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A Hybrid Model for Predicting the Operation Status and Power of Residential Air Conditioning based on Coupled Indoor-Outdoor Hygrothermal Variations

Ziyi Cao¹, Lili Chen², Zhiwen Luo³, Fanzhe Zeng⁴, Xinyan Yang⁵, Kai Wang^{1*}

1. China-UK Low Carbon College, Shanghai Jiao Tong University, Shanghai, China

2. School of Public Health, Southeast University, Nanjing, China

3. Welsh School of Architecture, Cardiff University, Cardiff, UK

4. Institute for Environmental Design and Engineering, The Bartlett, University College London, London, UK

5. China Academy of Building Research, Beijing, China

* Correspondence: kai.wang@sjtu.edu.cn

Abstract: With the ongoing climate change, building cooling energy demand is projected to rise. At the same time, it would be further exacerbated by the urban-induced warming, as well as the more frequent extreme heat events. Enhancing our understanding and prediction capability of the building cooling demand can improve urban energy security and climate resilience. However, significant challenges remain in representing occupant-driven residential air conditioning (AC) operation, which responds dynamically to outdoor environmental conditions yet is difficult to observe directly. To address these, we developed a hybrid modelling framework that infers residential AC operation and energy use from indoor-outdoor hygrothermal dynamics, without requiring historical energy consumption or explicit occupancy data. By integrating machine learning (XGBoost and the PELT algorithm) with physics-based RC building energy balance model, the approach detects the AC operational status from characteristic temperature and humidity patterns, and estimates AC power from the cooling load. In doing so, occupant behaviour is treated as an emergent signal embedded within environmental responses, rather than an external input requiring direct measurement. The model was validated against the data from a residential building in Beijing. It achieved an AC-on F1-score of 81.2%, which is the harmonic mean of precision and recall and a balanced classification metric for the imbalanced dataset, and a median error of 27.09% in estimated AC power. This work enables the integration of occupant behavior into building energy modelling in data-sparse contexts, particularly in residential buildings where AC operation is primarily human-driven. By linking outdoor climate conditions to indoor responses and behavioural

patterns, the proposed framework supports improved assessment of future cooling demand and indoor overheating risks under climate change.

Key words: cooling demand; human behaviour; machine learning; building energy model; hygrothermal variations

1. Introduction

Buildings account for a substantial part of global energy consumption and carbon emissions (Desai, 2022), among which, space cooling alone can constitute up to 40% of building energy consumption, especially in hot climate regions (International Energy Agency, 2018). While we are making improvement in the efficiency of air conditioning system, the energy consumption from air conditioning is expected to increase due to climate change, increased urbanisation and improved living standards (Du and Chen 2024; Hunt et al., 2022). Moreover, global warming also intensifies the frequency and severity of heatwaves (Intergovernmental Panel on Climate Change (IPCC), 2023) and urban heat island (UHI) effects further elevate local temperatures in cities (Enteria et al., 2021), both exacerbate the rising demand for building cooling. Notably the operation of air conditioning is highly responsive to the outdoor hygrothermal environment (Cho et al., 2023), but a key parameter driving this energy use is occupant behavior. In residential buildings, AC switching is primarily human-driven. Therefore, understanding occupant-driven AC operation behavior is essential for providing realistic operation schedules in building energy models, enabling accurate energy predictions, and supporting the decarbonization of the building sector.

Currently, the prediction of building energy use can be broadly categorized into physics-based models and data-driven approaches. Physics-based models, such as building energy model, apply thermodynamic principles to estimate power usage based on system characteristics and environmental conditions (Fumo, 2014). Through the heat balance of building zones, the cooling energy demand can be estimated analytically (Duan et al., 2019; Wang et al., 2022) or with more complex numerical models (Shi et al., 2019; Tonini De Araújo et al., 2022). In general, there are mainly 4 types of information that are required for these models, i.e., the thermal physical properties of the building envelope, the appliance and HVAC systems, the outdoor weather files, and the occupant behaviour. The first two types of information are difficult to obtain for existing buildings, as deploying comprehensive sensor networks for building fabric monitoring is very challenging and rarely available outside research or high-end commercial facilities (Ruz et al., 2015). Such data is typically only available in specific scenarios, including new constructions with documented building codes (Anireddy, 2024). The outdoor weather files can be derived from the weather station data (Shi et al., 2019), field measurements (Yang et al., 2025), as well as the regional (Haddad et al., 2020) to global models (Grimmond et al., 2010). These

75 datasets are primarily used to evaluate changes in building energy demand under
76 future climate change scenarios. Additionally, assessing urbanization impacts, such as
77 the urban heat island effect, requires either high-resolution urban climate models or
78 global/regional models coupled with urban surface parameterizations (Tang et al.,
79 2021). While downscaling from aggregate energy statistics to individual buildings is
80 possible, it often fails to capture individual user behaviour due to the heterogeneity of
81 occupant preferences and building characteristics.

82 To reduce dependency on exact physical parameters, Resistance-Capacitance
83 (RC) network model has been widely adopted as a grey-box approach that balance
84 physical interpretability with computational efficiency. In the RC framework, thermal
85 resistances (R) characterize heat transfer pathways while thermal capacitances (C)
86 capture the heat storage capacity of building elements, with network architectures
87 typically ranging from simple 1R1C configurations to more elaborate structures such
88 as 2R2C or 3R2C models (Bacher & Madsen, 2011; Reynders et al., 2014). In these
89 configurations, resistances are conventionally assigned to envelope conduction and
90 ventilation/infiltration pathways, while capacitances partition the thermal mass into
91 distinct nodes representing the building fabric and internal air volume. Parameters are
92 typically identified via constrained optimization against measured indoor temperature
93 trajectories (De Rosa et al., 2019). However, the occupant behaviours, including the
94 AC operation and occupant hours, have always been the most challenging issues in
95 building energy models.

96 On the other hand, data-driven models leverage machine learning techniques to
97 predict energy consumption based on historical data and environmental factors. It has
98 emerged as a powerful tool, particularly with the rapid development of artificial
99 intelligence and data analytics technologies. Different models, such as Random
100 Forest(RF), Support Vector Regression(SVR) (Chen et al., 2017), Gradient Boosting
101 Machine (GBM) (Touzani et al., 2018), Deep Convolutional Neural Network
102 (DCNN) (Khan et al., 2019), Long Short-Term Memory (LSTM) (Wang et al.,
103 2021), hybrid Convolutional Neural Network-LSTM (CNN-LSTM)(Kim et al.,
104 2023), Convolutional Residual Gated Informer(CRG-Informer)(Zou et al., 2024),
105 Empirical Mode Decomposition-Long Short-Term Memory -Markov(EMD-LSTM-
106 Markov) chain hybrid model(Huang et al., 2024), Beetle Antennae Search (BAS) –
107 General Regression Neural Network (GRNN) & LSTM(Gao et al., 2024), have been
108 used to model and predict the building energy demand in good accuracy. These

methods can capture complex patterns and relationships, even without requiring detailed knowledge of the underlying physical processes.

Despite their predictive capabilities, these data-driven approaches fundamentally rely on extensive historical power consumption data for model training and calibration. Recent research has explored methods to reduce data dependencies through physics-informed machine learning (PINNs) that embed physical constraints to enhance generalization with limited observations (Raissi et al., 2019), or transfer learning approaches that leverage pre-trained models from similar buildings (López Santos et al., 2023). However, these methods typically still require at least minimal historical data for fine-tuning or validation. More relevant to the present work, several studies have attempted to predict building energy consumption using solely environmental parameters and physical principles without historical power data. For instance, inverse modelling techniques have been proposed to estimate HVAC energy use from indoor-outdoor temperature differentials, though these approaches required detailed building envelope specifications (Darwazeh et al., 2021). Similarly, physical-statistical hybrid approaches for AC energy estimation relying on outdoor meteorological variables and simplified building models have been developed, yet necessitated empirical calibration against limited field measurements (Rasheed et al., 2020). These attempts, while reducing reliance on historical data, still depend on detailed building physical parameters and comprehensive occupancy information.

Recognising these shortcomings, integrating occupancy and human behaviour data into prediction models is an emerging research direction with significant potential for improving prediction accuracy and control strategies. Incorporating dynamic human behavior helps the system to adjust dynamically, avoid overcooling, and informs more efficient control strategies. Recent advancements include incorporating human behaviour patterns into building electricity load prediction through K-Medoids clustering and Derivative Dynamic Time Warping (DDTW) with hybrid GNN (Graph Neural Network)-LSTM model to capture the spatiotemporal behaviour features (Dong et al., 2025). Similarly, a new Non-Intrusive Thermal Load Monitoring (NITLM) framework was developed to forecast future sub-loads by modelling human behaviour through occupant loads related to HVAC systems (Kaneko et al., 2024). Other studies have utilised behavior-oriented RF models for predicting short-term AC energy consumption in buildings (Li et al., 2023), integrated thermal stimuli into immersive virtual environments (IVE) to reveal how energy-

efficient renovations impact personal heater use and door opening behaviours which in turn affect building energy performance (Feng et al., 2024), and classified split AC users based on high and low air conditioning dependency to reveal how low-carbon strategies such as natural ventilation, fan usage, and clothing adjustments, deduce air-conditioning energy use (Yan et al., 2025).

To address these interconnected limitations, including the structural identifiability constraints of standalone RC models, the fundamental data dependency of pure machine learning approaches, and the practical barriers of occupant behaviour monitoring, we propose a hybrid modelling framework that leverages the strengths of both methodologies while eliminating the need for both historical power data and detailed building fabric specifications. Rather than explicitly measuring or prescribing occupant behaviour, the proposed approach infers AC operation indirectly from its impact on indoor hygrothermal conditions. The use of AC changes the indoor hygrothermal conditions by altering the heat and moisture balance of the indoor environment (Duan et al., 2019; Li et al., 2023), creating distinct environmental signatures that can be detected through coupled temperature and humidity measurements. By leveraging these signatures, the model identifies AC operational states using time-window-based analysis and subsequently estimates cooling power through a physics-informed energy balance formulation. We employ the RC model as a physics-based load estimator coupled with a machine learning component that detects AC operation status via environmental signatures. This coupling mitigates the identifiability challenges and parameter uncertainty inherent to standalone grey-box modelling by disaggregating behaviour detection (data-driven) from load estimation (physics-based). Unlike prior research that relies on user surveys or predefined/empirical outdoor temperature thresholds to activate air conditioning, this approach reframes occupant behaviour as an observable outcome embedded within environmental dynamics, rather than an external input requiring direct measurement. In doing so, it enables the extraction of behaviourally meaningful AC operation patterns from environmental monitoring data. The proposed framework would be able to capture the dynamic and context-dependent nature of occupant decisions, providing a more realistic representation of AC usage in real-world settings.

