Machine Learning-Enhanced Control System for Optimized Ceiling Fan and Air Conditioner Operation for Thermal Comfort

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Abstract

This paper proposes and tests the implementation of a sustainable cooling approach that uses a machine learning model to predict operative temperatures, and an automated control sequence that prioritises ceiling fans over air conditioners. The robustness of the machine learning model (MLM) is tested by comparing its prediction with that of a straight-line model (SLM) using the metrics of Mean Bias Error (MBE) and Root Mean Squared Error (RMSE). This comparison is done across several rooms to see how each prediction method performs when the conditions are different from those of the original room where the model was trained. A control sequence has been developed where the MLM's prediction of Operative Temperature (OT) is used to adjust the adaptive thermal comfort band for increased air speed delivered by the ceiling fans to maintain acceptable OT. This control sequence is tested over a two-week period in two different buildings by comparing it with a constant air temperature setpoint (24ºC).

Analysis of the data showed that the MLM is more consistent with lower errors than the SLM across a variety of rooms. The MLM is robust enough to predict temperatures in rooms that the model was not trained in. Compared to the constant air temperature setpoint control, the OT control sequence showed improved comfort reported by 70 occupants in the study and a cooling electrical energy savings of over 90% during the test conditions.

Keywords: sustainable cooling, ceiling fans, adaptative comfort, air speed, machine learning, AI, control sequence

Introduction

Per capita annual electricity consumption for space cooling in India is only at 69 kWh compared to the global average of 272 kWh (IEA, 2018). With global warming, rising temperatures will increase India's cooling energy requirement and more people will need access to cooling. The India Cooling Action Plan calls for synergistic actions to provide sustainable space cooling that is affordable. Much of the new construction is planned for air-conditioning (AC) and the existing building stock is increasingly retrofitted with AC systems. India thus has a large stock of buildings that are operated in spatial or temporal mixed mode (Brager, G., 2006). Mixed mode buildings present a significant opportunity for energy savings while providing exceptional levels of comfort to occupants (Angelopoulos, C., Cook, M., Spentzou, E., & Shukla, Y., 2018). "Mixed mode" in space conditioning blends natural ventilation from operable windows with mechanical systems for air distribution and cooling, optimizing natural ventilation during periods of the day or year when it is feasible or desirable (Brager & Borgeson, 2007). The adaptive comfort model for mixed mode operation can be a promising approach to the cooling energy challenge. However, adaptive models use indoor operative temperature (OT), which requires the measurement of air temperature, air velocity, and globe temperature in a space. Collecting real-time and long-term data for these is difficult. On a previous work we showed a method that uses machine learning to predict operative temperature with minimum measurement equipment (De, A., Thounaojam, A., Vaidya, P., Sinha, D., & Raveendran, S. M., 2020). While that work demonstrated that the RMSE of prediction of OT was less than 0.09ºC, the testing was limited to the room that the MLM was trained on. To use this approach for developing a control sequence that can be used more widely, it is important that the MLM provides acceptable prediction of OT across a range of rooms. This paper tests the MLM in the following ways:

- The OT prediction of the MLM is compared with that of a SLM in 4 additional rooms that have different thermal characteristics.
- The OT prediction of the MLM is tested further to see if training the MLM in a specific room with different thermal condition improves its prediction.

Then, the MLM approach is used to develop a control sequence for the India Model or Adaptive Comfort (IMAC). Using the IMAC and the Corrective Power of ceiling fans, the control sequence prioritises ceiling fan operation over AC. to minimise or eliminate the use of ACs and reduce energy consumption. The control sequence is tested in two different rooms; one, in a passively designed building with an insulated envelope, and another, in a typical uninsulated building, tested for these conditions:

- Base case of 24°C (AC set-point suggested by the Bureau of Energy Efficiency, India) with no ceiling fans operating.
- Ceiling fan prioritised control sequence

The aim of this research is to provide energy efficient and comfortable cooling while maintaining thermal comfort of the occupants. We demonstrate the robustness of the MLM, and we summarise the development, implementation and testing a control sequence, which prioritizes the use of ceiling fans over ACs. We use fan and AC products available in the market.
The significant contributions of this work are to demonstrate that OT predicted in real time with ML can be used in a control sequence that automates the prioritisation of ceiling fans, and that in tropical conditions such as those prevailing in India, occupants report higher levels of comfort with ceiling-fan induced air movement and higher temperature set points. The findings of this study point to a method of space cooling that takes full advantage of the IMAC and can be an affordable and sustainable cooling approach.

