Impacts of climate change on mechanical ventilative cooling in high-rise buildings

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Abstract
Mechanical ventilation systems have great potential to provide cooling in high-rise buildings and reduces cooling energy consumption, i.e. mechanical ventilative cooling (MVC). However, the energy performance of MVC highly depends on weather conditions. In the previous studies, the energy performance of MVC usually was investigated under the typical or historical weather conditions. Considering that weather conditions will change due to global warming, it is necessary to assess the influences of climate change on the energy performance of MVC. This study uses the morphing method to predict the future weather conditions and a hybrid model to simulate the energy performance of MVC. The hybrid model combines the machine learning model built by multilayer perceptron and energy models. With a case study building in Montreal, the results show that the amount of energy saving of MVC will increase slightly due to climate change. This study contributes to the application of MVC systems in high-rise buildings.

Key Innovations
- Investigate the prediction accuracy of building cooling loads of five machine learning techniques
- Propose a control strategy based on a new hybrid model for mechanical ventilation systems, which utilizes machine learning techniques
- Investigate the effects of climate change on mechanical ventilative cooling

Practical Implications
This study contributes to the application of mechanical ventilative cooling systems in high-rise buildings: take the influences of climate change on designing MVC system into account; avoid directly using the optimal ventilation rates obtained from the typical meteorological year.

Introduction
Ventilative cooling (VC) is a solution to reduce building cooling load and cooling related energy consumption (IEA-EBC, 2018; Sha & Qi, 2020a) through introducing the outdoor cool air to remove indoor excessive heat. Ventilative cooling can be achieved by mechanical ventilation systems, i.e. mechanical ventilative cooling (MVC). The mechanical ventilation system refers to the air movement into or out of a building controlled by using mechanical equipment, which is widely used in high-rise buildings, because it can easily control the fresh air flow rate and has fewer risks of fire safety than natural ventilation or hybrid ventilation systems (ASHRAE, 2017). Previous studies have shown that with proper operation and design, the reduction of MVC on cooling energy consumption can reach around 50% (Bakhtiari, Akander, Cehlin, & Hayati, 2020; Sha & Qi, 2020b; Zhang, Wang, & Hu, 2018).

However, the energy performance of VC highly depends on outdoor conditions. The potential for utilizing VC strategies can vary largely due to different climates, for example, Northern Europe with a cold climate has a high potential for VC (Artmann, Manz, & Heiselberg, 2007; Chen, Tong, & Malkawi, 2017). Meanwhile, the weather conditions will change due to global warming. The Intergovernmental Panel on Climate Change (IPCC) report highlights that the globally averaged surface temperature will increase around 1.4 to 5.8 °C over the period 1990 to 2100 under different CO₂ emission scenarios (IPCC, 2001). The previous study showed that the use of natural VC will no longer fulfil the cooling demand in San Diego due to climate change (H. Wang & Chen, 2014). Therefore, climate change will influence the energy performance of MVC, because MVC relies on the outdoor conditions as same as the natural VC. The impacts of climate change on the energy performance of MVC must be discussed, but the relevant studies are absent in the previous studies.

This study aims to investigate the impacts of climate change on the energy performance of MVC in high-rise buildings. A real high-rise institutional building in Montreal is selected as a case study. The future weather data are predicted by the HadCM3 model and morphing method. The energy performance of MVC is predicted by a hybrid model with an optimal control strategy. The hybrid model combines a machine learning model to predict the building cooling load and energy models to predict the building cooling related energy consumption, i.e. the energy consumption of mechanical ventilation system and chiller system. In this study, the machine learning model, multilayer perceptron, is selected from five different machine learning techniques. The energy models and the optimal control strategy were established by the approach presented in our previous paper (Sha & Qi, 2020b).

Methods
In this section, the case study building will be firstly introduced. Then, the method to predict future weather data is presented. The hybrid model to predict the energy performance of MVC and the optimal control strategy are elaborated finally.
Case study

A 16-storey high-rise institutional building in Montreal (Canada) was chosen as the case study. A centralized chiller system and a mechanical ventilation system are installed on the 16th floor, which serve around 178551 m² occupied space. The chiller cooling system consists of a scroll chiller with one chilled water pump and two cooling water pumps, a centrifugal chiller with one chilled water pump and a cooling water pump, a backup screw chiller, and two cooling towers. Four supply air fans and four exhaust air fans assemble the mechanical ventilation system to maintain indoor air quality.

