

# A Data-Driven Thermal Model of a Building with an Inverter-Based Air-Conditioner for Demand Dispatch\*

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**Abstract**—The paper presents a low-order dynamic model of a thermal zone that is served by an inverter air conditioner (AC), and a method to identify the model from measurements. The motivation for the model comes from its application in demand dispatch, in which many ACs are coordinated to manipulate aggregate demand while ensuring each AC maintains its indoor temperature within bounds. The presence of unmeasured disturbance from heat gains due to occupants and appliances is a challenge. The power consumption model of an inverter AC can be overly complex or unrealistically simple; striking the right balance is challenging. We use a first-order RC network model for the thermal dynamics sub-model and cast the identification problem as a convex optimization problem. An  $\ell_1$  penalty enables estimating the unmeasured heat gain assuming that it is piecewise constant. The power consumption is modeled as a static nonlinearity with a first-order filter in series. Experimental data from a testbed in IIT Guwahati is used to fit the sub-models. The data also shows that for the specific AC used, there are additional features in the power consumption compared to what is hypothesized in recent related work.

## I. INTRODUCTION

Demand management is now recognized to be a valuable resource in balancing the demand and supply of electricity in the power grid, especially as the share of intermittent renewable energy sources increases. Loads such as air conditioners (ACs), heat pumps, and water heaters are flexible loads. They can vary their electricity demand within limits without adversely affecting consumers' quality of service (QoS). By coordinating many loads, large variations in the aggregate demand can be affected [1], [2], [3]. The loads can then serve the same purpose as a dispatchable battery or a generator; hence, the idea is referred to as *virtual energy storage* (VES) [4] or *demand dispatch* [5]. The key differences from demand response is that VES are meant to (i) operate 24 by 7 and (ii) ensure consumers' QoS is maintained.

Air conditioners are the most promising for VES due to their high power consumption and flexibility: fast changes in their power consumption do not lead to noticeable changes in the indoor temperatures due to the thermal inertia of buildings. Additionally, by coordinating many ACs that individually change power consumption quickly, a slow change in the aggregate demand can be affected [4].

Simulation studies are required to compare the performance of multiple coordination algorithms under identical

conditions. For such a study, a dynamic model that can predict an AC's power consumption and indoor temperature is needed.

While there is a large literature on modeling indoor temperature, work on modeling AC power consumption - in a way that is useful for demand dispatch studies - is limited. Many studies for demand dispatch use a binary model of the power consumption of an AC: its demand is zero if it is off and equal to the rated power if it is on; see e.g. [1], [3], [2], [6] and references therein. However, in recent years, the so-called inverter air conditioners have become quite popular, especially in India [7]. They exhibit continuous power variation in a wide range, as experiments reported in this paper show, which on/off models do not capture. Though recent works have proposed models of inverter air conditioners, these models are either quite complex or are not experimentally validated. [8], [9], [10], [11], [12].

This paper provides a data-driven method to identify a simple dynamic model of a small building (a single thermal zone) that is served by a residential inverter air conditioner. The model predicts both the indoor temperature and the AC power consumption in response to the control commands: the AC temperature setpoint and on/off status. Results from the application of the method to data collected from an experimental testbed are presented.

The proposed model is a cascade of a power consumption sub-model and a thermal sub-model; the latter predicts the indoor temperature. The power consumption sub-model takes control commands as input and predicts the power consumption and cooling provided, which acts as an input to the thermal sub-model. The indoor temperature is modeled using a resistor-capacitor (RC) model. Models of this type have been extensively used in past work; see [13], [14] and references therein. The power consumption is modeled as a nonlinear static map in series with a first-order (dynamic) filter.

The method for identification of R and C values proposed here is inspired by the work in [15]. As in that work, we use an  $\ell_1$  penalty to identify the unknown disturbance - the internal heat gain - with an approximately-piecewise-constant assumption. We repeatedly use the method for various data segments to identify the mode of the estimated parameters, eliminating the chance of an outlier. To the best of our knowledge, no previous work has examined the distribution of the estimated models when identified with distinct datasets.

The power consumption sub-model is a simple first-order nonlinear dynamic model, and is fitted to experimental data.

