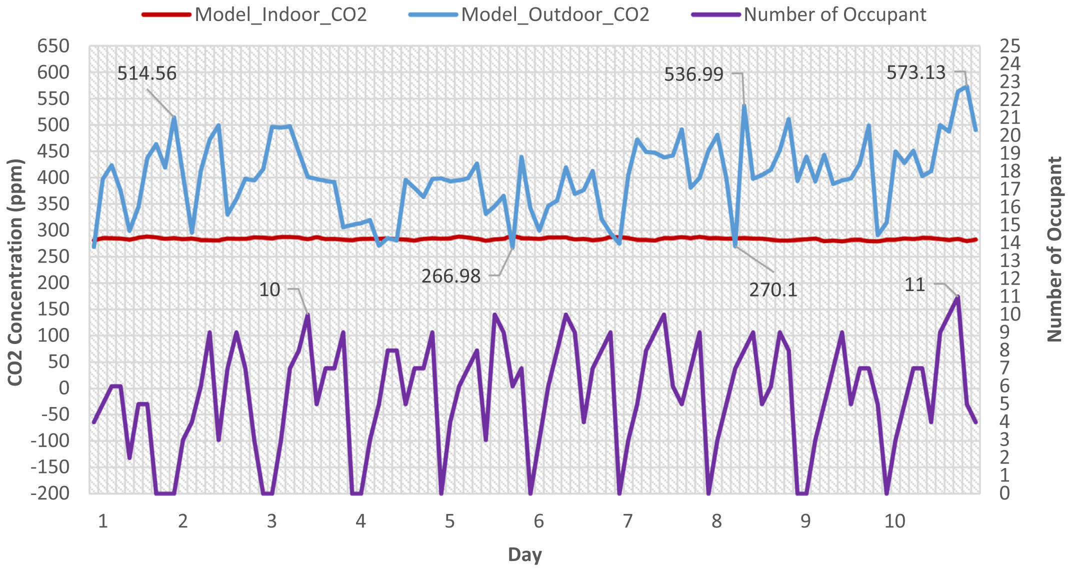

Fig. 7. Stochastic nature of occupants with indoor and outdoor CO_2 concentration (ppm).

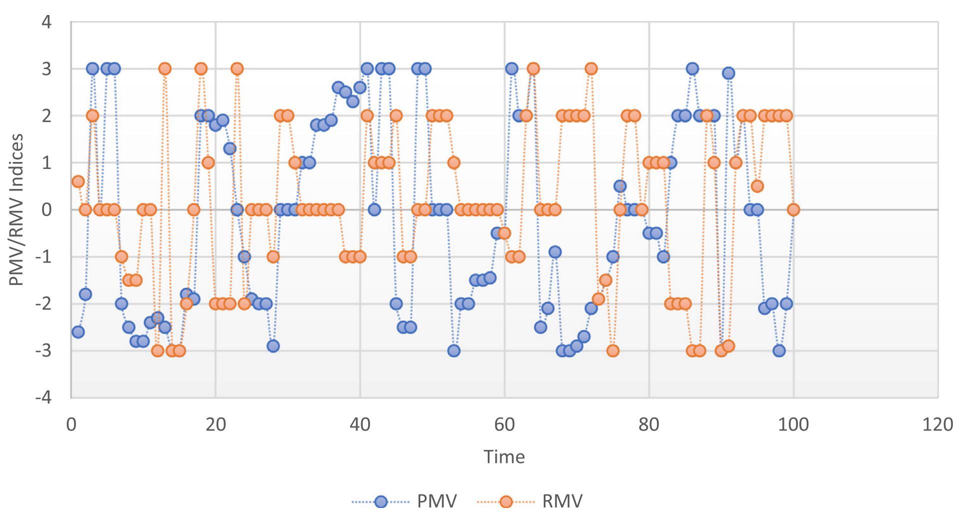

Fig. 8. Model-predicted PMV indices and occupant-reported RMV indices.

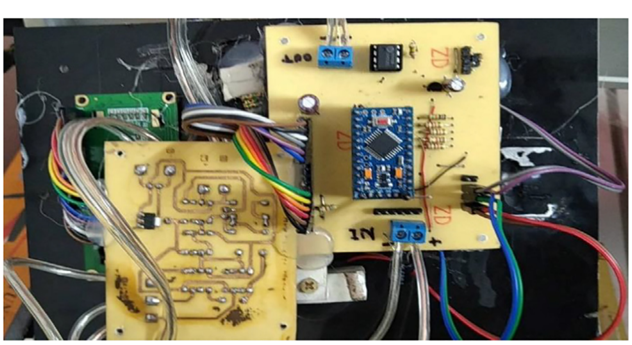

Fig. 9. Customized sensor panel.

also observed from these particular studies [56,61,62] as well. Naramura's [61] study revealed that the influence on the curve of indoor temperature trend is about 0.24 °C/5 min in the predictive model and about 0.28 °C/5 min in the calculated results. Also, in Smith et al. [62], the predictive model error was within ± 2 ○F (±1.11○C) of ground truth.

