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Predicting Operative Temperature with Machine Learning

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Abstract

With climate change, low carbon space-cooling approaches are becoming more important. Cooling energy demand can be reduced through new interventions, low energy systems, and optimised operation. 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.

This paper summarises a study on an affordable cooling approach to develop a machine learning algorithm to predict OT. 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 testing of the OT predicted with the random forest model shows an RMSE of 0.34%. In terms of classification of the thermal environment as being in/out of the adaptive comfort band, 0.88% of values were misclassified. When the predicted OT values were compared with the one-week measured OT values, the RMSE was found to be 3%.

The results demonstrate that our algorithm that uses indoor air temperature readings in a space and outdoor weather station data can reliably predict OT. This enables a scalable and affordable approach for accurate and long-term prediction of OT to determine the comfort condition.

This will enable control systems to use OT to determine thermal comfort in a space using adaptive comfort models and to account for ceiling fan usage to reduce or eliminate air-conditioning (AC).

Key Innovations

- Long Term operative temperature using minimal measurement equipment as a scalable solution.
- Mixed-mode adaptive thermal comfort control to maximise ceiling fan operation and minimise cooling energy.

Practical Implications

We demonstrate that indoor operative temperature (OT) can be predicted reliably using easily measured variables and machine learning (ML). This will enable control systems to use OT to determine thermal comfort in a space using adaptive comfort models. It will enable control systems to account for adaptive comfort parameters such as ceiling fan usage and reduce or eliminate air-conditioning (AC).

Introduction

According to the IEA (2021) report, the demand for global space cooling is growing. In the building sector, 16% of the overall electricity consumption is accounted for space cooling in 2020 (IEA, 2021). India is amongst the countries where 92% of homes do not have AC installed, and the per capita energy consumption for space cooling is at 69 kilowatt-hours (kWh), compared to the world average of 272 kWh (IEA, 2021). Since the cooling energy is expected to grow significantly in the next two decades, 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 at scale to maximise ceiling or wall-mounted fan operation and minimise air conditioning energy use.

The National Building Code (NBC) of India includes the Indian Model for Adaptive Comfort (IMAC) as the standard for thermal comfort. We intend to implement thermal comfort controls based on IMAC, where a thermal comfort band of indoor operative temperatures is a function of the 30-day running mean of historical outdoor temperature values. (Manu, et.al, 2016).

IMAC uses OT as the comfort metric. However, OT is not commonly used as a parameter for cooling system controls in buildings. This is because globe temperature, mean radiant temperature, and air velocity need to be measured to calculate OT. These parameters are difficult to measure in real-time and long-term level due to the nature of the equipment used, and the fact that OT varies across a space when there is radiant asymmetry and non-uniform airflow in the space. 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 ten 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 Effective Temperature (Wu et al., 2018). 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.

Our ML model uses an indoor air temperature and humidity sensor in the room to get indoor data, and a weather station installed on the building to get outdoor data. We used changes in the settings of ceiling and wall-mounted fans to adjust the OT as well as the upper limits of the comfort band. Using this information, our ML model will maximise 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 ceiling 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.

Method

This section describes 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 building and is built to test several technologies and operational practices that can then be applied in buildings on the rest of the 55-acre campus.

Figure 1: Experimental Building

Hourly measurements of indoor air, surface and outdoor weather parameters were collected for one-month in the experimental building in its free running non-air-conditioned mode. Using these, an Energy Plus thermal model of the building was calibrated. The calibrated model was tested against one-week hourly measured data of globe temperature and airspeed to validate the OT results of the simulation. The calibrated model was used to generate several annual datasets to be used for training and testing of the ML algorithm. The details are described below.

Data collection for calibrating the 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 was collected from the weather station on top of the building. Indoor environmental parameters like indoor air temperature, wall surface temperature, and humidity, were monitored through an Internet of Things (IoT) system installed in the building.

Calibrated Energy Plus thermal model

The Energy Plus Model describes the building 3-D geometry (see figure 2), thermal characteristics of the construction assemblies, internal loads, and operational schedule of the building. The hourly indoor temperature and surface temperature outputs of the simulation were compared with the measured data and the Mean Bias Error (MBE) and Root Mean Squared Error (RMSE) were calculated. Iterative corrections were done to the model to bring the MBE and RMSE below the ASHRAE Guideline 14 thresholds.