2. Methodology

In this study, we aim to develop a hybrid model to predict the AC status and estimate the AC power exclusively from coupled indoor-outdoor hygrothermal variations. The methodology comprises three interconnected stages: 1) feature engineering to capture hygrothermal decoupling; 2) a data-driven classification module utilising Extreme Gradient Boosting (XGBoost) and the Pruned Exact Linear Time (PELT) algorithm to pinpoint exact AC state transitions; and 3) a grey-box Resistance-Capacitance (RC) model that dynamically estimates the cooling load based on the identified AC schedules. A detailed workflow of the methodology is shown in Fig.1.

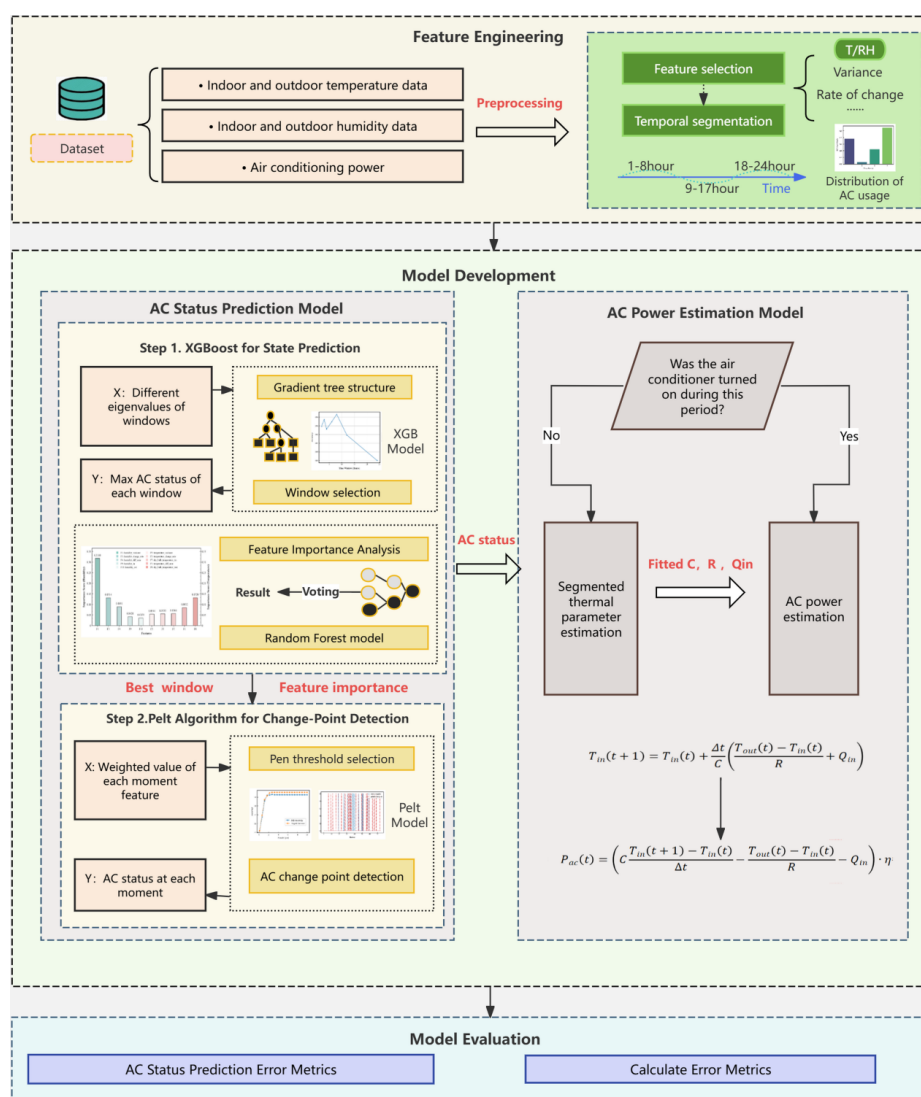


Fig.1. The workflow of the methodology, including feature engineering, development of the hybrid model consists of AC operation status prediction and power estimation model, and the model evaluations.

2.1. Feature Engineering and Thermal-Humidity Feature Selection

Feature selection was conducted to identify the most relevant predictors of air conditioning (AC) state transitions for the XGBoost model. We focused on selecting temperature and humidity-related features that are most influential in predicting AC state changes. The target variable for this analysis was the maximum AC activation state, defined as a binary indicator (0/1) of whether the air conditioning was turned on at any point during a given time window. The input features included indoor and outdoor absolute values, indoor-outdoor differentials, temporal change rates, and rolling variances. To further validate the selected features, here, we use the indoor and outdoor temperature and humidity trends over three consecutive days (August 21-23, 2021, data source is given in section 2.4) as the example to show the differences in temperature and humidity variations between different AC statuses (Figure 2). The outdoor variations for the three days are very similar, while the indoor variations are distinctive between AC on and off days. Moreover, for days without AC operation, the indoor outdoor hygrothermal variations are coupled, as they showed similar temporal variations. However, a decoupling of indoor-outdoor appeared when AC started to operate.

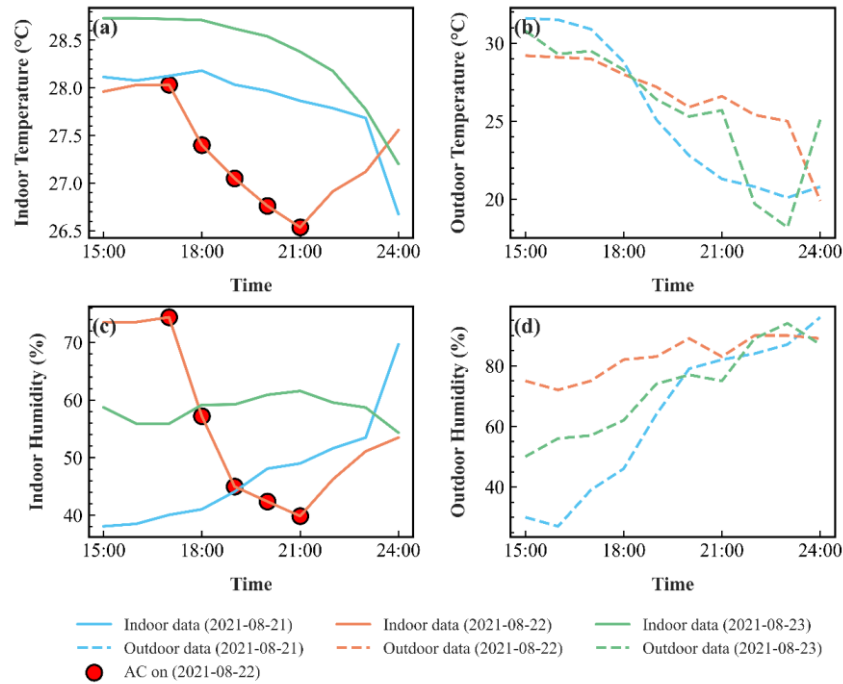


Fig. 2. Indoor and outdoor temperature and humidity variations for 15:00-24:00 in three consecutive dates from 21 to 23 August 2021. The outdoor temperature (b) and humidity (d) variations are similar between three different days; however indoor temperature (a) and humidity (c) showed distinct variations for the day with AC on.

To provide a more detailed analysis, we calculated specific metrics for temperature (T) and relative humidity (RH) during both AC-on and AC-off periods. These metrics include the average change rate and the total change over the period from 17:00 to 21:00 each day.

These observations underscore the significance of temperature and humidity variations as critical indicators for predicting AC state transitions. Specifically, the differential between indoor and outdoor temperatures serves as a robust predictor of AC usage, as it directly correlates with the cooling demand required to maintain thermal comfort. Additionally, abrupt fluctuations in indoor temperature and humidity are frequently linked to AC activation, after which the system operation can regulate and stabilise indoor hygrothermal conditions within a comfortable range, making it possible to locate the transition time of AC. In the examined case, AC activation was accompanied by marked changes in indoor temperature and humidity relative to the outdoor trajectories (Table 1).

Table 1: Comparison of the selected temperature and humidity metrics between AC-On (2021-08-22, shaded) and AC-Off (2021-08-21 and 2021-08-23) periods.

Date	T Change (°C)	RH Change (%)	T Avg Change Rate (°C/h)	RH Avg Change Rate (%/h)
2021-08-21	-0.26	8.93	-0.07	2.23
2021-08-22	-1.48	-34.52	-0.37	-8.63
2021-08-23	-0.34	6.68	-0.08	1.57

2.2 AC Operation Status Prediction Model

To identify the AC status, a suitable machine learning approach is needed for its capability to distinguish the difference in the indoor-outdoor hygrothermal variations between the AC on and AC off periods. There are three steps to achieve this.

First, the Extreme Gradient Boosting (XGBoost) model ([Appendix A3.1](#)) was employed to predict the AC's on/off state for a certain time window. XGBoost is a scalable implementation of gradient boosting, designed for high performance and accuracy in predictive modelling tasks (Chen & Guestrin, 2016). The optimal time window would be identified from the highest accuracy among the model's performance in different time windows.

Then, based on the optimal time window identified by XGBoost, we used Random Forest to calculate feature importance scores. These scores were then used to weight the feature values at each time point within the window, enabling the model to better detect AC on/off transitions.

Finally, the PELT algorithm ([Appendix A3.2](#)) was used to detect the exact AC on/off transition times. Within the selected time window, the Pelt algorithm scans the hour-level weighted feature sequence and detects all switch points of the AC, thereby locating the exact start and end times of each operating interval. The regularization parameter λ ([Equation A3.9](#)) balances detection sensitivity and false alarms. The rationale for using the PELT algorithm is its efficiency and accuracy in detecting change points in time series data. It allows us to pinpoint the exact moments when the AC is turned on or off, which is crucial for understanding the detailed operational patterns of the AC system.

The features were formulated at two temporal levels. For the XGBoost stage, indoor and outdoor temperature and relative humidity were aggregated within each candidate window; indoor–outdoor differentials, temporal change metrics, and within-window variances were then calculated to characterise the persistence of hygrothermal coupling or decoupling. For the PELT stage, the corresponding variables were evaluated at hourly resolution, with 8-hour rolling variances and one-step temporal changes. The exact formulations and units are summarised in Table A1. It should be noted that the time window segmentation is employed solely for coarse-grained classification and thermal parameter estimation, not for determining transition timing. The PELT algorithm independently detects both off-to-on and on-to-off transitions by monitoring feature value changepoints. For readers interested in the detailed mathematical formulations and objective functions of the XGBoost and PELT algorithms employed in this study, comprehensive theoretical descriptions are provided in [Appendix A3](#).

2.3 AC Power Estimation Model

Once the operational schedules are extracted, a physics-based RC model calculates the corresponding power consumption.

