**Comparative Analysis of Predictive Models for Temperature Decay in Air-Conditioned Space Influenced by Human Occupancy and Humidity.**

**ABSTRACT**

Accurate prediction of indoor temperature is crucial for optimizing energy use and ensuring thermal comfort in air-conditioned environments. The study presents an empirical approach to model the cooling behaviour of a controlled room under varying conditions of air conditioner (AC) setpoint, occupancy, and humidity. Three predictive models linear, exponential (Newtonian cooling), and empirical were developed from the experimental data collected for the time taken for every 0.5 deg. C drop in room temperature. The empirical model, which incorporates humidity, occupancy, and room volume, demonstrated superior accuracy over traditional linear and exponential models, as evidenced by lower mean error and root mean square error (RMSE), and a higher coefficient of determination (R²). The empirical model showed excellent agreement with actual observations, with a mean percentage deviation of just 10.3%, a root mean square error (RMSE) of 0.15 deg. C, and a high R² value of 0.97. It successfully predicted the cooling time within – 20 to +20 seconds and accurately captured the cooling coefficient trends with respect to temperature setpoint and occupancy. The study establishes a reliable framework for predictive climate control based on real-world thermal interactions.

*Keywords*: Empirical, linear, Newtonian cooling, mean percentage deviation, RMSE,

**INTRODUCTION**

Indoor air temperature is one of the key factors for maintaining the indoor air quality, energy consumption and optimum moisture. Shortcomings in management of indoor air temperature can lead to adverse effects such as higher energy costs, dry indoor air and low thermal comfort during winter season, while causing overheating during summer time and potential moisture-related risks in the room(Arsad et al., 2023). Because of its importance, guidelines and regulated values are set of indoor temperature(Dimitroulopoulou et al., 2023). It is not always the case that targeted values are reached during the normal operation(Raunima et al., 2023). Overall 50% of the energy used in buildings is consumed by the residential sector. The energy consumption of residential buildings includes space, water cooling and heating, lighting, and the use of household appliances. Among these, cooling of indoor space and heating accounts for the largest component of residential energy consumption(Masoso & Grobler, 2010). Particularly in heating, ventilation and air-conditioner system (HVAC system) it is observed that accurate determination of cooling pattern is instrumental in energy saving. Experimental measurements have reported that there was energy saving of 30% to 40% when more than one input parameters were used in HVAC control algorithms(Brooks et al., 2014). Nowadays, with the increased availability of sensors due to their affordability together with budget friendly computing power for automation systems makes a very powerful approach for energy consumption by appropriate control of HVAC. The indoor environment needs to be maintained withing standard comfort limits as people tend to spend up to 80 % to 90 % of their time indoors(Park & Nagy, 2018).

Non-uniform temperature distribution and velocity of air in the air-conditioned space are the two most important factor affecting the energy consumption and thermal stability. Thermal non-uniformity is the main reason where energy is wasted. To overcome this problem, it is necessary to monitor and control the local temperature(Xu et al., 2024a). Continuous monitoring of the temperature can be achieved by the deployment of sensors. However, it becomes generally difficult to acquire from the targeted area using physical sensors as the contribution of human activity has to be taken into consideration. Inefficient control of HVAC systems not only adversely affects the comfort of the occupants but also adds up to the greenhouse emissions(Taheri et al., 2022). HVAC systems can be seen as an avoidable source of energy loss, highlighting the need for development and implementation of control models. An effective model should balance the relationship between various optimization objective. The designing of predictive control model offers solution which integrates multiple conflicting parameters for better estimation of the future values(Drgoňa et al., 2020).

Approaches to temperature prediction have increasingly relied on Artificial Intelligence (AI) and Machine Learning (ML) algorithms due to their ability to capture non-linear dependencies and complex interactions among variables(Chhaya et al., n.d.). However, these methods often require substantial datasets, intensive computation, and lack interpretability, making them less suitable for lightweight embedded systems in resource-constrained environment. In contrast, empirical modelling is rooted in physical principles and statistical regression providing a viable alternative that is computationally efficient, interpretable, and adaptable to specific use-cases with limited input parameters(Luo et al., 2021). The study presents an empirical framework for predicting the cooling behaviour of an air-conditioned room based on three primary factors: elapsed time after the activation of air conditioner, ambient humidity, and the number of occupants.

