FARU FACULTY OF ARCHITECTURE RESEARCH UNIT
UNIVERSITY OF MORATUWA, SRI LANKA

FARU Journal
www.faru.uom.lk

Independence and Interdependence of
Sustainable Spaces

IMPLEMENTING AT-SCALE ADAPTIVE THERMAL COMFORT CONTROLS FOR MIXED MODE BUILDING USING MACHINE LEARNING

DE. A[1*], THOUNAOJAM. A[2], VAIDYA. P[3], SINHA. D[4], RAVEENDRAN. M.S[5], GOPIKRISHNA[6] & UTHEJ. D[7]
[1] School of Planning and Architecture, New Delhi, India
[1,2,3,4,5,6,7]Indian Institute for Human Settlements, Bengaluru, India
[1]aritro3159arch18@spa.ac.in, [2]amandat@iihs.ac.in, [3]pvaidya@iihs.ac.in, [4]dsinha@iihs.ac.in,
[5]soorajmr@iihs.ac.in, [6]gopikrishna@iihs.ac.in, [7]uthejd@iihs.ac.in

Abstract: With climate change, low carbon space-cooling approaches are becoming more important. 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, 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. We used machine learning to predict operative temperature with minimum measurement equipment, for controls to optimise fan operation and minimise AC energy use. Field measurements and Energy Plus simulation were used to create large datasets, 75 % of which were used to train the machine learning algorithm to predict operating temperature, and the remaining 25% were used for testing the algorithm. The random forest model in R from the tidymodels library using the ranger engine proved successful. The Operative Temperature prediction Root Means Square Error value is **0.090°C**. The algorithm classified data for being in/out of the comfort band, and **0.88%** of the values are misclassified. While this paper demonstrates the machine learning approach that makes this possible, future work will demonstrate the implementation of the control algorithm and its testing.

Keywords: *Adaptive Thermal Comfort; Machine Learning; Mixed mode; low energy cooling; fan operation.*

1. Introduction

According to the IEA (2021) report, the demand for global space cooling is growing. In the building sector, 16% of the final electricity use is for space cooling in 2020. India is amongst the countries with the lowest access to cooling, with per capita energy consumption levels for space cooling at 69 kilowatt-hours (kWh), compared to the world average of 272 kWh (IEA, 2021). Hence, there is a need to transform space cooling approaches in buildings. Cooling energy demand can be reduced through new interventions, low energy systems, and optimised operation. This paper reports on how adaptive comfort controls can be implemented to maximise ceiling or wall-mounted fan operation and also minimise air conditioning energy use.

The National Building Code of India has the Indian Model for Adaptive Comfort (IMAC). We intend to implement thermal comfort controls on the basis of the IMAC, where a thermal comfort band of indoor operative temperatures is a function of the 30-day running mean of historical outdoor temperature values. The 'IMAC' model was developed from the data collected over four survey campaigns in office buildings conducted over a period of one year. (Manu, et.al, 2016).

IMAC model uses operative temperature (OT) as the comfort metric and is dependent on the outdoor dry bulb temperature. OT is not commonly used as a parameter for controls as it is difficult to calculate at a space level. This is due to the requirements of measuring globe temperature, mean radiant temperature, and air velocity to calculate OT. These parameters are difficult to measure at a real-time and long-term level as the process of measurement is sophisticated due to the nature of the equipment used. Therefore, the prediction of operative temperature in this study has been proposed using machine learning (ML). For training the model of machine learning, physical measurements and simulated results from a calibrated EnergyPLus thermal model were used to get nine annual datasets.

Previous work on thermal comfort and machine learning included the ensemble-based machine-learning method to predict the Thermal Sensation, Predicted Mean Vote, the Predicted Percentage of Dissatisfied, and the Standard

*Corresponding author: Tel: +91 8660820131 Email Address: aritro3159arch18@spa.ac.in
FARU Journal: Volume 09 Issue 02 DOI: http://doi.org/10.4038/faruj.v9i2.172

