London School Building Stock Model for Cognitive Performance Assessment

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Abstract

Climate change is one of the biggest challenges facing humankind in the 21st century. In the building sector, a warming climate will significantly alter building occupant health, comfort and wellbeing. School buildings in the UK, in particular, might face additional challenges, such as indoor overheating risks due to high internal gains in classrooms, and their current reliance on natural ventilation, which might offer limited cooling capacity in the future, while simulation and assessment of students' exposure to built environment is limited.

This paper presents a methodological framework for modelling cognitive performance of students at population level and applies the framework in the case of London secondary schools to calculate and evaluate students' cognitive performance level under different climate scenarios. The aim of the present study is to explore the applicability of this framework on investigating the impacts of ongoing and future climate change on schoolchildren's cognitive performance levels.

Using the PDSP (Property Data Survey Programme) dataset and a basic set of school building archetypes for London, a set of archetype models was developed. Weather files based on existing Test Reference Years (TRY) incorporating the UK Climate Projections 2009 scenarios were used for EnergyPlus dynamic simulation. It was found that outdoor temperature, building geometry and ventilation rates can function as reliable predictors of students' cognitive performance. Future work will include a sensitivity analysis aiming to identify the relative importance of these factors as part of ongoing research.

Introduction

Climate change is a major challenge facing humankind in the 21st century, and it might have adverse impacts on buildings and occupants in the built environment sector.

People spend almost 90% of their time indoors (Vardoulakis et al., 2015), and their health and performance inside buildings are significantly affected by indoor environmental conditions (Wargocki & Wyon, 2017), which are driven by outdoor climatic conditions (Fisk, 2015). Thus, it is crucial to promote human health, comfort and performance in the built environment in the context of climate change (de Wilde & Coley, 2012). In particular, attention should be paid to primary and secondary schools due to the additional challenges facing school environments: Children's bodies are still immature, and they are more vulnerable to a range of indoor environmental exposures compared to adults (Chatzidiakou, Mumovic, & Summerfield, 2012). Classrooms typically have high occupancy density, which could results in high internal heat gains, high carbon dioxide (CO_2) levels, emissions of body odours and a wide range of indoor air pollutants. These may have negative consequences on children's health and learning performance. Furthermore, maintaining adequate thermal comfort in UK schools could become increasingly challenging in the future warming climate, as they traditionally rely on natural ventilation rather than active cooling systems (Jenkins, Peacock, & Banfill, 2009). The needs to optimise classroom indoor environments have been highlighted in several studies (Chatzidiakou et al., 2012; Jenkins et al., 2009; Montazami, Gaterell, & Nicol, 2015).

This study will focus on cognitive performance of students' in schools because school is the main place where student gain knowledge and develop skills. Cognitive performance reflects the ability of an individual to undertake different mental tasks; there is evidence that indoor thermal conditions affect cognitive performance in schools (Mumovic, Chatzidiakou, & Ahmed, 2018). To avoid cognitive performance to be impaired, careful consideration of current and future school building performance is essential (Montazami et al., 2015). Existing studies have suggested cognitive performance is strongly related to indoor temperature (Haverinen-Shaughnessy & Shaughnessy, 2015; Wargocki, Porras-Salazar, & Contreras-Espinoza, 2019; Wargocki & Wyon, 2007) or ventilation rate (Haverinen-Shaughnessy & Shaughnessy, 2015; Wargocki, Porras-Salazar, Contreras-Espinoza, & Bahnfleth, 2020) by experimental or field studies. However, in assisting educators and policymakers to develop evidence-based policy and best practice guidance for the improvement of classroom environments, modelling cognitive performance under a wide range of weather and operation scenarios is necessary, especially in the context of ongoing and future climate change.

When informing policymakers in the built environment, decisions should consider the total number of buildings in a region or country. This study is, therefore, aimed at the population level, and the effects of classroom thermal conditions on cognitive performance is analysed at the building stock level. Previous building stock modelling studies have mainly focused on energy consumption and associated CO_2 emissions , while building stock models with a focus on indoor environment and occupants' comfort and performance are still limited. To the knowledge of the authors, no building stock modelling studies currently exist that predict the impacts of climate change on students' cognitive performance in classrooms. A school building stock indoor environment modelling framework for London is presented in this paper in order to quantify the effects of ongoing and future climate change on schoolchildren's cognitive performance levels.

