Optimal scheduling strategy for enhancing IAQ, visual and thermal comfort using a genetic algorithm

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ABSTRACT

Buildings account for 40% of total global energy use and contribute towards 30% of total CO_2 emissions. Heating ventilation and air conditioning (HVAC) systems are the major sources of energy consumption in buildings, and there has been extensive research focusing on efficiently control them. However, in most cases, this is achieved at the cost of sacrificing thermal, visual and/or IAQ comfort. High level of carbon dioxide – which is commonly used a metric for measuring air quality, can affect student's ability to concentrate on academic tasks. This research is aimed at developing a method for optimizing the operation of the window opening to facilitate natural ventilation, window blinds to reduce energy consumption and heat recovery unit (HRU) to provide thermally comfortable environment in a low energy educational building (rated BREEAM excellent ≈ LEED platinum). The research employs model-based optimization using a daylight-coupled thermal model in EnergyPlus to model the interrelationships between blind positions; window opening; lighting and heating/cooling energy consumption; and thermal comfort. A simple genetic algorithm has been used to minimize energy consumption, enhance IAQ, thermal and visual comfort (which are competitive constraints with each other). The optimization takes into account the scheduling of the window opening, HRU and blind' operation in case study building. Optimization results highlighted the potential cost savings while considering energy consumption as an objective function and, thermal comfort, IAQ and visual comfort as constraints. The paper also reports on the directions for further research, in particular on the use of surrogate models and machine learning techniques so that the proposed optimization methods can be used without significant computation overheads.

INTRODUCTION

Buildings are responsible for 40% of global energy consumption and contribute towards 30% of the total CO_2 emissions (Costa et al. 2013, Ahmad et al. 2016). In the European Union, buildings account for up to 40% of the total energy consumption and approximately 36% of the greenhouse gas emissions (Grözinger et al. 2014). Energy is used in buildings for heating and cooling, lighting, domestic hot water and appliances, and the majority of this energy comes from burning fossils fuels. Global greenhouse gas (GHG) emissions are rapidly increasing, and it will be difficult to limit the long-term rise in global average temperature to 2°C below pre-industrial levels (Birol et al. 2013). It is essential to address the issue of global climate change and reverse the trend of rising energy consumption to reduce the impact of climate change to a 2°C rise in global average temperature (Birol, Cozzi et al. 2013). The European Commission recognizes that the improvement of the energy performance of Europe's building stock is crucial for meeting both short- (20% by 2020) and long-term (88%–91% by 2050) targets of significant GHG reductions from 1990 levels and the move towards a low carbon economy by 2050 (EC 2011). These figures show the importance of buildings and the need to develop advanced control and optimization methods for HVAC systems to achieve both societal and economic goals of low energy use and GHG emissions.

The occupied spaces must meet the requirements of thermal comfort and indoor air quality (IAQ) as we spend most of our life indoors. Indoor air quality (IAQ) plays an important role in our daily lives and should be within the

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acceptable range. CO_2 is commonly used as metric for measuring indoor air quality (Daisey et al. 2003). It should be noted that this metric (CO_2) concentration may not represent all air containments and therefore, this may not give an indication about insufficient ventilation rate. Kolokotsa et al. (2002) used an optimized fuzzy controller to control the environmental parameters at the building zone level. Kolokotsa (2003) compared the performance of five different fuzzy logic controllers to minimize energy consumption. A study to examine optimal control strategies for a variable air volume system (VAV) system was carried out by Mossolly et al. (2009). The authors used a genetic algorithm (GA) to maintain temperature set-points in different zones while assuring IAQ.

The use of artificial lighting is also increased with the sustained reduction in heating and cooling energy. For commercial buildings in the USA, artificial lighting accounts for 25-40% of the total electricity energy consumption (Ihm et al. 2009). Previous research suggests that the use of movable insulations (e.g. roller shades, Venetian blinds, etc.) can have an impact on occupants' visual comfort and artificial lighting usage. Kim and Park (2009) optimally control the slat angle of a blind system by minimizing the heating, cooling and lighting energy. A study by Kim et al. (2016) used EnergyPlus to generate training data for artificial neural networks. They also used a GA to control blind slat angle and HVAC operation to satisfy occupants' thermal and visual comfort. The GA optimization lead to a 13.7% reduction in energy consumption whilst maintaining the comfort level within the preferred range. Lee et al. (1998) studied the effect of automated blinds on artificial lighting energy consumption and outside view. It was found that automatic blinds resulted in energy savings as compared to static blinds with the same dimmable electric lighting system. Ahmad et al. (2015) also optimized the scheduled operation of window blind to reduce energy consumption while enhancing occupants' visual comfort. The authors used GA for optimization purposes and found that the GA provided better blinds' schedules in all simulated weather conditions as compared to other test cases. Kurian et al. (2008) used a fuzzy rule-based controller to reduce glare, increase daylight uniformity and thermal comfort, and minimize energy consumption.