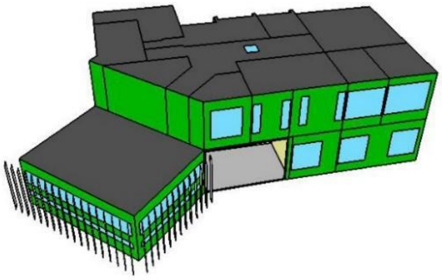

Figure 2: Calibrated energy plus thermal model

Data collection and validation of the simulated operative temperature

Globe temperature, air temperature, and airspeed data were measured at hourly intervals for one week and mean radiant temperature and OT values 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 values.

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.

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 metres and 3 metres from the fan. This was used to calculate the operative temperature at different speeds and distances.

The calibrated model was simulated for the same week using the weather data. The OT calculated from the measured data and the simulated OT results were compared and MBE and RMSE were calculated. Acceptable MBE and RMSE results validated the approach to use calibrated model to generate training datasets.

Simulated datasets to be used for machine learning

To generate datasets for training the ML algorithm, different scenarios (see Table 1) were simulated for an entire year with the calibrated model in Energy Plus for a room in the southwest corner of the building. See Table 1. Scenarios 1, 2, 3, 4 were simulated in Energy Plus and 2a, 2b, 2c, 2d, 2e, 2f have OT values that are post processed from scenario 2 using equation 2.

Table 1: Different scenarios that form the training dataset

(The airspeed measured for different fan settings of 1, 2, 3 at 3 meters were 0.87m/s, 1.27m/s, and 1.47m/s respectively and at 2.5 meters were 1.17m/s, 1.4m/s, and 1.57m/s respectively)

S. No.	Scenario
1	Windows closed
2	Windows open
3	Windows open with changed equipment power density
4	Windows open with changed occupancy
2a	Windows open with Fan setting 1 at 3.0m
2b	Windows open with Fan setting 2 at 3.0m
2c	Windows open with Fan setting 3 at 3.0m
2d	Windows open with Fan setting 1 at 2.5m
2e	Windows open with Fan setting 2 at 2.5m
2f	Windows open with Fan setting 3 at 2.5m

Adjustments to the thermal comfort band for the impact of airspeed

It was observed that the change in airspeed in scenarios 2a through 2f resulted in the minimal variation in the operative temperature. This is because equation 3 for OT uses the square root of the air speed. However, the thermal comfort tool by the Center for Built Environment (CBE) (Tartarini, et.al, 2020), shows a larger shift in the upper limit of temperature of the adaptive comfort model when airspeed is increased in the space. This would enable control algorithms to reduce AC energy in response to increase in fan-speed. Our discussions with CBE researchers indicated that the calculation method used in the shift to the upper limit of the adaptive comfort model was based on their work that was unpublished, and we could not access the calculation method. Hence, we created several scenarios in the CBE tool to reverse-engineer the shift in the upper limit temperature of the comfort band.

Training the ML algorithm

The goal of the ML algorithm is to use a set of easily measured indoor parameters and the weather station data to predict the indoor operative temperature. The Energy Plus simulation outputs of ten scenarios described above provided the data for training the model. An iterative process was used to arrive at the final set of explanatory variables.

The data from the ten scenarios give ten years' worth of data, or 87,600 hours of data. We used a train-test split ratio of 0.75-0.25 (75% data used for training and 25% data used for testing) from this dataset.

Testing the ML algorithm

In the first step of testing, the OT predicted by the ML algorithm was compared with the actual OT values in the dataset. The first metric looked at is the RMSE of the predicted values for OT. The second evaluation metric is misclassification of whether the OT lies within, or outside the comfort band of IMAC.

In a second step of testing, one-week hourly data of globe temperature, air temperature, and air speed were collected to calculate the measured OT in the space for August 17th to August 31st. Outdoor weather conditions were also recorded for this week. The ML algorithm was run to predict OT for this week. This predicted OT was then compared with the measured OT for this one-week data. Mean bias error (MBE) and Root mean squared error (RMSE) were calculated to validate the predicted OT.

Results and Discussion

This section presents the results of the measured data collection, the Energy Plus model calibration, validation of OT, characterisation of the ten scenarios, the selection of ML model, and the error metrics of the ML model.