Effective Temperature. Indoor and outdoor environment conditions were used in this study for ML (Wu et al., 2018). An Artificial Neural Network (ANN) and ensemble based-model to predict the thermal comfort in an indoor environment by the thermal sensation and behaviour of the occupant were proposed by Deng and Cheng (2018). Kim et al. (2018) also conducted another study on a model of machine learning based on personal comfort. A study on effects of vegetation on outdoor thermal comfort had shown that vegetation had little or no impact on comfort in daytime and adverse effects at night (Weerakoon, L.R.T. and Perera, N.G.R., 2021). Sandagomika et al. (2020) studied on drivers and barriers for using IoT for successful lean implementation in Sri Lankan construction industry and the results highlighted increased product and process quality; reduced unnecessary delays in the construction process; reduced unnecessary costs; enhanced inventory management system. These studies used different models to define comfort on personal level, ensemble based, although the aspect of measuring operative temperature is not touched upon.

Our ML model uses an indoor air temperature and humidity sensor in the room, and a weather station installed on the building to get indoor and outdoor data. We use adjustments to ceiling and wall-mounted fans to adjust the operative temperature as well as the upper limits of the comfort band. Using this information, our learning model will maximize the natural ventilation and fan operation in the space and minimise the energy used for air conditioning. The special contribution of this work is to demonstrate how operative temperature-based controls can be implemented with a feasible sensor regime, in a way that makes the approach scalable for use in most buildings. This is intended to be used for mixed-mode thermal comfort standards, with control algorithms that maximise fan operation and minimise cooling energy. While this paper demonstrates the machine learning approach that makes this possible, future work will demonstrate the implementation of the control algorithm and its testing.

2. Method

This section delineates the method of collecting datasets for developing training datasets for machine learning to predict operative temperature, adjustments to the thermal comfort band based on airspeed, the machine learning algorithm, and testing of the approach for prediction errors.

We are implementing adaptive thermal comfort controls in an Experimental Building at an educational campus in Bangalore, India (See Figure 1). It is a 400 sqm office building and is built as a prototype to test several technologies and operational practices that can then be applied to the rest of the 55-acre campus.

Figure 1: Experimental Building

Hourly data of physical measurements for one entire month were collected and used to calibrate an Energy Plus thermal model of the building. The calibrated model was used to generate several datasets that included the operative temperature and the mean radiant temperature. Then hourly physical measurement data for one week was collected in the building to also measure globe temperature and airspeed to validate the operative temperature of the simulation. This gave us confidence in using the Energy Plus simulated datasets for machine learning to predict operative temperatures.

2.1 DATA COLLECTION FOR CALIBRATING A THERMAL MODEL

To develop a calibrated Energy Plus thermal model, as-built drawings of the building were used, this included information on wall assembly, roofs, and windows. A detailed energy audit of the building provided internal loads for lighting, equipment, and people. Weather data (Actual Meteorological Year) was retrieved from the weather station on top of the building. Indoor environmental parameters like indoor air temperature, wall surface temperature, CO_2, and humidity, were monitored in each room through an Internet of Things (IoT) system in the building.

2.2 CALIBRATED ENERGY PLUS THERMAL MODEL

This involved the making of the building 3-D geometry, physical and operational characteristics of the building, and simulating the model in Energy Plus (see figure 2). The hourly indoor temperature and surface temperature outputs of the model were compared with the measured data to calculate the Mean Bias Error (MBE) and Root Mean Squared Error (RMSE). Iterative corrections were done to the model to bring the MBE and RMSE below the ASHRAE Guideline 14 thresholds.