The paper addresses the optimization of energy consumption while considering all aspects of occupants' comfort, which to the best of authors' knowledge has not been addressed before. All these comfort parameters are interrelated and need to be included in the problem formulation.

SIMULATION MODEL DESCRIPTION

The energy performance, objective function and constraint evaluation have been modeled and simulated using EnergyPlus (Crawley et al. 2001). Energyplus is an open source simulation tool developed by Lawrence Berkeley National Laboratory. It is a well-known and acknowledged simulation engine due to its multi-domain modeling capabilities and therefore it was chosen over a dedicated lighting simulation tool e.g. Radiance. The classroom was modeled as an independent zone with the internal partition wall treated as adiabatic heat transfer surfaces.

A hydronic system is modeled to meet classroom's heating requirement. The ventilation requirements can be met by opening window (natural ventilation) and/or by using a heat recovery unit (HRU), with zero recirculation flow rate. The ventilation requirement is met by varying air flow rate supplied by the HRU and/or varying the window opening size. The cooling and heating set points are defined according to the CIBSE Guide A (CIBSE 2006) i.e. 22°C for heating. The classroom operation time is from 8:00 am to 5:00 pm and 30 people were considered in the room with an activity level of 60 W/m^2.

Geometry and construction

The school building is located in Wales, UK and is a BREEAM excellent rated building. The energy simulation model of the building is shown in Figure 1. The total floor area of the classroom is 85.5m^2, with a height of 3.60m. It is assumed that the classroom has 30% WWR (window-to-wall ratio) on its southern façade, and the window consists of a double-glazing (3mm Generic PYR B Clear + 13mm air gap + 3mm Generic Clear). This window also has an inside slat-type blind with a thermal conductivity of 0.9 W/mK and a slat beam reflectance of 0.8 for both front and back sides.

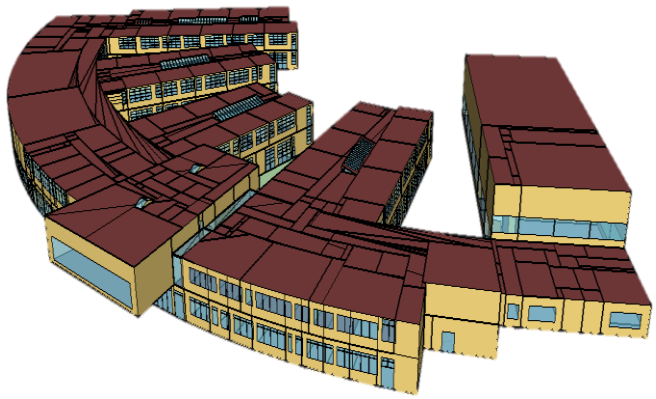

Figure 1 Energy simulation model of the School building

Lighting control strategy

Artificial lighting is modeled to be used to supplement daylight illuminance levels by an amount so that it maintain the illuminance set-point (500 lx). The illuminance level was calculated at a reference point, which is located in the middle of the classroom. A continuous dimming control was employed to control the artificial lighting based on the lux level calculated at a reference point, the minimum power consumption from the lighting was 0.1129kWh.

GENETIC ALGORITHM BASED OPTIMIZATION

HVAC optimization aims to find the best solution from feasible alternative solution, collectively referred to as solution space (Ahmad et al. 2016). An objective function (e.g. run period total energy consumption in this case) is minimized subject to various constraints (e.g. Number of hours when CO_2 is greater than 600 ppm). This paper focused on single-objective optimization problem. The general definition of a single-objective optimization problem is;

$$\min_{\mathbf{x}\in X} f(\mathbf{x}) \quad (1)$$

Subject to:

$$g_j(\mathbf{x}) \leq 0 \quad j = 1,2, \dots, m \quad (2)$$
$$h_k(\mathbf{x}) = 0 \quad k = 1,2, \dots, p \quad (3)$$
$$s_i^{lower} \leq s_i^{upper} \quad i = 1,2, \dots, n \quad (4)$$

Where in above equations, $X \subseteq \mathbb{R}^n$ is the search space, $\mathbf{x}$ is a decision vector $[x_1, x_2, \dots, x_n]^T$, n being the number of variables; f is the objective function to be minimized, $\forall j \in \{1, \dots, m\}$ g_j is an inequality constraint; $\forall k \in \{1, \dots, p\}$ h_k is an equality constraint; and s_i^{lower} and s_i^{upper} are the lower and upper bounds of the decision variable x_i.