There is a building Automation System (BAS) in the case study building. The BAS is a centralized control of the building’s HVAC (heating, ventilation and air-conditioning) system. Both the chiller cooling system and the mechanical ventilation system are controlled and monitored by the BAS. For example, the BAS will check the water temperature of the cooling system and outdoor temperatures to control the chiller system, and the chiller cooling system usually operates when the outdoor temperature is higher than 15 °C. In the practice, the mechanical ventilation system is controlled by indoor CO₂ concentration instead of providing MVC. During workdays, the occupied period of this building is from 5:00 to 24:00. The indoor temperature setpoint is 23 °C.

To investigate the impacts of climate change on the energy performance of MVC, six cases with different settings of MVC are proposed, as shown in table 1. Six cases are named as: Baseline, Baseline-EF, VC 1, VC 2, VC 3, and VC 4. The case Baseline is a reference case, which does not have MVC. All the settings of the case Baseline are the same as the real building. The previous study has shown that without a low specific fan power (SFP) and enough nominal ventilation rate, MVC cannot reduce cooling energy consumption (Sha & Qi, 2020b). SFP is the ratio of the nominal (maximum) electric power of both supply and exhaust fans to fresh air flow rate, which is used to quantify the energy efficiency of mechanical ventilation system (Schild & Mysen, 2009). Therefore, in cases VC 1~4, the SFP is all set as 0.86 kW/m³/s and the nominal ventilation rates increase from 1.1 to 7.2 ACH. In case Baseline-EF, only the SFP of the mechanical ventilation system is lowered to 0.86 kW/m³/s. Case Baseline-EF is used to make a comparison between Baseline-EF and VC 1~4 to highlight the effects of MVC.

Weather scenarios

Weather conditions that influence the building’s cooling energy consumption can include outdoor dry-bulb temperature, outdoor relative humidity, wind speed, wind direction, solar radiation (Yalcints & Akkurt, 2005). In this study, the future weather data are generated by using a morphing method with a climate model called HadCM3. HadCM3 (Hadley Centre Atmospheric Model version 3) model is a widely used climate model, which divides the lands and oceans into cells (2.5° in latitude and 3.75° in longitude over land) and simulates monthly climate change in each cell based on CO₂ emission (Pope, Gallani, Rowntree, & Stratton, 2000). Considering that the HadCM3 only has data on monthly climate change. The morphing method is used for downscaling the monthly climate change data to hourly data (Belcher, Hacker, & Powell, 2005). The morphing method has three downscaling formulas, which are shown as equations (1), (2), and (3) respectively.

\[ x = x_0 + \Delta x_m \]  
\[ x = a_m x_0 \]  
\[ x = x_0 + \Delta x_m + a_m (x_0 - \langle x_0 \rangle_m) \]

where \( x \) represents the future climate parameters, \( x_0 \) is the existing climate parameters (e.g. dry-bulb temperature), \( \Delta x_m \) is the climate change in monthly mean climate parameters for the month \( m \) (from HadCM3), \( a_m \) is the fractional change in monthly mean climate variable for the month \( m \), and \( \langle x_0 \rangle_m \) is the monthly mean value for the existing month \( m \).

Eq. (1) is used to calculate the future relative humidity. Eq. (2) is used to obtain the future solar radiation and wind speed. The fractional change \( a_m \) in Eq. (2) is:

\[ a_m = 1 + \frac{\Delta x_m}{\langle x_0 \rangle_m} \]

where \( \Delta x_m \) is the monthly mean change in solar irradiance, W·h/m², or wind speed, m/s, and \( \langle x_0 \rangle_m \) is the current monthly mean solar irradiance or wind speed.

Eq. (3) is used for obtaining the future hourly dry-bulb temperature. The fractional change \( a_m \) in Eq. (3) is

\[ a_m = \frac{\Delta T_{max,m} - \Delta T_{min,m}}{(T_{max,m} - T_{min,m})/m} \]

where \( \Delta T_{max,m} \) and \( \Delta T_{min,m} \) are the monthly mean changes in daily maximum temperature and minimum temperature, which can be obtained from HadCM3. \( T_{max,m} \) and \( T_{min,m} \) are the monthly mean values in daily maximum temperature and minimum temperature, °C. In morphing method, the wind direction is unchanged in future conditions.