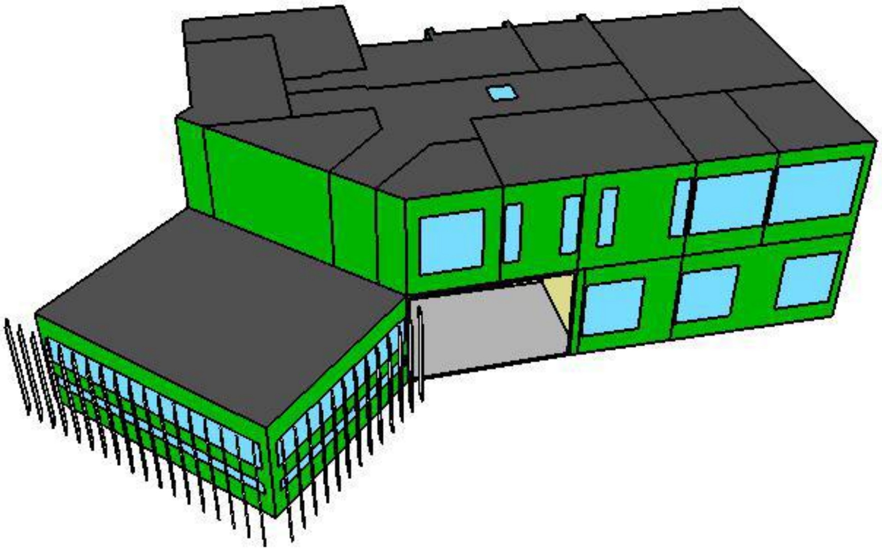

Figure 2: Calibrated energy plus thermal model

2.3 DATA COLLECTION FOR VALIDATING SIMULATED OPERATIVE TEMPERATURE OUTPUTS

After the development of the calibrated model, physical data were collected for a week to calculate operative temperature and validate with the calibrated model. Three parameters such as air temperature, air velocity, and glove temperature were measured. Hourly data was collected from 11:00 hours till 17:00 hours. With the above measurements, mean radiant temperature and operative temperature were calculated. The mean radiant temperature is calculated using the following formula.

$$T_{mrt} = \left[\frac{(Tg+273)^4 + 1.1*10^8 * Va^{0.6}}{e*D^{0.4}(Tg-Ta)}\right]^{0.25} - 273 \qquad (1)$$

[Where T_{mrt}=mean radiant temperature, T_G=globe temperature, V_a= air velocity, D=diameter of the black ball, T_a=air temperature, e=emissivity (0.95 for black globe)]

Here, the mean radiant temperature is a calculated value (equation 1) while the globe temperature, air temperature, and the air velocity are measured value.

The operative temperature was calculated using the formula obtained from ISO 7726-1998:

$$T_o = \frac{Ta(\sqrt{10Va}) + Tmrt}{(1+\sqrt{10Va})} \qquad (2)$$

[Where T_O=Operative temperature, T_a= Air temperature, V_a= Air Velocity, T_{mrt}= Mean radiant temperature]

Here, the mean radiant temperature is the calculated value (equation 1) while the air temperature and the air velocity are measured value.

Apart from the collection of airspeed at room level, the air speed of the wall-mounted fans was also collected on different fan speed operations at two different distances of 2.5 meters and 3 meters from the fan. This was used to calculate the operative temperature at different speeds and distances elaborated in section 2.5.

2.4 VALIDATION OF THE CALIBRATED MODEL

The calibrated model was simulated for the same week as section 2.3. The calculated operative temperatures were compared with the simulated operative temperature results. MBE and RMSE were calculated for these datasets.

2.5 SIMULATED DATASETS TO BE USED FOR MACHINE LEARNING

To obtain more datasets for training the machine learning algorithm, different scenarios were simulated with the calibrated model in Energy Plus for a southwest-facing workstation room. The fan speeds were obtained from the data collection as in section 2.3. The different scenarios are

1. ***Windows closed-*** The calibrated model was simulated with windows closed.
2. ***Occupancy-*** The calibrated model was simulated by changing the density from 0.29 person/m2 to 0.5 person/m2
3. ***Equipment load-*** The equipment load of the workstation room in the calibrated model is 29.9W/m^2. For this scenario, the equipment load was increased to 50.1W/m^2 by increasing the number of plug loads.
4. ***Natural Ventilation with fan speed 1-*** For this scenario, the model was simulated with natural ventilation mode, and further calculated with fan speed 1 at 3 meters.

5. ***With fan speed 2-*** For this scenario, the model was simulated with natural ventilation mode, and calculated with fan speed 2 at 3 meters.
6. ***With fan speed 3-*** The model was simulated with natural ventilation mode and calculated with fan speed 3 at 3 meters.
7. ***With fan speed 1 at 2.5 meters-*** The model was simulated with natural ventilation mode, calculated with fan speed 1 at 2.5 meters from the fan.
8. ***With fan speed 2 at 2.5 meters-*** The model was simulated with natural ventilation mode, calculated with fan speed 2 at 2.5 meters.
9. ***With fan speed 3 at 2.5 meters-*** The model was simulated with natural ventilation mode, calculated with fan speed 3 at 2.5 meters.