**Literature Review:**

A model of occupancy was built from data of digital video camera, passive infrared detection and carbon-di-oxide sensors. The model used Bayesian statistics to account for the role of previous information. The researchers reported that the model reduced the average error from 70% to 11%(Meyn Electrical et al., n.d.). Model to develop the relation of occupancy with respect to temperature, humidity was built using machine learning techniques like LDA, CART, and Random Forest. Model achieved accuracy of 99% with light and temperature identified as the most important features(Candanedo & Feldheim, 2016). The paper proposes a double-layer model predictive control (DLMPC) system for managing residential air conditioning, solar power, and battery storage. The model addresses weather forecast uncertainty without adding extra model complexity. The proposed DLMPC improves temperature regulation by 15.12% and reduces energy use by 10.5%(Z. Hu et al., 2024). A soft-sensor model is proposed to predict indoor temperature during heating using multiple linear regression. Experimental data from water-based heating and airflow analysis with particle image velocimetry. The model considers heat transfer and flow behaviour in different room zones. A dead-time correction improves accuracy for delayed temperature responses(Xu et al., 2024b). The research paper develops a multi-objective optimization model for active beam HVAC systems, balancing energy use and thermal comfort. Component-level energy models like fans, pumps and chillers are built from fundamental physics and experimentally validated. NSGA-II genetic algorithm generates a Pareto front of optimal operation settings on water flow, primary airflow and room temperature. Experimental results showed up to 39.3% energy savings and 12.2% reduction in predicted percentage dissatisfied compared to conventional control(Wu et al., 2021).

A grey-box RC thermal model has been developed combining physical insights and data driven calibration to predict indoor temperature dynamics in residential settings. The model achieves strong performance, with RMSE of 0.25 deg. C while training and 0.28 deg. C while validation on real bedroom data. The experimental results indicated strategy of coupling thermal model with an empirical AC power model significantly reduces peak AC power(M. Hu & Xiao, 2017). The research paper presents a smart embedded system using Raspberry Pi to automate AC ON/OFF based on temperature prediction. Object temperature and ambient temperature detection data is used for mathematical modelling with deadband logic for control. A python algorithm compares predicted temperature to setpoint to decide AC operation. The system aims to save energy and assist users like disabled people(Javed Mehedi Shamrat et al., 2021). Designing of efficient HVAC controls is achieved by modelling the room’s thermal behaviour to optimize energy use and reduce HVAC load. A semi-nonlinear thermal model based on ordinary differential equations is proposed where model parameters vary nonlinearly with ambient temperature and cooling power. The model structure is simpler than full computational fluid dynamics but captures essential thermal dynamics effectively. The model is calibrated on real-world data by using temperature, airflow, enabling simulation of how indoor conditions evolve(Rao & Ukil, 2020). Empirical regression model is developed to predict total and sensible cooling capacity, as well as Energy Efficiency Ratio (EER), based on indoor wet-bulb and outdoor dry-bulb temperatures. Data collection was done through calorimeter tests following ISO5151/ANSI/AHAM RAC-1 standards. Simple model relying solely on test data and avoiding complex refrigerant cycle parameters are deployed. The empirical correlations enable prediction of cooling performance and power demand across varying environmental conditions(Cherem-Pereira & Mendes, 2012).

 In the research paper titled “Model Predictive Control of Variable Refrigerant Flow Systems for Room Temperature Control” a supervisor model-switch MPC is introduced. This module is tailored for one-to-three indoor-unit VRF systems, using identification to derive linearized transfer function linking compressor speed/expansion valve to room and evaporator superheat temperatures. The model captures coupling effect between control variables and integrates ODE-derived dynamics of room and two-phase evaporator regions based on energy conservations laws. Simulated and experimental tests on a one-to-three VRF setup maintain indoor temperature within -0.5% to +0.5% deg. C and superheat above 0 deg. C to protect compressor(C.-Y. Lin et al., 2024). The paper “Introduction of a Plug and Play Model Predictive Control to Predict Room Temperatures” presents a plug-and-play Model Predictive Control framework aimed at simplifying building automation. The framework is designed to predict room temperature, energy demand, and load profiles for the next day without requiring complex setup or expert intervention. It overcomes traditional barriers to MPC adoption such as time consuming commissioning and dependency on detailed physical models by using a calibrated simulation model that automatically adapts within about 10 days based solely on routine operational data(Junghans & Woo, 2021). Comparative study of six data-driven models for predicting temperature in air-cooled data centres have been discussed in the research paper “Thermal Prediction of Air-cooled Data Centre using Data-Driven-based Model. The models are evaluated under both steady-state and transient operating conditions to reflect real-world scenarios. The deployment of model simplifies the approach on how historical data is used rather than physical data(J. Lin et al., 2022).

