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## Applying machine learning for building natural ventilation control

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### SUMMARY

Although natural ventilation is applicable to most buildings, architects and engineers today struggle to integrate it as an alternative to mechanical ventilation systems due to its uncertainty. This paper presents the application of regression algorithms and identification methods to single-sided natural ventilation with two openings (SS2). The result of this work provides a predictive control-oriented model which co-optimize the  $CO_2$  level and thermal comfort for natural ventilation with SS2 configuration.

### KEYWORDS

*single-sided natural ventilation,  $CO_2$  demand control, regression algorithms, system identification*

## 1. INTRODUCTION

Natural ventilation is a promising passive technology to reduce energy consumption and to alleviate the sick building syndrome. However, it is challenging to control natural ventilation. Limited research is conducted on the controller design in the real world, compared to the control design in simulation [1-3]. Many factors can influence the quality of natural ventilation control, including the window shape, built environment etc. The empirical formula or CFD may not respond effectively to the consequence of modern passive design in the motorized window, external shading, thick thermal mass. MPC is applied in the ventilation system control but focuses mainly on the mechanical ventilation system [4-7]. In this paper, a systematic methodology is proposed to bridge this gap for the control of single-sided natural ventilation with two openings.

### 1.1. Cold draught in $CO_2$ demand ventilation

In the winter, the  $CO_2$  demand ventilation with unconditioned cold fresh air may cause the cold draught for the occupancy near the window. The cold draught is a natural ventilation “local effect” which can be described as a complex heat and mass transfer.

**Table 1: Cold draught as a local effect of natural ventilation**

| Mass and Heat Transfer phenomenon   | Description                                                 | Human feeling/<br>Sensor reading                                 | Space scale                                           | Time scale | Sensor required to measure                                   |
|-------------------------------------|-------------------------------------------------------------|------------------------------------------------------------------|-------------------------------------------------------|------------|--------------------------------------------------------------|
| <b>Cold draught or Local effect</b> | Immediate effect on a part of room air by fresh outdoor air | It can be sensed by human and observed by sensor in-situ quickly | only the part of room air which is sampled by sensors | Minutes    | Room air Temperature / $CO_2$ /RH sensor in zone of interest |

The “local effect” is felt quickly by the occupant and is the main cause of thermal discomfort during winter. The model predictive control (MPC) is selected to deal with this unexpected cold local effect in winter. The system dynamics of the controlled object is the crucial part of MPC. In this paper, the two related system dynamics ( $\text{CO}_2$  level and specific area air temperature) are identified through machine learning algorithms from the collected natural ventilation data.

## 2. MATERIALS AND METHODS

### 2.1. Experimental Setting

#### Building and Windows

The experiment site is a retrofitted 3-story building in Cambridge, Massachusetts. On the third floor, the south-facing office is chosen for the experiment.



**Figure 2: Motorized window in the experiment**



**Figure 1: Window's opening in 40%**

The office has a floor plan of  $10 \text{ m}^2$  (3.85 in-depth, 2.6 in width), and a volume of  $30 \text{ m}^3$ . Four windows and one roof skylight are installed: the roof skylight and the two upper windows (Figure 2) are motorized; the two bottom windows are manually operated. With the intention to study single-sided natural ventilation of two openings, only the two upper motorized windows are utilized in this experiment; their opening angle (Figure 1) is kept the equal through the same window motor controller.

The motorized windows have a complex air path passage (Figure 1): from the external shading devices, thick thermal mass wall to the bottom-hinged opening.

#### Sensors

The sensors in this experiment are as follows:

**Table 2: Sensors in Experiment**

| Sensor                            | No.<br>° | Purpose                 | Location                       | Symbol            | Measurement             | Sampling method | Range and Accuracy                                                                  |
|-----------------------------------|----------|-------------------------|--------------------------------|-------------------|-------------------------|-----------------|-------------------------------------------------------------------------------------|
| Outdoor temperature sensor        |          | Data collection/Control | On the roof in weather station | $T_{\text{atm}}$  | Outdoor air Temperature | Change of value | Range: from $-30 \text{ }^\circ\text{C}$ to $+55 \text{ }^\circ\text{C}$            |
| Wind Direction sensor             |          | Data collection/Control |                                | $\alpha$          | Wind direction          | Change of value | Range: from $0^\circ$ to $359^\circ$ ; Accuracy: $< 2^\circ$                        |
| Wind Speed sensor                 |          | Data collection/Control |                                | $V_{\text{wind}}$ | Wind speed              | Change of value | Range: from $0 \text{ m/s}$ to $75 \text{ m/s}$                                     |
| Indoor $\text{CO}_2$ /temperature | 1        | Data collection         | South window                   | $T_1$             | Air temperature         | 5 min interval  | Temperature: Ranges from: $0 \text{ }^\circ\text{C}$ to $50 \text{ }^\circ\text{C}$ |