These scenarios were used to create more datasets for the machine learning algorithm's training.

2.6 ADJUSTMENTS TO THE THERMAL COMFORT BAND FOR THE IMPACT OF AIRSPEED

Post simulation and calculation with the airspeeds mention in scenarios 4 to 9 in section 2.5, the obtained operative temperature. It was observed that the variation in the operative temperatures in these scenarios was very minimal and the change in airspeed did not make any significant change in operative temperature.

A thermal comfort tool by the Center for Built Environment (Tartarini, et.al, 2020), shows an upward shift in the upper limit of the comfort model when airspeed is increased in the space. With further discussions with CBE researchers and the information of equations being in unpublished works. Therefore, the tool was used to obtain the upper shift for several conditions, and an equation (equation 5) was built to apply the effect of air speed on the IMAC band.

2.7 TRAINING THE MACHINE LEARNING ALGORITHM

The algorithm aims to use a set of parameters that are measured and the weather station to predict the Operative Temperature as closely as possible. The actual data used for training the model came from the Energy Plus simulation outputs. The final set of explanatory variables used was arrived at after an iterative process. Indoor operative temperature in a room can be reliably predicted using easily measured variables Indoor Air Speed, Indoor Air Temperature, Outdoor Dry-Bulb Temperature, Outdoor Wind Speed, and Outdoor Relative Humidity. With these parameters, there were systemic issues such as under prediction of operative temperature in the summer months, and to combat these, the month of the year, and the hour of the day were added to the parameter list. As the air speed is not directly available, we try to create the model without using the airspeed as a measured parameter. Instead we will assume the air speed to be 0 when the fan is off, and have a lookup table for when the fan is on, with the air speed depending on the fan setting. The values for the lookup table are the mean values across scenarios 2 to 7. Initially, a linear regression model was tried before arriving at the better-performing random forest model. We used the random forest model in R from the tidymodels library using the ranger engine.

The data used is from the 3 scenarios (Scenario 1, Scenario 2, and Scenario 3) of Energy Plus simulated data. Scenario 1 was further augmented by replacing the indoor air speed with the airspeed generated by the fan and recalculating the operative temperature for those conditions. As this was done at two separate distances from the fan and three different air speeds, there was a total of six additional years (Scenarios 2 to 7) worth of data available for a total of nine years, or 78,840 hours of data. We used a train-test split ratio of 0.75-0.25 for the above-simulated scenarios.

2.8 TESTING THE MACHINE LEARNING ALGORITHM

The first metric looked at is the RMSE of the predicted values. The second evaluation metric is the classification of whether the operative temperature is within, or outside the comfort band of IMAC.

3. Results and Discussion

This section presents the results from the physical data collection, calibration model, validation of operative temperature, different scenario outputs, the selection of different ML models, the error percentages of the models.

3.1 DATA COLLECTION FOR CALIBRATING A THERMAL MODEL

For the collected data, it was observed that the average outdoor temperature was 23.93 °C, with a maximum temperature of 31.2 °C and a minimum of 19.5 °C. Similarly, the average outdoor wind speed was 5.94 m/s with a minimum and maximum of 0 m/s and 17.7 m/s respectively. For the indoor conditions, it was observed that the average indoor temperature was 29.57 °C with minimum and maximum temperatures being 26.2 °C and 31.9 °C respectively. The average surface temperatures of indoor walls were found to be 27 °C with minimum and maximum being 24.6 °C and 28.8 °C.

3.2 CALIBRATED ENERGY PLUS THERMAL MODEL

The results from the calibrated model were analysed to look at the Mean Bias Error (MBE) and Root Mean Squared Error (RMSE). According to ASHRAE Guideline 14, it considers a building model is calibrated if hourly MBE values fall within 10% and hourly CV (RSME) values fall below 30%. The errors were analysed for both indoor air temperature and surface temperature between the measured and the simulated results. After several iterations in the calibrated model, the Mean Bias Error (MBE) and Root Mean Squared Error (RMSE) were at 1% and 17% respectively through the calibration process which is within the prescribed threshold.