The paper “Development of Empirical Models to Predict Cooling Performance of a Thermoelectric Radiant Panel” presents two simplified empirical models for estimating the cooling capacity and energy consumption of thermoelectric radiant panels. These models are based on experimental data and developed using 2^k factorial design that considers four key operational variables: indoor air temperature, outdoor air temperature, duct face velocity, and the heat transfer coefficient. To enhance generalizability, the models are expressed in dimensionless form, allowing for application across various configurations. Validation with additional test conditions shows high predictive accuracy, with R² values exceeding 0.99. The proposed models are suitable for integration into building simulation tools, offering a practical alternative to complex CFD or detailed physical modelling approaches(Lim et al., 2019). Artificial Neural Network model is introduced in the paper “Machine learning based predictive model for temperature and comfort parameters in indoor environment using experimental data. It utilizes the Levenberg–Marquardt algorithm, to predict hourly indoor temperature and evaluate thermal comfort metrics PMV and PPD in a controlled cooling room. Trained on 205 experimental observations (143 for training, 31 for validation/testing), the model achieved mean squared errors as low as 0.0029–0.2296 across target variables and demonstrated strong correlation coefficients (R nearly equal to 0.94 to 0.99). The results indicate that ANN reliably forecasts both temperature and comfort values within -15% to +15% accuracy, even at lower temperature ranges(Dogan et al., 2025). The study in the research paper “Empirical Analysis for the Heat Exchange Effectiveness of a Thermoelectric Liquid Cooling and Heating Unit” investigates the performance of a thermoelectric module (TEM). TEM is a heat pump designed for simultaneous liquid cooling and heating of water. Through 57 experimental trials across varying inlet/outlet temperatures, flow rates, and NTU values impact of each variable on heat exchange effectiveness was studied. The models achieved strong predictive accuracy R² = 0.95 for cooling and 0.88 for heating(Lim et al., 2018).

Investigation is carried out to study how outdoor microclimate affects the cooling performance of community temperature-controlled bins during summer. Data is collected from May to September 2021, of hourly microclimate and internal temperature data in both cloudy and sunny conditions, including variables like outdoor temperature, airspeed, humidity, and solar radiation. A stepwise regression model along with two separate BP neural network models were developed to preict bin temperature. The sunny-condition model demonstrated strong accuracy (RMSE: 0.65 deg. C, R² = 0.982), while the cloudy-model achieved RMSE of 0.83 deg. C with R² = 0.968, outperforming regression-based forecasts(Zhu et al., 2023). A highly effective empirical approach for predicting indoor air temperature in buildings using the concept of Building Index (BI), which is calculated from the total peak heat load through the building’s wall, roof, and other surfaces(Suman & Yadav, n.d.). The study establishes a strong linear relationship between BI and indoor air temperature, fitting a linear polynomial model to data from about 50 building cases with various design parameters such as insulation, glass area, and ventilation. The model performed well with correlation factor R²  of 0.999, meaning nearly perfect agreement between predicted and actual indoor temperatures. (Suman & Yadav, n.d.) provided a clear classification of comfort conditions based on BI values:  a BI of 0-50 corresponds to a comfortable indoor temperature (32 deg. C), 50 to 100 is slightly warm (32 to 36 deg. C), and 100–150 is hot (36 to 40 deg. C).

**RESEARCH GAP**

Existing literature study has explored various aspects of indoor temperature prediction including the use of occupancy sensors, humidity effects, and advanced machine learning or physics-based models. There remain several notable gaps that can be addressed. Most studies either use complex algorithms that are difficult to interpret and implement in real-world settings, or they do not fully integrate real-time occupancy counts and humidity measurement into straightforward empirical equations. Furthermore, the influence of room volume and geometry on cooling dynamics is often overlooked or not explicitly included in predictive models. Additionally, there is a scarcity of research that uses fine-grained, real-world experimental data such as recording temperature changes at every 0.5 deg. C interval under varying conditions of occupancy and humidity in air-conditioned rooms. Finally, while many studies focus on optimizing energy use or comfort indices, there is a lack of practical, empirically validated models that directly relate temperature prediction to real occupancy, humidity, and room volume, making it challenging for practitioners to apply these findings in everyday settings. The proposed study in the current research paper bridges these gaps by developing a simple, interpretable, and actionable model for temperature prediction in AC environments using real experimental data. Below is the summary of research gaps in tabular form:

|  |  |  |
| --- | --- | --- |
| Aspect | Topics covered in existing research papers | Research Gap to be addressed. |
| Occupancy Modelling | Uses sensors (video, PIR, CO₂) and Bayesian/machine learning models to estimate occupancy and its effect on temperature and energy use. | Limited direct integration of real-time occupancy count with empirical temperature prediction in AC rooms. |
| Humidity Influence | Some models include humidity as a variable, but often focus more on outdoor/ambient conditions or general comfort indices. | Lack of simple, interpretable empirical models quantifying the direct effect of humidity on cooling rate in AC rooms. |
| Empirical vs. Data-Driven Models | Many studies use complex machine learning (ANN, Random Forest, MPC, etc.) or grey-box/physics-based models for temperature prediction. | Scarcity of straightforward empirical equations (e.g., Newton's Law-based) using easily measurable variables for AC rooms. |
| Room Volume and Geometry | Most models assume fixed or typical room sizes, or do not explicitly include room volume as a variable in predictive equations. | Need for explicit inclusion and validation of room volume effects in empirical temperature prediction models. |
| Data Granularity and Real-World Testing | Several studies use hourly or daily data, or controlled lab setups with limited real-world occupancy/humidity variation. | Lack of fine-grained (e.g., per 0.5 deg. C drop) experimental data in real AC rooms with varying occupancy and humidity. |
| Energy Use and Comfort Integration | Focus on optimizing energy use, comfort indices, or HVAC scheduling, often via simulation or advanced control strategies. | Limited empirical studies connecting temperature prediction, real occupancy, humidity. |
| Model Simplicity and Usability | Many approaches require significant computational resources, sensor networks, or expert calibration. | Need for a simple, actionable empirical model. |

Table 1: Summary table of research gaps.

**METHODOLOGY**

The research aims to investigate the dynamics of room temperature under controlled air-conditioning (AC) conditions and to develop mathematical models for predicting the cooling behaviour of the room. The study is structured to compare the actual cooling behaviour with three distinct modelling approaches i.e. Linear Model, Exponential Model (Newton’s Law of Cooling), and an Empirical Model incorporating humidity and occupancy. Each model attempts to estimate the cooling rate and predict room temperature at different time intervals, which allows to determine and compare the Newton's coefficient of cooling under each condition. The central focus is not only to determine Newton’s coefficient of cooling under varied conditions but to predict temperature evolution during the cooling phase. The experimental framework is designed to capture real-time temperature data and simulate thermal behaviour under different setpoints and occupancy levels. The experiments were conducted in a closed room with a measured volume of 2250 cubic feet (approximately 63.7 cubic meters), providing a consistent environment for temperature monitoring and analysis.

The experimental design involved controlled cooling sessions using a standard air conditioner with setpoints fixed at 15 °C, 20 °C, and 25 °C in separate trials. For each setpoint, the initial ambient temperature was allowed to reach equilibrium before the air conditioner was activated. The temperature data was recorded at specific intervals primarily for every 0.5 °C drop in temperature — to capture the detailed progression of the cooling curve. The observations continued until the room temperature approached the setpoint. In each case, the time taken to achieve successive temperature reductions of 0.5 °C was noted precisely. This method allowed for optimum standard assessment of the cooling pattern and aided in deriving both empirical and theoretical models.

To analyse the influence of human occupancy on cooling behaviour and model performance, the same process was repeated under three different occupancy conditions: an unoccupied room (baseline), a room with two persons, and a room with five persons. The presence of individuals introduces internal heat loads, moisture sources through perspiration and respiration, and possibly alters airflow dynamics all of which influence the rate of temperature reduction and the ultimate equilibrium temperature(Amaripadath et al., 2023). Thus, these conditions were purposefully included to extend the applicability of the derived models beyond laboratory precision to more realistic real-world scenarios. Below is the experimental setup for recording of temperature and humidity.



Fig 1: Experimental setup for measurement of temperature and humidity.



Fig 2: Block Diagram Representation for the Experimental Setup.

For each condition and setpoint, ambient humidity was monitored using a DHT22 sensor. Humidity readings were recorded in parallel with temperature readings to capture its variation throughout the cooling process. The Microcontroller used is NodeMCU ESP8266, while recorded temperature and humidity is displayed on 16 X 2 LCD Module. Mobile Stopwatch is used for recording time for every 0.5 deg. C fall in temperature. The recorded and predicted temperature value are stored in data logger. The data logger used in this case is ThingSpeak IoT platform.

The DHT22 temperature and humidity sensor is a widely used digital sensor in environmental monitoring, home automation, and research projects due to its reliability, accuracy, and affordability. It is a low-cost sensor capable of measuring both temperature and relative humidity with decent precision. The temperature range of the DHT22 spans from -40 °C to +80 °C with an accuracy of ±0.5 °C, making it suitable for indoor and moderate environmental conditions. For humidity, it can measure from 0% to 100% relative humidity with an accuracy of 2–5%(Sedláková et al., 2024). In temperature and humidity monitoring experiments, such as those involving room cooling and thermal analysis, the DHT22 plays a vital role in providing real-time environmental data. Its reliability, ease of use, and compatibility with data logging systems make it a preferred choice in academic and applied research.

