamic monitoring the deviation of the measured temperature and absolute humidity from their baselines (see **Fig. 4**). The baselines used to calculate the dynamical temperature deviation (DevT) and humidity deviation (DevH) are defined as the moving mean of the daily maximum values of the corresponding parameters. When a room is being mechanically cooled, the room temperature and humidity will deviate significantly from their respective baselines at the same time. Therefore, comparing whether the deviation exceeds a certain threshold can be used as a basis for determining the AC operating status of in that room. The threshold is defined as the product of the threshold factor and the mean dynamic deviation for the period in question. If the climatic and building conditions are similar, a uniform threshold factor can be used, e.g. in this study 1.5 and 2.5 are used to determine the DevT-threshold and DevH-threshold respectively. Since the mean dynamic deviation is calculated separately for each room, this method allows for self-tuning of parameters to suit different rooms. This method applies to "part-time occupant AC behaviour", which means that the room is not constantly air-conditioned. This AC behaviour is typical in most residential buildings.

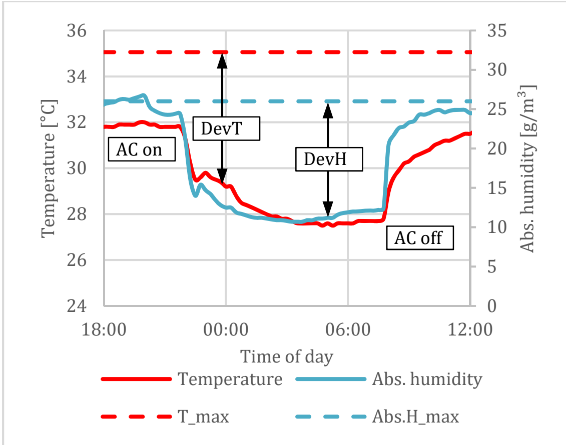

Fig. 4 - Determination of the dynamic deviation

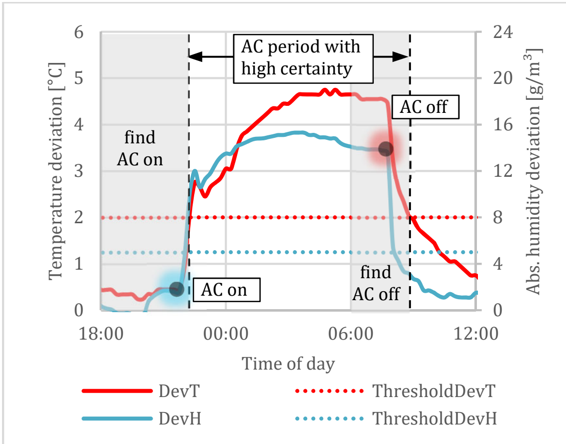

Fig. 5 - Principle of the deviation monitoring

A concrete example is presented in **Fig. 5** to show how this method works. Whenever DevT and DevH simultaneously exceed and fall below their respective thresholds again after a certain time, the air conditioner is considered to be in use during this time period. In contrast to the LEA-method, the AC event is determined first rather than the AC on/off moments. The advantage is that the misrecognition rate can be reduced by increasing the threshold factor. Although the preliminary derived AC event time period will be narrower than the actual one, it is more reliable. The AC on/off moments are then searched additionally by finding the local extreme value of room temperature and absolute humidity in the area near the edge of each AC event (grey area). Although the recognition can already be improved by using this method, a checking procedure is still used to reduce the misrecognition rate further.

2.4 Performance evaluation

Fig. 6 illustrates the workflow used to evaluate the two automatic recognition algorithms (LEA and DM). The direct observation method is first used to analyse indoor climate data collected from long-term monitoring to prepare a reference dataset for a quantitative comparison of results based on the other two automatic recognition methods. Next, information on occupant AC usage collected through online and telephone surveys was used to verify the accuracy of the reference dataset generated. However, the data on AC operation obtained through the questionnaire is in fact a summary of the AC usage over a period of time and cannot be compared directly with the time series AC on/off dataset. The frequency of AC usage, the duration of each AC operation and the typical cooling setpoints were therefore statistically analysed based on the recognition results to make a semi-quantitative comparison with the occupant survey. Although AC operation data obtained by direct measurements (i.e. power measurements) would be more suitable for evaluation, in this study it was not possible to install such measurement devices because the AC power cables were all enclosed in the wall.