Literature Review

Earlier standards of thermal comfort were formed around static thermal comfort models that were applied universally, but they relied on air conditioning to maintain thermal comfort of occupants (de Dear, & Brager, 1997). A location specific adaptive comfort model for India, which includes the building's ventilation type (naturally ventilated, AC, or mixed mode) was developed by Manu et al., to help in maintaining thermal comfort of occupants but also helps in reducing energy consumption (de Dear, et. al., 2016 and ASHRAE, 2017). It allows buildings to operate within a broader range of indoor operative temperatures.

ASHRAE Standard 55 included an elevated air speed comfort zone method, which allows us to define limits for comfort for indoor operative temperature for increased air speed in the space, when other parameters like met value and clo value are held constant. In the 2017 version of the ASHRAE Standard 55, the upper limit of airspeed was increased to 1.6 m/s. Angelopoulos et al., (2018) used a simulation approach to assess a variety of control algorithms and showed that mixed mode controls with adaptive comfort models provide flexibility of use, improved thermal comfort, and energy savings of about 40% in Indian cities.

Another study by Fanger and Toftum (2002) showed that occupants in warmer countries who have adapted to high temperatures prefer warmer temperatures, especially in naturally ventilated buildings where the outdoor temperature has significant influence on the indoor comfort parameter. Candido & de Dear (2012), also state that occupants who feel hot prefer more air movement, while Zhai et al. (2017) concluded that the provision of air movement is more important than temperature control in such warm environments.

Ceiling fans are an efficient adaptive comfort strategy to induce air movement, improve comfort, and have a corrective power index (CP) of -1K to -7K, when the air speed is as high as 1 m/s and the ambient temperature is as high as 33°C (Zhang, Arens, & Zhai, 2015). Corrective power is defined by ASHRAE 55 as the ability of a PCS to correct the thermal sensation of a person towards comfort zone. It is expressed as the difference in operative temperatures between two instances, where equal thermal sensation is achieved, one with PCS and one without PCS (ASHRAE, 2020). Raftery, Miller, & Zhang, (2020) and Raftery et. al., (2021) conducted a thermal comfort study in California showed a CP of over 4ºK in 10 buildings with air conditioners, where ceiling fans with air movement provided comfort at 26.7°C while only air conditioning provided comfort at 22.2°C. In another study conducted in the tropics, ceiling fans provided comfort up to 27°C, but if given a preference the occupants preferred to have minimal air conditioning along with the ceiling fans to attain comfort (Lipczynska, Schiavon, & Graham, 2018). A study by Bongers et al., (2022) in Australia also found that use of ceiling fans can increase the temperature limit at which the air conditioning needs to be switched on. The study reports annual energy savings up to 76%. A thermal comfort tool by the Center for Built Environment (CBE) shows that the upper limit of the comfort model shifts further upwards in response to increased airspeed in the space (Tartarini, Schiavon, Cheung, & Hoyt, 2020). In our earlier work, we used the tool to obtain the upward shift for several conditions and developed an equation to apply the effect of air speed on the IMAC band (De et. al., 2020).

Methodology

Developing the Machine Learning Model (MLM)

As described in De 2022, for a 400 m2 building in Bangalore, with a naturally ventilated room that houses workstations, a calibrated thermal model was developed. The model was then used to develop 10 scenarios consisting of different building characteristics and building operations. The simulations of these 10 scenarios provided 87,600 data points for hourly results consisting on outdoor conditions, indoor air temperature, indoor humidity, and indoor OT. Using a train-test ratio of 0.75-0.25 (75% data used for training and 25% data used for testing), a random forest algorithm was trained to give a machine learning model (MLM) that predicted OT based on a combination of indoor air temperature and outdoor conditions that could be measured by a weather station.

Testing the robustness of the MLM

While this MLM predicted OT with errors (RMSE and MBE) in an acceptable range for the workstation room (Room 1), we needed to test the robustness of the MLM to predict OT for other rooms with different thermal characteristics. If the MLM predicted the OT for other rooms with errors in acceptable ranges, the model would be considered robust. The ASHRAE method for low airspeed uses a simple average of the indoor air temperature (Ta) and the mean radiant temperature (MRT) to calculate OT, which is essentially a linear relationship between Ta and OT (ASHRAE, 2017). Using the data for Room1, we developed a straight line model (SLM) for Room1 where a linear equation predicted the OT based on the Ta. Prediction errors were compared between the SLM and the MLM across 4 additional rooms (Rooms 2, 3, 4 and 5). See Table 1 for a summary of the differences between Rooms 1, 2, 3, 4 and 5. All rooms are located in Bangalore.