Methodology

Currently, three main building stock energy modelling approaches exist: top-down, bottom-up and hybrid (Kavgic et al., 2010; Swan & Ugursal, 2009). This study has adopted a bottom-up engineering approach, which uses building property data and thermodynamic principles to calculate indoor air temperature. A set of school building archetypes were developed and defined as representative buildings of the whole London stock. These archetypes were subsequently modelled using EnergyPlus - a dynamic thermal simulation tool, and the simulation results were used to calculate students' cognitive performance, as described in Figure 1.

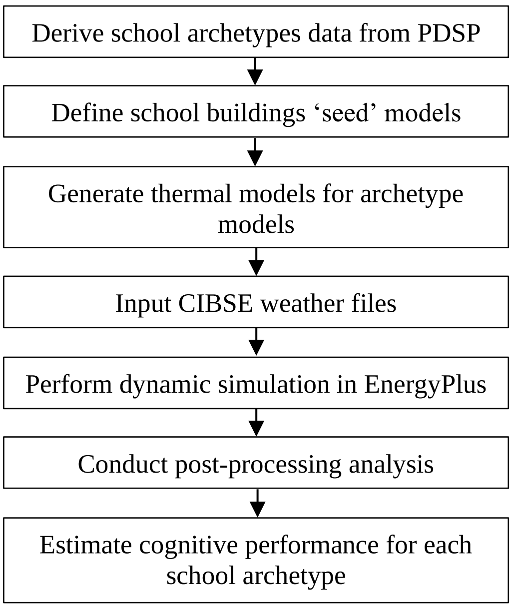


Figure 1 The workflow of schoolchidren's cognitive performance modelling

School Building Archetype Development

The archetypes in this study were derived through a statistical analysis of the Property Data Survey Program (PDSP) database, commissioned by the Department for Education (DfE). PDSP's original aim is to collect up-to-date information on the physical conditions of education estates across the UK for maintenance and upkeeping purposes. The PDSP database includes information for more than 18,000 establishments across the country, including primary schools and secondary schools, but also nurseries and special institutions. The database holds purely descriptive data and generic information on the physical properties of each school in the UK. These, however, include some parameters that could be useful for modelling and simulation purposes, e.g.: the number of buildings in each school's premises, the assumed construction age of each school building, the buildings' footprint area, the number of stories, Window-to-Wall Ratio (WWR) etc. The database lacks, however, detailed geometrical descriptions for each building in the stock.

The PDSP database was firstly studied and analysed carefully, to identify shared schools' properties that would enable the generation of 'Archetype' models. Following data processing from the PDSP database, schools were divided into groups based on their built era, namely: pre-1919, inter-war, 1945-1966, 1967-1976, post-1976 (Table 1). Mechanically ventilated schools were excluded from this study, as the aim here was examining the performance under the naturally-ventilation scenarios. Next, a statistical analysis was carried out to find the average building properties of schools at each built era (i.e., their average footprint, floor area, WWR, number of floors etc.) (Table 2) . These data points were later used to generate the schools' archetype models.

Table 1 Number of schools represented by each archetype

Pre-1919	**Inter-War**	**From 1945-1966**	**From 1967-1976**	**Post 1976**
140	118	350	158	69

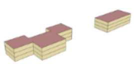
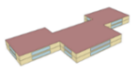
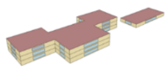
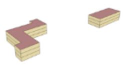
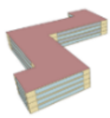
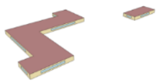
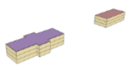
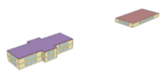
Table 2 Geometric properties of schools at each built era

Arche types	**Average Floor Area (m^2)**	**Average Number of Floors**	**Average Percentage of Windows and Door (%)**
Pre-1919	2548	2	25
Inter-War	3760	2	28
From 1945-1966	5646	2	33
From 1967-1976	8537	2	30
Post 1976	17061	2	55

To generate the archetype's thermal model (EnergyPlus), a series of 'seed' models were defined. These were .idf files that only held basic geometrical building characteristics (as shown in Table 3) and their associated build-ups. The aim of the 'seed' models is to represent the form (shape) of the schools of the different built eras. These were based on (Steadman, 2014)and visual inspection of schools across London. Once the 'seed' models had been established, a computer program was developed to automatically modify their relevant parameters, based on the relevant data that had been extracted from PDSP, e.g., overall floor area, number of floors, WWR etc. (as shown in Table 1).