From Eqs. (1) ~ (5), it can be found that the existing weather data is required to generate the future weather data. Since the case study building is in Montreal, the typical meteorological year (TMY) data of Montreal, which is compiled from historical data from 1998 to 2014 and called CWEC 2016, are used as the existing weather data. In terms of CO₂ emission of HadCM3, two different scenarios (A1FI and A2) and periods (2050s and 2080s)

<table>
<thead>
<tr>
<th>Cases</th>
<th>Specific fan power (kW/m²/s)</th>
<th>Nominal ventilation rate (ACH)</th>
<th>MVC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>3.76</td>
<td>0.7</td>
<td>No</td>
</tr>
<tr>
<td>Baseline-EF</td>
<td>0.86</td>
<td>0.7</td>
<td>No</td>
</tr>
<tr>
<td>VC 1</td>
<td>0.86</td>
<td>1.1</td>
<td>Yes</td>
</tr>
<tr>
<td>VC 2</td>
<td>0.86</td>
<td>2.2</td>
<td>Yes</td>
</tr>
<tr>
<td>VC 3</td>
<td>0.86</td>
<td>4.3</td>
<td>Yes</td>
</tr>
<tr>
<td>VC 4</td>
<td>0.86</td>
<td>7.2</td>
<td>Yes</td>
</tr>
</tbody>
</table>
are considered. The weather scenarios are summarized in Table 2. A1FI refers to a future world with rapid development and high CO₂ emission, and A2 is a future world with mild CO₂ emission.

Table 2: Weather scenarios.

<table>
<thead>
<tr>
<th>Weather scenarios</th>
<th>CO₂ emission scenarios</th>
<th>Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMY</td>
<td>/</td>
<td>Historical: 1998~2014</td>
</tr>
<tr>
<td>50s A2</td>
<td>A2</td>
<td>Future: 2040~2069</td>
</tr>
<tr>
<td>50s A1FI</td>
<td>A1FI</td>
<td>Future: 2040~2069</td>
</tr>
<tr>
<td>80s A2</td>
<td>A2</td>
<td>Future: 2070-2099</td>
</tr>
<tr>
<td>80s A1FI</td>
<td>A1FI</td>
<td>Future: 2070-2099</td>
</tr>
</tbody>
</table>

The morphing method with HadCM3 to predict future weather conditions is widely used in building energy simulation (Berardi & Jafarpur, 2020; Shen & Lukes, 2015). With this morphing method, Wang and Chen generated future weather data for 15 cities in the U.S and proved that the predicted dry bulb temperature and dew point temperature are acceptable for building energy prediction (H. Wang & Chen, 2014). Considering that this study focuses on the MVC instead of natural VC, the weather conditions other than temperature and humidity can influence the energy performance of MVC slightly. For example, wind speed can only influence building thermal conditions rather than influencing the operation of MVC directly. It is generally believed that the influences of wind on building cooling load are relatively insignificant (Guan, 2009). Therefore, the predicted future weather conditions can be reasonable for investigating the energy performance of MVC.

Machine ventilative cooling model

To predict the energy performance of MVC, this study builds a hybrid model that combines a machine learning model and energy models.

The machine learning model is a kind of data-driven model. The establishment of machine learning models to predict building cooling load is less complex than that of physics-based models but still accurate, which gets more and more concerns in recent years (Amasyali & El-Gohary, 2018). However, there is no agreement on the best machine learning techniques (Fan, Xiao, & Wang, 2014; Z. Wang, Hong, & Piette, 2020). Therefore, to have an accurate model, this study selects five different machine learning algorithms and compare their prediction performance. The five machine learning algorithms are linear regression, ridge regression, elastic net (ELN), support vector machine regression (SVR), and multilayer perceptron (MLP). These machine learning techniques can be found in the Python library, Scikit-Learn (Pedregosa, Weiss, & Brucher, 2011). The key settings are shown in Table 3. These settings are selected based on the references, and the other settings of the machine learning methods are in default value (Kusiak, Li, & Tang, 2010; Pedregosa et al., 2011). From the results in Table 4, it can be found that many machine learning methods with these settings satisfy the accuracy of the requirement of ASHRAE guideline-14, which means that these settings are acceptable for these machine learning methods.