2.3.1 Heat Balance Equations for Room Thermal Parameters

To estimate the power consumption of the air conditioning (AC) system, we established a heat balance model for the room, considering both AC-on and AC-off states. The room thermal dynamics are governed by the heat balance equation. By ignoring the radiation heat and simplifying all the other internal heat gain except AC as Q_{in} , changes in the indoor temperature T_{in} can be expressed as the following first-order RC model (Song et al., 2022), as shown in Eq. (1):

$$C \frac{dT_{in}}{dt} = \frac{T_{out} - T_{in}}{R} + Q_{in} - P_{ac} \cdot COP \quad (1)$$

where C is the effective thermal capacitance of the room ($J/^\circ C$), R is the effective thermal resistance of the room envelope ($^\circ C/W$), Q_{in} represents a bulk internal heat gain term (W), P_{ac} is the electrical power consumption of the AC system (W), COP is the coefficient of performance of the AC system, defined as the ratio of cooling capacity to electrical power consumption. T_{out} is the outdoor temperature ($^\circ C$). The term $COP \times P_{ac}$ represents the total cooling capacity provided by the AC system, which is subtracted as it removes heat from the indoor environment.

In discrete form, this becomes as Eq. (2):

$$T_{in}(t+1) = T_{in}(t) + \frac{\Delta t}{C} \left(\frac{T_{out}(t) - T_{in}(t)}{R} + Q_{in} - P_{ac} \cdot COP \right) \quad (2)$$

where Δt is the time step (s). Using the estimated thermal parameters (C , R , Q_{in}) obtained during AC-off periods, the AC power consumption during operation is calculated through the heat balance equation as illustrated in Eq. (3):

$$P_{ac}(t) = \left(\frac{T_{out}(t) - T_{in}(t)}{R} - C \frac{T_{in}(t+1) - T_{in}(t)}{\Delta t} + Q_{in} \right) \times \frac{1}{COP} \quad (3)$$

We acknowledge that the above heat balance formulation considers only sensible heat transfer, omitting latent heat exchange associated with humidity removal. While humidity dynamics are critical triggers for AC activation (as demonstrated in Section 3.2 where humidity variance showed the highest feature importance), the current RC model simplifies the thermal balance to estimate power magnitude.

2.3.2. Segmented Thermal Parameter Estimation

The parameter estimation was performed during AC-off periods ($P_{ac} = 0$) using the heat balance equation Eq. (1). The estimation procedure involved the following steps:

1) Temporal Segmentation: Each 24 hours is divided into time segments based on the identified optimal time windows, which are determined by considering the temperature fluctuations between day and night and occupants' behavioural patterns.

2) Robust Windowed Regression: For each segment k , parameters $\theta_k = (C_k, R_k, Q_{in,k})$ were estimated by solving Eq. (4):

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N_k-1} \left[T_{in}^{obs}(i+1) - \left(T_{in}(i) + \frac{\Delta t}{C} \left(\frac{T_{out}(i) - T_{in}(i)}{R} + Q_{in} \right) \right) \right]^2 \quad (4)$$

Outliers were filtered via the inter-quartile criterion:

$$\theta_k^{valid} = \left\{ \theta_k^{(j)} \mid \theta_k^{(j)} \in [Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR] \right\} \quad (5)$$

where $\theta_k^{(j)}$ means the parameter estimates (including C , R , Q_{in}) of the j sliding window in the k th time period. Q_1 is the lower quartile of the parameter estimates, Q_3 is the upper quartile of the parameter estimates, and is the IQR interquartile range

$Q_3 - Q_1$, 1.5 is the standard multiplier for IQR . In this study, the AC power curve fit function was employed with physically plausible bounds: $C \in [10^5, 10^7]$, $R \in [0, 0.1]$, $Q_{in} \in [0, 1000]$.

It should be noted that COP varies with different AC systems, the outdoor temperature and load rate (Ye et al., 2025). As information about COP is not available in the dataset, considering that Beijing residential buildings have suggested an average in-situ COP of approximately 2.5 (Zhou et al., 2017) and omitting the latent heat load (dehumidification) in the prediction mode, a fixed value of 2.0 was adopted for the baseline evaluation in section 3. Moreover, a sensitivity study of COP was conducted by using the range $[1.0, 5.0]$ with a step size of 0.5 to calculate the median relative error (MRE) of power estimation for each time segment (Appendix A6).

3) Parameter Aggregation: Final estimates were derived as the median of valid solutions:

$$\bar{\theta}_k = median(\theta_k^{valid}) \quad (6)$$

These median values serve as the definitive thermal parameters for each time period, and are subsequently used in the complete heat balance equation (Eq. (3)) to calculate AC power consumption during operational periods.

2.4. Model Training and Evaluation

The dataset for model training and evaluation is sourced from the public CN-OBEE dataset (Wang et al., 2024), which includes indoor and outdoor temperature, humidity, and AC power data from a study room with a split AC in a Beijing residential apartment. While the full dataset spans May 2021 to May 2022, the July-August 2021 subset used here captures the peak summer period. July and August represent the peak summer season in Beijing when AC operation is most frequent within the annual cycle, offering the highest density of behavioral observations for robust training. Importantly, the fundamental physical laws governing indoor-outdoor hygrothermal coupling and the physiological drivers of occupant thermal comfort do not change significantly over few years' timeframe, ensuring the dataset remains representative for the purpose of methodological validation. The original dataset contains minute-level indoor measurements and hourly outdoor meteorological data. For consistency, the indoor data was resampled to hourly intervals, with continuous variables (e.g., temperature, humidity) aggregated by mean values and discrete variables (e.g., AC state) by maximum values. The original records showed that missing indoor and outdoor temperature and humidity observations occurred only outside the selected July–August analysis period. The hygrothermal variables used as predictors were therefore complete throughout the selected period after hourly aggregation, and no interpolation was required for these variables. Data unavailability

was confined to the AC-operation-status record from 20:00 on 4 July to 08:00 on 8 July 2021, comprising 85 consecutive hourly observations (5.71% of the 1,488-hour period). Following the preprocessing convention used in the original analysis, these records were coded as AC-off (0). No hourly observations were removed. The final dataset thus comprised 1,488 hourly observations, including 87 AC-on observations (5.85%). Although the hygrothermal feature construction was unaffected, this treatment introduces potential uncertainty into the binary target labels during the unavailable interval.

Because AC-on observations constituted only 5.85% of the hourly dataset, overall accuracy alone could overstate model performance. We therefore report precision, recall, and F1-score together with accuracy. Precision reflects the model's exactness, mitigating false alarms. Conversely, Recall indicates the model's completeness, mitigating missed detections. The F1-score provides the harmonic mean of Precision and Recall, serving as the most rigorous and balanced metric for this highly imbalanced scenario. Details of the metrics for each model are listed in [Appendix A4](#).

3. Results

3.1. Optimal Time Window for AC Status Prediction

The XGBoost model was employed to predict the operational status of the air conditioning system. As shown in Fig. 3, AC usage exhibits a distinct bimodal diurnal pattern with significant variation across different periods. The highest usage concentrations occur during late evening and night hours (21:00-01:00), with AC usage ratio larger than 0.15, reflecting residents' preference for thermal comfort during pre-sleep and initial sleep periods. Usage then drops sharply during the early morning transition (01:00–02:00), and early morning hours (02:00-08:00) exhibit minimal to zero usage, indicating near-complete AC shutdown during these hours.

Daytime hours present a typical pattern that core working hours (09:00-15:00) show minimal usage which aligns with reduced occupancy. However, usage begins recovering in the late afternoon (16:00-19:00), reaching 0.05 usage ratio as residents return, before surging dramatically after 20:00. This creates a clear transition from daytime shutdown to evening activation.

The time window approach serves as the coarse-grained classification layer in our hybrid framework. Unlike hourly point-in-time prediction, we aggregate consecutive

hourly observations into sliding windows (e.g., 8-hour windows) to capture the temporal persistence of AC operation and its thermal effects. This window-based classification determines whether the AC was activated at any point within the period. Subsequently, the PELT algorithm performs fine-grained change-point detection within each identified window to locate the exact transition times. This two-tier architecture ensures that the XGBoost model captures these distinct diurnal phases through window-level features, while the PELT algorithm resolves precise operational boundaries.

The 24-hour diurnal cycle was segmented using different time windows (2, 3, 4, 6, 8, 12, and 24 hours). The dataset was split into training and testing sets with an 80%-20% ratio using stratified sampling. Time window selection was performed using 5-fold cross-validation exclusively on the training set, with the optimal configuration selected based on the highest mean validation F1-score. All performance metrics reported in Table 2 represent the independent test set evaluation only. The XGBoost model demonstrated peak performance with the 8-hour time window, achieving an accuracy of 0.986, precision of 0.986, recall of 0.833, and an F1-score of 0.909 on the test set. Shorter time windows (2-6 hours) were susceptible to noise from transient environmental fluctuations, particularly during the volatile evening transition period (19:00–21:00) where usage escalates rapidly, while longer windows (12-24 hours) oversimplified usage patterns by conflating the distinct nighttime peak (21:00-01:00) with the early morning shutdown (02:00-08:00). The 8-hour window effectively captures distinct building occupancy phases including the evening AC preparation (19:00-21:00 surge), sustained nighttime operation (21:00-01:00 high-usage plateau), and the daytime shutdown period. This window size optimally balances behavioural rhythm capture with thermal inertia effects, providing reliable coarse-grained state identification that enables subsequent fine-grained transition detection within each window.

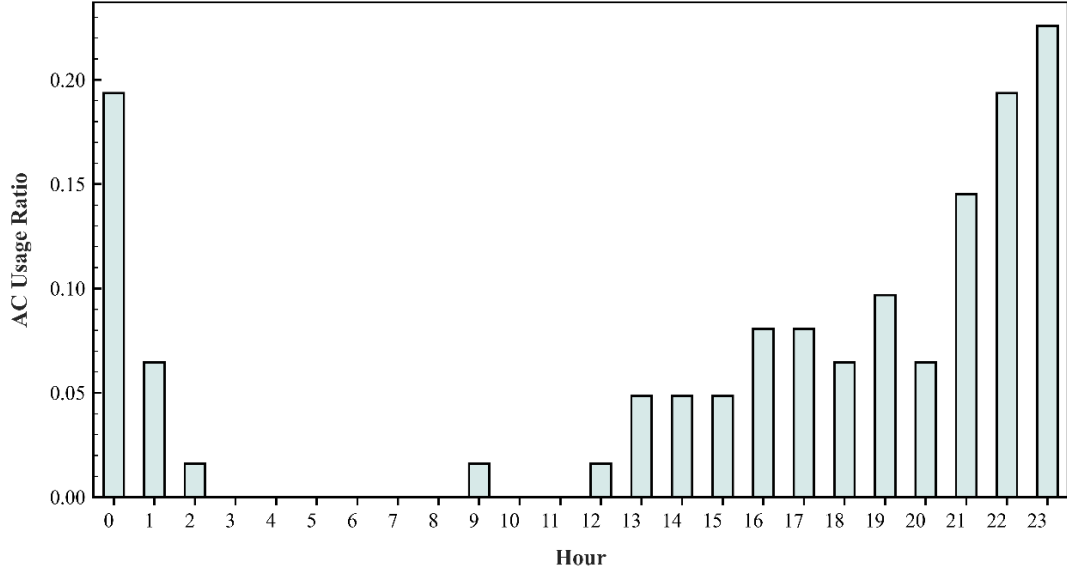


Fig.3. Hourly statistics of air conditioner usage ratio (operation hours/total hours), the significant diurnal pattern of AC operation suggests the need for a time window to differentiate the variations of human activities.