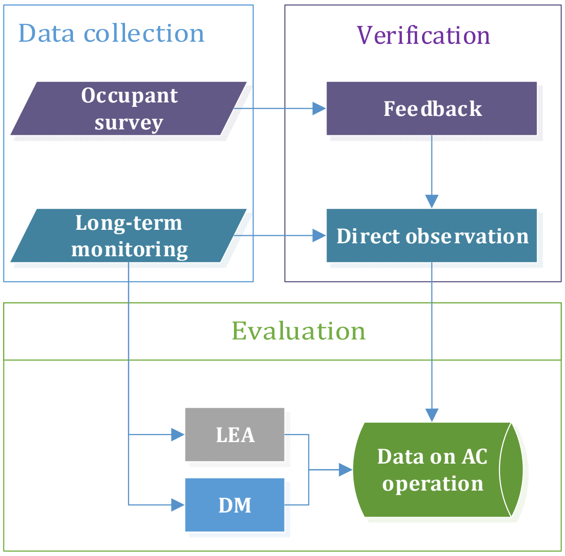

Fig. 6 - Workflow of the performance evaluation

In previous studies [14], [15] on AC-related energy consumption, the operating rate (OR) of AC and F_1 score are commonly used as important evaluation indices. They were introduced in this study to analyse the performance of the recognition algorithms. OR, calculated according to **equation (2)** is the ratio of the sum of the AC running time (t_{AC_on}) to the total observed time period (t_{total}).

$$OR = \frac{\sum t_{AC\_on}}{t_{total}} \tag{2}$$

The F_1 score is calculated from precision and recall (see **Tab. 1**) using **equation (3)**, where the precision is the number of true positive results divided by the number of all positive results, including those not recognised correctly **(Eq. 4)**, and the recall (known as sensitivity) is the number of true positive results divided by the number of all samples that should have been recognised positive **(Eq. 5)**.

Tab. 1 - Precision and recall

		Reference result (DO)	
		AC on	*AC off*
LEA & DM	*AC on*	True positive (TP)	False positive (FP)
	AC off	False negative (FN)	True negative (TN)

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{3}$$

$$precision = \frac{TP}{TP + FP} \tag{4}$$

$$recall = \frac{TP}{TP + FN} \tag{5}$$

3. Study cases

As a part of the research project CAMaRSEC [16], a comprehensive technical survey campaign with accompanying measurements was conducted in 49 households living in high-rise buildings in urban Hanoi, Vietnam from June 2020 to June 2021.

Indoor climate data (air temperature and humidity, CO_2 concentration, ambient pressure) were collected from 49 living rooms and 49 bedrooms using wall-mounted WiFi data loggers testo 160 IAQ with a measurement interval of 15 minutes. (see **Tab. 2**).

Tab. 2: - Technical data of the measuring instrument

Parameter	*Range*	*Accuracy*
Temperature	0 ~ 50 °C	± 0.5 °C
Relative Humidity	0 ~ 100 % (non-condensing)	± 2.0 % at 20 ~ 80 %RH (±3.0% at remaining range)
Ambient CO_2	0 ~ 5000 ppm	± 50 ppm
Atmospheric Pressure	600 ~ 1100 mbar	± 3 mbar

Hanoi features a warm and humid subtropical climate, with summer lasting from May to September. Winters in Hanoi are generally mild. This climate results in a large demand for space cooling using AC in summer and relatively low heating demand in winter. Based on this AC usage characteristic, measurements from June to November 2020 were defined as the observation period in this study. According to the household survey, the frequency of AC use in Summer in the 98 rooms investigated was categorised as 'rarely', 'sometimes' and 'often'. Three bedrooms (BR) and a living room (LR) from three households (No. 17; No. 25; No. 34) were chosen as representative rooms to evaluate the performance of the recognition algorithms. The basic information about these rooms is listed in **Tab. 3.**