Some possible reasons for this error or discrepancy include the random door operations, a computer or other electronic device turns on for a longer period of time, and window or blind operation with the constant alternation of opening or closing during the experiment. Also, the model did not consider any heat loss/heat gain or infiltration issues during the simulation process. On the other hand, it has been observed that the proposed model offered an acceptable range of RMSE (2.73%) and MBE (-2.28%) for indoor temperature evaluation as compared with other previous studies [63,64]. Hence, the computational effects of the integrated framework may be regarded as correct as no additional calibration is required. Turning to the assessment of outdoor temperature, there was a very slight difference between the model- and sensor-estimated outdoor temperatures as the model employed atmospheric data from the local weather station. The model-estimated maximum and minimum outdoor temperatures were 29.87 °C and 25.5 °C respectively whereas the sensor-estimated maximum and minimum outdoor temperatures were 28.20 °C and 25 °C correspondingly. It is also noted that the RMSE and MBE values for outdoor temperature were 1.20% and 0.45% respectively which lie within an acceptable limit.

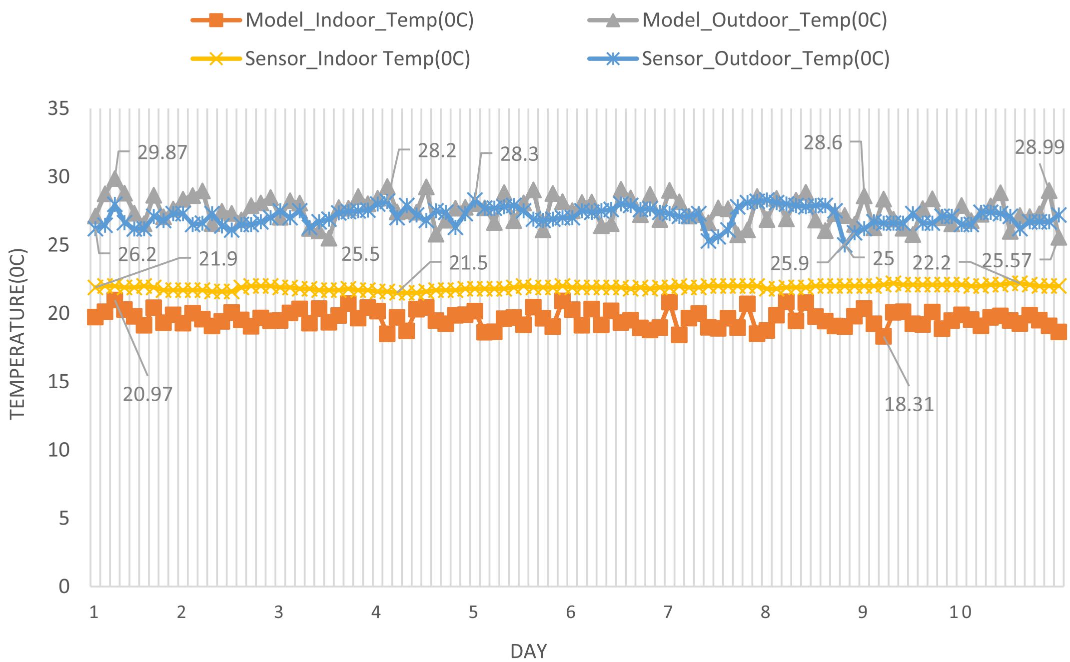

Fig. 10. Model-predicted and sensor-calculated indoor and outdoor temperatures (^{0}C).

5.3. Model- and sensor-estimated CO_2 data

Fig. 11 shows the indoor and outdoor CO_2 variations for the simulated model and the real data obtained from the CO_2 sensor. The results show that the simulated model slightly underestimated both the indoor and outdoor CO_2 level. The maximum and minimum simulated outdoor CO_2 concentrations for this study were 514.56 ppm and 266.98 ppm respectively while sensor-estimated maximum and minimum outdoor CO_2 were 580 ppm and 255 ppm, correspondingly. However, there is a significant gap between the simulated and sensor-estimated indoor CO_2 concentration data. Sensor-estimated indoor CO_2 data provided a higher level of variation (for June3rd, June4th, June 8th, and June9th) than model-estimated indoor CO_2 level. A study [65] also showed a similar discrepancy of hourly CO_2 value for three monitored rooms (i.e., office 1, office 2, and library room) in Singapore. Nesibe et al. [66] also found a similar gap between the measured and predicted CO_2 concentration while ignoring the occupants (i.e., students). However, here the stochastic nature of occupant presence, and indoor and outdoor CO_2 level during the HVAC operation were derived from both the model and experimental records. Turning to RMSE and MBE checking, the outdoor CO_2 level (RMSE: 25.94%, MBE:10.01%) was more significantly deviated than indoor CO_2 level (RMSE: 19.22%, MBE: −9.47%). However, in all cases,