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Among the recent literature on inverter AC power consumption modeling, some provide models that need hard-to-obtain information such as compressor frequency, expansion valve area, and refrigerant to simulate [16], [17], [11]. Another body of work do present models that are simple enough for demand dispatch studies; they model an AC's power consumption as a piecewise linear function of the frequency of the AC voltage produced by the inverter; e.g. [18], [8]. Among these, only [8] provides experimental evidence of the model's predictive power. The model proposed here is fitted to experimental data and is simple enough to be useful for demand coordination studies.

The rest of the paper is organized as follows. Sec. II describes the problem statement precisely, Sec. III describes the proposed method, Sec. IV describes the experimental setup, and Sec. V describes the results of applying the method to the experimental data collected from the testbed. Sec. VI concludes the paper.

## II. PROBLEM STATEMENT

Recall that the system we study is a thermal zone, e.g., a small building or room, that is served by an inverter AC. Time is discrete:  $k = 0, 1, \dots$  is the discrete-time index corresponding to a sampling time period denoted by  $\delta t$ . The control command  $u_k$  to the system is  $u_k \triangleq [m_k, T_k^{\text{STPT}}]^T$ , in which  $m_k$  is the on/off status:  $m_k \in \{0(\text{OFF}), 1(\text{ON})\}$ , and  $T_k^{\text{STPT}}$  is the AC setpoint temperature at time  $k$ . The output  $y_k$  consists of indoor temperature  $T_k^{\text{in}}$  and electrical power consumption  $P_k^{\text{AC}}$  of the AC:  $y_k = [T_k^{\text{in}}, P_k^{\text{AC}}]^T$ . The control command is chosen by an user during normal operation. When the AC is used to provide VES, the command can be varied by the coordination algorithm. Some algorithms assume the setpoint will be varied (e.g. [1]) while others assume the on/off status will be directly varied [2], [6]. The indoor temperature must be maintained within limits to ensure the consumer's QoS. The choice of the output  $y_k$  is dictated by these considerations. The system is also affected by disturbance  $w_k$ , which consists of outdoor temperature  $T_k^{\text{out}}$ , solar irradiance  $\eta_k^{\text{sol}}$  and internal heat gain  $\dot{q}_k^{\text{int}}$  from occupants and appliances, so  $w_k = [T_k^{\text{out}}, \eta_k^{\text{sol}}, \dot{q}_k^{\text{int}}]^T$ . The state  $x_k$  depends on the choice of the model structure.

*Our goal is to obtain a low-order dynamic model relating the inputs ( $u_k$  and  $w_k$ ) to the output  $y_k$  from measurements of  $u$ ,  $T^{\text{in}}$ ,  $P^{\text{AC}}$  and  $\eta^{\text{sol}}$ .* The commercial availability of sensors dictates the choice of measurement signals. A challenge in model identification is the unmeasurable disturbance: the internal heat gain.

We choose a cascade model structure: the control and disturbance inputs determine the cooling produced (power consumption sub-model), which in turn affects the indoor temperature (thermal sub-model); see Fig. 1. Because of the cascade structure, and since the output of the first sub-model is measurable, one can identify the two sub-models independently.

We use an RC network for the thermal sub-model; see Fig. 1. It consists of a resistor of resistance  $R$  and a capacitor of capacitance  $C$ . The model is a first-order ordinary

differential equation with one state, the temperature of indoor air, denoted by  $T^{\text{in}}$  [15]:

$$C\dot{T}^{\text{in}} = \frac{T^{\text{out}}(t) - T^{\text{in}}(t)}{R} + A^{\text{eff}}\eta^{\text{sol}}(t) - q_u^{\text{AC}}(t) + \dot{q}^{\text{int}}(t) \quad (1)$$

where  $T^{\text{out}}(^{\circ}\text{C})$  is the outdoor air temperature,  $A^{\text{eff}}(\text{m}^2)$  is the effective area through which solar radiation enters the room,  $\eta^{\text{sol}}(\text{kW}/\text{m}^2)$  is solar irradiance, and  $q_u^{\text{AC}}(\text{kW})$  is the rate of heat removed by the AC unit.

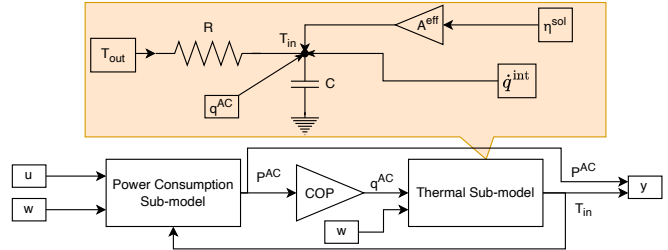


Fig. 1. Structure of the proposed model, with the two sub-models.