Table 2: XGBoost performance metrics for prediction across different time windows

Time window	Accuracy	Precision	Recall	F1 Score
2	0.959	0.789	0.652	0.714
3	0.974	0.867	0.812	0.839
4	0.952	0.909	0.625	0.741
6	0.969	0.857	0.750	0.800
8	0.986	0.986	0.833	0.909
12	0.939	0.857	0.750	0.800
24	0.880	0.833	0.714	0.769

3.2. Feature Importance Analysis

We further conducted Random Forest-based feature importance analysis to evaluate the predictive influence of humidity and temperature dynamics in relation to AC activation ('on' state) on 8-hour sliding windows. The results revealed that indoor humidity variance is the most influential predictor, with the importance score greater than 0.3, followed by temperature variance and humidity change rate, both around 0.13 (Fig. 4). The importance scores of other factors were all below 0.1. These findings highlight the high sensitivity of humidity dynamics along the transition of

AC status, suggesting that humidity-related dynamics provide strong discriminatory information for distinguishing AC operational states.

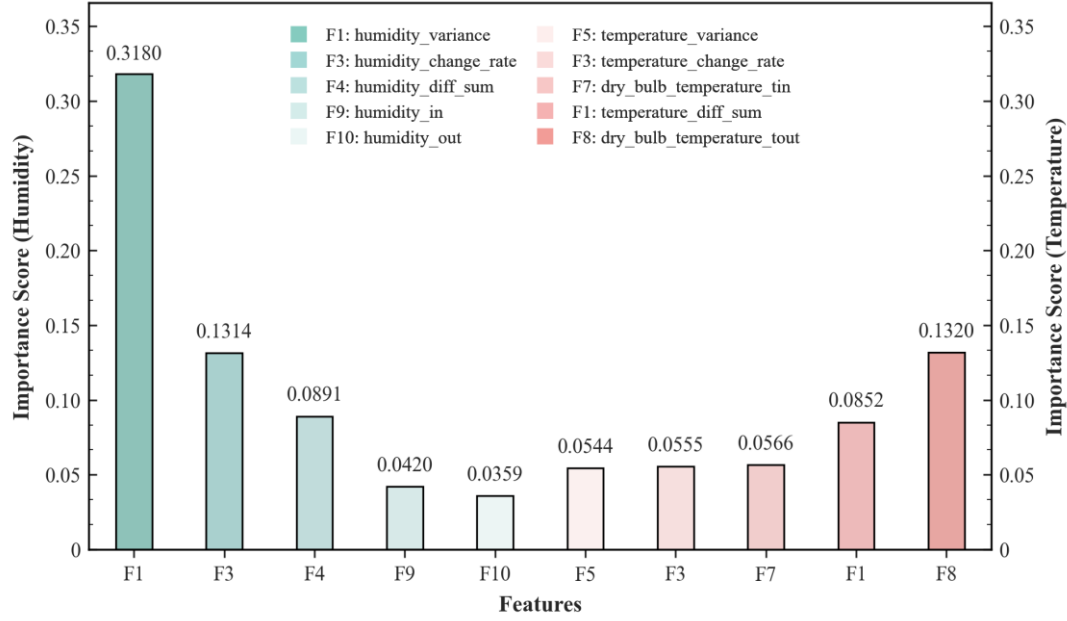


Fig.4. The important score for different temperature (red) and humidity (blue) parameters that were calculated based on the Random Forest model using an 8-hour time window

3.3. Detecting the transition of AC status based on the PELT algorithm

3.3.1 Feature Distribution for State Transition Detection

Once the AC operational status within each time window was determined, the PELT algorithm was applied to detect change points indicating transitions between AC-on and AC-off states. Figure 5 shows the distributions of the weighted feature $Z(t)$ (where $Z(t)$ denotes the aggregated hygrothermal signature at time t , computed as the weighted sum of indoor-outdoor temperature and humidity features; see [Appendix A2](#) for detailed formulation) and its hourly change rate $\Delta Z/\Delta t$, stratified by AC status. In Fig. 5(a), AC-off periods exhibit a median $Z(t)$ of 3.2, while AC-on periods show a significantly lower median of 1.3, reflecting a 60% downward shift. The near absence of IQR (interquartile range, defined as the range between the 25th and 75th percentiles) overlap indicates strong class separability. In Fig. 5(b), the change rate $\Delta Z/\Delta t$ is markedly more negative during AC-on (median = -63.5) than during AC-off (median = -3.4), confirming that indoor conditions stabilise more rapidly under active cooling. These contrasting distributions enhance the detectability

of state transitions and support the PELT algorithm in accurately identifying change points within each time window.

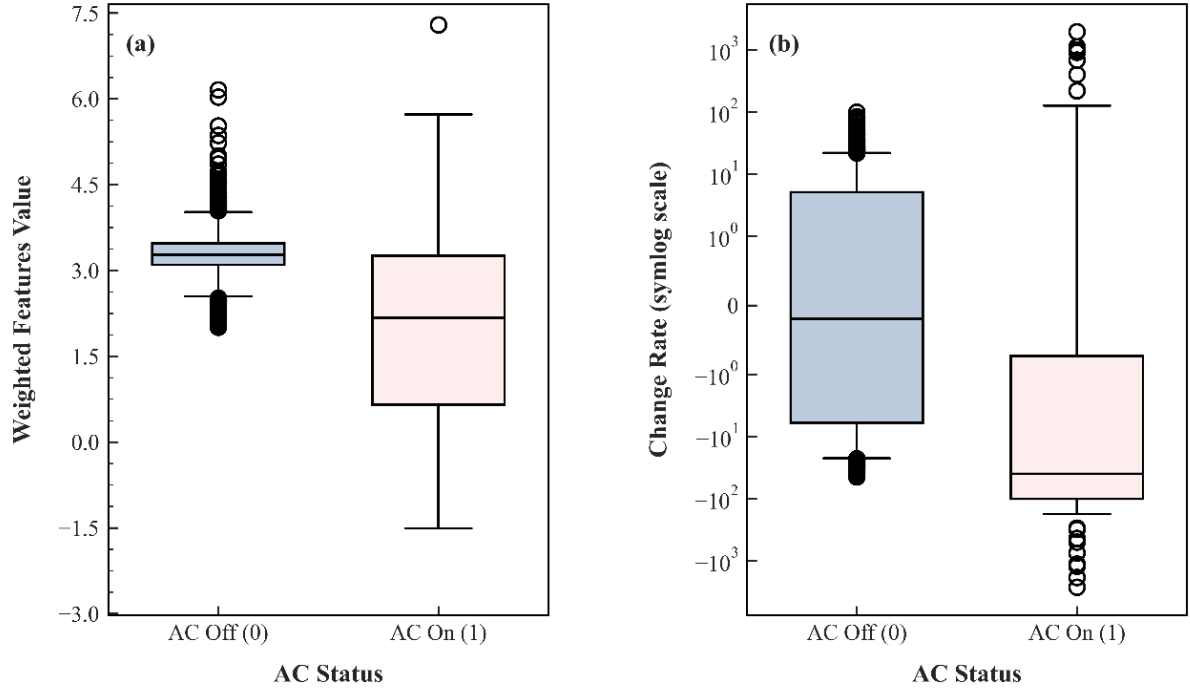


Fig.5. Comparison of the PELT algorithm feature value distributions between AC-On and AC-Off status

3.3.2 Penalty Parameter Selection

The PELT algorithm, implemented with a Radial Basis Function (RBF) kernel, requires careful selection of the penalty parameter ($\text{pen}(\lambda)$) that governs the sensitivity of change-point detection. According to the PELT algorithm's mathematical formulation, larger pen values inherently produce fewer detected change points by imposing stronger constraints on segment partitioning.

Given the extreme class imbalance in the dataset where AC-off observations exceed 94%, we adopted a segment-based detection framework to address this asymmetry and ensure reliable detection of rare AC-on events. Rather than classifying individual time steps, we first used the PELT algorithm to partition the weighted feature time series into homogeneous segments (representing distinct operational periods) for varying penalty parameters ($\lambda = 0.5-10$). Statistical features (mean, standard deviation, and maximum) were extracted from each segment to characterize intra-segment thermal stability, and a RF classifier with class-weight balancing to offset the 94:6 distribution assigned an AC state to each segment. Stratified 5-fold

cross-validation ensured that both AC-on and AC-off segments were represented in performance evaluation, preventing inflated accuracy from the majority class.

Figure 6 illustrates the sensitivity of detection performance to the penalty parameter. To dispel any ambiguity regarding the model's true capability, we present all applicable metrics—Precision, Recall, and the F1-score (Appendix A4). At low λ values (<1.5), excessive segmentation produces numerous short fragments, yielding high Precision (~ 0.85) for AC-On states but compromised Recall (~ 0.65) due to false positives during stable AC-Off periods. Conversely, high λ values (>5) cause over-merging of segments, achieving high Precision for the majority class but drastically compromising Recall for AC-On events (dropping below 0.5), thereby missing critical state transitions essential for energy estimation. The optimal penalty parameter ($\lambda = 2.0$) was selected based on the maximal F1-score of 0.81 for AC-On detection, achieving a balanced Precision of 0.87 and Recall of 0.77 (Fig. 6).

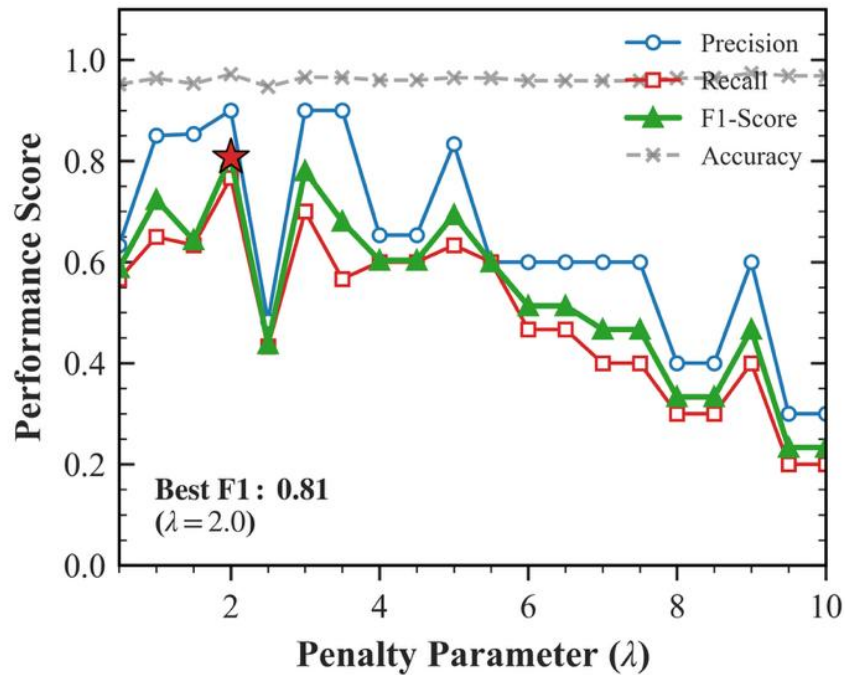


Fig.6. Changes in the precision, recall, F1-score, and accuracy for different penalty parameter values (λ), with the optimal point appearing around $\lambda=2$.