3.3 DATA COLLECTION FOR VALIDATING SIMULATED OPERATIVE TEMPERATURE OUTPUTS

The collection of weeklong data for the calculation of operative temperature showed that the average indoor air temperature was 30.3 °C, with a minimum of 28.6 °C and a maximum of 31.4 °C. The globe temperature showed an average of 30.4 °C with a minimum and maximum of 29 °C and 32 °C respectively. The measured air velocities showed an average of 0.2 m/s with minimum and maximum air velocities of 0 m/s and 0.8 m/s respectively.

As explained in section 2.3, the different fan speeds that were obtained at the 3 meters were 0.87m/s, 1.27m/s, and 1.47m/s at fan settings of 1, 2, and 3 respectively. Similarly, the speed obtained at 2.5 meters were 1.17m/s, 1.4m/s, and 1.57m/s at fan settings of 1, 2, and 3 respectively. These speeds and the other measured parameters (air temperature, globe temperature) were used to calculate the operative temperature as in section 2.3.

3.4 VALIDATION OF THE CALIBRATED MODEL

After the collection of weeklong measured data, the air temperature, globe temperature, and air velocity, these were used to calculate the operative temperature. The calibrated model was also simulated using the same weather data of this week. The calculated operative temperature was then compared with the calibrated model output. The CV (RMSE) value for operative temperature between the simulated and calculated value was 10%. The MBE for the same was 3%. These values were less than the prescribed value of 15% RMSE and 5% MBE as per the ASHRAE Guideline 14 thresholds.

3.5 SIMULATED DATASETS TO BE USED FOR MACHINE LEARNING

As discussed in section 2.4, 9 scenarios were identified and the model was simulated for these scenarios (see table 1). It is observed from the table that, in three of the nine scenarios, the percentage of comfortable hours is more than 90%, and the remaining 6 scenarios show 89% comfort. Hence, it shows that in all the scenarios most of the people are comfortable at all times.

Table 1: Different scenarios for training and total comfort hours

Sl. No.	**Scenario**	**Operative temperature range**	**Number of hours inside the comfort band of 8760 hours in a year**
1	Windows closed	22.6°C - 30.2°C	8171 (93.3%)
2	Naturally ventilated with Fan speed 1 (0.87m/s)	22.7°C - 31.1°C	7876 (89.9%)
3	Naturally ventilated with Fan speed 2 (1.27m/s)	22.7°C - 31.1°C	7853 (89.6%)
4	Naturally ventilated with Fan speed 3 (1.47m/s)	22.8°C - 31.1°C	7845 (89.6%)
5	Naturally ventilated with Fan speed 1 (1.17m/s) at 2.5m	22.7°C - 31.1°C	7859 (89.7%)
6	Naturally ventilated with Fan speed 2 (1.4m/s) at 2.5m	22.7°C - 31.1°C	7847 (89.6%)
7	Naturally ventilated with Fan speed 3 (1.57m/s) at 2.5m	22.7°C - 31.1°C	7841 (89.5%)
8	Naturally ventilated- changed Equipment power density	21.8°C - 30.9°C	8085 (92%)
9	Naturally ventilated- changed Occupancy	22.6°C - 30.4°C	8080 (92%)

3.6 ADJUSTMENTS TO THE THERMAL COMFORT BAND FOR THE IMPACT OF AIRSPEED

From the comparisons of operative temperature for the scenarios 5 to 9, it was observed that the average differences between the operative temperatures were 0.0185 °C, 0.006 °C, 0.25 °C for 0.87m/s, 1.27m/s and 1.47m/s. These values of difference were significantly low, hence, the thermal comfort tool was used to understand the impact of airspeed as mentioned in section 2.6.