Each seed model consists of an 'original' building, which is assumed to be the largest building in a school, and an additional building that is an aggregation of the rest of the buildings in the school (in case there are any extensions). Parameters in the seed models are then automatically modified, based on relevant data from PDSP, and 8 archetype models are than generated. The footprint area and WWR of each archetype model are set for the average of the variants it represents.

Table 3 Examples of 'Seed' models and automatically-generated archetype models

	'seed' model	**Automatically -generated archetype models**	
From 1967-1976			
Post 1976			
Pre1919			

Thermal Models

The thermal models were created in EnergyPlus and converted into Input Data Files (IDF). Each floor in the original and additional building was defined as a thermal zone. Construction, material characteristics and internal gains from lighting, equipment and people's activities were determined according the recommended values prescribed in *Building Bulletin 101* (BB101, *Guideline on ventilation, thermal comfort and indoor air quality in schools*) (DfE, 2018) and the *National Calculation Methodology* (NCM) (BRE, 2017). A heating set-point temperature of 20℃ was set, and it was assumed that no active cooling system was installed in any of the modelled buildings. Occupancy schedules were assumed to be 9:00-16:00 every school day which is also suggested in BB101.

Weather Files

TRY weather files are used to represent the external weather conditions for a whole year (CIBSE, 2016). As there are many uncertainties due to climate change, a novel probabilistic approach that can quantify these uncertainties was developed by the UK Climate Impacts Programme (UKCIP) (UKCIP). As the latest projections - Climate Projections 2018 (UKCP18) have not yet been converted into weather files for building simulation, those in UKCP09 were used in this study. UKCP09 provides probability projections for future climates, which can be seen as the relative degree to which each possible climate outcomes are supported by the evidence available, based on our current understanding of climate science and observations, as generated by the UKCP09 method (Murphy et al., 2009). The UKCP09 Weather Generator produces hourly or daily projections in a number of climate variables for seven future overlapping 30-year time periods (from 2020s to 2080s) and under three different carbon emission scenarios (low, middle and high) (Jones, Harpham, Kilsby, Glenis, & Burton, 2010). In addition, the Weather Generator can produce 100 TRYs and rank them according to average monthly temperature from lower to higher, and then the required percentiles (10^{th}, 50^{th}, 90^{th}, etc.) can be selected. 90^{th} percentile weather files, for example, mean there is 90% probability that the external temperatures will be lower than those in the weather files, so 90^{th} percentile represents worst-case scenarios, while 50^{th} represents median-case scenarios and 10^{th} represents best-case scenarios. Considering these three scenarios will allow policy makers to better manage uncertainties and inform risk-based decision-making. The following climate change scenarios were explored in this study for different purposes: a) 2050s medium emissions TRY (10^{th}, 50^{th}, 90^{th} percentile) b) 2080s low, medium and high emissions TRY (10^{th}, 50^{th}, 90^{th} percentile).

Dynamic Simulation

School archetype models were subsequently run in the dynamic simulation engine - EnergyPlus version 8.9 (US DoE, 2018). The whole simulation process was managed by scripts written in Python, which allows for batch mode runs, thus facilitating a large number of simulations in a time effective manner. All simulations were run for the time when the classrooms are occupied throughout a year, and the only output needed for post-processing analysis were indoor temperature.

Post-Processing Analysis

For the purposes of cognitive performance modelling, calculations were performed at an hourly basis. Quantitative relationships were established to link outputs of hourly mean temperature generated by EnergyPlus simulation to cognitive performance. A model quantifying cognitive performance as a function of indoor temperature from a recently published paper was used for this analysis (Wargocki et al., 2019).