Applying first-order forward Euler method of discretisation  $\dot{T}_k^{\text{in}} = \frac{T_{k+1}^{\text{in}} - T_k^{\text{in}}}{\delta t}$  to (1), the discrete-time model is obtained:

$$T_{k+1}^{\text{in}} = (1 - \theta_1)T_k^{\text{in}} + \theta_1 T_k^{\text{out}} + \theta_2 \eta_k^{\text{sol}} - \theta_3 \cdot \text{COP} \cdot P_k^{\text{AC}} + \theta_k^{\text{int}} \quad (2)$$

where the  $\text{COP}$  is the coefficient of performance of the AC, which is the ratio of the cooling output ( $q_u^{\text{AC}}$ ) to the electrical energy input ( $P^{\text{AC}}$ ), and  $\theta_1 \triangleq \frac{\delta t}{RC}$ ;  $\theta_2 \triangleq \frac{\delta t}{C} \cdot A^{\text{eff}}$ ;  $\theta_3 \triangleq \frac{\delta t}{C}$ ; and  $\theta_k^{\text{int}} \triangleq \frac{\delta t}{C} \cdot \dot{q}_k^{\text{int}}$ . Note that the original parameters (i.e.,  $R, C, A^{\text{eff}}, \dot{q}_k^{\text{int}}$  where  $k = 1, 2, 3, \dots, N$ ) can be obtained from the values of the new parameters  $\theta \triangleq [\theta_1, \theta_2, \theta_3, \theta_1^{\text{int}}, \theta_2^{\text{int}}, \dots, \theta_N^{\text{int}}]^T \in \mathbb{R}^{N+3}$ .

The first problem is to estimate  $\theta$  from measurements of  $T_k^{\text{in}}, T_k^{\text{out}}, \eta_k^{\text{sol}}$ , and  $P_k^{\text{AC}}$  for  $k = 1, 2, 3, \dots, N$ . A challenge is that the internal heat gain is not measurable.

The second problem is identifying a low-order AC power consumption model.

## III. PROPOSED METHOD

### A. Thermal Sub-model Identification with Unmeasured Disturbance

We pose the parameter estimation problem as the following optimization problem:

$$\begin{aligned} \theta^* &= \min_{\theta} J(\theta) \\ \text{s.t. } &\theta \geq 0, \theta \in \mathbb{R}^{N+3}, \end{aligned} \quad (3)$$

where the objective function is:

$$J(\theta) \triangleq \|T^{\text{in}} - T^{\text{in,m}}\|_2 + \lambda \|A_{\text{diff}} \dot{q}^{\text{int}}\|_1 + \alpha \|\dot{q}^{\text{int}}\|_2 \quad (4)$$

where  $T^{\text{in}} \triangleq [T_1^{\text{in}}, T_2^{\text{in}}, \dots, T_N^{\text{in}}]^T$  is the  $N$ -dimensional vector of predicted indoor temperatures from model (2), and  $T^{\text{in,m}} \triangleq [T_1^{\text{in,m}}, T_2^{\text{in,m}}, \dots, T_N^{\text{in,m}}]^T$  is the vector of measured indoor temperatures. Similarly,  $\dot{q}^{\text{int}} \triangleq$

$[\dot{q}_1^{\text{int}}, \dot{q}_2^{\text{int}}, \dots, \dot{q}_N^{\text{int}}]^T$ , and  $\alpha, \lambda$  are tuning parameters, and  $A_{\text{diff}} \triangleq [\mathbf{0}_{(N+2) \times 1} \quad \mathbf{I}_{N+2}] - [\mathbf{I}_{N+2} \quad \mathbf{0}_{(N+2) \times 1}]$ .

The objective function  $J : \mathbb{R}^{N+3} \rightarrow \mathbb{R}$ , defined in (4), is convex over the convex set  $\{\theta \in \mathbb{R}^{N+3} \mid \theta \geq 0\}$ .

Computation for parameter estimation (3) is done using CVX [19] in MATLAB R2024b on a MacBook Air M2 with 16GB RAM and 512GB storage. CVX is a modeling system for solving convex optimization problems.