Table 1: Summary of differences in rooms used for testing

Item/Room	**Room 1**	**Room 2**	**Room 3**	**Room 4**	**Room 5**
MLM Training	Trained in this room	Non trained in this room	Non trained in this room	Non trained in this room	Non Trained in this room
Room Function	Offices	Offices	Offices	Conference	Conference
Room Area (m^2)	35	30	18	17	58
Building Type	Office, passive design	Office, business-as-usual design	Office, business-as-usual design	Office, business-as-usual design	Office, passive design
Floor	Ground Floor	First Floor	Second Floor	Third Floor	Ground Floor
Wall construction and U value (W/m^2K)	Rammed earth wall with 50 mm insulation and stone cladding 0.54	Uninsulated brick wall with plaster 2.4	Uninsulated brick wall with plaster 2.4	Uninsulated brick wall with plaster 2.4	AAC and CSEB wall with insulation and china mosaic 0.35
Windows facing	West	South	North and East	North	North-east and North-west
WWR (%)	27	53	41	18	40

Exterior shading	Overhangs	Trees only	None	Overhangs	Overhangs
Window U value (W/m²K)	2.68	4.4	4.4	4.4	2.68
Internal loads (W/m²)	35	9.2	5.8	12.5	107

Figure 1: Images of Rooms 1, 2, 3, 4, and 5 (bottom) clockwise from top left.

Developing and testing of the control sequence for ceiling fan prioritisation

Two conference room spaces in Bangalore were selected for the study. One was in a passively designed, insulated office building, and the other was in a business-as-usual, uninsulated office building. Both rooms had split AC units and were operated in mixed mode. Brushless direct current (BLDC) smart fans were installed in both rooms. Indoor environmental quality (IEQ) boxes were installed in both rooms to collect air temperature and relative humidity data. Outdoor weather parameters are collected with a weather station on the buildings. Energy meters were installed to collect energy consumption data for the AC and the ceiling fans. Infrared (IR) blasters were installed to control the ceiling fans and the AC units. See figure 2.

Figure 2. Images of the hardware installed in each room (a) BLDC ceiling fan, (b) IEQ box, (c)IR blaster, (d) energy meters

The control sequence uses the IMAC for determining the thermal comfort band. Based on the National Building Code 2016, Volume 2, the 90% acceptability range for mixed-mode buildings band is calculated as

IMAC_upper = ((0.28 x outdoor temperature) + 17.87) + 3.46   (eq. 1)

IMAC_lower = ((0.28 x outdoor temperature) + 17.87) - 3.46   (eq. 2)

Where IMAC_upper, and IMAC_lower are the upper and lower limits respectively, of the thermal comfort band. *The IMAC_upper is used as the threshold for determining comfort.*

The OT prediction ML model runs every minute using the data from the IEQ box and the weather station. The predicted OT is compared with the upper limit of the thermal comfort band. To determine the upward shift of the upper limit of the band when air speed is introduced as a variable in the space, we use the equation determined by De et al., (2022)

$$y = -1.39x^2 + 4.92x - 1.38 \qquad \text{(eq. 3)}$$

Where y is the shift in the upper limit of the band (OT) and x is the air velocity.

Average of the air speeds measured where the users are seated in the space is noted as the spatial average air speed of the space. The air speed at each user's location is also measured at the heights of 0.6 m and 1.1 m from the floor level (Gao et. al., 2017). This gave us pre-calculated the airspeeds achieved for each fan speed setting in the room. The shift of the extended upper limit (extended_IMAC_upper) of the comfort band is calculated using the airspeed achieved at each setting and equation 3 (also see figure 3).

- If the predicted OT is lower than IMAC_upper, the control sequence keeps the ceiling fan and AC off.
- If the predicted OT is higher than IMAC_upper, but lower than the extended_IMAC_upper, the control sequence turns on the ceiling fan to the appropriate airspeed but keeps the

AC off.