Wargocki et al. (2019) summarised the existing literature on the effects of classroom temperature on the performance of schoolwork or of learning outcomes in primary, middle and secondary schools, and then developed a model describing these relationships (Figure 2). Students' performance at 20 ℃ is used as a reference and assumed to be 1, and relative performance at a certain temperature is the measurement of cognitive performance in relation to the performance at the temperature of 20℃.

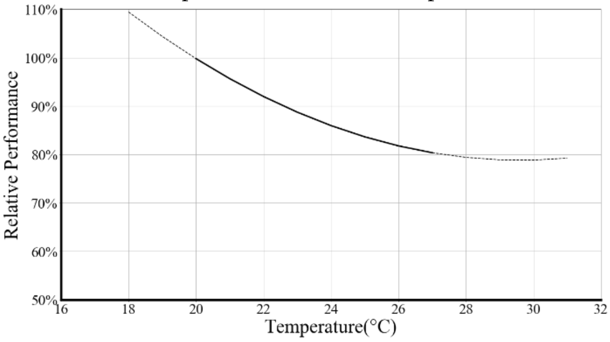


Figure 2 Relationships between indoor temperature and performance. The functions describing relationship between relative performance and temperature is as follows: $y = 0.2269 \cdot t^2 - 13.441 \cdot t + 277.84$, where t is the air temperature.

Considering that indoor temperature in schools could be below 20℃ or above 28℃ in the simulations, the Wargocki et al. model was extrapolated below 20℃ and above 28℃. It is worth noting, however, that additional field data are required in order to confirm the validity of the model outside the range of 20℃ to 28℃ .

Another paper (Wargocki et al., 2020) provides a prediction of the influences of classroom air quality on the performance of students by summarizing the existing data (Figure 3). As ventilation rate is usually used as a proxy for indoor air quality, a model was developed in the paper showing cognitive performance as a function of ventilation rate. The assumptions made in this study could lead to ventilation rate below 2 l/s/person or above 7 l/s/person. Similar to the way that we deal with the relationship out of its valid range in the paper of Wargocki et al. (2019), the function was assumed to be applicable out of the range between 2 l/s/person and 7 l/s/person, so the solid line will be extended from the end at 2 l/s/person and at 7 l/s/person in this study.

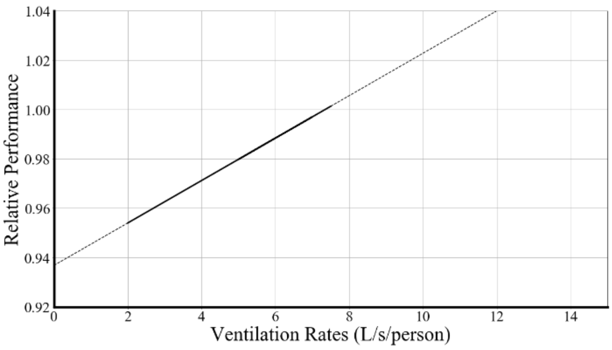


Figure 3 Relationships between ventilation rates and cognitive performance. The functions describing relationship between relative performance and ventilation rate is as follows: $0.0086 \cdot (VR) + 0.9368$, where VR is ventilation rate.

Table 1 Analysis framework of cognitive performance modelling

Analysis	**Methodology**
Impacts of climates	the post-1976 archetype model was chosen to be simulated under different weather files
Impacts of building characteristics	five school archetype models were simulated in 2050s climate scenarios with different ventilation rates imposed
Impacts of building operation (ventilation rates)	An school archetype run at different ventilation rates will be estimated and compared

The assessment framework proposed in this study includes three stages of analysis (Table 3):

1. Investigation of the climate change impacts in different periods and under different carbon emission scenarios on cognitive performance for a specific school archetype. In this case, the post-1976 archetype model was chosen to exemplify the impacts of climate change on London schools. in order to examine the differences in performance driven by various climate scenarios for a certain school.
2. Comparison of the differences in cognitive performance across five school archetype models under a range of weather scenarios. For each archetype, the model with original and additional buildings was simulated.
3. Examination of the impacts on cognitive performance of different ventilation rates for a specific archetype. The post-1976 model was simulated again and the simulations were first run at the ventilation rate of 5 l/s/person as the baseline, and then at 8 l/s/person and 15 l/s/person. The analysis needs to assume the building has constant ventilation regardless of natural ventilation or mechanical ventilation mode, when students are in classrooms. The cognitive performance was calculated by combining the results from Figure 2 and Figure 3. The cognitive performance levels were calculated by using the temperature-performance function from simulated indoor temperature, and then by multiplying the relative performance levels at each ventilation rate found in Figure 3.