*Rationale:* Each of the three terms of (4) has a specific role. The first term  $\|T^{\text{in}} - T^{\text{in,m}}\|_2$  is for penalizing error between measured and predicted indoor temperature values. The second term  $\|A_{\text{diff}} \dot{q}^{\text{int}}\|_1$  acts as an  $\ell_1$ -penalty on the discrete derivative of disturbances. It is well known that the  $\ell_1$  penalty encourages a sparse solution [20], [15]. Therefore the optimal  $A_{\text{diff}} \dot{q}^{\text{int}}$  is likely to be sparse. Since  $A_{\text{diff}} \dot{q}^{\text{int}}$  is a vector with entries of that from  $\dot{q}_{k+1}^{\text{int}} - \dot{q}_k^{\text{int}}$ , a sparse  $A_{\text{diff}} \dot{q}^{\text{int}}$  is equivalent to  $\dot{q}^{\text{int}}$  being mostly constant. Such a solution is consistent with physical intuition: internal heat gain is primarily due to human occupancy. Since the number of people present changes slowly, so does the internal heat gain. However, there is a large degree of freedom in the model (2), any such difference between measured and predicted values can be explained by using  $\dot{q}^{\text{int}}$ . The third term is introduced to prevent this behavior by penalizing the amplitude of  $\dot{q}^{\text{int}}$ , which was not done in [15]. The choice of  $\alpha$  and  $\lambda$  is made using trial and error.

### B. Power Consumption Sub-model Identification

Based on the discussion in Sec. I, we aim for a simple model structure that can be easily simulated. Meaning, the model should not be highly complex and should not require hard to obtain information as inputs. Among the reviewed literature, models in [18], [8] satisfy these criteria, and our proposed model - discussed next - is inspired by them. However, a weakness that we address is that the input in [18], [8] is inverter frequency, which is not a suitable control command for demand dispatch since it is not as easily commanded as the setpoint temperature or on/off status.

The power consumption of a commercially available residential air conditioner is primarily due to the compressor and secondarily due to the condenser and evaporator fans. These components are operated by an on-board control system based on multiple sensors, but the details of the control logic are not available in the public domain. There is an air temperature sensor that is located right before the air filter at the inlet, which measures an aggregate indoor temperature. The on-board controller meters the cooling provided by the AC. It is clear from observing the behavior of the AC that this metering is done by operating the compressor and the fans in response to the difference between the indoor and setpoint temperatures. There are additional sensors to measure the state of the refrigerant loop, but how these data are used by the controller is not known. Thus, a sensible choice of input to the power consumption model is the difference  $\Delta T_k \triangleq T_k^{\text{in}} - T_k^{\text{STPT}}$ . We hypothesize that the steady state power consumption is determined solely by  $\Delta T$ . Experimental data reported later in the paper indicate that there is a non-trivial

transient in the power consumption in response to a change in setpoints, which is captured by putting a first-order filter in series with a static map, leading to a model of the following form:

$$z_k = g(T_k^{\text{in}} - T_k^{\text{STPT}}), P_{k+1}^{\text{AC}} = aP_k^{\text{AC}} + bz_k \quad (5)$$

where  $g : \mathbb{R} \rightarrow \mathbb{R}$  is a potentially nonlinear function and  $a, b$  are parameters, all to be determined from measurements.

## IV. EXPERIMENTAL SETUP

We selected a room on the ground floor of the academic complex of IIT Guwahati. The room has a height of 280 cm, and its dimensions are illustrated in Figure 2. It contains one door and two windows. The windows are made of sliding glass panels. The door is 200 cm  $\times$  90 cm and made of 3 cm thick wood. The walls are of concrete with a thickness of 35 cm. The room is a faculty office. During the daytime (9 am to 7 pm), it is mostly occupied by one person, and occasionally more than one. At other times, it is empty.

In this experimental setup, we use an LG 1.5 Ton 5 Star Split Inverter AC (Model: PS-Q19BNZE) with a power requirements of 220 - 240 V, 50 Hz. The AC has a maximum cooling capacity of 5 kW with COP of 5.