Measured data

The one-week measured data between the dates of 29th March to 4th April for indoor air temperature was for between 28.6 °C and 31.4 °C, globe temperature was between 29 °C and 32 °C and the air speed was between 0 m/s and 0.8 m/s. During this period the weather data showed outdoor air temperature was between 21ºC and 34ºC. The airspeed measured for different fan settings of 1, 2, 3 at 3 metres were 0.87m/s, 1.27m/s, and 1.47m/s respectively and at 2.5 metres were 1.17m/s, 1.4m/s, and 1.57m/s respectively. It was observed that the average temperature difference between the globe temperature and air temperature was 2 °C and between the mean radiant temperature and operative temperature was 1.4 °C.

Energy Plus thermal model calibration

For the one-month hourly data comparison of indoor air temperature and surface temperature values between the simulation results and the measured data, the final calibrated model had a Mean Bias Error (MBE) of 1% and and Root Mean Squared Error (RMSE) of 17%. These were below the ASHRAE Guideline 14 thresholds of 10% MBE and 30% RSME for hourly data.

For the one-week hourly data comparison of the OT values between the simulation results and the measured data, the MBE was 3% and the RMSE was 10%. These too were below the ASHRAE Guideline 14 thresholds for hourly data, and the model was considered sufficiently reliable to generate the training datasets.

Datasets used for machine learning

For the ten scenarios presented in Table 2, hourly simulation results were produced. Indoor OT ranges between 21.8ºC and 31.1ºC, and the comfort hours range between 89.5 and 93.3% of the year. The highly insulated building provides the most comfort when the windows are closed and increasing fan speed reduces the comfort hours. Note that the comfort hour assessment does not include the upward shift of the IMAC upper limit.

Table 2: Different scenarios for training and total comfort hours

Sl. No.	Scenario	Operative temperature range	hours inside the comfort band of 8760 hours in a year
1	Windows closed	22.6°C - 30.2°C	8171 (93.3%)
3	Windows open with changed equipment power density	21.8°C - 30.9°C	8085 (92%)
4	Windows open with changed occupancy	22.6°C - 30.4°C	8080 (92%)
2a	Windows open with Fan setting 1 at 3.0m	22.7°C - 31.1°C	7876 (89.9%)
2b	Windows open with Fan setting 2 at 3.0m	22.7°C - 31.1°C	7853 (89.6%)
2c	Windows open with Fan setting 3 at 3.0m	22.8°C - 31.1°C	7845 (89.6%)
2d	Windows open with Fan setting 1 at 2.5m	22.7°C - 31.1°C	7859 (89.7%)
2e	Windows open with Fan setting 2 at 2.5m	22.7°C - 31.1°C	7847 (89.6%)
2f	Windows open with Fan setting 3 at 2.5m	22.7°C - 31.1°C	7841 (89.5%)

Adjustments to the thermal comfort band for the impact of airspeed

For scenarios 2a through 2f, the change in the upper limit temperature of the adaptive comfort band as a function of the airspeed, observed in the CBE Tool, is shown in figure 3.

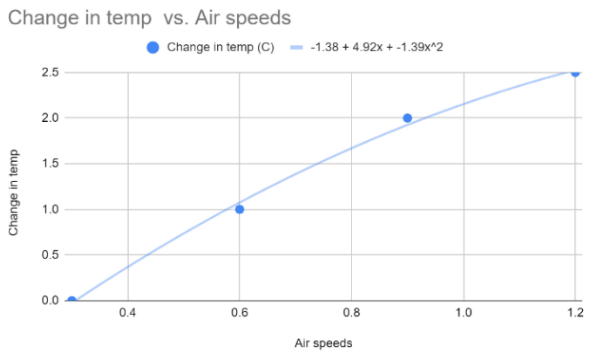

Figure 3: Airspeed and the change in the upper limit temperature of the adaptive comfort band

This upward shift widens the IMAC thermal comfort band and can be used to raise the AC setpoints and reduce energy consumption. This logic can also be used to control the ceiling fans and prioritise their use over the AC equipment.

Training the machine learning algorithm

The training of the algorithm found that the explanatory variables were indoor air temperature, outdoor dry-bulb temperature, outdoor wind speed, and outdoor relative humidity. With these parameters, there were some systemic issues such as under-prediction of operative temperature in the summer months were found. To combat these issues, the month of the year, and the hour of the day were added to the explanatory variables. Initially, a linear regression model was tried before arriving at the better-performing random forest model. The random forest model in R is from the tidy models library using the ranger engine.