- If the predicted OT is higher than the extended_IMAC_upper for the highest fan speed setting, the fan is switched on at the highest speed to use its full potential and the AC is switched on with the highest set-point possible. This setpoint is calculated in the following steps:

  1. By using the OT formula from ISO 7726-1998, MRT in the space was calculated by using the predicted OT value.

$$T_{mrt} = \left[\frac{(T_g+273.15)^4+1.1\times10^8\times V_a^{0.6}}{e\times D^{0.4}(T_g-T_a)}\right]^{0.25} - 273.15 \qquad \text{(eq. 4)}$$

$[Where\ T_{mrt} = mean\ radiant\ temperature,\ T_g = globe\ temperature,\ \ V_a = air\ velocity, D = diameter\ of\ the\ black\ ball\ (0.04m\ for\ ping\ pong - ball), T_a = air\ temperature,\ \ e = emissivity\ (0.95\ for\ black - globe)]$

$$T_o = \frac{T_a(\sqrt{10V_a})+T_{mrt}}{(1+\sqrt{10V_a})} \qquad \text{(eq. 5)}$$

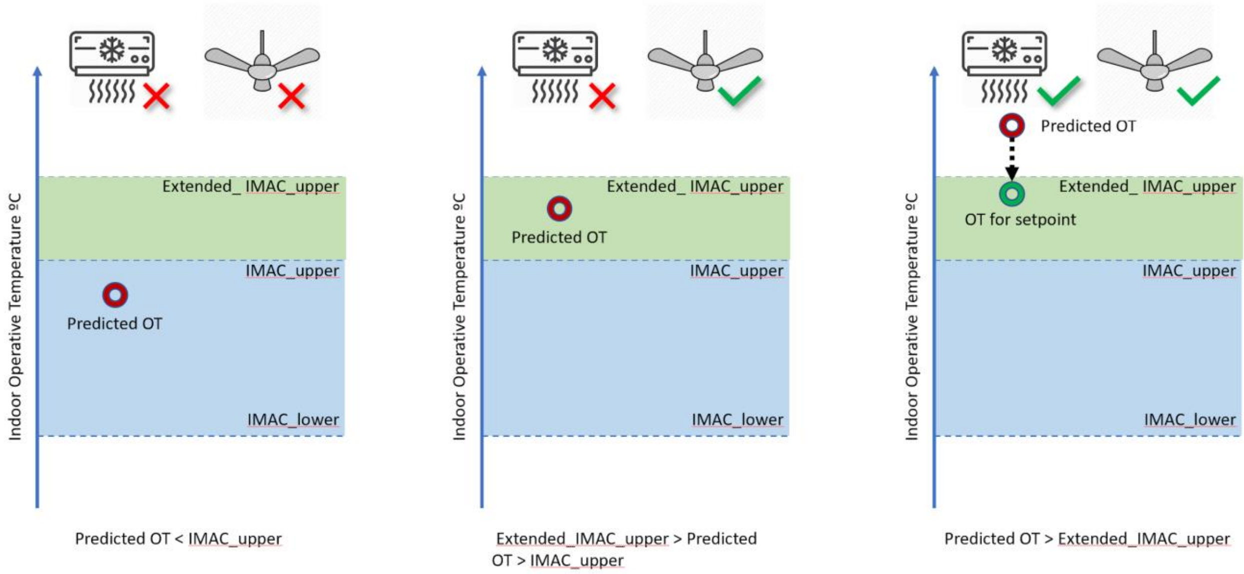
$[Where\ T_o = operative\ temperature, T_{mrt} = mean\ radiant\ temperature,\ T_g = globe\ temperature,\ \ V_a = air\ velocity,, T_a = air\ temperature\ ]$

  2. Then the air temperature in the space is calculated using the same formula since MRT and the desired OT values are known.

$$T_a = \frac{T_o(1+\sqrt{10V_a})-T_{mrt}}{(\sqrt{10V_a})} \qquad \text{(eq. 6)}$$

  3. The calculated air temperature is sent as set-point temperature to the AC.

Figure 3: Three scenarios for the control sequence



For the thermal comfort study and energy testing, a total of 70 respondents participated in the study. Data was collected about age, gender, height, and weight, history of their space cooling adaptations and preferences, recent physical activity and documentation of the clothing that they were wearing.

The respondents were exposed to 3 different conditions for 30 minutes each, with 5 minute break outside the test room between the 3 conditions. The conditions were: condition 1 - room maintained at a constant 24°C setpoint without ceiling fans; condition 2 - room maintained at IMAC band neutral temperature without ceiling fans, and; condition 3 - room comfort maintained using the proposed control sequence. The study was carried out between 14th March, and 28th of March. Energy used by the air conditioners and ceiling fans was recorded by the meters.