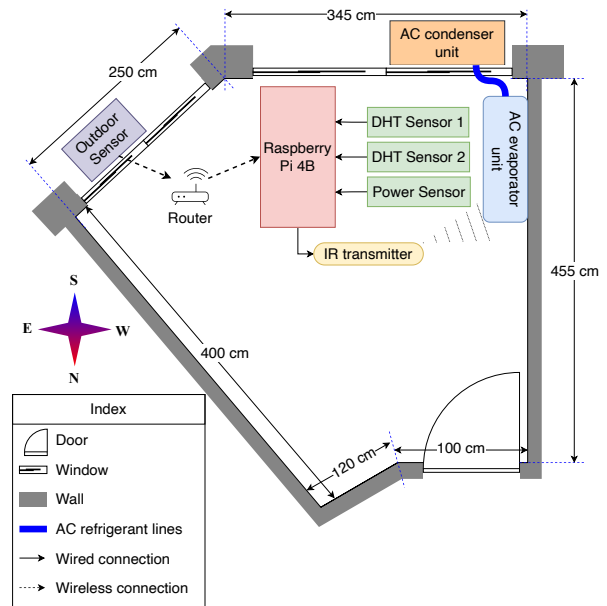


Fig. 2. The room and the experimental set up.

The heart of our experimental setup is a Raspberry Pi 4 Model B, a single-board computer. A Python script running on the Raspberry Pi sends the setpoint to an Arduino UNO R3 microcontroller board through a USB port. The Arduino is programmed to convert the setpoint temperature value to the appropriate IR signal, which the AC IR receiver can detect. The signal is then sent to the AC through an IR transmitter. As depicted in Fig. 3, two DHT11 sensors measure the indoor air temperature to provide redundancy. Both DHT sensors are connected to the Raspberry Pi using GPIO pins. A PZEM-004T power sensor is connected to a

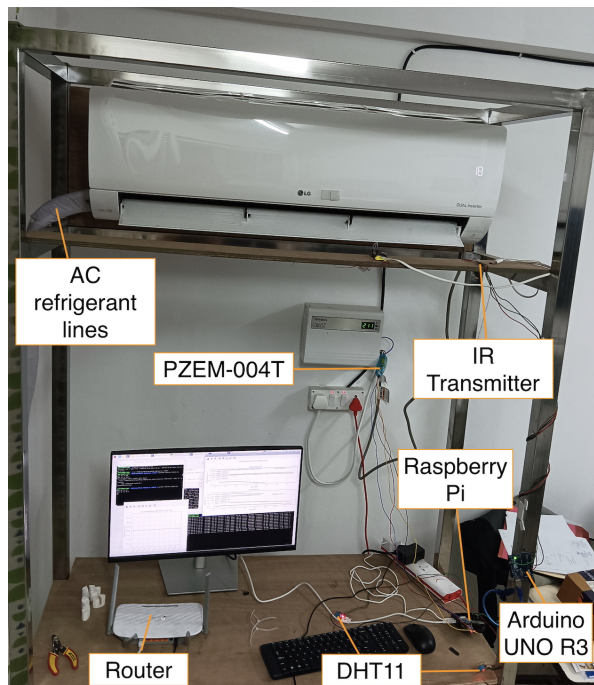


Fig. 3. Experimental setup for data collection

USB port, which measures the power consumption of the AC. A Python script collects sensor data and stores it in the Raspberry Pi.

Figure 4 shows the block diagram of the outdoor temperature logging process. The outdoor temperature sensor is battery-powered, and a solar panel charges the batteries. A solar power manager module charges the batteries and delivers power to the sensor. An ESP32 microcontroller is used to collect data from a DHT11 sensor. The ESP32 sends the data to Raspberry Pi via a client-server protocol over a local WiFi network, and the Raspberry Pi stores the data. As shown in Fig. 4, the outdoor unit is placed in a specially designed 3D-printed enclosure. The enclosure is engineered to protect sensitive electronic components from rain and sunlight, while exposing the sensor to outside air. The sensor is placed in a dedicated compartment with a mesh-designed opening that allows airflow while preventing direct water splashes during rainfall.

## V. RESULTS

### A. Thermal Sub-model

We recorded indoor and outdoor temperatures, the AC's power consumption, and solar irradiance from 14<sup>th</sup> to 21<sup>st</sup> May, 2025. Solar irradiance data is collected from a pyranometer that is installed in the IIT Guwahati campus, while the other variables are collected using sensors described in Sec. IV. The AC temperature setpoints are varied periodically between 18°C and 26°C to produce rich data to aid in parameter estimation. The setpoint temperature is changed by 1°C every hour while the data is logged every minute. Figure 5 shows the recorded data.