3.3.3. AC State Transition Detection Results

Figure 7 shows the detected AC state transitions using the PELT algorithm with the optimal penalty parameter ($\lambda = 2.0$) identified in Section 3.3.2, at a 1-hour time resolution. Comparing the predicted and actual AC states, the hybrid model

demonstrated an overall accuracy of 97.1% (where accuracy represents the global proportion of correctly classified hourly samples across both states combined, calculated as $(TP+TN)/Total$; see detailed metric definitions in [Appendix A4](#)), with detailed per-class performance metrics presented in Table 3.

The dataset exhibits significant class imbalance typical of residential summer cooling operations: out of 1,488 hourly samples, AC was active in only 87 instances (5.85%), while inactive periods dominated with 1,401 samples (94.15%). Table 3 reveals the performance asymmetry between states: the majority 'Off' class achieves near-perfect state-specific accuracy (equivalent to Recall = 98%) and high precision (97%), while the minority 'On' class achieves high precision (87%) and recall (77%), yielding an F1-score of 0.81. The overall accuracy of 97.1% is predominantly driven by correct classification of the abundant 'Off' hours, but the model successfully captures 77% of actual operating hours (Recall = 77%) with high reliability (Precision = 87%).

Table 3: Classification performance of the PELT algorithm for AC state detection

(penalty parameter $\lambda = 2.0$)			
State	Precision	Recall	F1 Score
AC Off	0.969	0.987	0.972
AC On	0.867	0.769	0.812
Total	0.923	0.872	0.898

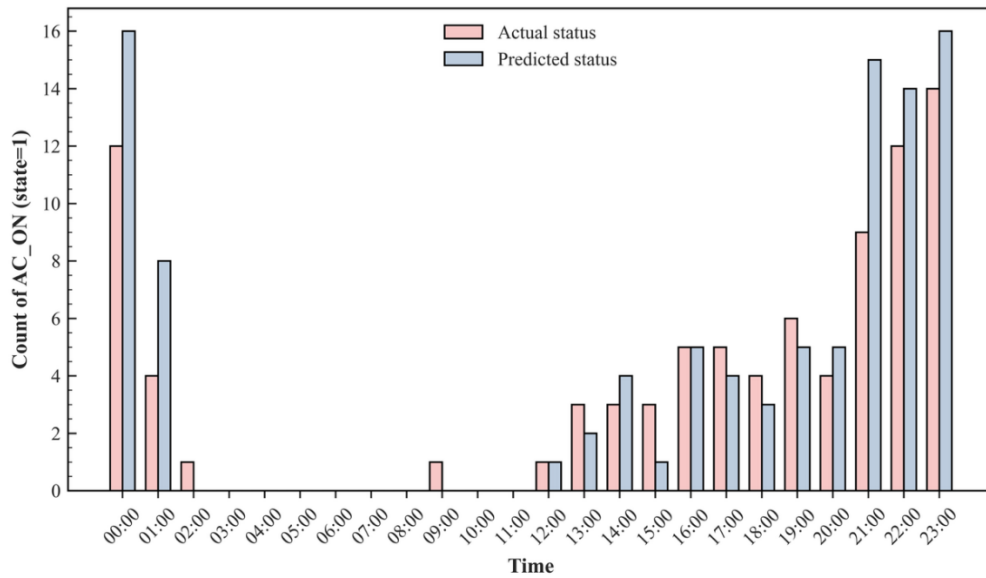


Fig.7. Comparison of the number of AC operations for different hours of the day between the detected AC status through the PELT algorithm with the monitored actual AC running data.

According to Fig. 7, the model exhibits higher accuracy (recall) during evening hours (approximately 19:00–23:00) when AC activation events concentrate and indoor-outdoor hygrothermal decoupling is most pronounced. During these periods, sharp WF (weighted feature) declines create distinct change points that the PELT algorithm detects with high reliability, corresponding to the successfully captured 77% of 'On' events (Table 3). Conversely, accuracy deteriorates during early morning hours (approximately 02:00–07:00) when outdoor temperatures decrease and AC units transition to 'Off'. Early-morning discrepancies were dominated by delayed detection of AC shut-off. The model occasionally retained the predicted AC-on state after the monitored system had switched off, producing false-positive AC-on hours. This behaviour is consistent with gradual post-cooling thermal recovery and may also reflect sleep-related routines that are less tightly coupled to instantaneous thermal conditions.

This performance asymmetry stems from the interplay between dataset imbalance and distinct physical transition dynamics captured by the weighted feature (WF). As detailed in [Appendix A2](#), WF represents the aggregated indoor-outdoor hygrothermal signature computed via Random Forest importance weighting. Table 4 quantifies these physical characteristics: AC activation ($0 \rightarrow 1$) was associated with a negative mean WF step change ($\Delta = -1.351$), whereas deactivation was associated with a positive mean step change ($\Delta = +1.895$). The average maximum WF within the transition window was higher for deactivation (6.235) than for activation (4.448). This peak metric describes the magnitude of the feature excursion and is not interpreted as a measure of temporal sharpness or transition duration. This gradual thermal convergence generates feature overlap with transient environmental fluctuations and contributes to classification errors during ambiguous transition periods. The complete hourly record set, comprising 1,488 time points from July to August 2021 along with corresponding WF values and detected change points, is provided in Appendix A5 (Fig. A5.1) for detailed verification.

Table 4: Physical quantification of AC state transition characteristics based on

Transition Type	weighted feature (WF) dynamics		
	Avg WF Change (Δ)	Typical WF Level (On/Off)	Average maximum WF
Turn ON ($0 \rightarrow 1$)	-1.351	2.038	4.448
Turn OFF ($1 \rightarrow 0$)	+1.895	3.933	6.235

Note: WF represents the aggregated indoor-outdoor hygrothermal signature (Appendix A4.3). Avg WF Change (Δ) denotes the step change in WF at the transition instant, indicating the abruptness of environmental shift; negative values reflect indoor stabilization upon AC activation, while positive values reflect gradual equilibration with outdoor conditions upon deactivation. Typical WF Level represents the mean WF value during the post-transition state, characterizing the typical indoor environmental signature of that operational mode. For each detected transition event, the maximum WF value is identified within the transition window centred on that event. Average maximum WF denotes the arithmetic mean of these event-level maxima across all detected transitions of the same type (0→1 or 1→0). It describes the typical magnitude of the feature excursion during state switching.

3.4. Estimation of AC power based on RC model

3.4.1 Fitted thermal parameters of the RC model

After detecting the AC operation periods, we separated the data series into AC-on and AC-off status. The data from the AC-off period were used to get the thermal parameters of the RC model through segmented thermal parameter estimation. To reflect the diurnal variations of occupant activities and outdoor-indoor heat exchange, the data were separated into different time segments, and the fitted results of the room thermal parameters are shown in Table 5.

Table 5: Fitting Results of the thermal parameters of the RC model using the actual indoor-outdoor temperature data during AC off period

Time period	Sliding window count	$C(J/^{\circ}C)$	$R(^{\circ}C/W)$	$Q_{in}(W)$
[0,8)	959	6.03e+06	0.033	498.75
[8,16)	965	6.97e+06	0.056	161.38
[16,24)	917	6.86e+06	0.065	259.37

Thermal parameter estimation yielded plausible values for most time segments. Specifically, the thermal capacitance (C) exhibited relatively small fluctuations across different time periods, ranging from approximately $6.03 \times 10^6 J/^{\circ}C$ to $6.97 \times 10^6 J/^{\circ}C$, with a median thermal capacitance (C) of around $6.65 \times 10^6 J/^{\circ}C$ for the daytime hours. On the contrary, the thermal resistance (R) and internal heat source Q_{in} demonstrated more pronounced diurnal variations. The thermal resistance R ranges from $0.033^{\circ}C/W$ to $0.065^{\circ}C/W$, and Q_{in} ranges from $161.38W$ to $498.75W$. Notably, the evening segment [16,24) exhibited the highest fitted effective resistance

($R=0.065^{\circ}\text{C}/\text{W}$), whereas the early-morning segment $[0,8)$ exhibited the lowest effective resistance ($R=0.033^{\circ}\text{C}/\text{W}$) and the highest Q_{in} . The fitted C and R values are broadly consistent with order-of-magnitude estimates derived from building code-based thermal properties (Yang et al., 2021). Here, an approximate envelope area (on the order of $60\text{--}100\text{ m}^2$) was assumed to provide a rough scaling reference, rather than an exact geometric representation of the space. Because detailed architectural blueprints were unavailable in this dataset, this simplification is used solely to verify that the estimated parameters fall within physically reasonable ranges.

The relatively stable C values suggest consistent lumped thermal storage characteristics of the room environment. However, the observed variability in R and Q_{in} should be interpreted with caution. The fluctuations in R during the daytime may reflect changes in air exchange rates due to occupant behaviour, such as window operation. However, the parameter values from midnight to early morning exhibit physically counterintuitive results, notably the highest Q_{in} occurring when actual solar and appliance gains should be at their lowest. Rather than reflecting true physical heat gains, these values are mathematical artifacts inherent to 1st-order (1R1C) models. As the model does not explicitly account for thermal lag, this delayed heat transfer is partially absorbed into the Q_{in} term, leading to elevated estimates. Similarly, variations in R may reflect changes in effective heat transfer pathways, including ventilation and window opening behaviour, as well as compensation for unmodelled dynamics.

Overall, while C retains clear physical interpretability, the parameters R and Q_{in} should be interpreted as effective quantities that enable the model to reproduce observed indoor temperature dynamics under simplified assumptions. The individual parameters for the early morning window reflect structural compensations for unmodeled thermal mass rather than absolute physical metrics. Their temporal variation is therefore expected and reflects the influence of transient processes not explicitly represented in the model.

3.4.2 AC Power Estimation Results

After determining the three key thermal parameters in the RC model, the heat equations can be used to estimate the air conditioning (AC) power consumption. Figure 8 presents the comparison between the calculated power and the actual power for the identified AC-on periods at the COP of 2. The scatter plot of prediction errors

under the optimal conditions is presented in [Appendix A6](#). Note that 4.2% of power estimates were below 0 (not shown in the Figure), primarily during abrupt outdoor temperature drops, which results in the negative results from the calculation of Equation (3). These values were excluded from the error analysis.