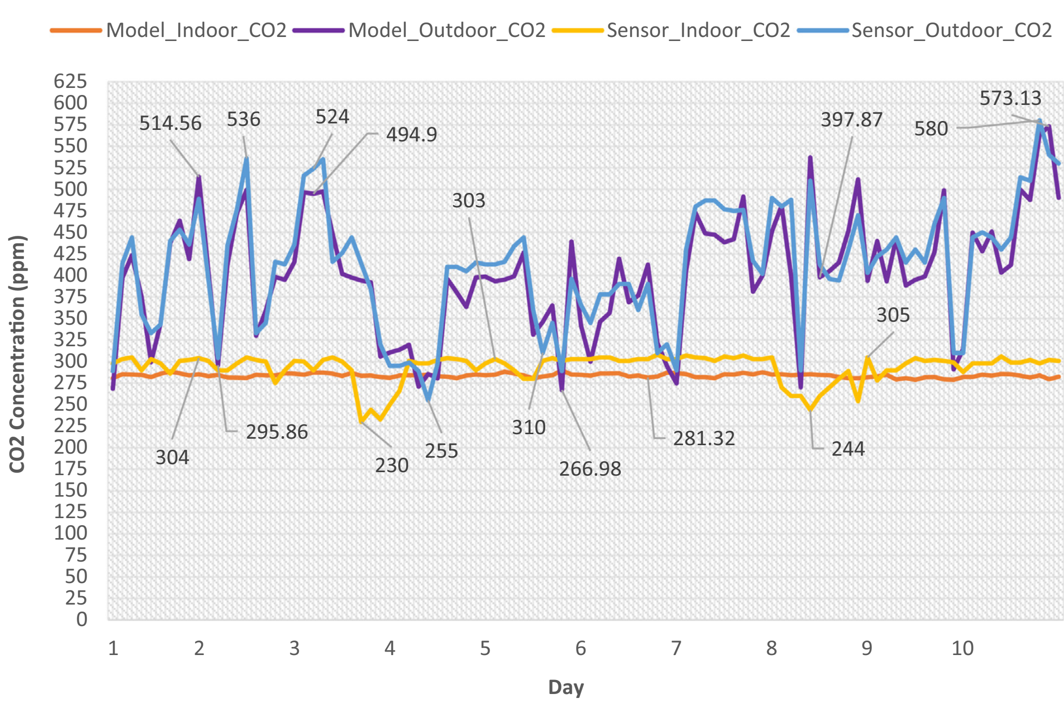

Fig. 11. Model-predicted and sensor-calculated indoor and outdoor CO_2 (ppm).

CV(RMSE) and MBE values lay within the acceptable range. This study [67] also has shown a higher value of CV(RMSE) and MBE for an office building model located in Turkey. Several factors may be involved in this issue, for instance, Hong Kong is a hot-humid climatic zone, and there was a sudden change in the weather conditions during the experiment, i.e., sudden rain, clouds outside of the room, the office occupants may still keep the window open even though the indoor environment is only a little comfortable, or highly stochastic movement of occupants in the office space. Similarly, blinds operation and the control of doors are also influenced by environmental factors. So, further model improvement may require the resolution of these issues.