Results and Discussion

For simplicity, only the outputs from the largest building of each school (the 'original' building) are evaluated and compared in this section (the 'additional' buildings have been omitted). The results were plotted as cumulative curves illustrating the distribution of percentage of occupied hours during a year across all different cognitive performance levels. In all graphs presented below, for a certain level of cognitive performance (x value), its y value means the percentage of hours when the cognitive performance is below it, so the higher curve suggests that the percentage of hours accumulates more across lower levels of performance and less across the higher levels of performance compared to the lower curve, which suggests student's performance in that school or scenario is not as good as others.

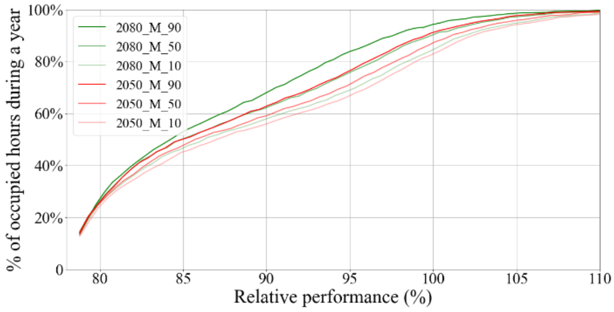


Figure 4 Cumulative distribution of relative performance (2050s and 2080s TRY,10th,50th,90th percentile)

Figure 4 illustrates how cognitive performance is affected in post-1976 schools under medium carbon emissions scenario for different TRY time slices (2050s and 2080s) with different percentiles. For the same time slices (e.g. 2050s), performance levels at 90th percentile have almost 6% more of hours distributed below 95% than 50th percentile and about 12% more than 10th percentile. This can be explained that the average temperature of weather files at 90th percentile (worst-case scenarios) are always higher than those at 50th percentile (median-case scenarios) and 10th percentile (best-case scenarios), so the cognitive performance levels at 90th percentile are correspondingly lower than the other two scenarios.
Additionally, the figure shows that for 2080s TRYs, they generally accumulate more hours below the cognitive performance level of 95% compared to 2050 TRYs. This means that under 2080s weather scenarios, students will have more time performing at the relatively low levels than 2050s weather scenarios. The fact that the average outdoor temperature of the 2080s weather files is predicted to be warmer than 2050s is the reason that cognitive performance levels of the former are generally lower than the latter. From the paper of Wargocki et al. (2019), it is known that students tend to perform worse when temperature gets higher, while these two analyses quantify the extent to which the decrease in future cognitive performance level is due to an increase in outdoor air temperatures.
Figure 5 shows the variations in students' cognitive performance in the post-1976 archetype under 2050 TRYs projected under low, medium, high carbon emission scenarios, while it does not show apparent impacts on students' performance.

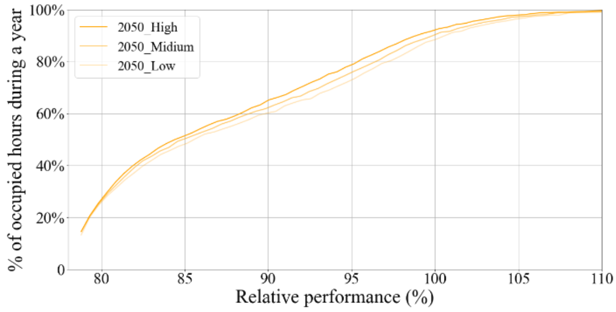


Figure 5 Cumulative distribution of performance (Labels: 2050s_High: TRY weather files with high carbon emission in 2050s ; 2050_Medium: TRY weather files with medium carbon emission in 2050s; 2050_Low: TRY weather files with low carbon emission in 2050s)