To identify the upward shift in the temperature of the comfort band, an increase in temperature shift was recorded with an increase in airspeed as shown in table 2 and figure 3. When the shift in the upper band against the increase in air velocity was plotted it gave a quadratic equation (5) where x is the air velocity and y is the resultant shift in temperature. The equation is below:

$$y = -1.39x^2 + 4.92x - 1.38 \qquad (5)$$

Table 2: Airspeeds and the change in temperature of the band

Air speeds (m/s)	Change in temp (°C)
0.3	0
0.6	1
0.9	2
1.2	2.5

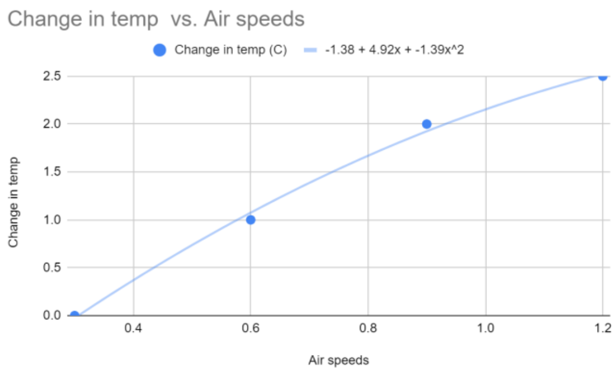

Figure 3: Airspeeds and the change in temperature of the band

This effect of the upward shift in the band was incorporated in the existing IMAC NV and MM bands using the equation.

3.7 TRAINING AND TESTING THE MACHINE LEARNING ALGORITHM

Using the random forest algorithm, with the aforementioned explanatory variables (Indoor Air Temperature, Outdoor Dry-Bulb Temperature, Outdoor Wind Speed, and Outdoor Relative Humidity) the operative temperature prediction RMSE value is 0.090°C. Figure 4 shows the difference between the predicted and the simulated operative temperature. As the operative temperature is always between the Air Temperature and the mean radiant temperature, and the assumption is that the Air Temperature is known, the prediction is to be made in a fairly narrow band leading to such high accuracy.

In terms of the classification of the operative temperature as being in/out of the comfort band, 0.88% of the values are misclassified, with 0.46% of the values being classified as being outside the comfort band and 0.42% being classified as being inside as the band (Figure 5).

While these results appear very accurate, caution should be taken in interpreting these results. As only one year's worth of outside weather conditions' data is being used and only one physical room has been used, there is a risk of the model overfitting to the given data. Only 9 scenarios have been taken into account, and adding other scenarios to the model like the Mixed-Mode scenario, will worsen the classification. Also, as the Air Temperature in the model's case is simulated, moving to a real-world environment with Air Temperature being measured can introduce further errors.