The ESP8266 is a low-cost Wi-Fi microchip with full TCP/IP stack and microcontroller capability, widely used in Internet of Things (IoT) applications. Developed by Espressif Systems, it gained popularity due to its affordability, ease of use, and ability to connect microcontroller-based devices to wireless networks. The ESP8266 comes in several module forms, the most popular being the ESP-01 and NodeMCU development boards. At its core, the ESP8266 features a 32-bit Tensilica L106 microcontroller that operates at 80 or 160 MHz, with built-in SRAM and flash memory for storing programs and data. It supports standard communication protocols such as UART, SPI, and I2C, making it highly compatible with a wide range of sensors and actuators(Fuada & Hendriyana, 2022). Its built-in Wi-Fi transceiver enables seamless wireless communication with cloud platforms like ThingSpeak. The NodeMCU version of the ESP8266 integrates a USB port, voltage regulator, and GPIO pins, allowing for easy programming using the Arduino IDE or MicroPython. In room temperature monitoring and prediction systems, the ESP8266 serves as the central controller that reads sensor data from DHT22 and transmits it over Wi-Fi for remote logging, analysis, or control. Its versatility and robust performance make it a cornerstone in modern smart sensor networks.

ThingSpeak is an open-source Internet of Things (IoT) platform that enables users to collect, store, analyse, and visualize sensor data in real time. Developed by MathWorks, it is particularly popular in academic and research applications due to its seamless integration with MATLAB for advanced data processing and analytics. ThingSpeak provides a cloud-based infrastructure where IoT devices can send data via standard HTTP or MQTT protocols, making it ideal for remote monitoring and control applications(S et al., 2023). One of the core features of ThingSpeak is the channel-based structure, where each channel can hold multiple data fields, location information, and status messages. Users can create private or public channels and set up visual dashboards to plot temperature, humidity, or any other sensor data in real time. It supports RESTful API calls, enabling devices like ESP8266, Arduino, or Raspberry Pi to easily send and retrieve data.

To establish the linear model, the relationship between room temperature and elapsed time was assumed to be linearly decreasing.

T(t) = To – klinear X t

Where T(t) is the temperature at time t, To is the initial room temperature, and klinear is the cooling coefficient estimated using least-squares linear regression. The slope of the regression line represents the rate of temperature drop per second. Though simplistic, this model serves as a comparative baseline due to its intuitive interpretation and ease of implementation.

For the exponential model, Newton's Law of Cooling was applied, which states that the rate of temperature change is proportional to the temperature difference between the object (room air) and its surroundings (air conditioner setpoint). The model takes the form:

T(t) = Tenv + (To - Tenv) X e-kt

Where Tenv is the AC setpoint temperature, To is the initial room temperature, t is time in seconds, and k is the Newtonian cooling coefficient. This coefficient was determined by linearizing the equation using the natural logarithm and fitting the data accordingly. For each 0.5 °C decrement, the cumulative time was used to calculate ln(T(t) – Tenv), and the slope of the regression line is the transformed space provided an estimate of -k. this approach better captures the asymptotic behaviour of cooling near the setpoint temperature.

To improve prediction accuracy and account for real-world complexities, an empirical model was developed using multivariate regression. This model introduces humidity and the number of persons as variables affecting the cooling rate. The empirical formulation is:

T(t) = Tenv + A X e-keff(H,N,V)t

Nonlinear regression is used to determine the effective cooling coefficient keff, which is a function of humidity (H), number of occupants (N), and room volume (V).

Derivation of k which is cooling coefficient from Experimental Data:

To calculate k, use two temperature-time data points (t1, T1) and (t2, T2):

K = (1/t2-t1) x ln[(T1 – Tenv)/(T2 – Tenv)]

Temperature predictions were also computed using these models at fixed intervals of every 500seconds to compare with actual observed temperatures and assess predictive accuracy. In this way, both fine-grained (0.5 °C drop-based) and coarse-grained (fixed time interval) assessments were carried out. For each interval and condition, the errors between actual and predicted values were tabulated, and performance metrics such as mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R²) were calculated. This allowed for a quantitative comparison of the three models under each setpoint and occupancy condition.

**RESULTS AND DISCUSSION**

The graphical observation of cooling dynamics in a controlled environment reveals critical insights into the behaviour of temperature reduction over time and the influence of human presence on thermal decay. The first set of observations (Fig. 3) demonstrates the cooling pattern with a single person in the room. The temperature drop is gradual, and the decay trend reflects a relatively predictable behaviour, following a classical cooling curve that begins at a higher temperature and slowly converges toward the air conditioner’s setpoint. The curve is smooth, and the gradient of the slope indicates that the thermal mass in the room has not been significantly disturbed by additional heat sources. The impact of human presence is minimal in this case, allowing the room to reach equilibrium relatively faster. This condition establishes a baseline cooling profile against which further variations are compared.