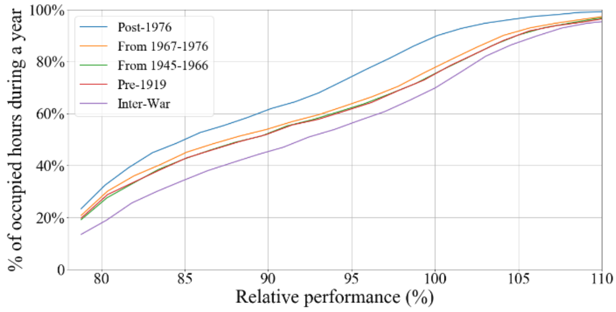


Figure 6 Cumulative distribution of performance across all five archetypes (2050s TRY, medium, 50th percentile)

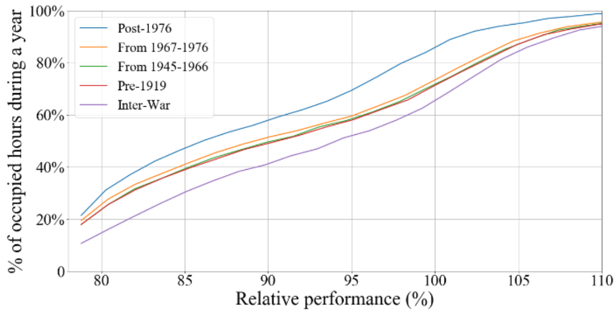


Figure 7 Cumulative distribution of performance across all five archetypes (2050s, medium, 10th percentile)

Only the performance in the original building of each archetype model was investigated when comparing how students' cognitive performance will be affected across all five archetypes for a specific weather scenario (2050s, medium, 50th percentile) (Figure 6). A similar distribution of hours across all archetypes is observed. Cognitive performance levels below 95% accounts for approximately 65% of the occupied hours during a year. Additionally, there are no major differences between performance in different percentiles (Figures 7, 8). However, it is noted that in all given weather scenarios more recent-built buildings have more time when the cognitive performance levels below 95% than older buildings. This can be explained by the fact that the geometric properties of models of Inter-war has the largest surface area-to-volume ratio (it is very compact), , so a lot of surface through which heat escapes in summertime, which maintains the indoor temperature within the ranges for good cognitive performance, while the post-1976 model has the lowest one it has less surface through which heat escapes, and the higher temperature will impair students' performance.

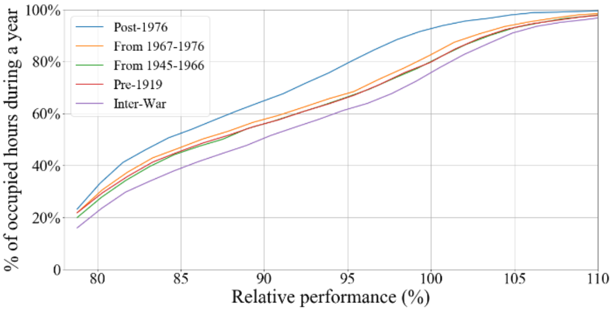


Figure 8 Cumulative distribution of performance across all five archetypes (2050s, medium, 90th percentile)

The analysis above are based on simulation run at baseline ventilation rate (5 l/s/person). Figures 9 and 10 illustrate the impact of ventilation rates of 8l/s/person and 15 l/s/person on cognitive performance across all archetypes. Inter-war schools are the best performing with the shortest time with cognitive performance levels below 95%, showing similar results among all three ventilation rates.

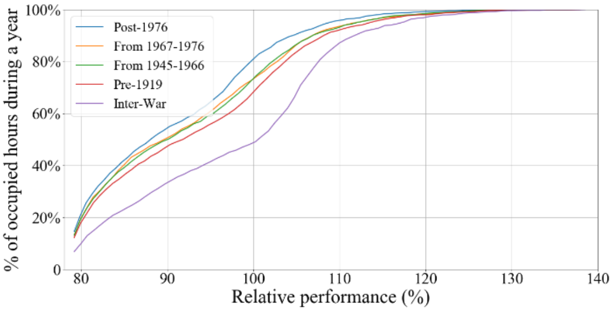


Figure 9 Cumulative distribution of performance across all five archetypes (8 l/s/person)