Figure 4: Thermal comfort study in progress

Results

Developing the Machine Learning Model (MLM)

The testing of the Machine Learning algorithm to predict OT for a seven-day period with hourly data resulted in an RMSE = 4% and MBE = 3%. The accuracy was found to be 96.77 %.

Testing the robustness of the MLM

The SLM based on the data of Room 1 yielded the following results with its equation (see figure 5). The correlation is

OT = 1.28 (AT) – 5.1 (eq 7)

Where OT is calculated operative temperaure using the measured data and AT is the mesaured Air temperature.

Figure 5: Straight Line Method correlation between OT and AT for room 1

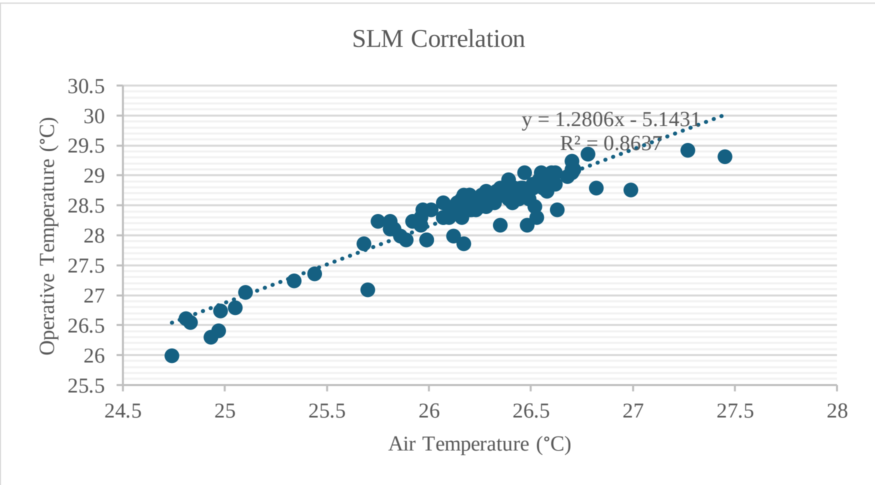
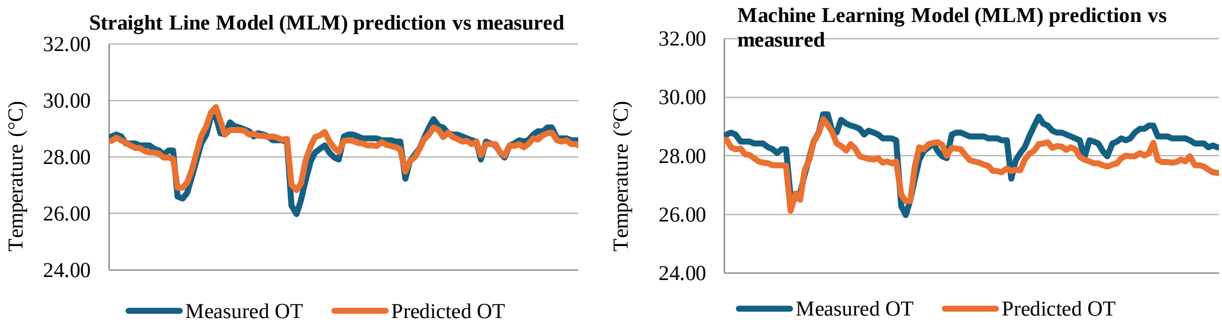


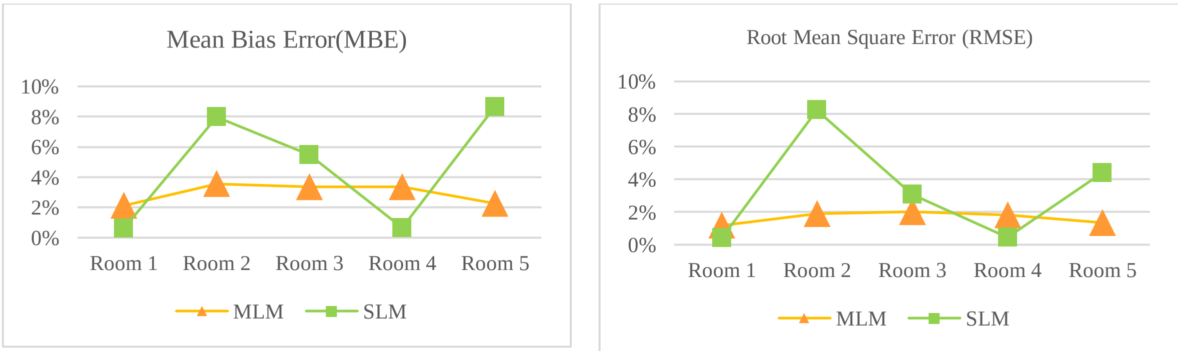
Figure 6 shows the comparison of the SLM with the MLM for Room 1, where both models were trained. For this room, the SLM has lower error than the MLM with an RMSE = 1% and MBE = 1%.