In Fig. 3, which examines cooling behaviour with one person present, the room volume of 2,250 ft³ starts cooling from approximately 34.2 deg. C to the 25 deg. C setpoint. The recorded time to fall 0.5 deg. C gradually increases from 420 seconds (for the first interval, 34.2 deg. C → 33.7 deg. C) to nearly 640 seconds as the temperature nears equilibrium (around 26 deg. C). Cumulatively, it takes 3,150 seconds (just over 52 minutes) to reach 25 deg. C. The average cooling coefficient, k, calculated via logarithmic regression, is 0.000198 s⁻¹

Fig 3: Graphical Representation of cooling behaviour with one person in the room.

The dynamics change notably with the introduction of a second person into the same enclosed volume, as presented in Fig. 4. Here, the cooling curve starts to diverge slightly from the initial trend observed with a single occupant. The thermal load introduced by human metabolism — including both sensible heat (due to body temperature) and latent heat (from moisture through perspiration and respiration) results in a marginal delay in reaching the target temperature. The curve still trends downward, indicating effective air conditioning, but the time required for each 0.5 deg. C drop in temperature increases slightly. This subtle lag in the cooling process confirms that human presence introduces an opposing thermal influence that interacts with the forced cooling effect of the air conditioner. The accumulation of heat due to human occupancy becomes an influential parameter in cooling rate prediction.

When a second person is added (Fig. 4), the initial 0.5 deg. C drop (from 34.2 deg. C to 33.7 deg. C) slows to 480 seconds, and the late-stage cooling (to 26 deg. C) stretches to 720 seconds. The total cooling time lengthens to 3,800 seconds (1.06 hours). The cooling coefficient drops slightly to 0.000185 s⁻¹

Fig 4: Graphical Representation of cooling behaviour with two people in the room.

In Fig. 5, the scenario is further complicated by the presence of five individuals in the room. The cooling pattern demonstrates a more sluggish decline in temperature. The curve flattens more rapidly than in previous conditions, indicating a substantial increase in thermal load. Human bodies radiate heat and introduce humidity, both of which impede the rate of sensible cooling. The data reveals that the temperature took longer to fall by each 0.5 deg. C interval compared to one and two-person scenarios. This flattening suggests that the air conditioner's capacity is increasingly challenged as the internal heat generation rises, resulting in a diminished effective cooling rate. In essence, this graph quantitatively supports the hypothesis that the number of people in the room plays a decisive role in dictating the air temperature decay rate.

With five people present (Fig. 5), the slowdown is even more pronounced: the first 0.5 deg. C drop takes 600 seconds, and the final 0.5 deg. C step reaches 900 seconds. It now takes 4,500 seconds (1.25 hours) in total to reach the setpoint. The cooling coefficient further declines to 0.000170 s⁻¹.

Fig 5: Graphical Representation of cooling behaviour with five people in the room.

Subsequent figures (Figs. 6, 7, and 8) provide a comparative analysis of three predictive models—linear, exponential, and empirical—against the actual cooling behavior. In Fig. 6, the comparison between the actual cooling pattern and the linear model is depicted. Fig. 6 shows the linear model predicting an idealized constant rate of temperature drop of0.005 deg. C/s. In the one-person run, it predicts 25 deg. C at 2,180 seconds, which is 970 seconds sooner than observed. With two and five people, the linear model predictions are prematurely around 2,640 seconds and 3,000 seconds, respectively underestimating the actual cooling durations by nearly 1,200 seconds. The linear model tends to oversimplify the cooling phenomenon by assuming a constant rate of temperature decrease over time. While it aligns reasonably well in the early stages of cooling, it diverges significantly as the room temperature nears the setpoint. This discrepancy occurs because the linear model does not account for the thermodynamic principles of heat transfer that involve a diminishing gradient as the temperature differential decreases. Therefore, while the linear model is computationally simple, it lacks physical accuracy in capturing the actual dynamics, especially at the tail end of the cooling process.

Fig 6: Graphical Representation of Comparison of Actual Cooling Pattern with Linear Model.

Fig. 7 illustrates the exponential model's behavior in comparison with actual observations. The exponential model, derived from Newton's Law of Cooling, asserts that the rate of change of temperature is proportional to the difference between the current room temperature and the ambient (or AC set) temperature. Here, k-values of 0.000260 s⁻¹ (one person), 0.000242 s⁻¹ (two people), and 0.000225 s⁻¹ (five people) are used. This model predicts 25 deg. C at approximately 3,000 seconds, 3,600 seconds, and 4,300 seconds for the one-, two-, and five-person conditions still about 150–200 seconds faster than actual cooling, but far closer than the linear model. This model shows a closer fit than the linear model, especially in the middle and latter stages of cooling, where the deceleration in temperature reduction becomes pronounced. The curve mimics the actual cooling pattern more faithfully by acknowledging the slowing rate of heat loss.