Following this, the model achieved a median relative error (MRE) of 27.09%, with RMSE and MAE values of 205.85 W and 130.75 W, respectively. While the wide visual spread of the scatter plot might initially suggest higher variance, the relatively low MRE of 27.09% is driven by the high density of overlapping points clustered in the upper right quadrant. This dense "blob" represents stable AC operation and reflects the natural physical asymmetry of the dataset: AC units spend a small fraction of their time in transient phases (starting up or shutting down) and the vast majority of their active cycles running in a continuous, steady state near nominal load. Most predictions fall within a $\pm 30\%$ error range of the perfect prediction line. However, the scatter plot reveals a noticeable concentration of data points in the higher power range (approximately 500–700 W), corresponding to periods of stable AC operation. This clustering indicates that the dataset is dominated by steady-state cooling conditions, which contributes to the relatively low aggregate MRE, as errors at higher power levels have a smaller relative impact. Conversely, the scattered points outside the error band are dominated by transient phases. Specifically, a significant underestimation of power is observed during AC startup; the actual power draw is immediately high, but the model estimation remains low because the initial change in indoor temperature is delayed by the building's thermal mass. This leads to systematic underestimation of power during startup events.

Overall, the model demonstrates reasonable capability in estimating the magnitude of AC power consumption, particularly under quasi-steady operating conditions. Although the monitored appliance is documented as a split AC, the available metadata do not identify whether it was fixed-speed or variable-speed. Hourly intermediate power values may therefore represent within-hour cycling, continuous load modulation, or a combination of operational and aggregation effects. The present simplified on/off and fixed-COP formulation does not distinguish among these mechanisms. Future improvements may be achieved by increasing the temporal resolution of the data to better capture transient dynamics, and by incorporating the

higher order RC model and additional factors such as AC type, and humidity effects to further reduce errors during non-steady-state periods.

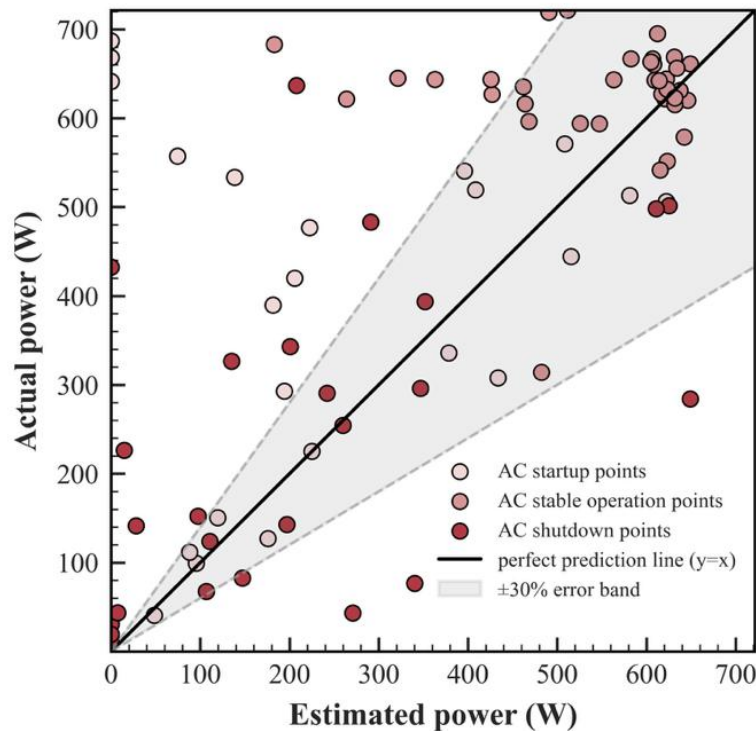


Fig.8. Scatter plot of relative error between estimated and actual power. Dots are divided into three types to differentiate the hours when the AC start up, runs stably, and shuts down(COP=2).

4. Discussion

4.1 Inferring Behavioural Dynamics from Hygrothermal Coupling

Occupant behaviours, such as the settings and operation patterns of air conditioning (AC) systems, remain among the most challenging variables to accurately represent in building energy modelling. In this study, we introduced a hybrid modelling approach that integrates machine learning with energy balance model to identify AC operational status based on indoor-outdoor hygrothermal coupling, without relying on prior energy consumption data. The XGBoost model achieved 98.6% accuracy in classifying AC on/off states using an 8-hour time window, a duration that aligns well with typical occupant daily schedules and captures prolonged AC operation cycles. Furthermore, the PELT algorithm detected AC state transitions with an F1-score of 81.2% at a 1-hour resolution, proving

sufficiently reliable for energy management applications despite minor delays under rapid environmental changes.

Outdoor temperature variations, such as HDD and CDD, can effectively predict the space cooling and heating demand, even at a large scale (Staffell et al., 2023). However, traditional building energy models typically translate these macro-indicators into simulations using static, deterministic occupancy schedules, such as a fixed thermostat and uniform daily patterns of cooling systems. This conventional approach fundamentally ignores the stochastic, highly individualised nature of occupant behaviour and real-time thermal comfort interventions. A key novelty and strength of our approach is the ability to bypass these static assumptions by utilising real-time indoor-outdoor hygrothermal data to infer actual, behaviour-driven AC usage as it happens. Furthermore, this insight underscores the critical need to integrate humidity-driven behavioural patterns into predictive models, moving beyond the traditional focus on dry-bulb temperature control alone.

The high importance of humidity variance should not be interpreted as evidence that humidity variance is the dominant causal determinant of steady-state thermal comfort. Standards such as ASHRAE 55 assign a more limited role to humidity within commonly encountered comfort conditions. The present target, however, is dynamic AC operation rather than a steady-state comfort vote. Humidity variance may be discriminative because it combines two processes: changing moisture conditions may contribute to perceived discomfort, while AC operation itself modifies and often suppresses indoor humidity variability through dehumidification and air recirculation. Feature importance therefore reflects the usefulness of humidity variance for distinguishing operational states, rather than a direct ranking of the physiological determinants of comfort.

Human thermal comfort is a coupled, subjective phenomenon; elevated humidity significantly alters the perceived temperature. In real-world settings, AC usage is not governed by temperature alone but by perceived thermal comfort, which is strongly influenced by humidity. By incorporating hygrothermal coupling, the proposed framework captures not only the physical state of the indoor environment but also the implicit behavioural triggers that lead occupants to activate or deactivate AC systems. This perspective reframes building energy modelling from a purely physics-driven problem to a coupled human–environment system, in which occupant actions can be indirectly observed through their impact on indoor environmental conditions. As a

684 result, the model provides a more behaviourally realistic representation of AC
685 operation, enabling the identification of usage patterns that would otherwise remain
686 hidden in traditional temperature-based or schedule-driven approaches.
687

4.2 Physical Interpretations of the Effective RC Parameters

Although the model adopts a discrete-time formulation rather than assuming strict steady-state conditions, its simplified first-order RC structure (1R1C) does not explicitly account for thermal lag effects. Previous studies have demonstrated that structural simplifications of low-order RC configurations introduce significant challenges in real-world applications, such as the influence of unmodelled dynamics (e.g., occupancy patterns, equipment heat gains) (De Rosa et al., 2019), and biased parameter estimates (Chen et al., 2026), which highlight the fundamental challenge of applying RC models in scenarios where detailed boundary condition data and building fabric specifications are unavailable. Such limitation is particularly evident during the early morning period, when indoor temperatures remain elevated relative to outdoor conditions due to delayed heat release from the building envelope. As a result, the estimated thermal resistance R and internal heat gain Q_{in} exhibit reduced physical interpretability in this time window, effectively acting as lumped parameters that compensate for unmodeled dynamics such as heat storage, solar gains, and time-varying internal loads. This mathematical compensation under slow-decaying temperatures highlights a fundamental challenge of applying simplified RC models in scenarios where detailed boundary condition data are unavailable.

4.3 Thermodynamic Assumptions and the In-situ COP

A critical thermodynamic assumption in our power estimation is the adoption of a fixed coefficient of performance (COP) of 2.0. While modern split AC systems typically exhibit a rated COP between 3.0 and 4.0 under standard laboratory conditions, field studies in Beijing residential buildings indicate that the actual operational COP (in-situ COP) drops to approximately 2.5 due to frequent part-load operations, on-off cycling, and equipment degradation (Zhou et al., 2017). Furthermore, our simplified 1R1C formulation exclusively accounts for sensible heat transfer, omitting the latent heat load (dehumidification) which typically constitutes 20 – 30% of the cooling capacity during Beijing's humid summers. Consequently, the sensible portion of the COP naturally falls around 1.75 to 2.0. COP = 2.0 was retained as a physically informed baseline equivalent sensible COP for the main analysis and serves as a practical scaling factor for the simplified sensible energy balance.

The sensitivity analysis produced a dataset-specific MAE minimum at an equivalent COP of 1.45 (Appendix A6). This empirical value may partly compensate for omitted latent cooling, transient thermal lag, hourly temporal aggregation, and

parameter lumping in the simplified model. It is therefore reported as a sensitivity result rather than adopted as the baseline physical COP. The difference between the two values illustrates the uncertainty involved in interpreting a single fitted COP within a low-order sensible-only model.

4.4 Limitations, Performance Trade-offs, and Future Generalisability

Our model also demonstrated the capability of estimating AC power consumption, with a median relative error of 27.09%. However, systematic underestimation and occasional negative power predictions, which were excluded from the error analysis, were observed. These errors primarily occurred under the following circumstances: 1) The initial cooling phase, when thermal mass delays indoor temperature response. 2) Low-frequency hygrothermal measurements that fail to capture sub-hourly dynamics. 3) Complex transient behaviours at AC startup, where actual temperature and humidity changes deviate from the assumptions embedded in steady-state thermal balance equations.

Early-morning discrepancies may reflect not only gradual post-cooling thermal recovery but also a change in the behavioural decision process. AC shut-off during sleep-related periods may be governed by habitual routines, timer settings, or pre-sleep decisions rather than by instantaneous temperature and humidity alone. Although globally fixed 2- and 3-hour windows underperformed the 8-hour window, a time-adaptive framework using a shorter window specifically during the early-morning transition period warrants further investigation.

A small proportion of AC-status observations was unavailable and coded as off during preprocessing. Although the hygrothermal predictor series was complete, further validation with fully observed status labels would reduce this source of uncertainty. Moreover, the compressor-control type of the split AC—fixed-speed or variable-speed—was not reported in the available metadata. Further validation should therefore distinguish fixed-speed and variable-speed systems, particularly because continuous compressor modulation and load-dependent COP may not be adequately represented by the present binary-state and fixed-COP formulation.