Tab. 3: - Basic information about the selected rooms and the AC usage in them based on the household survey

Room	Floor area [m²]	Main orientation	Window size [m²]	Location of data logger	AC usage frequency	Typical months for using AC	Typical time for using AC
17LR	36.1	NW	2.5	Internal wall, without direct sun irradiation	rarely	-	-
17BR	14.8	NW	4.1	Internal wall, opposite the window	often	May to Oct	Sometimes in the afternoon, always overnight
25BR	11.5	W	2.3	Internal wall, opposite the window	often	May to Aug	Overnight
34BR	14.3	E	1.2	Internal wall, without direct sun irradiation	sometimes	May to Jul	Overnight (9pm – 4am)

4. Results and discussion

4.1 Summary of direct observed AC events

Fig. 7 shows the monthly AC operating rates for the four selected rooms from June to November 2020, derived from direct observation of indoor climate data.

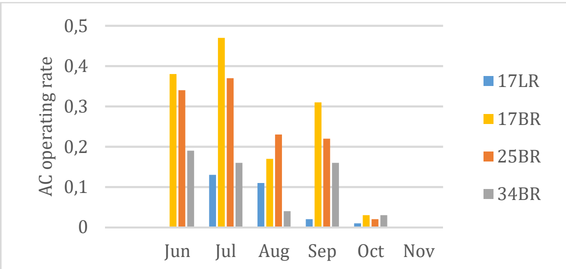

Fig. 7 - Overview of monthly AC operating rate derived by observation of indoor climate data (01.06 – 30.11)

July 2020 is the hottest month in Hanoi and this is well reflected in the usage of air conditioners. 25BR and 17BR have a significantly higher OR than 34BR and 17LR, which is consistent with the results of the occupant survey shown in **Tab. 3**. It is noticeable that although occupants responded in the survey that they rarely use AC in 17LR, the OR observed in this room in July and August exceeded 0.1. A further occupant survey revealed that one visitor slept in the living room during those two months, and sometimes, only the AC in the 17LR was turned on at night to cool the whole apartment. It can also be observed that the AC running time in the bedrooms significantly dropped in August, which could be a result of lower room occupancy due to holidays. This is confirmed by additional occupant surveys and low levels of CO_2 (< 500 ppm) in those rooms over a long period of time.

By comparing the operating rates in **Fig.** 7 with the occupant feedback for typical AC months in **Tab. 3**, it can be determined that the results derived from the direct observation of indoor climate data generally match the occupant responses. However, there are deviations in some details. For example, the occupant answered that the AC was usually used from May to July, but a similar AC usage frequency can be observed in September. This means that data on AC operation obtained from occupant surveys can only give a rough overview of AC usage information and is not suitable for analyses that require more detail.

To compare the results of direct observation with the occupant feedback at a higher temporal resolution, the AC operating probabilities over time were calculated from the derived AC operation data. Since the operating probability of AC is closely related to the month, two typical cooling months, June and July, are used for the comparison.

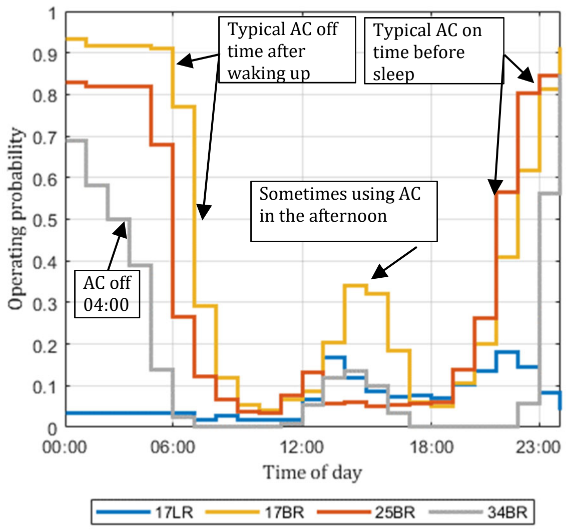

Fig. 8 - AC operating probabilities over time derived by observation of indoor climate data (01.06 – 31.07)