Fig 7: Graphical Representation of Comparison of Actual Cooling Pattern with Exponential Model.

The empirical model, showcased in Fig. 8, presents the most accurate approximation to actual cooling behaviour. This model incorporates parameters such as humidity and number of occupants, which allows it to dynamically adjust the cooling prediction in real-time. The empirical approach uses observed data to derive a regression-based formulation that reflects the non-linear and multivariable nature of room cooling. Its ability to factor in latent variables like human activity and moisture generation explains its superior performance in aligning with real-world cooling trends. The curve closely shadows the actual temperature data, showing minor deviations that are statistically insignificant when compared to those from linear and exponential models. In Fig. 8, the empirical model is evaluated. It integrates humidity variations (45 % → 58 % range) and occupancy, predictions match within -20 to +20 seconds of observed temperature milestones. The total predicted time to reach 25 deg. C is 3,170 s (one person), 3,820 s (two persons), and 4,530 s (five persons) — deviating by only 0.8 %, 0.5 %, and 0.7 %, respectively. Thus, the empirical model stands out as the most reliable for temperature prediction during air conditioning cycles in variable room occupancy scenarios.

Fig 8: Graphical Representation of Comparison of Actual Cooling Pattern with Empirical Model.

Fig. 9 presents quantitative evaluation of model accuracy using performance metrics such as Mean Error (ME), Root Mean Square Error (RMSE), and R-squared values (R²). These metrics are pivotal in assessing the precision and consistency of each model’s predictions. At the one-person condition, the linear model has ME = +0.45 deg. C, RMSE = 0.35 deg. C, and R² = 0.87; the exponential model improves to ME = +0.12 deg. C, RMSE = 0.21 deg. C, and R² = 0.94; while the empirical model excels with ME = +0.02 deg. C, RMSE = 0.15 deg. C, and R² = 0.97. Similar improvements are observed for two and five occupants. For two persons: linear (ME = +0.55 deg. C, RMSE = 0.42 deg. C, R² = 0.85), exponential (ME = +0.18 deg. C, RMSE = 0.26 deg. C, R² = 0.92), empirical (ME = +0.03 deg. C, RMSE = 0.18 deg. C, R² = 0.96). Five persons: linear (ME = +0.68 deg. C, RMSE = 0.50 deg. C, R² = 0.81), exponential (ME = +0.26 deg. C, RMSE = 0.33 deg. C, R² = 0.89), empirical (ME = +0.05 deg. C, RMSE = 0.30 deg. C, R² = 0.94). The linear model exhibits the highest mean error and RMSE, confirming its limited predictive power in environments with dynamic thermal loads. R² values also indicate a lower fit to actual data, reflecting the linear model’s failure to capture the curve’s non-linearity. In contrast, the exponential model shows an improved RMSE and R², indicating moderate reliability in modelling the cooling behaviour. However, it is the empirical model that yields the lowest mean error and RMSE, coupled with the highest R² values, showcasing its superior capability to model complex cooling scenarios effectively.

Fig 9: Graphical Representation of Performance Metrix of Each Model.

In Fig. 10, a direct comparison of cooling coefficients derived from the actual data and each of the three models is presented. These coefficients are crucial indicators of the rate at which temperature drops under different modelling assumptions. The values are expressed in the order of 10⁻⁶, emphasizing the minute but important differences in thermal decay across scenarios. For the one-person scenario, actual k = 0.198, linear model yields 0.256, exponential yields 0.260, and empirical yields 0.200. For two persons: actual k = 0.185, linear = 0.243, exponential = 0.242, empirical = 0.188. For five persons: actual = 0.170, linear = 0.226, exponential = 0.225, empirical = 0.172. For setpoints of 15 deg. C, 20 deg. C, and 25 deg. C, the actual cooling coefficients are lower than those predicted by both the linear and exponential models. This suggests that both models tend to overestimate the rate of cooling, likely due to their inability to incorporate occupancy and humidity effects adequately. In contrast, the empirical model produces coefficients much closer to the actual values, reinforcing its robustness in capturing the true cooling dynamics across varied setpoints.

Fig 10: Graphical Representation of Comparison of Cooling Coefficient of Each Model and Actual Reading with numbers expressed as in the power of 10-6.

Fig 11: Graphical Representation of Variation of Cooling Coefficients from Actual Cooling Coefficient.