Beyond technical performance, this study contributes a novel methodology for incorporating occupant behaviour into building energy models without historical energy data, which is a common obstacle in both research and practice. By establishing the direct link between outdoor and indoor temperature variations, the model provides a scalable approach for analysing energy use in data sparse

environments. Furthermore, the ability to differentiate AC operational states supports more detailed assessments of energy use patterns and indoor thermal comfort conditions. This capability has important implications beyond energy estimation. By linking AC operation to indoor environmental conditions, the framework can be extended to assess indoor overheating risks, particularly under future climate scenarios characterised by more frequent and intense heatwaves. Such analyses are critical for understanding the combined impacts of climate change on building energy demand and occupant health, and for informing adaptive building operation strategies.

Looking forward, while the proposed approach provides a computationally efficient and data-driven framework for AC operation and energy estimation, its performance under strong transient conditions could be improved through higher-resolution measurements, expanding the framework to include additional climatic variables such as humidity and solar radiation, and more advanced dynamic representations (e.g., multi-node higher-order RC models). Further investigation is therefore needed to enhance model robustness during early morning periods and rapid state transitions. These developments would further strengthen the model's applicability in smart building operations and urban-scale climate studies, ultimately supporting the development of more resilient and efficient energy systems.

5. Conclusion

This study presents a hybrid model for AC operation status prediction and power estimation using mainly temperature-humidity data. A comprehensive case study was conducted using data from a room in a residential building in Beijing to validate the proposed approach. The key findings are as follows: (1) The integration of XGBoost and PELT algorithms significantly improves AC state detection accuracy. The prediction accuracy reaches 98.6% with an 8-hour time window, demonstrating the effectiveness of this combined approach. (2) The hybrid model demonstrates superior performance in AC state transition detection, achieving F1-score of 81.2% with the PELT algorithm, while maintaining robust prediction capability across different operational conditions. (3) Performance validation shows the model achieves a median relative error of 27.09% in power estimation. The framework successfully addresses the challenge of power estimation without requiring historical power data. In conclusion, the proposed hybrid model effectively solves the problem of AC operation status prediction and provides reasonably accurate power estimation using environmental parameters. This approach demonstrates potential for improving

building energy management systems in scenarios with indoor environmental monitoring infrastructure and provides a foundation for demand response applications. Future work should focus on validating the method across diverse building types and climates, as well as integrating higher order models and higher-frequency sensing to improve power estimation accuracy during transient operations.

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Appendix

A1. Feature input of the AC state prediction algorithm

As described in the previous section, we selected time windows of [2, 3, 4, 6, 8, 12, 24] hours, and computed features based on temperature, humidity, and their variations over time as input data. The features calculated for each window are summarized in Table A1.

Table A1: The input features for the AC state prediction algorithm

Feature	XGBoost window-level formulation	PELT hourly formulation	Unit
Indoor Dry-Bulb Temperature	Window mean	Current value	°C
Outdoor Dry-Bulb Temperature	Window mean	Current value	°C
Indoor Relative Humidity	Window mean	Current value	%
Outdoor Relative Humidity	Window mean	Current value	%
Humidity Difference	Window aggregate/mean of absolute differential	Current absolute differential	%
Temperature Difference	Window aggregate/mean of absolute differential	Current absolute differential	°C
Humidity Variance	Variance within window.	Rolling 8-hour variance	% ²
Temperature Variance	Variance within window.	Rolling 8-hour variance	°C ²
Humidity Change Rate	Mean change rate within time window.	One-step change	%/hour
Temperature Change Rate	Mean change rate within time window.	One-step change	°C/hour

These features were aggregated for each time window and used as input to an XGBoost classifier. The model was trained to predict the maximum AC state within each window, which indicates whether the AC was turned on at any point during that period.

A2. Feature Weighting for PELT Algorithm Input

Based on the XGBoost results across different time windows, the optimal time window was selected for further analysis. To quantify the contribution of each feature in predicting AC operational states, we employed Random Forest importance scoring within this optimal window. This method evaluates feature importance by measuring the mean decrease in impurity across all decision trees. The importance score for each feature f_i is computed as shown in Eq. (A2.1):

$$Importance(f_i) = \frac{1}{N} \sum_{t=1}^N Reduction\ in\ Impurity(f_i, t) \quad (A2.1)$$

where N is the number of trees in the forest, and the reduction in impurity measures how much each feature contributes to improving the model's performance.

For each time point t , a weighted feature value was computed as the dot product of the feature values and their corresponding importance weights, as shown in Eq.(A2.2):

$$Weighted_{feature(t)} = \sum_{i=1}^n w_i \times f_i(t) \quad (A2.2)$$

where $f_i(t)$ is the value of feature i at time t , and w_i is its importance weight derived from the Random Forest model. This weighted feature value serves as the input for the PELT algorithm, enabling precise detection of AC state transitions within the optimal time periods. The feature variables used for weighted calculation at each moment are shown in Table A1.

A3 Technical details on XGBoost and PELT Algorithm

A3.1. Extreme gradient boosting (XGBoost)

Given a dataset with features $X = \{x_1, x_2, \dots, x_n\}$ and corresponding binary labels $y = \{y_1, y_2, \dots, y_n\}$, (where $y_i \in \{0,1\}$ represents the AC state), the goal is to learn a model $f(X)$ that predicts the probability of the AC being in the "on" state. The prediction is thresholded to produce a binary output $\hat{y}_i = \delta(f(x_i) \geq 0.5)$, where $\hat{y}_i^{(t)}$ is the AC state prediction for instance i at iteration t .

The XGBoost algorithm minimises a regularised objective function at iteration t , as defined in Eq. (A3.1):

$$\mathcal{L}^{(t)} = \sum_{i=1}^n \ell(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (A3.1)$$

where $\ell(y_i, \hat{y}_i)$ is the loss function for binary classification as Eq. (A3.2):

$$\ell(y_i, \hat{y}_i) = -y_i \log(\hat{y}_i) - (1 - y_i) \log(1 - \hat{y}_i) \quad (A3.2)$$

The regularization term $\Omega(f_k)$ in the objective function is inspired by the work of Friedman (Friedman, 2001), controls model complexity, as shown in Eq. (A3.3):

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (\text{A3.3})$$

where T is the number of leaf nodes in tree f_t . w_j represents the weight of the j -th leaf. γ and λ are regularisation parameters that help prevent overfitting.

At each iteration t , a new tree f_t is added to minimize Equation (A3.1). The prediction is updated as Eq. (A3.4):

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \quad (\text{A3.4})$$

where η is the learning rate, controlling the contribution of each tree to the final prediction.

In each iteration of XGBoost, an attempt is made to find a decision tree that minimises the loss function, thereby progressively enhancing the model's performance (Zhang et al., 2025), until a stopping condition is met.

A3.2 PELT Algorithm for AC State Transitions

Based on a time series of AC operational states $\{y_t\}_{t=1}^n$, we assume the existence of m change points at positions $\tau_1, \tau_2, \dots, \tau_m$, where each $\tau_j \in \{1, 2, \dots, n-1\}$ (Lang et al., 2024). These change points partition the series into $m+1$ distinct segments: $\{y_1, \dots, y_{\tau_1}\}, \{y_{\tau_1+1}, \dots, y_{\tau_2}\}, \dots, \{y_{\tau_m+1}, \dots, y_{\tau_n}\}$. Each segment corresponds to a stationary operational phase S_j , with transitions between segments indicating state changes. The detection problem is formulated as a constrained optimization described in Eq. (A3.5):

$$\min_{\tau_1, \dots, \tau_m} \left[\sum_{j=0}^m c(y_{\tau_j+1:\tau_{j+1}}) + \lambda m \right] \quad (\text{A3.5})$$

where $c(y_{(\tau_{j-1}+1):\tau_j})$ is the cost function that quantifies the variability within a segment, indicating the degree of change in the AC operation state within that segment. λ is regularization parameter controlling model complexity and m is the number of change points

The Pruned Exact Linear Time (PELT) algorithm solves Equation (A3.5) through dynamic programming with optimality guarantees. The recursive formulation is, as given in Eq. (A3.6):

$$F(t) = \min_{\tau < t} [F(\tau) + c(y_{\tau+1:t}) + \lambda] \quad \forall t \leq n \quad (\text{A3.6})$$

where $F(t)$ represents the minimal cost up to time t (Killick et al., 2012).

For AC state transitions, we employ the L_2 cost function for mean shift detection, as shown in Eq. (A3.7):

$$c(y_{a:b}) = \sum_{t=a}^b (y_t - \bar{y}_{a:b})^2 \quad (\text{A3.7})$$

where $\bar{y}_{a:b} = \frac{1}{b-a+1} \sum_{t=a}^b y_t$. Let $\{\tau_k^*\}_{k=1}^K$ denote detected change points. The predicted state sequence alternates between operational modes as Eq. (A3.8):

$$\hat{y}_t = \begin{cases} 0 & t < \tau_1^* \\ 1 & \tau_1^* \leq t < \tau_2^* \\ K \bmod 2 & t \geq \tau_K^* \end{cases} \quad (\text{A3.8})$$

The regularization parameter λ balances detection sensitivity and false alarms. We determined it by maximizing the prediction accuracy on the July and August dataset, as given in Eq. (A3.9):

$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} Acc(\lambda) \quad (\text{A3.9})$$

where Acc is the prediction accuracy.

The PELT algorithm detects changepoints where the AC state switches within a windowed sequence. However, the initial state at the first timestep of each window can hardly be determined. To address this, we conservatively initialise the state s_{t_0} to AC status off event (0) for all sequences, as true AC status on events are rare in the dataset. A transition to on ($s_{t_0} = 1$) is triggered only when two empirical conditions are simultaneously satisfied:

- 1) Feature Threshold: The raw observation x_{t_0} falls below a low quantile Q_{low}^α , derived from the empirical distribution of x_t during genuine off-to-on transitions.
- 2) Change Rate Threshold: The one-step difference $\Delta x_{t_0} = x_{t_0} - x_{t_0-1}$ exceeds a high quantile Q_{high}^β , computed from transition rates in training data.

The initialisation rule is formally defined as Eq. (A3.10):

$$s_{t_0} = \begin{cases} 1 & \text{if } x_{t_0} < Q_{low}^\alpha \wedge \Delta x_{t_0} > Q_{high}^\beta \\ 0 & \text{otherwise.} \end{cases} \quad (\text{A3.10})$$

where Q_{low}^α represents a low quantile of the raw observation values during genuine off-to-on transitions, indicating a threshold below which the system is considered to potentially switch to the "on" state. Q_{high}^β is a high quantile of the change rate (the difference between consecutive observation values), setting a threshold for a significant change in the system's state. Only when both conditions are met does the system initialize the state as "on", ensuring the transition is valid and not caused by any noise. The dual-threshold heuristic mitigates error propagation across windows:

inheriting the state from the prior window's endpoint (s_{t-1}) risks cascading inaccuracies, especially if s_{t-1} was misclassified. The thresholds Q_{low}^α and Q_{high}^β are calibrated based on monitoring data to reflect the joint distribution of feature values and change rates during unambiguous transitions, ensuring robustness to sparse on events.