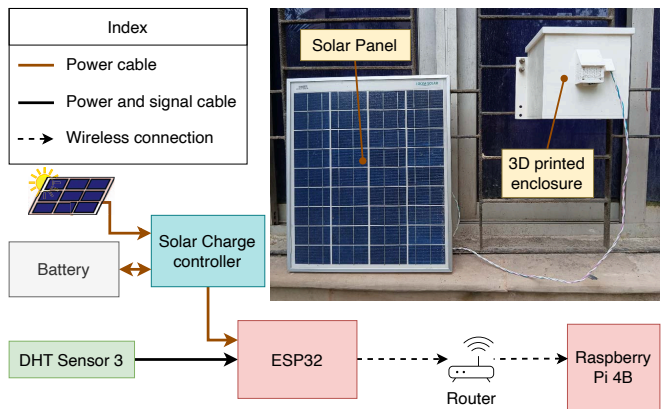


Fig. 4. Outdoor sensor functional diagram with the physical setup.

We solve the convex optimization problem of (3) with  $\alpha = 0.05, \lambda = 0.5$ . We divided the 8-day-long data into multiple datasets of different lengths, such as 8 datasets of one-day duration, 7 datasets of 2-days duration, and so on. The resulting  $R$  and  $C$  estimates are shown in a scatter plot in Fig. 8. From the plot we observe that with increase in the amount of data, the results become similar. The center of the densest cluster of points, inside the circle in the figure, is chosen as the “final”  $R$  and  $C$  values:  $C = 1.024 \text{ kWh/K}$ ,  $R = 4.580 \text{ K/kW}$ . The estimated effective area ( $A^{\text{eff}}$ ) is  $3.5 \times 10^{-10} \text{ m}^2$ . We suspect the effective area is so small due to the room's location among trees restricting direct sunlight and the cloudy weather conditions during the data collection.

The measured and predicted indoor temperature is shown in Fig. 6. The Root Mean Square Error (RMSE) is 1.03°C, and the Mean Absolute Error (MAE) is 0.80°C. The estimated internal heat gain over a specific 24 hour long period - from three distinct datasets each of 3-day duration - are shown in Fig. 7.

### B. Power Consumption Sub-model

The data from the previous experiment did not show power consumption varying throughout its full range. The rated power of the AC is 3 kW, while we see from Fig. 5 that power consumption rarely exceeds 500 W. We therefore conducted another experiment in which the setpoint temperature was changed periodically from its highest to lowest values so as to drive the power consumption to large values. The resulting data is shown in Fig. 9. We collected six readings per minute and averaged them, achieving a temperature resolution of approximately 0.17°C.

To identify the form of the static map  $g$  in (5), we first plot the steady state values of inputs and outputs:  $\Delta T$  and  $P^{\text{AC}}$  after removing all data within 10 minutes of setpoint change; see Fig. 10. From this data, we choose the following piecewise linear model for the steady state power consumption:

$$\begin{aligned}
 g(\Delta T) &= c_0 && \text{for } \Delta T \leq 0.0 \\
 &= m \cdot \Delta T + c_1 && \text{for } 0.0 < \Delta T \leq 3.3 \\
 &= c_2, && \text{for } \Delta T > 3.3
 \end{aligned} \quad (6)$$