6. Conclusions and future work

This study proposes a combined framework to integrate building indoor performance and human comfort simulation with the help of emerging BIM and SD-ABM models. The demonstrative example presented a new modeling framework in the field of building occupant study. The case study model along with the validation and reliability test were implemented in a realistic educational office building to represent the applicability and robustness of the framework. The proposed framework allows the estimation of several key parameters, namely occupant presence and comfort level in terms of PMV indices, indoor/outdoor temperature, and CO_2 concentration. Although some major to minor variations occurred between the observed and modeled data, most of the data fell within the calibration tolerance (i.e., RMSE and MBE) limit defined by ASHRAE Guideline 14–2002 and FEMP standards. Thus, the research aim was satisfied by establishing a hybrid framework and evaluating the realistic profile as well as analyzing building performance in depth. The outcomes established that the preferred parameters could be suitably determined and accomplished in other building spaces as well. The study also presents a more precise dynamic building indoor performance and occupant comfort transformation between the BIM and SD-ABM which significantly improved the conventional BPS-based modeling. Furthermore, it enables building geometry development in the simulation framework and helps engineers, researchers, and policymakers to improve building design. However, a limitation of the study was the fact that due to procedural constraints, only hourly environmental data could be obtained. So, it is appropriate to assume that a higher sampling frequency of data will produce more comprehensive output. Moreover, in order to improve the model's accuracy and efficiency, further inclusive and diverse real-world building projects are required. So, future study will expand the framework (additional behavioral rules will be recognized and added to the framework) with test cases to cover other building models, including occupants and their adaptive behavior as well.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table A1
Agent-Based Modeling (ABM).

```
@Override
public void executeActionOf( TransitionCondition
self ) {
  if ( self == Occupant_Enter ) {
   exitState( State_Normal, self, true );
     enterState( Office_Temp_Rise, true );
   return;
  }
  if ( self == Occupant_Leave ) {
   exitState( Office_Temp_Rise, self, true );
     enterState( Office_Temp_Decrease, true );
   return;
  }
  if ( self == Return_To_Busy_State ) {
   exitState( Office_Temp_Decrease, self, true );
     enterState( Office_Temp_Rise, true );
   return;
  }
  if ( self == Transition_normal ) {
   exitState( Office_Temp_Decrease, self, true );
   {
Outdoor_Temp = Max_Indoor_Temp
;}
     enterState( State_Normal, true );
   return;
  }
  if ( self == Return_To_Normal_State ) {
   exitState( Office_Temp_Rise, self, true );
   {
Outdoor_Temp = Max_Indoor_Temp
;}
     enterState( State_Normal, true );
   return;
  }
  super.executeActionOf( self );
 }
```

```
@Override
 public boolean
testConditionOf( TransitionCondition _t ) {
  if ( _t == Occupant_Enter ) return
PMV_Value>1
;
  if ( _t == Occupant_Leave ) return
PMV_Value<1
;
  if ( _t == Return_To_Busy_State ) return
PMV_Value>1
;
  if ( _t == Transition_normal ) return
PMV_Value>=0
;
  if ( _t == Return_To_Normal_State ) return
PMV_Value>=0
;
  return super.testConditionOf( _t );
 }
```

Table A2
System Dynamics (SD).

<table>
<tr><th>Static Variable</th><th>Dynamic Variable</th></tr>
<tr><td>@Override
public boolean setParameter(String _name_xjal, Object _value_xjal, boolean _callOnChange_xjal) {
switch (_name_xjal) {
case "Ambient_Temp":
if (_callOnChange_xjal) {
set_Ambient_Temp(((Number) _value_xjal).doubleValue());
} else {
Ambient_Temp = ((Number) _value_xjal).doubleValue();
}
return true;
case "Infiltration_Tight":
if (_callOnChange_xjal) {
set_Infiltration_Tight(((Number) _value_xjal).doubleValue());
} else {
Infiltration_Tight = ((Number) _value_xjal).doubleValue();
}
return true;
case "Respiratory_quotient":
if (_callOnChange_xjal) {
set_Respiratory_quotient(((Number) _value_xjal).doubleValue());
} else {
Respiratory_quotient = ((Number) _value_xjal).doubleValue();
}
return true;
case "Wall_Area":
if (_callOnChange_xjal) {
set_Wall_Area(((Number) _value_xjal).doubleValue());
} else {
Wall_Area = ((Number) _value_xjal).doubleValue();
}
return true;
case "Metabolic_for_single":
if (_callOnChange_xjal) {
set_Metabolic_for_single(((Number) _value_xjal).doubleValue());
} else {
Metabolic_for_single = ((Number) _value_xjal).doubleValue();
}
return true;
case "Floor_Characteristics_fs":
if (_callOnChange_xjal) {
set_Floor_Characteristics_fs(((Number) _value_xjal).doubleValue());
} else {
Floor_Characteristics_fs = ((Number) _value_xjal).doubleValue();</td><td>// Dynamic (Flow/Auxiliary/Stock) Variables
public double Outdoor_Temp;
public double Max_Indoor_Temp;
public double Indoor_CO$_2$;
public double Environmental_CO$_2$;
public double Building_Characteristics;
public double Surface_Charactersitics;
public double Min_Outdoor_Temp;
public double Max_Outdoor_Temp;
public double PMV_Value;
public double Max_CO$_2$;
public double Min_CO$_2$;
public double V_O$_2$_Consumption;
public double DuBois_surface_area_AD;
public double Total_Metabolic_rate;
public double Cooling;
public double Room_Surface_Temp;
public double Room_Static_CO$_2$;</td></tr>
</table>