Testing the machine learning algorithm

In the first step of testing, OT values predicted by the random forest algorithm, with the explanatory variables were compared with the 25% of the 87,600 data points. RMSE for the predicted OT was 0.34%. Figure 4 shows the difference between the predicted and the simulated operative temperature. The operative temperature lies between the indoor air temperature and the mean radiant temperature of a space. In this building, the data shows that the indoor air temperature and the surface temperatures are typically within 2ºC of each other. This is likely to be the reason why the prediction within a narrow band between those two variables has such high accuracy. In terms of the classification of the operative temperature as being within or outside the adaptive comfort band, 0.88% of the values are misclassified, with 0.46% of the values being misclassified as being outside and 0.42% being classified as being within the band (Figure 5).

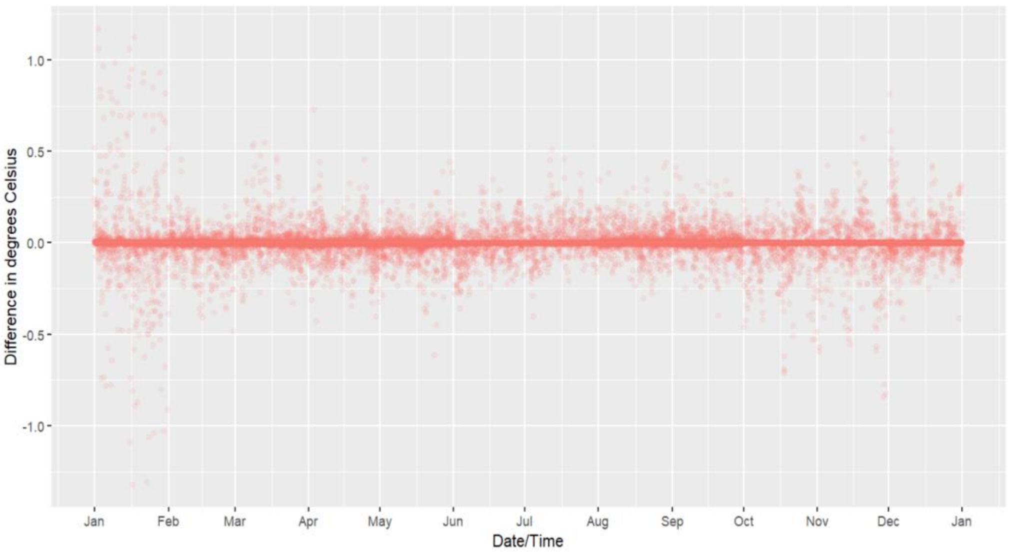

Figure 4: Difference between predicted and simulated operative temperature

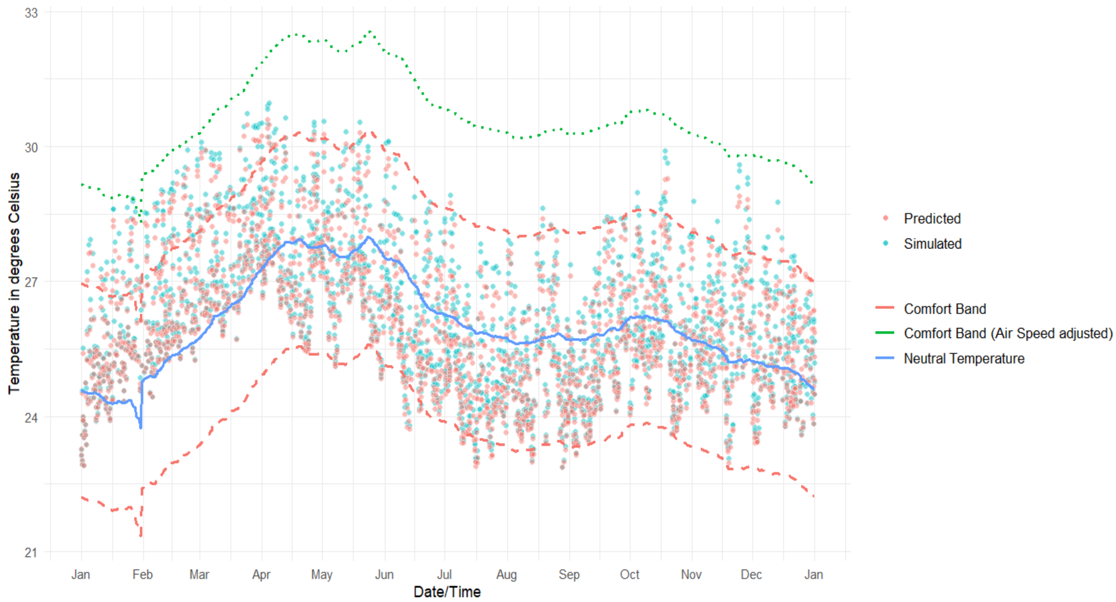

Figure 5: Classification of the operative temperature as being in/out of the comfort band.