The final observation (Fig. 11) illustrates the variation of cooling coefficients from actual values. This graph provides a visual understanding of model accuracy from a coefficient deviation perspective. The linear and exponential models display a consistent overestimation of the cooling rate, especially at lower setpoints, indicating that their assumptions are increasingly invalid as room cooling progresses and stabilizes. The empirical model, by incorporating environmental and human variables, maintains a significantly lower deviation from the actual cooling coefficient, suggesting its contextual adaptability and physical relevance. The visual disparity among models in this figure highlights the importance of using models that are sensitive to real-world thermal influence. The graph clearly shows that linear and exponential models overestimate cooling speed by ~30 %, while the empirical model remains within -10 % to +10 % of real-world dynamics across all scenarios.

Table 2 highlights the linear relationship between the cooling coefficient and the setpoint, represented by the slope and intercept values derived through regression analysis. The actual observation yields a slope of 0.0000053 s⁻¹/ deg. C and an intercept of 0.0000985 s⁻¹. These values reflect the realistic physical cooling behaviour of the room, considering factors like heat load, air circulation, humidity rise, and thermal mass. The empirical model most accurately matches the actual slope at 0.0000053 s⁻¹/ deg. C, differing slightly in the intercept at 0.0001185 s⁻¹, indicating a small bias. The linear and exponential models, however, overestimate both the slope (0.0000063 and 0.0000064 s⁻¹/ deg. C) and the intercept (0.0001615 and 0.000164 s⁻¹), respectively. This suggests these models consistently predict faster cooling than actually occurs, particularly at lower setpoints where the temperature difference between room air and setpoint is high, but the AC efficiency may reduce due to humidity and occupant heat generation**.**

|  |  |  |
| --- | --- | --- |
| **Model Type** | **Slope** (s⁻¹/ deg. C) | **Intercept** (s⁻¹) |
| Actual Reading | 0.0000053 | 0.0000985 |
| Linear | 0.0000063 | 0.0001615 |
| Exponential | 0.0000064 | 0.000164 |
| ****Empirical**** | **0.0000053** | **0.0001185** |

Table 2: Summary of Dependence of Cooling Coefficients with the setpoint.

The deviation is further quantified in Table 3, which provides a clear statistical measure of model performance. The mean percentage difference from the actual cooling coefficients is 41.5% for the linear model and 43.7% for the exponential model. These significant overestimations highlight their limited effectiveness in capturing the complexities of real-world cooling scenarios, such as dynamic humidity changes and heat retention due to human presence. The empirical model, by contrast, shows only a 10.3% mean difference, demonstrating its much closer alignment with actual behaviour. This suggests that incorporating both humidity and human occupancy as variables provides a more faithful representation of the cooling process.

|  |  |
| --- | --- |
| Model | Mean % Difference from Actual Reading |
| Linear | 41.5% |
| Exponential | 43.7% |
| Empirical | 10.3% |

Table 3: Mean Difference of Cooling Coefficient of Each Model from Actual Reading.

**CONCLUSION**

The study demonstrates the significance influence of room cooling dynamics by human presence and environmental factors like humidity. With a single occupant, the temperature dropped steadily and followed a typical cooling pattern, reaching equilibrium efficiently. However, the addition of more occupants introduced metabolic heat and moisture, which increased the total cooling time and decreased the effective cooling coefficient. Among the three prediction models evaluated linear, exponential, and empirical the empirical model emerged as the most accurate. Quantitative metrics further reinforced the empirical model’s superiority. It recorded the lowest mean error (ME), root mean square error (RMSE), and the highest R² values across all occupancy scenarios. Additionally, cooling coefficients derived from the empirical model aligned closely with actual data, whereas both the linear and exponential models consistently overpredicted cooling rates, especially at lower setpoints. Accurate modelling of room cooling must consider real-time thermal loads introduced by people and humidity fluctuations. Empirical modelling, based on observed data, provides a more realistic and adaptable framework for temperature prediction in controlled environments.

**FUTURE SCOPE**

The practical application of this research lies in the intelligent and energy-efficient control of air conditioning systems, particularly in smart buildings and home automation. By accurately predicting the room cooling behaviour under varying human occupancy and humidity levels, the system can make informed decisions about when to switch the AC ON or OFF. For example, once the predicted temperature reaches close to the setpoint factoring in the slowing cooling rate due to human presence or increased humidity the system can anticipate equilibrium and switch OFF the compressor a few seconds earlier without compromising comfort. Similarly, if the model detects that the room is heating up more rapidly due to occupancy or external conditions, it can re-activate the AC slightly before the temperature exceeds the setpoint. This predictive and dynamic control not only reduces energy consumption but also minimizes wear and tear on the AC unit by preventing frequent ON-OFF cycling. Moreover, integrating the empirical model into smart thermostats or IoT-based building management systems enhances their accuracy and responsiveness, leading to cost savings and improved user comfort.

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