A4. Model evaluation metrics

A4.1. Evaluation Metrics for AC State Prediction

The performance of the XGBoost model in predicting AC states across time windows was evaluated using standard classification metrics. Specifically, four commonly used metrics, including accuracy, precision, recall and F_1 score were computed for each time window, as defined in Equations. (A4.1) - (A4.4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (A4.1)$$

Accuracy measures the overall correctness of classification by quantifying the proportion of correctly labelled time windows, encompassing both positive and negative predictions.

$$Precision = \frac{TP}{TP + FP} \quad (A4.2)$$

Precision evaluates the proportion of correctly predicted "on" states among all predicted "on" windows, reflecting the model's ability to avoid false-positive predictions.

$$Recall = \frac{TP}{TP + FN} \quad (A4.3)$$

Recall, also known as sensitivity, quantifies the proportion of actual "on" windows that are successfully identified, thereby capturing the model's ability to minimize false negatives.

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (A4.4)$$

The F_1 -score, defined as the harmonic mean of precision and recall, provides a balanced assessment of the model's performance, particularly in the presence of class imbalance or asymmetric error costs.

In these equations, TP (true positives) denotes correctly identified "on" states. TN (true negatives) refers to correctly identified "off" states. FP (false positives) represents incorrectly predicted "on" states, and FN (false negatives) indicates "on" states that were incorrectly classified as "off".

All metrics were computed individually for each time window length (e.g., 2, 3, 4, 6, 8, 12, 24 hours) and stored for comparative analysis across models and configurations.

A4.2. Evaluation Metrics for Change-Point Detection

The performance of the change-point detection model was evaluated using standard classification metrics.. For each hourly time period, the algorithm predicted change points in the weighted feature sequence, and the predicted AC states were compared with the true states.

The overall accuracy, representing the global proportion of correctly classified hourly samples across both states combined (as referenced in Section 3.3.3), is defined in Eq. (A4.1). Per-class recall (equivalent to state-specific accuracy in Table 3) quantifies the proportion of actual instances of each state correctly identified: for AC 'On' as per Eq. (A4.3), and for AC 'Off' as $TN/(TN+FP)$. Precision and F1-score follow Eq. (A4.2) and Eq. (A4.4).

A4.3. Calculation of Physical Transition Metrics

The physical quantification metrics presented in Table 4 are derived from the PELT-detected change points as follows:

Average WF change (Δ):

$$\Delta WF = \overline{WF}_{post} - \overline{WF}_{pre} \quad (A4.5)$$

where $\overline{WF}_{pre}$ is the mean weighted feature value in the hour preceding the transition, and $\overline{WF}_{post}$ is the mean value in the hour following the transition. This metric quantifies the abruptness of environmental shift at the switching instant. For AC activation ($0 \rightarrow 1$), negative Δ indicates rapid indoor environmental stabilization (decoupling from outdoor conditions); for deactivation ($1 \rightarrow 0$), positive Δ indicates gradual recoupling with outdoor hygrothermal conditions.

Typical WF level (On/Off):

$$Typical\ WF = \overline{WF}_{state} \quad (A4.6)$$

This represents the steady-state signature of each operational mode—the mean WF value during stable AC-on or AC-off periods, excluding transition windows. Lower values (~ 2.0) correspond to stable air-conditioned environments with minimal indoor-outdoor gradients; higher values (~ 3.9) correspond to naturally ventilated conditions with stronger hygrothermal coupling.

Average peak spike:

$$Peak\ spike = \max(WF_{window}) \quad (A4.7)$$

This metric records the maximum WF value within the 2-hour transition window. It characterises the magnitude of the feature excursion and is not interpreted as a measure of temporal sharpness or transition duration.

A4.4. Evaluation Metrics for AC Power Fitting

To assess the performance of the AC power fitting model, a set of standard regression metrics was employed to quantify the accuracy of the predicted power values. The evaluation involved three commonly used error metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Median Relative Error (MRE), as defined in Equations (A4.8)–(A4.10):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (A4.8)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (A4.9)$$

$$MRE = Median \left(\left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \cdot 100\% \quad (A4.10)$$

A5. Complete Hourly Records of AC State Detection

The complete hourly validation dataset comprises 1,488 observations from July 1 to August 31, 2021. Figure A5.1 illustrates the temporal dynamics of the weighted feature (WF) and the comparison between actual monitored AC states and PELT algorithm predictions (penalty parameter $\lambda = 2.0$) for the entire study period.

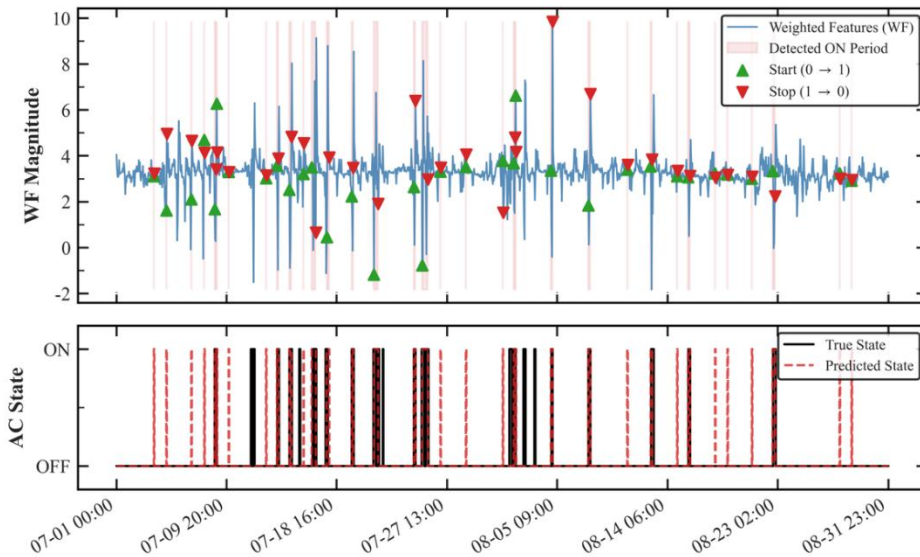


Fig. A5.1. Hourly comparison of weighted feature (WF) values with detected change points (red markers), and actual vs. predicted AC operational states (0 = Off, 1 = On) from July to August 2021.

A6. COP Sensitivity Analysis

A sensitivity study was conducted by varying COP in the range [1.0, 5.0] with a step size of 0.5. For each COP value, thermal parameters (C , R , Q_{in}) were first estimated during AC-off periods, and then used to calculate AC power during AC-on periods. The median relative error (MRE) was computed for each time segment to identify the estimation error.

Table A6.1 AC Power Estimation Performance under Different COP Values by Time

COP	Period			Overall MRE(%)	MAE(W)
	0-8h MRE(%)	8-16h MRE(%)	16-24h MRE(%)		
1.0	165.43	64.02	38.11	29.13	131.52
1.5	110.65	49.24	33.04	23.38	123.21
2.0	85.43	42.76	34.72	27.09	130.75
2.5	73.43	46.27	39.07	33.07	156.64
3.0	68.80	53.29	43.70	42.90	181.57
3.5	65.79	59.23	48.79	51.06	202.46
4.0	65.39	64.33	53.97	56.40	225.52
4.5	66.26	68.29	58.17	61.24	245.08
5.0	67.28	71.46	61.88	65.12	262.57

Table A6.1 and Fig. A6.1 show that the empirical MAE minimum for this dataset occurs at an equivalent COP of 1.45. Figure A6.2 presents the corresponding sensitivity result; this empirical value is not used as the baseline COP in the main analysis. As shown in Table A6.1 above, the COP is between 1 and 2, and the MAE value has the smallest error. Figure A6.1 shows how the prediction error MAE fluctuates as the parameter COP changes between 1 and 2. We used an optimization algorithm to find the parameter value that results in the minimum error. Figure A6.2 is a scatter plot of the overall optimal COP prediction error. For the steady-state condition, the air conditioning power points are concentrated in the upper right corner.

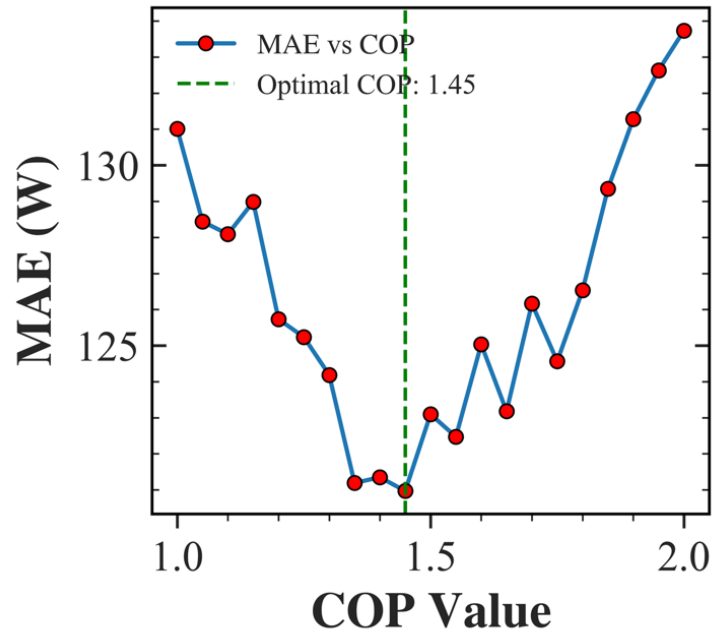


Fig. A6.1. Sensitivity of mean absolute error to the assumed equivalent COP. The empirical MAE-minimising value for the present dataset is 1.45.

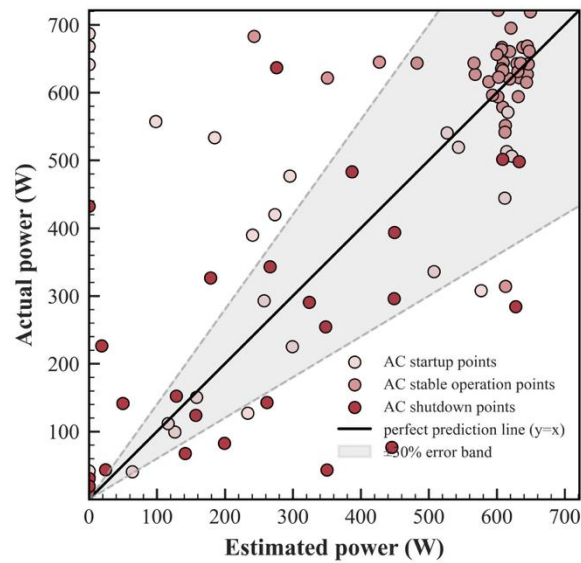


Fig. A6.2. Scatter plot of relative error between estimated and actual power. Dots are divided into three types to differentiate the hours when the AC start up, runs stably, and shuts down (cop = 1.45).

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