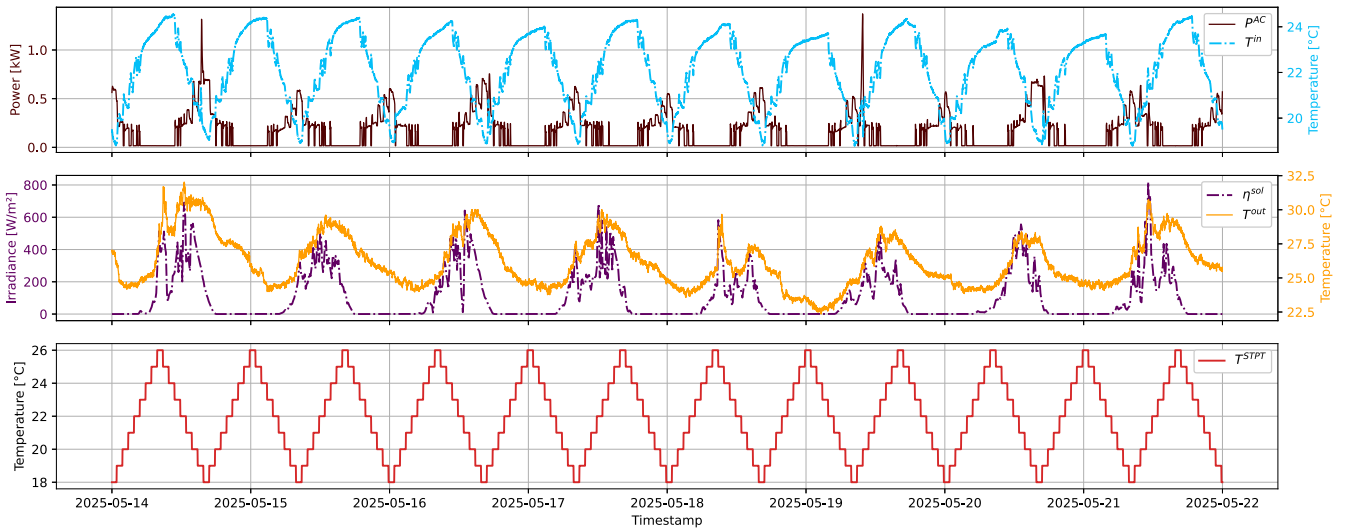


Fig. 5. Experimental data (control command, measurable disturbance, and outputs) used for fitting indoor temperature sub-model.

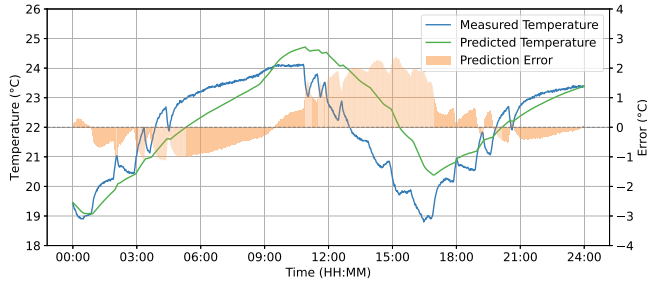


Fig. 6. Comparison between predicted and measured indoor temperature

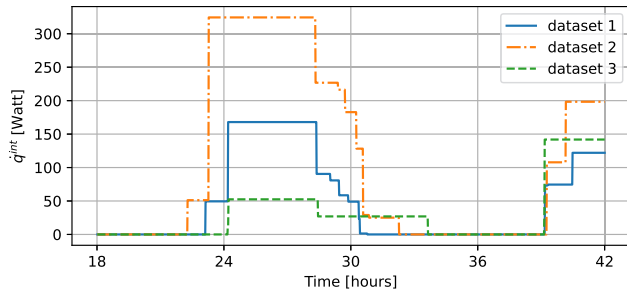


Fig. 7. Estimated internal heat gain ( $\dot{q}^{int}$ ) signal for different datasets.

where the  $m, c_i$ 's are parameters that are to be estimated from samples of  $z_k$ . This model divides the functioning of the air conditioner into three distinct regions:

- 1) **Standby Mode** ( $\Delta T \leq 0$ ): The only power consumed is that needed to power the electronics components such as its sensors, LEDs, and infrared receiver.
- 2) **Active Mode** ( $0.0 < \Delta T \leq 3.3$ ): Power consumption changes linearly with  $\Delta T$ .
- 3) **Saturation Mode** ( $\Delta T > 3.3$ ): The compressor and fans are operated near their maximum capacity.

The equations (5)-(6) together completely specify the AC power sub-model.

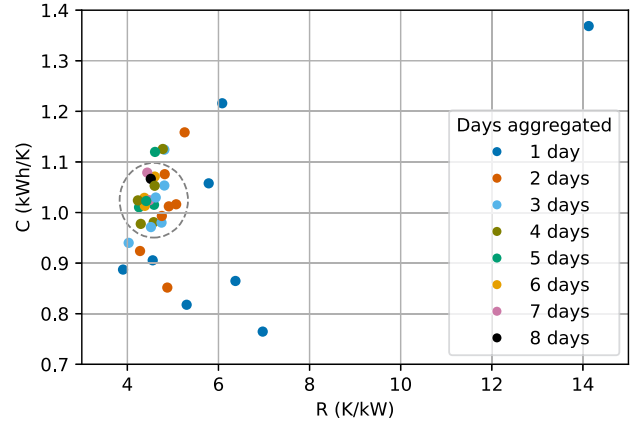


Fig. 8. Estimated  $R, C$  values.