Figure 6: Predicted OT, comparison between SLM and MLM for room 1



When comparing the errors for the SLM and MLM across rooms 1, 2, 3, 4, and 5 (see Figure 7), it is evident that the MLM trained on Room 1 consistently yields lower errors than the SLM trained on Room 1. Both the Mean Bias Error (MBE) and Root Mean Square Error (RMSE) of SLM increase significantly for rooms 2, 3, and 5, with the exception of Room 4.
The SLM for Room 4 exhibits lower errors because the air temperature (AT) and operative temperature (OT) in this room follow a trendline similar to that of Room 1. This similarity results in a high correlation between the regression equations of Room 1 and Room 4. However, this scenario is unique and may not always be replicable. In the case of MLM, the MBE and RMSE across the rooms have average of 1% difference between each other.

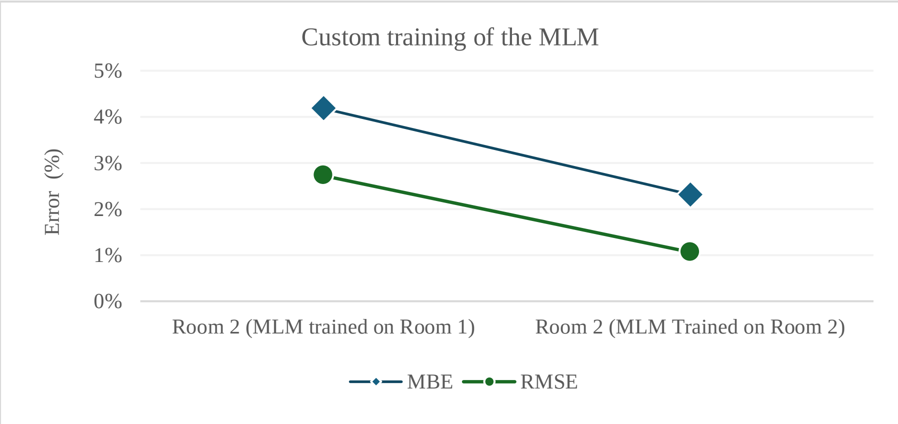
Figure 7: MBE and RMSE comparison between SLM and MLM for different rooms



Given that the MLM demonstrates greater robustness in predicting OT in rooms it was not specifically trained on, it is important to evaluate the potential improvement in MLM predictions when it is custom-trained for a specific room. This analysis will provide insights into the enhanced accuracy and reliability that can be achieved through room-specific training of the MLM.

Figure 8, shows that the RMSE improves from 3% (non-custom trained) to 1% (custom trained), while the MBE improves from 4% (non-custom trained) to 2% (custom trained), a reduction by 2 percentage points on each error metric.

Figure 8: Impact of training the MLM on individual room (custom training)