Table 3: Settings of machine learning techniques

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear regression</td>
<td>No adjustable setting</td>
</tr>
<tr>
<td>Ridge regression</td>
<td>alpha=1.0</td>
</tr>
<tr>
<td>ELN</td>
<td>alpha=1.0; l1 ratio=0.5</td>
</tr>
<tr>
<td>SVR</td>
<td>kernel=rbf; C=1.0; epsilon=0.1</td>
</tr>
<tr>
<td>MLP</td>
<td>Hidden layers = 3; Neurons = 100; Max iteration=15000</td>
</tr>
</tbody>
</table>

The machine learning model predicts the building cooling load based on the inputs. Besides the weather conditions (see section weather scenarios), the internal heat gain also influence the building cooling load significantly, which should be the inputs of the machine learning model. Therefore, the time variables and fresh airflow rates (reflect the number of occupancies) are used as inputs to reflect the effects of the internal heat gain (Fan, Xiao, & Zhao, 2017; Nassif, 2012). The time variables include year, month, day, hour, minute, and weekday. In summary, the inputs for machine learning models are outdoor dry-bulb temperature, outdoor relative humidity, wind speed, wind direction, solar radiation, and time variables.

To generate and evaluate the machine learning models, the data from April to October 2019 collected from the BAS system of case study building and city weather station are used. The data collected from the BAS system include the outdoor temperature, relative humidity, fresh air flow rate, and building cooling load, which have three different time intervals six minutes, half-hour, and one hour. The data from the weather station are in one-hour interval, including solar radiation, wind speed, and wind direction. To get an accurate prediction, the machine learning models are tested by three different time intervals respectively. The data from April to August are used to build the machine learning models, and the data of September and October are used to make a comparison and validation. To enhance the reliability of the training, only the record data sets when the chiller system was operating for cooling remain, and other data sets are removed. The outliers of building cooling load were also detected and removed by the interquartile range rule.

Energy models are used to predict the energy consumption of the chiller system and mechanical ventilation system. The models can simulate the cooling capacity of VC and the power of chillers ($P_{CH}$), cooling towers ($P_{CT}$), pumps ($P_P$), and fans ($P_F$), which are based on thermal dynamics and correlation. Through multiplying the power by time, the energy consumption can be obtained. To avoid duplication, the details can be found in our previous study (Sha & Qi, 2020b). The validation of the hybrid model is presented in the result section.

Optimal control for MVC

To achieve the MVC, the cost function to minimize the energy consumption can be

$$J = \min \{ P_{total} \} = \min \{ P_{CH} + P_P + P_F + P_{CT} \} \quad \text{(6)}$$

Proceedings of the 17th IBPSA Conference
Bruges, Belgium, Sept. 1-3, 2021

https://doi.org/10.26868/25222708.2021.30234
where \( J \) is the electric power of all the components in the cooling systems multiplying by the unit of time. In Eq. (6), the total energy consumption, \( P_{\text{total}} \), can be converted to a function that only relates to the supplied fresh airflow rate, \( V_a \), with multiple constraints.

The multiple constraints are:

\[
\begin{align*}
V_{IAQ} & \leq V_a \leq V_{\text{nom}} \\
Q_{c,\text{min}} \cdot Z & \leq Q_c \cdot Z \leq Q_{c,\text{nom}} \\
T_{oa,\text{min}} & \leq T_{oa} \leq T_{oa,\text{max}} \\
W_{oa} & \leq W_{oa,\text{max}}
\end{align*}
\]

where \( V_{\text{nom}} \) and \( V_{IAQ} \) are the nominal fresh airflow rate of the MVC and the minimum fresh airflow rate to maintain IAQ, \( m^3/s \); \( Q_{c,\text{nom}} \) and \( Q_{c,\text{min}} \) are the maximum and minimum cooling capacity of chillers, \( kW \); \( Z \) represents the chiller operating state (\( Z = 1 \): chiller start-up; \( Z = 0 \): chiller stop). \( T_{oa,\text{min}}, T_{oa,\text{max}} \), and \( W_{oa,\text{max}} \) are the temperature and humidity ratio setpoints to ensure that the control strategy fulfills the thermal comfort, which means that the VC control strategy can only be applied when the outdoor air temperature and humidity ratio are within the constraints. In the case study, the temperature setpoints \( T_{oa,\text{min}} \) and \( T_{oa,\text{max}} \) for VC are set as 15°C and 23°C because of the practical operation. The humidity ratio setpoint is set as 11.6 g/kg\(_{\text{sat}}\), which aims to satisfy the thermal comfort requirement (Yuan, Vallianos, Athienitis, & Rao, 2018). The more details can be found in our previous study (Sha & Qi, 2020b).