Responses from three households regarding the typical time for using AC in the bedroom are all "overnight", which can also be clearly seen in **Fig. 8.** Both 17BR and 25BR have a probability of turning on the AC after 22:00 of more than 0.8, coinciding with the occupant responses regarding the AC usage frequency ("often"). The occupant specified that the AC in 17BR was sometimes used in the afternoon, which is also well represented in the diagram. After 04:00, the AC operating probability in 34BR drops significantly, which matches the typical AC off time given by the occupant. However, the typical AC time for this room, as derived from the diagram, should be after 23:00, later than the 21:00 given by the occupants. This may be due to a discrepancy between the response of the occupants and the actual situation or because the AC cannot immediately change the indoor climate in hot and humid environments.

The cooling setpoint is the last parameter used to compare the derived data on AC operation with the occupant responses. The indoor air temperature measured after the cooling process has become stable is estimated as the cooling setpoint for each AC event. **Fig. 9** presents the boxplots of estimated cooling setpoints for the different rooms from 1 June to 31 July 2021.

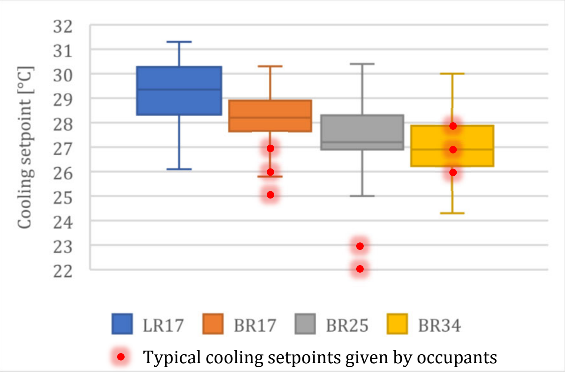

Fig. 9 - Comparison of the derived cooling setpoints with the occupant responses (01.06 – 31.07)

According to the occupant survey, the common cooling setpoints in 34BR are 26 to 28 °C, which is in line with the statistics for the typical AC months. However, it is noticeable that the cooling setpoint statistics for 17BR and 25BR are generally higher than the occupant responses. In particular, in 25BR, the estimation results completely deviate from the occupant responses. By analysing the room information in **Tab. 3**, it can be seen that the data loggers in both rooms are located on internal walls that are exposed to direct sunlight in the afternoon. This causes the walls to gain and store a lot of heat. As the data logger is mounted on the wall, its temperature measurement is also influenced by the wall surface. When the room is not cooled by the AC, the deviation of the temperature measured by the sensor from the actual indoor air temperature is not apparent. However, when the room is in the cooling phase, the temperature in the near-wall region will be higher than the temperature in the AC dominated area, resulting in an overestimation of the cooling setpoint. At this point the temperature measured by the wall-mounted data logger is closer to the operative temperature. In addition, the AC temperature set by the occupant does not mean that the room can actually be cooled to that temperature, which also depends on the cooling capacity and control accuracy of the AC, as well as the cooling load and the thermal performance of the room.

Another reason that causes the estimated cooling temperature to be sometimes higher than the actual set temperature is the short operating time. **Fig. 11** presents the indoor climate measured in 17BR around a typical afternoon short AC event. The increase in CO_2-concentration in the room after the AC has been turned on indicates that the occupant has closed the internal door and windows to cool down the room quickly. With the AC running, the humidity in the room also drops very significantly. However, the hot and humid indoor environment makes it impossible for the AC to cool the room to the set temperature in such a short time. This also explains why in the same apartment, the measured (estimated) cooling setpoints in 17LR are generally higher than that in 17BR, since **Fig. 8** shows that the 17LR is usually cooled only briefly in the afternoon or evening rather than overnight.