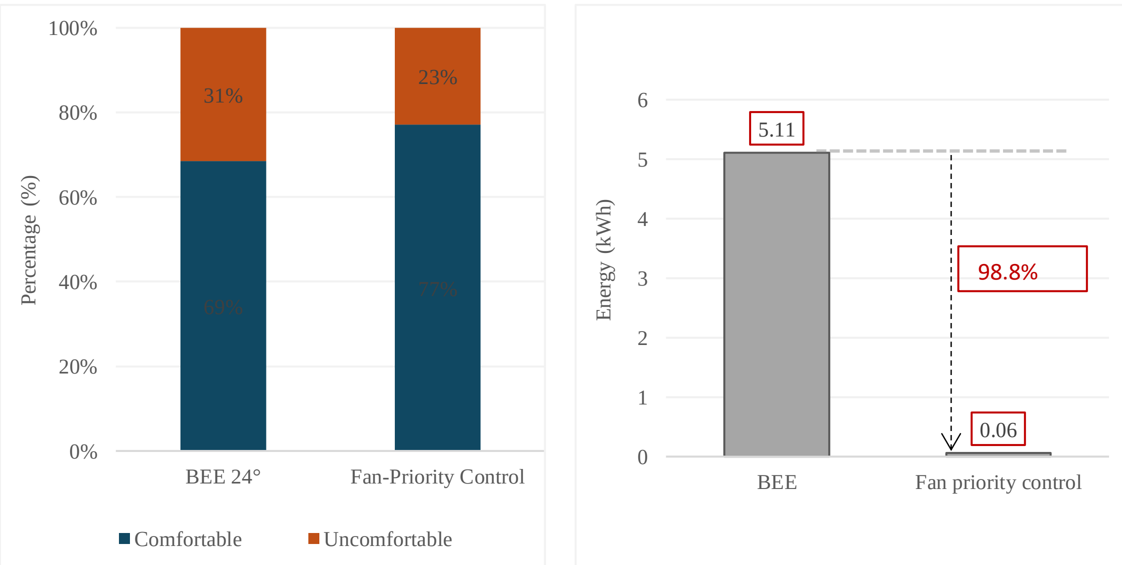


Developing and testing of the control sequence for ceiling fan prioritisation

About 60% of the respondents were in the age group of 20 to 39 years and the gender ratio was almost equal. Most of the respondents were involved in sedentary activities before their sessions in the study. 98% of the respondents answered that they use ceiling fans for space conditioning in their residence, followed by operable windows and usage of curtains/blinds. But in their workplaces ceiling fans were used by 68% of the participants, operable windows and air conditioners were used by about 49% of the participants. As a method for space conditioning, ceiling fans were preferred by 49%, operable windows by 35%, and ACs preferred by only 15% of the respondents.

During the two-week testing of the control sequence, the outdoor dry bulb temperature was in the range of 29 °C to 35°C. During the study period, the IMAC neutral temperature setpoint was calculated at 24°C. This resulted in identical setpoints for condition 1 and condition 2, and the results for thermal comfort and energy for those conditions are very similar. Therefore, the thermal comfort and energy analyses results below only show condition 1 and condition 3.

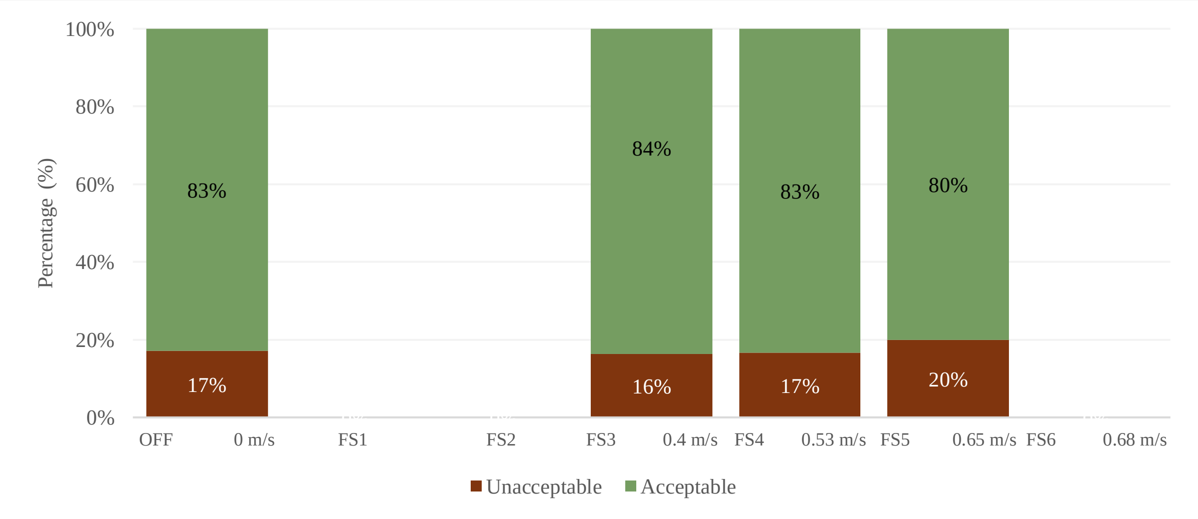
Figure 9: Results of thermal comfort left (left) and energy measurements (right) during the testing of the control sequence



About 77% of the respondents reported being comfortable in condition 3, i.e. fan prioritized control sequence condition compared to about 69% in the other condition of the study (see figure 9, left hand graph).