**Results and discussion**

**Future weather data**

Four future weather scenarios (50s A2, 50s A1FI, 80s A2, and 80s A1FI) were generated based on the TMY of the case study. To evaluate the influence of climate change, the MVC hours are defined as the number of hours when MVC is available (i.e. outdoor temperature is within 15~23°C and outdoor humidity ratio is lower than 11.6 g/kg\(_{\text{sat}}\)). Figure 1 presents the variation of annual MVC hours and monthly MVC hours.

The results of Figure 1 (a) indicate that the annual MVC hours decrease in the future. From TMY to the 80s A1FI, the MVC hours drop around 30% from 1693 to 1211 hours. Figure 1 (b) further shows the details of the change of MVC hours. Under a warming climate, the MVC hours decrease from June to September (summer time), but increase during the shoulder seasons, March ~ May and October ~ November. It can be found that the weather scenario 80s A1FI has the largest change. The MVC hours in summertime decrease from 1243 hours to 382 hours, while the MVC hour in the shoulder season increase from 450 hours to 829 hours.

**Validation of hybrid model**

In this section, the comparison between different machine learning techniques is firstly presented, and then the energy simulation based on the selected machine learning model and energy models, i.e. the whole hybrid model, is presented.

Table 4 presents the Coefficient of Variation of Root Mean Square Error, CV(RMSE), of five machine learning models trained by three time intervals. The ASHRAE guideline specifies that if the prediction CV(RMSE) is below 30% hourly, the prediction accuracy of a model is acceptable. To make the comparison, the results of the models of six mins and half hour intervals are converted to hourly results.

It can be found that the prediction accuracy of the MLP with six mins interval is most accurate, which has CV(RMSE) of 15.5% and is selected as the machine learning model used for building cooling load prediction. It is worthwhile to point out that the other machine learning models perform well. Except SVR trained by the one-hour interval data, all the rest models satisfy the requirement of the ASHRAE guideline.

**Table 4: CV (RMSE) of machine learning models.**

<table>
<thead>
<tr>
<th>Time interval</th>
<th>MLP</th>
<th>ELN</th>
<th>Linear</th>
<th>Ridge</th>
<th>SVR</th>
</tr>
</thead>
<tbody>
<tr>
<td>One hour</td>
<td>19.6%</td>
<td>20.3%</td>
<td>20.6%</td>
<td>20.6%</td>
<td>31.5%</td>
</tr>
<tr>
<td>Half hour</td>
<td>19.4%</td>
<td>19.8%</td>
<td>20.0%</td>
<td>20.0%</td>
<td>27.1%</td>
</tr>
</tbody>
</table>
Figure 2 compares the predicted and measured cooling energy consumption based on the hybrid model (i.e., cooling load predicted by the MLP model, cooling energy consumption predicted by the energy models) in September and October of 2019. For most of the time (89%), the differences are less than 25%. CV(RMSE) of the cooling energy consumption prediction is also evaluated, which is 12.5% and satisfies ASHRAE guideline, i.e., 30% hourly. Therefore, the hybrid model that combines the machine learning model and the energy models is validated.

**Future MVC energy performance**

With the future weather data and validated hybrid model, the future energy performance of MVC is investigated. Figure 3 shows the building cooling load prediction from March to November when the outdoor air temperature is higher than 15 °C (the operating period of the cooling system of the case study). As shown in Figure 3, the building cooling load will increase due to global warming. The 80s A1FI has the largest growth of building cooling load. The increase of cooling load during the shoulder season is higher than during the summer season. For example, compared with TMY, the cooling load in the shoulder season of 80s A1FI increase 531 MWh (around 18%) whereas the cooling load in the summertime of 80s A1FI increase around 331 MWh (around 144%).