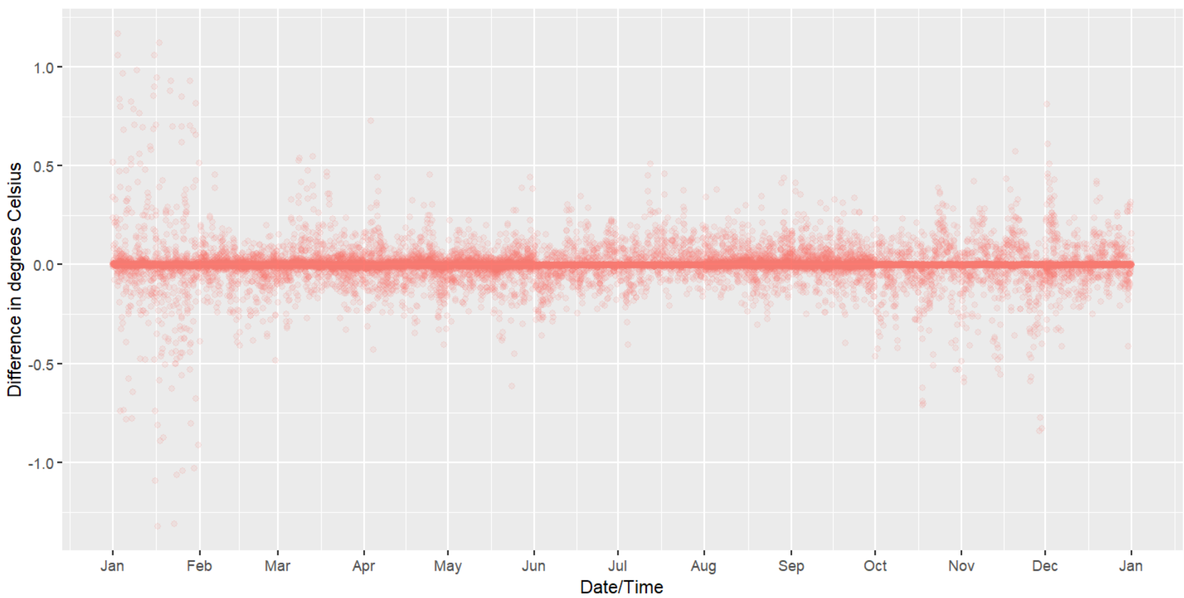

Figure 4: Difference between predicted and simulated operative temperature

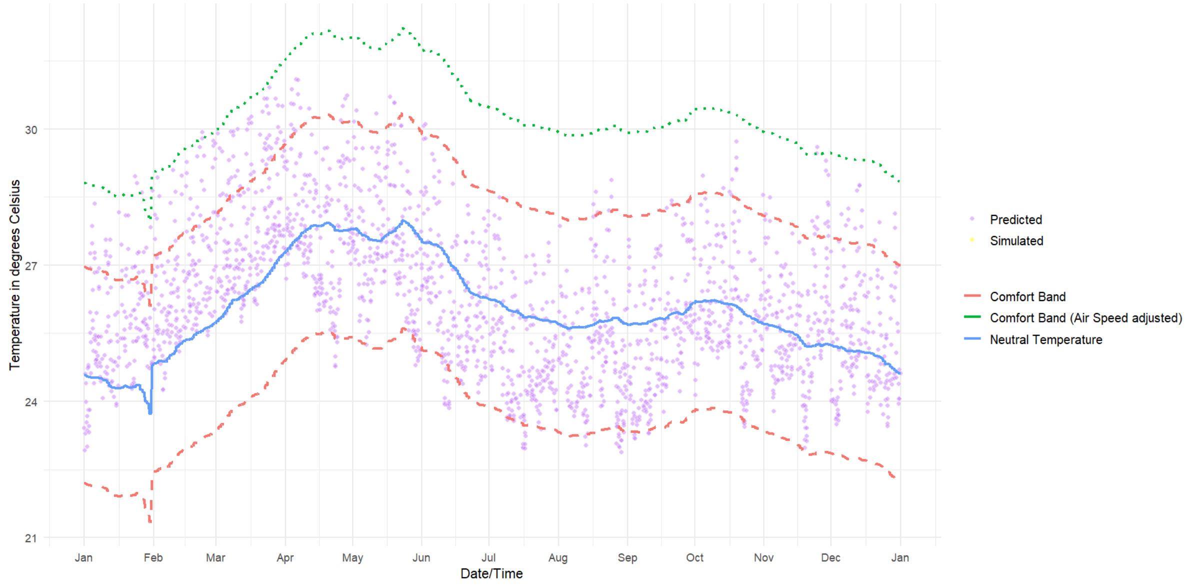

Figure 5: Classification of the operative temperature as being in/out of the comfort band

4. Conclusion

This work developed a machine learning model for the prediction of operative temperature with a scalable measurement approach of an indoor air temperature sensor and a weather station mounted on a building. The machine-learning algorithm predicts the operative temperature and classification of data points as being in/out of the IMAC band. The goal is to integrate this work into a control system to maximise the fan operation and minimise the AC energy use in buildings.

The calibrated Energy Plus thermal model that was used to generate additional datasets has MBE and RMSE that were well within the thresholds of ASHRAE Guideline 14.

The testing of predicted data for operative temperature with a random forest model shows an RMSE of 0.090° C. Whereas in terms of classification of operative temperature as being in/out of the comfort band, 0.88% of values are misclassified, where 0.46% of the values are classified as outside the comfort band when it is inside, and 0.42% being classified as being inside as the band when it is outside.

Although the results appear promising, it is worth noting that only a year's worth of outdoor weather conditions are being used and simulated results of only a single type of room. Also, the air temperature used in the model is simulated, and real-world scenarios will introduce further errors. These will be taken into account in future work when the model is tested against more physical measurements across multiple rooms before the model can be considered robust enough to provide useful actionable predictions.