The respondents were also asked whether the airspeeds they experienced were acceptable to them. When the ceiling fan was off, 83% found this unacceptable. Since the fans did not come on at settings of 1, 2 and 6 (FS1,FS 2, FS6) during the study, the data on these are not available. The airspeed of 0.4 m/s was acceptable to 89% of the respondents. The acceptability decreases when the air speed is 0.53 m/s and 0.65 m/s (see figure 10).

Figure 10: Results of fan-speed setting preference survey during the testing of the control sequence



Electrical Energy consumption for each scenario was determined by calculating the difference in electrical energy meter readings at the beginning and end of the respective scenario. It is observed that under the BEE 24°C baseline, a total of 5.11 kWh was consumed across all sessions, whereas the fan prioritized control sequence showed a consumption of 0.06 kWh, resulting in 98.8% reduction in cooling energy usage (refer to figure 9, right-hand graph). It is important to note that the outdoor dry bulb temperature ranged between 29°C and 34°C during the study. According to the thermal comfort survey that was done (refer to Figure 10), there was a decrease of 1% in unacceptable preference when transitioning from fan mode OFF to Fan mode ON at Fan-speed setting 3 (FS3), and an increase of 4% from Fan-speed setting 3 (FS3) to Fan-speed setting 5 (FS5). Due to this small incremental difference in unacceptable fan-speed setting preference, it is inconclusive to determine whether increasing fan-speed settings makes people more uncomfortable.

In the room in the business-as-usual (BAU) building, cooling energy savings were at 98.6%, while in the passively designed building, savings were 100%. The 100% savings in the passive building can be attributed to the fact that due to the passive features, the indoor temperature generally remained within the comfort range. In the rare instances when it exceeded this range, it never went above the extended_IMAC_upper. As a result, the ceiling fan was activated only on a few occasions, and the AC unit remained unused in this building. The low energy consumption of the BLDC fans was not recorded in the passive building because of the least count display of the energy meters.

In the BAU building, although the outdoor temperature often exceeded the IMAC_upper, it generally remained below the extended_IMAC_upper. This led to frequent activation of the ceiling fans. Throughout the study in the BAU building, the air conditioner was turned on for a total of only 5 minutes during condition 3. During that event the AC setpoint was 30ºC. Consequently, the energy savings during this 5-minute interval, compared to the BEE 24ºC condition, reached 82%. This demonstrates the significant potential for energy savings with a ceiling fan prioritized control sequence. It is important that this approach is further tested under conditions with higher outdoor temperatures, where the AC is likely to be used more frequently.

Conclusion

This paper demonstrates the use of a machine learning model (MLM) for predicting operative temperature as a scalable approach to providing comfort based on the adaptive model of the National Building Code of India. The analysis has shown that the MLM is robust enough to predict temperatures in rooms that the model was not trained in. The MLM does this consistently with low errors compared to a straight line (correlation) model (SLM) across a range of rooms varying in thermal characteristics. While custom training on the MLM for a specific room reduced the RMSE and MBE by 2%, a custom training approach is not scalable.

In this study, a control sequence was developed that employs the corrective power of ceiling fans to adjust the upper threshold of the adaptive thermal comfort band, taking into consideration the airspeed of the fan to raise the AC temperature set-point within the room. The control sequence places a priority on utilizing ceiling fans and was tested in two conference rooms in 2 different buildings. The results of the testing reveal that 77% of the respondents reported feeling comfortable in the space when the fan-prioritized control sequence was employed, as opposed to only 69% for the constant setpoint of 24ºC. Additionally, the fan-prioritized control sequence achieved 98.8% reduction in cooling energy consumption during the study period, even in the face of outdoor temperatures ranging from 29ºC to 34ºC.

These substantial cooling energy savings, coupled with the observation that ceiling fans were sufficient to provide comfort without the use of air conditioners on multiple occasions throughout the study, underscore the potential of ceiling fan-prioritized controls, or even just ceiling fans for cooling, as a pathway to affordable and sustainable cooling.

The key contributions of this study are:

- While existing controls are mostly based on air temperature because OT is difficult to measure in real time, this work uses a novel method to predict OT in a space and uses ceiling fans as an affordable cooling solution, resulting in significant cooling energy savings.
- While most studies performed on ceiling fans focus on giving control to occupants, this work automates the fan and AC controls with increased air speeds to make this approach appropriate for office and institutional buildings.

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