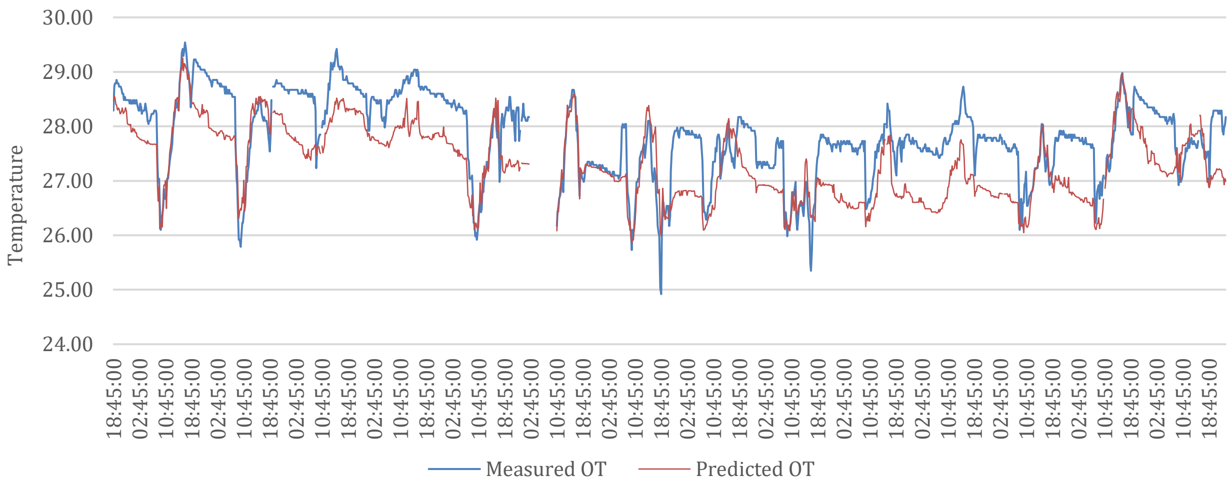

Figure 6: Measured and Predicted OT validation data.

In the second step of testing, when the predicted OT values were compared with the one-week measured OT values, the RMSE was found to be 3%. Figure 6 shows the measured OT and the predicted OT. Maximum OT was measured at 29.54°C and the average OT was measured at 27.8°C. The maximum error in OT was 1.37°C, and the average error was 0.60°C.

Conclusion

This work developed a machine-learning model for the prediction of OT that uses only an indoor air temperature sensor inside a space and a weather station mounted on a building. This approach is more affordable, scalable, and reliable in terms of the sensor regime, compared to doing air temperature, airspeed and globe temperature measurements in each space in the building. The machine-learning algorithm predicts the PT and classifies the data points as being within or outside the adaptive thermal comfort band of the IMAC in India's National Building Code. The next step is to integrate this work into a control system that takes advantage of the adaptive thermal comfort model to maximise the fan operation and minimise the AC energy use in buildings.

The training and testing datasets were prepared with a calibrated Energy Plus thermal model.

The testing of the OT predicted with the random forest model shows an RMSE of 0.34% when compared with the simulation outputs of ten annual scenarios and 21,900 data points and an RMSE of 3% when compared with one week of measured OT values. In terms of classification of the thermal environment as being in/out of the adaptive comfort band, 0.88% of values are misclassified.

The results demonstrate that our random forest model that uses indoor air temperature readings in a space and outdoor values for dry-bulb temperature, wind speed, and relative humidity, along with the month and date stamp can reliably predict OT. This enables a scalable and affordable approach for accurate and long-term prediction of OT to determine the comfort condition according to the adaptive model in the National Building Code of India, filling in a significant implementation gap to use OT for building system controls.

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 adaptive 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.

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