This work demonstrates that the indoor operative temperature in a room can be reliably predicted using easily measured variables Indoor Air Temperature, Outdoor Dry-Bulb Temperature, Outdoor Wind Speed, and Outdoor Relative Humidity. This enables high frequency, periodic, and long-term prediction of the operative temperature, and determination of the comfort condition according to the IMAC. This could be leveraged to provide recommendations that would not only improve the comfort but also maximise fan usage and minimise AC energy usage.

4.1 OUR CONTRIBUTION

The special contribution of this work is to demonstrate how operative temperature-based controls can be implemented with a feasible sensor regime, in a way that makes the approach scalable for use in most buildings. This is intended to be used for mixed-mode thermal comfort standards, with control algorithms that maximise fan operation and minimise cooling energy. While this paper demonstrates the machine learning approach that makes this possible, future work will demonstrate the implementation of the control algorithm and its testing.

5. References

Ashrae.org. 2022. Standard 55 – Thermal Environmental Conditions for Human Occupancy. [Online] Available at: <https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy> [Accessed 31 May 2022].

Deng Z, Chen Q (2018) Artificial neural network models using thermal sensations and occupants' behaviour for predicting thermal comfort. Energy Build 174(September):587–602.

IEA. 2022. Cooling – Analysis - IEA. [Online] Available at: <https://www.iea.org/reports/cooling> [Accessed 31 May 2022].

ISO. 2022. ISO 7726:1998. [Online] Available at: <https://www.iso.org/standard/14562.html> [Accessed 31 May 2022].

Kim J, Zhou Y, Schiavon S, Raftery P, Brager G (2018) Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behaviour and machine learning. Build Environ 129(December 2017):96–106.

Kumar, T. and Kurian, C., 2022. Real-time data-based thermal comfort prediction leading to temperature set point control. Journal of Ambient Intelligence and Humanized Computing.

Lipczynska, A., Schiavon, S. and Graham, L., 2018. Thermal comfort and self-reported productivity in an office with ceiling fans in the tropics. Building and Environment, 135, pp.202-212.

Manu, S., Shukla, Y., Rawal, R., Thomas, L. and de Dear, R., 2016. Field studies of thermal comfort across multiple climate zones for the subcontinent: India Model for Adaptive Comfort (IMAC). Building and Environment, 98, pp.55-70.

Rawal, R., Shukla, Y., Vardhan, V., Asrani, S., Schweiker, M., de Dear, R., Garg, V., Mathur, J., Prakash, S., Diddi, S., Ranjan, S., Siddiqui, A. and Somani, G., 2022. Adaptive thermal comfort model based on field studies in five climate zones across India. Building and Environment, 219, p.109187.

Sandagomika, N.M.G.H., Sandanayake, Y.G. and Ekanayake, B.J., 2020. Drivers and Barriers of Using Intrenet of Things for Successful Lean Implementation in Construction Projects in Sri Lanka. FARU Journal, 7, pp.12–19. DOI: http://doi.org/10.4038/faruj.v7i0.26

Schiavon, S., Yang, B., Donner, Y., Chang, V. and Nazaroff, W., 2016. Thermal comfort, perceived air quality, and cognitive performance when personally controlled air movement are used by tropically acclimatized persons. Indoor Air, 27(3), pp.690-702.

Tartarini, F., Schiavon, S., Cheung, T., Hoyt, T., 2020. CBE Thermal Comfort Tool : online tool for thermal comfort calculations and visualizations. SoftwareX 12, 100563. https://doi.org/10.1016/j.softx.2020.100563

Webstore.ansi.org. 2022. ANSI/ASHRAE 55-2017 - Thermal Environmental Conditions for Human Occupancy. [online] Available at: <https://webstore.ansi.org/Standards/ASHRAE/ANSIASHRAE552017> [Accessed 31 May 2022].

Weerakoon, L.R.T. and Perera, N.G.R., 2021. Vegetation Cover Effects on Outdoor Thermal Comfort Around High-rise Developments; A Case Study of Havelock City, Colombo, Sri Lanka. FARU Journal, 8(1), pp.46–56. DOI: http://doi.org/10.4038/faruj.v8i1.86

Wu, Z., Li, N., Peng, J., Cui, H., Liu, P., Li, H. and Li, X., 2018. Using an ensemble machine learning methodology-Bagging to predict occupants' thermal comfort in buildings. Energy and Buildings, 173, pp.117-127.