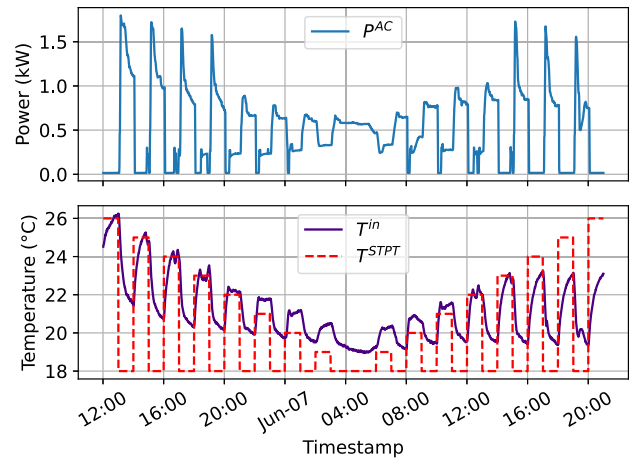


Fig. 9. Experimental data used for identifying power sub-model.

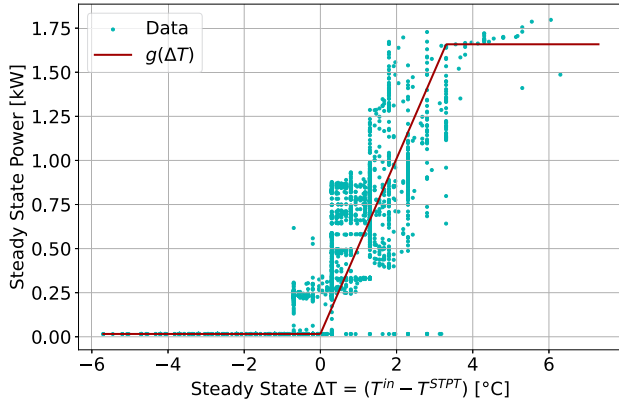


Fig. 10. Steady state power data  $z_k$  vs. temperature difference  $\Delta T$ , and the function  $g$  fitted to this data.

The values of  $c_0, c_1$ , and  $c_2$  obtained from fitting the model above to the data on  $z_k$  are 16.0 W, 16.0 W, and 1658.64 W respectively. The slope is  $m = 497.43$  W/K. Next, we fit the filter parameters to the power data  $P_k^{AC}$  to (5) using least squares and obtain  $a = 0.941994, b = 0.063426$ .

The comparison between the measured and predicted values of power consumption is shown in Fig. 11. We can see that the prediction closely matches the data with RMSE 63.5 Watts and MAE 26.8 Watts.

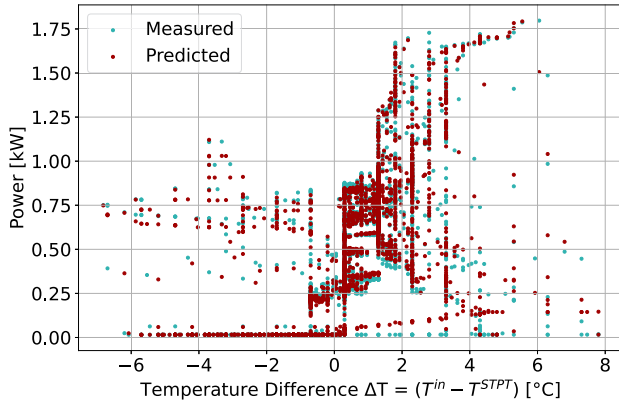


Fig. 11. Comparison between measured and predicted power consumption.

## VI. CONCLUSIONS

The paper presents a low-order dynamic model of a thermal zone that is served by an inverter air conditioner (AC), and a method to identify the model from measurements. There are many avenues for improvement in the future. Humidity is not considered in this work, though it is an important consideration in hot-humid climates. Both the user's QoS and electrical power demand depend on humidity. We plan to extend this work to include humidity in the future. Another avenue is to determine a parameterized family of power consumption models for a range of commercially available inverter ACs.

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