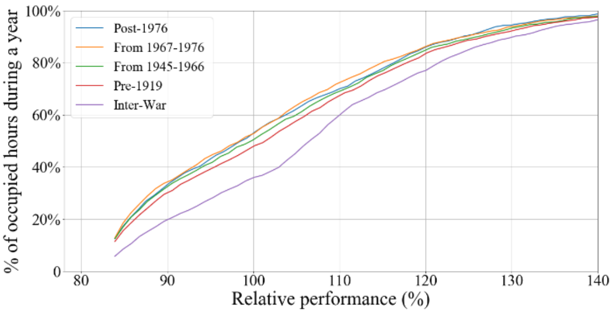


Figure 10 Cumulative distribution of performance across all five archetypes (15 l/s/person)

The impacts of different ventilation rates on cognitive performance in a certain archetype (post-1976 schools) is shown in Figure 11. The model assigned to 8 l/s/person has less time accumulated below the cognitive performance levels of 95% than the one with 5l/s/person. Furthermore, the one with 15 l/s/person has much less hours (about 10% less than the one with 8 l/s/person and 18% less than 15 l/s/person) distributed below the cognitive performance level of 95% compared to the other two. This could probably be attributed to the fact that higher ventilation rates can remove more heat from indoors in the summer, thus students perform better when the indoor temperature gets lower. However, higher ventilation do not always contribute to higher cognitive performance level. The change of ventilation rate of higher than 15 l/s/person is reported to have minimal influences on the increase in performance because the impacts of ventilation rate on cognitive performance are diminished (Seppänen and Fisk, 2006), so the model was not run with ventilation rates higher than 15 l/s/person in this study.

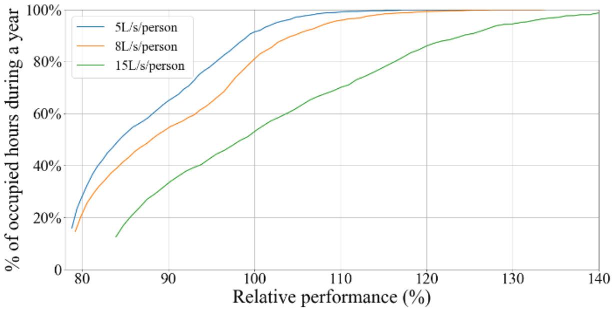


Figure 11 Cumulative distribution of performance at different ventilation rate

There is a number of limitations in the present study:

1) This study assumes the operative temperature to be the same as air temperature as they are found to be very approximate. Although the temperature variable in Wargocki's model (Wargocki et al., 2019) is air temperature, zone operative temperature was linked to cognitive performance using the temperature-cognitive model in order to investigate the impacts of outdoor climates and characteristics of building envelope on cognitive performance.

2) This study tested different ventilation rates but did not distinguish between natural and mechanical ventilation mode. The impact of different ventilation strategies on cognitive performance was beyond the scope of this study.

3) The occupancy assumptions and associated internal gain values used for simulation were based on the recommended values in guidelines rather than real occupancy schedules and data.

4) The way in which cognitive performance may be affected by indoor temperature and ventilation rates outside of the range of existing curves needs to be validated by empirical data.

5) The archetypes which represent a set of building cohorts may overlook the differences within the building cohorts, so if the results of the archetypes can be extrapolated needs to be validated as well.

Conclusion

The impacts of climate change on cognitive performance in London secondary schools were investigated in this paper. The assessment framework comprising of three analysis stages in this study is the first step towards the development of an integrated tool to inform policymakers and stakeholders (head teachers, facility managers) in the sustainable school building design and management field.

Outdoor temperature is a key determinant factor for students' cognitive performance. Future warmer climates could decrease learning performance in schools, so further measures need to be taken to the classrooms in the future. In addition, Thermal properties and ventilation rate provided to the classrooms also contribute to students' cognitive performance, so appropriate ventilation/cooling strategies are needed to avoid high indoor temperature in classrooms. Holistic design thinking should be applied to future building retrofit.

As part of ongoing work, the school building stock model presented in this paper will be extended to include all the school buildings in England and Wales to quantify the influences of school locations on cognitive performance. Moreover, we will further investigate which extent specific building physics parameters contribute to cognitive performance when additional input data from empirical studies are available. A sensitivity analysis aiming to identify the relative importance of all relevant factors on cognitive performance in schools will also be conducted in the future work.

Acknowledgement

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