|                |   |                         |                                   |                       |                 |                                                                            |
|----------------|---|-------------------------|-----------------------------------|-----------------------|-----------------|----------------------------------------------------------------------------|
| <b>sensors</b> |   | still                   | C <sub>1</sub>                    | CO <sub>2</sub> level | 5 min interval  | Accuracy: ± 0.3 °C                                                         |
|                | 2 | Reading desk            | T <sub>2</sub>                    | Air temperature       | 5 min interval  | CO <sub>2</sub> :<br>Ranges from: 0 to 5,000 ppm                           |
|                |   |                         | C <sub>2</sub>                    | CO <sub>2</sub> level | 5 min interval  | Accuracy: ± 50 ppm (from 0 to 1,000 ppm) or ± 5% (from 1,000 to 5,000 ppm) |
|                | 3 | Above entrance          | T <sub>3</sub>                    | Air temperature       | 5 min interval  |                                                                            |
|                |   |                         | C <sub>3</sub>                    | CO <sub>2</sub> level | 5 min interval  |                                                                            |
|                | 4 | Data collection/Control | Flesh mount on wall near entrance | Air temperature       | Change of value | Ranges from: 0 °C to 50 °C                                                 |
|                |   |                         |                                   | CO <sub>2</sub> level | Change of value | 390–10.000 ppm                                                             |

**Table 3: 3 zones for the experiment room**

| Zone No° | Zone in office               | Involved sensors (Table 2)                | Temperature                                                                  | CO2 level                                                                    |
|----------|------------------------------|-------------------------------------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| 1        | Near the window              | Sensor No°1<br>Sensor No°2                | T <sub>z1</sub> = weighted mean (T <sub>1</sub> : 80%, T <sub>2</sub> : 20%) | C <sub>z1</sub> = weighted mean (C <sub>1</sub> : 80%, C <sub>2</sub> : 20%) |
| 2        | Near the table: working area | Sensor No°1<br>Sensor No°2<br>Sensor No°3 | T <sub>z2</sub> = mean (T <sub>1</sub> , T <sub>2</sub> , T <sub>3</sub> )   | C <sub>z2</sub> = mean (C <sub>1</sub> , C <sub>2</sub> , C <sub>3</sub> )   |
| 3        | Near the entrance door       | Sensor No°2<br>Sensor No°3                | T <sub>z3</sub> = mean (T <sub>1</sub> , T <sub>2</sub> , T <sub>3</sub> )   | C <sub>z3</sub> = mean (C <sub>1</sub> , C <sub>2</sub> , C <sub>3</sub> )   |

## 2.2. Methods

### Data collection

The data is collected from the sensors (Table 2) through the building management system and the online management interface. In order to collect the data, two rule-based control strategies are implemented:

- 1) Fixed time interval: window controller will open and close the window in a pre-defined time interval (20 mins or 30 min).
- 2) CO<sub>2</sub> demand control: window controller will open the window at CO<sub>2</sub> level of 1000 ppm, and close it at 800 ppm via the sensor No°4 (Table 2).

### Raw Data Process for Flowrate Calculation

The natural ventilation rate is calculated based on the data from the sensors, using the following formula:

$$v \frac{C_{z2}(k+1) - C_{z2}(k)}{\Delta t} = nG - \overline{V_{NV}}(C_{z2}(k) - C_{atm}) \quad (1)$$

$v$ : the volume of room space ( $m^3$ )

$C_{z2}(k+1)$ : the CO<sub>2</sub> concentration for zone 2 at (k+1)<sup>th</sup> time interval, (ppm)

$C_{z2}(k)$ : the CO<sub>2</sub> concentration for zone 2 at k<sup>th</sup> time interval, (ppm)

$C_{atm}$ : the CO<sub>2</sub> concentration in local atmosphere, (assumed as 400 ppm)

$\Delta t$ : the time interval, (1 min)

$n$ : number of persons inside the room, (1 ~ 4 persons)