Table 5 shows the annual cooling energy consumption of six different cases under five weather scenarios. It can be found that the annual cooling energy consumption of baseline increases significantly, which increases from 601 MWh in TMY to 1070 MWh in 80s A1FI because the annual cooling load increases as seen in Figure 3. The largest energy saving of MVC increases. The largest energy saving of MVC in TMY is 187 MWh, but it is 204 MWh in 80s A1FI. Although the amount of the energy savings of MVC increase, the energy saving rates decrease due to the increase of baseline cooling energy consumption. The largest energy saving rate of MVC in TMY is 31%, but it is 19% in 80s A1FI.

Furthermore, it can be found that the optimal nominal fan rates can be changed under future weather scenarios. In TMY, the optimal nominal fan flow rate is 4.3 ACH in case VC 3. When the nominal fan flow rate increases from 4.3 (VC3) to 7.2 ACH (VC4), the energy saving of MVC does not increase. However, in 80s A1FI, the optimal nominal fan flow rate can be 2.2 ACH in VC 2. When the nominal fan flow rate increases from 2.2 (VC2) to 4.3 ACH (VC3), the cooling energy consumption only reduce 6 MWh, which is relatively small. Therefore, when designing the MVC system, the influences of climate change must be considered to balance the nominal ventilation rate and energy savings of MVC.

**Table 5: Annual cooling energy consumption, MWh**

<table>
<thead>
<tr>
<th>Cases</th>
<th>TMY</th>
<th>50s A2</th>
<th>50s A1FI</th>
<th>80s A2</th>
<th>80s A1FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>601</td>
<td>789</td>
<td>856</td>
<td>936</td>
<td>1070</td>
</tr>
<tr>
<td>Baseline-EF</td>
<td>475</td>
<td>641</td>
<td>702</td>
<td>776</td>
<td>901</td>
</tr>
<tr>
<td>VC 1</td>
<td>452</td>
<td>622</td>
<td>685</td>
<td>759</td>
<td>885</td>
</tr>
<tr>
<td>VC 2</td>
<td>427</td>
<td>603</td>
<td>668</td>
<td>744</td>
<td>872</td>
</tr>
<tr>
<td>VC 3</td>
<td>415</td>
<td>595</td>
<td>660</td>
<td>737</td>
<td>866</td>
</tr>
<tr>
<td>VC 4</td>
<td>415</td>
<td>594</td>
<td>660</td>
<td>737</td>
<td>866</td>
</tr>
</tbody>
</table>

From Table 5, it can be found that MVC has the best energy performance (i.e., reduction in energy consumption) in TMY but has the worst energy performance in 80s A1FI. Therefore, to show the details of MVC energy savings, Figure 4 present the monthly energy savings of MVC. From Figure 4 (a), the energy savings mainly concentrate on the summertime from June to September, which can achieve 147 MWh (VC3) in total. However, in 80s A1FI, the energy savings decrease...
during summertime but increase during the shoulder seasons. The highest energy saving (achieved by VC3) during summertime reduces to 122 MWh. The highest energy saving during the shoulder season in 80s A1FI reaches 82 MWh, increasing from 40 MWh in TMY. The change of energy savings of MVC matches the change of MVC hours (see Figure 1 (b)).

Therefore, the use of MVC can mitigate climate change and it is suggested to apply the MVC in the high-rise buildings.

2. Under a warming climate, the total amount of energy savings of MVC increases slightly but the energy saving rates decrease due to the higher baseline cooling energy consumption. It can be found that the energy savings of MVC increase during shoulder seasons (i.e. March ~ May and October ~ November), but the energy savings drop from June to September.

3. Under a warming climate, the optimal nominal ventilation rates for MVC will vary. In the case study, under the TMY, the optimal nominal ventilation rate is 4.3 ACH. However, under the 2080s A1FI weather scenario, the optimal nominal ventilation rate reduces to 2.2 ACH. Therefore, when designing the MVC system, the influences of climate change must be considered to balance the nominal ventilation rate and energy savings of MVC.

Acknowledgement
We thank Mr. Michaël Ménard, from the Building Service Department of the Université de Sherbrooke (UdeS), for his support in the case study. This work was supported by the Start-up Fund of the UdeS and Discovery Grants of Natural Sciences and Engineering Research Council of Canada (NSERC) (Grant number: RGPIN-2019-05824).

References
Environment, 122, 386–396.


IPCC. (2001). Climate change 2001: the scientific basis. https://doi.org/10.1016/S1058-2746(02)86826-4