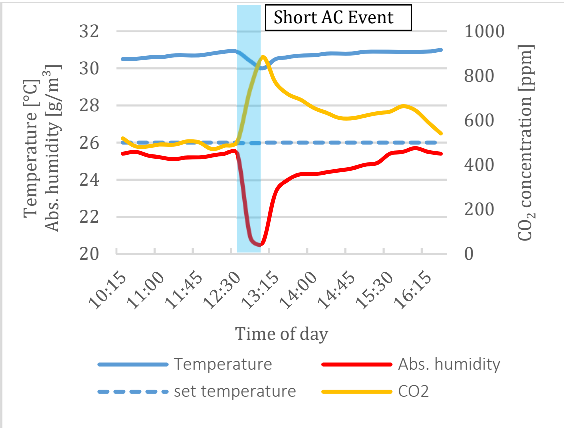

Fig. 10 - Indoor climate measured in 17BR around a short AC event

The AC operation data derived by the direct observation method generally matches the occupant feedback regarding the typical AC time and usage frequency, which can be used as a reference to evaluate the performance of the other two recognition algorithms.

4.2 Evaluation of the recognition algorithms

Data from 1 June to 30 September 2021 was chosen for the performance evaluation as the period after October is no longer a typical AC usage period. As shown in **Fig. 11**, for all four representative rooms, the AC operating rates derived from the two automatic recognition algorithms are very close to the reference (DO), and the performance of the DM-method is slightly better.

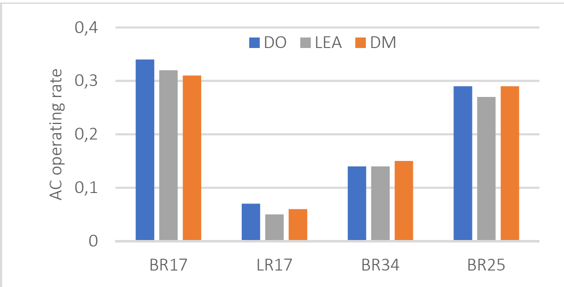

Fig. 11: - Comparison of OR derived by different methods (01.06 – 30.09)

Tab. 4 shows a comparison of the F_1 scores, precision and recall of the two developed algorithms, assuming the reference data derived by the DO-method as the true result. The F_1 scores for the DM are overall higher than those for the LEA. Although the LEA has higher precision scores, this comes at the cost of reduced sensitivity. This means that some AC operations are ignored, especially in rooms where the AC is not used regularly, such as 17LR.

Tab. 4 - The results of F1 scores for different methods

	LEA	**DM**
	F_1/precision/recall	*F_1/precision/recall*
17LR	*0.78/0.88/0.71*	*0.82/0.80/0.84*
17BR	*0.85/0.89/0.82*	*0.90/0.82/0.86*
25BR	*0.84/0.89/0.80*	*0.86/0.87/0.86*
34BR	*0.86/0.86/0.87*	*0.87/0.84/0.90*

5 Conclusion

Occupant AC behaviour plays an essential role in the indoor environment and energy consumption in residential buildings in hot and humid regions. However, collecting and processing data on AC operation can be very challenging in practice. To improve the efficiency of data processing and analysis regarding AC operations, two algorithms have been developed to automatically recognise AC events based on the analysis of indoor climate data. To evaluate the performance of the two algorithms, AC operation data for four representative rooms were determined using direct observation of indoor climate data and verified by comparing with occupant responses. The results show that both algorithms perform well in analysing OR, while the DM has higher F_1 scores. Compared to the LEA, the DM is easier to adapt to process different cases and its result is more robust (without repeated on/off events within a short time period). Therefore, the DM algorithm will be used in the further work to analyse the AC operation in all measured rooms. In addition, the preliminary derived AC usage patterns differ from the "full time" (always on) patterns commonly used in building simulations. It would therefore be more reasonable to introduce these "part-time" AC usage patterns into the building simulation.

6 Acknowledgement

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The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.