$G$ : the CO<sub>2</sub> generated by the one occupant inside the room, approximately 11 (ppm/min)

$\overline{V_{NV}}$ : the natural ventilation flow rate ( $m^3/min$ )

$C_{atm}$ : the CO<sub>2</sub> concentration in the local atmosphere, (400 ppm)

### Regression Analysis

Based on the natural ventilation flowrate  $\overline{V_{NV}}$ , the regression analysis is realized to select the best group of natural ventilation features:

$$\overline{V_{NV}} = U * f_1(\text{Natural Ventilation Feature})$$

$U$ : the opening of the motorized window, 0 – 100

$f_1()$ : the linear function of selected natural ventilation features

### System identification

The selected natural ventilation features are used as parameter candidates for the 1<sup>st</sup> order system dynamics for the temperature in zone 1 (Table 3) and CO<sub>2</sub> level in zone 2 (Table 3).

The subspace method and the predictive error method (PEM) will be applied together to identify the system dynamics in the following form:

$$C_{z2}(k+1) = a_1 * C_{z2}(k) + U * g_C(\text{natural ventilation features}) + nG$$

$$T_{z1}(k+1) = a_2 * T_{z1}(k) + U * g_T(\text{natural ventilation features})$$

$a_1, a_2$ : the coefficient to be identified

$g_C, g_T$ : the linear function of natural ventilation features, to be identified.

The realization of system identification is through Multi-Experiment Data/Merging Models method in Matlab System Identification Toolbox (2019b).

## 3. RESULTS

The data set records the daytime of 17 days in January and February of 2020, including the weather data and indoor environmental data. Firstly, all the data is classified into three datasets by the wind speed and wind direction: low wind speed, high wind speed windward, and high wind speed leeward (Table 5). Based on the three datasets, the regression analysis returns the best selection of features in terms of flowrate estimation in the winter season:

$$\Delta T, T_{z1}, \sqrt{\Delta T}, V_{wind}, V_{wind} \cos \theta, V_{wind} \sin \theta, |V_{wind} \cos \theta|$$

The parameters represented by this feature group are illustrated in Table 2, Table 4, and Equation 1.

**Table 4: the elements in natural ventilation features**

| Elements   |                                                                                       |
|------------|---------------------------------------------------------------------------------------|
| $\Delta T$ | $\Delta T = T_{z1} - T_{atm}$ , the difference between indoor/outdoor air temperature |
| $\theta$   | Wind incident angle, a function of wind direction angle $\alpha$                      |
| $V_{wind}$ | Wind speed                                                                            |

**Table 5: the regression analysis based on selected features**

| Dataset                                         | R <sup>2</sup> score for regression |
|-------------------------------------------------|-------------------------------------|
| Low wind speed data (<1.5 m/s)                  | 0.404                               |
| High wind speed windward data ( $\geq 1.5$ m/s) | 0.596                               |
| High wind speed leeward data ( $\geq 1.5$ m/s)  | 0.252                               |

Secondly, the entire dataset is split into 79 experiments: each represents a CO<sub>2</sub> decreasing process (between window opening and window closing)—most of the experiments last 15-20 mins.

The identified system dynamics:

$$C_{z2}(k+1) = 1.002 * C_{z2}(k) + U * (3.128\Delta T - 15.63\sqrt{\Delta T} + 4.661 V_{wind} \sin \theta - 1.665 V_{wind} \cos \theta - 3.98 V_{wind}) + nG$$

$$T_{z1}(k+1) = 1.001 * T_{z1}(k) + U * (0.02169 V_{wind} \sin \theta - 0.03477\sqrt{\Delta T} + 0.01619 |V_{wind} \cos \theta| - 0.01235 V_{wind})$$

The quality of identified system dynamics is verified through the validation of every single experiment in the given 79 cases. For first-order CO<sub>2</sub> level dynamics, 58 cases report the accuracy larger than 60%; for first-order Temperature dynamics, 54 cases report the accuracy larger than 60% (

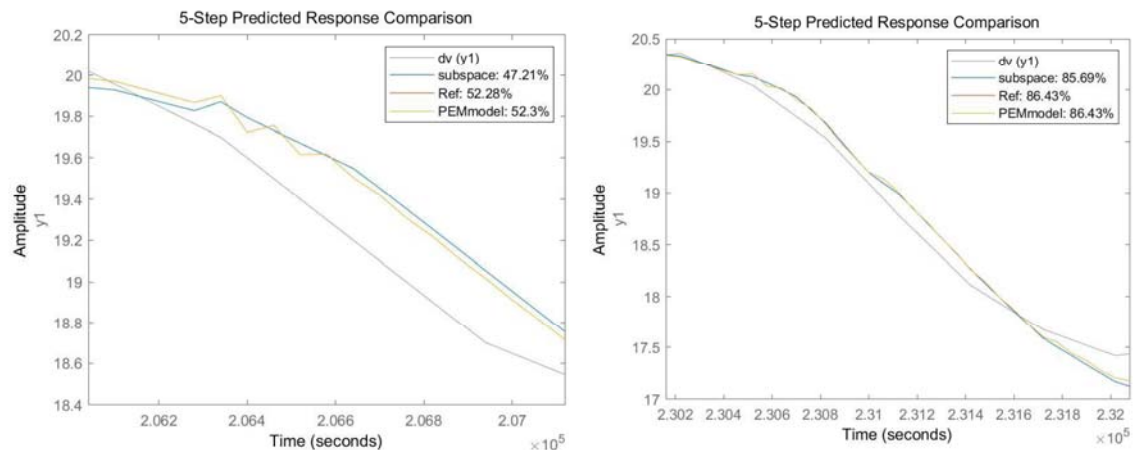
Table 6).

**Table 6: the result of system identification**

| System dynamics                 | No° of experiments with validated prediction accuracy >60% | Accuracy of Natural Ventilation System Dynamics |
|---------------------------------|------------------------------------------------------------|-------------------------------------------------|
| CO <sub>2</sub> level in zone 2 | 58                                                         | 73.4%                                           |
| Temperature in zone 1           | 54                                                         | 68.4%                                           |

#### 4. DISCUSSION

**Figure 3: the temperature dynamics validation cases with accuracy of 52.3% (54<sup>th</sup> experiment) and 86.4% (59<sup>th</sup> experiment)**



Comparing the two validation cases above (54<sup>th</sup> and 59<sup>th</sup> experiments), the concept of accuracy worth a discussion: the case of 52.3% accuracy is capable to trace the temperature change trend in about 15 mins, the prediction dynamics (orange curve) has a good fitting with the experiment data (grey curve) at first 5 mins (Figure 3). If the control command time interval is set as 5 mins, the case of 52.3% accuracy is indeed a high-quality validation of temperature dynamics. The case of 86.4% accuracy shows a perfect match between prediction dynamics (orange curve) and experiment data (grey curve). This comparison suggests the identified system dynamics will have a better performance than the accuracy indicates.

#### 5. CONCLUSIONS

Based on machine learning algorithms, this paper proposes a new data-driven approach for control design of natural ventilation. The identified linear system dynamics have the potential to be implemented in the natural ventilation controller through the predictive control framework. As future work, the two system dynamics will be implemented soon in the window controller at the same experiment site to verify the performance in the real world.

#### 6 REFERENCES

1. Chen, Y., et al., *Transfer learning with deep neural networks for model predictive control of HVAC and natural ventilation in smart buildings*. Journal of Cleaner Production, 2020. **254**: p. 119866.
2. Chen, Y., et al., *Achieving natural ventilation potential in practice: Control schemes and levels*

- of automation. Applied Energy, 2019. **235**: p. 1141-1152.
3. Schulze, T., D. Gürllich, and U. Eicker, *Performance assessment of controlled natural ventilation for air quality control and passive cooling in existing and new office type buildings*. Energy and Buildings, 2018. **172**: p. 265-278.
  4. Koehler, S. and F. Borrelli. *Building temperature distributed control via explicit MPC and "Trim and Respond" methods*. in *2013 European Control Conference (ECC)*. 2013.
  5. Parisio, A., et al., *Implementation of a Scenario-based MPC for HVAC Systems: an Experimental Case Study*. IFAC Proceedings Volumes, 2014. **47**(3): p. 599-605.
  6. Ma, Y., J. Matuško, and F. Borrelli, *Stochastic Model Predictive Control for Building HVAC Systems: Complexity and Conservatism*. IEEE Transactions on Control Systems Technology, 2015. **23**(1): p. 101-116.
  7. Afram, A. and F. Janabi-Sharifi, *Theory and applications of HVAC control systems – A review of model predictive control (MPC)*. Building and Environment, 2014. **72**: p. 343-355.