Genetic algorithm (GA) iteratively produces a set of optimal/potential solution(s) to a problem. The initial set is composed of randomly generated solutions. A generation is a new population of individuals that is created after each iteration of the algorithm. The GA creates a new generation by selectively applying operators to the solutions of the current population. There are two GA operators: crossover and mutation. These operators control the evolution of future generations. The crossover operator involves swapping of the variables of two stochastically chosen solutions (x, y) to create two new solutions (x',y'). The mutation generates modifications on variable x_i in order to generate a new solution x'. The crossover operator allows to refine the current population, whereas the mutation operator allows to jump to new unexplored areas of the search space (Goldberg 1989). To evaluate a single solution, GA utilizes a cost/fitness function that measures the performance (i.e., fitness) of the solution. The probability of an individual to be selected for the next generation depends on its fitness value and the selection process. The following sections detail the specific single-objective optimization problem considered in this research.

Decision variables

The 27 decision variables used in this research are the window blind, fraction of maximum flow rate through HRU and opening fraction of the window for each occupied hour (i.e. one 9-hour schedule for each of these variables). These schedules can take 11 decimal values between 0 and 1 with a 0.1 step. These values are discretized in the GA as 11 integer values from 0 to 10. Therefore, a solution $\mathbf{x}$ of the optimization problem is a vector of 27 real numbers with a 0.1 decimal precision.

Objective function

In this study, the objective function is the run period (i.e. daily) energy consumption of the studied classroom. The run period energy consumption is the sum of heating, lighting, and supply and return fans. The objective function f of the run period energy consumption can be expressed as below, for a solution $\mathbf{x}$:

$$f(\mathbf{x}) = [Q_H(\mathbf{x}) + Q_L(\mathbf{x}) + Q_F(\mathbf{x})]/3.6 \times 10^6 \qquad 5$$

where, Q_H, Q_L and Q_F are the classroom's run period heating, lighting and fans energy consumption respectively. The denominator is used to express energy consumption in kWh instead of Joules.

Problem constraints

The optimization problem studied in this paper considers three different types of constraints to tackle different aspects of occupants' comfort: visual comfort, indoor air quality and thermal comfort. Quantity and quality of daylight can be accessed by using different daylight performance indicators. Daylight factor – a classical illuminance-based indicator, has been used in different studies to evaluate daylight performance. However, it has received a lot of criticism as it is calculated under an overcast sky (worst sky conditions) and other sky conditions are not considered. In this paper, daylight performance is evaluated by using "Useful Daylight Illuminance" (UDI), which was proposed by Nabil and Mardaljec (2005). This study considers four ranges of UDI i.e. UDI 'fell-short' – daylighting illuminance lower than 100 lx, UDI 'supplementary' – illuminance between 100 lx and 500 lx, UDI 'autonomous' – daylighting illuminance between 500 lx and 3000 lx, and UDI 'exceeded' – illuminance is greater than 3000 lx. For thermal comfort, 28°C is considered as the upper threshold of the room air temperature. The IAQ of the classroom is measured in terms of carbon dioxide (CO_2) concentration during the occupied hours, as a high level of CO_2 in classrooms can affect students' ability to concentrate on academic tasks. It is commonly used as a metric for measuring air quality, however it may not reflect all air contaminants. In any case, a high level of CO_2 concentration can indicate towards insufficient ventilation of indoor spaces and therefore it is aimed that it should be lower than 600ppm (Li et al. 2015). All of these constraints were calculated by using the Energy Management System (EMS) feature of EnergyPlus. This results in the following penalized objective function f' that can be expressed as below, for a solution $\mathbf{x}$:

$$f'(\mathbf{x}) = f(\mathbf{x}) \times \left[1 + \frac{N_T(\mathbf{x}) + N_{IAQ}(\mathbf{x}) + 0.4 \cdot N_{100}(\mathbf{x}) + 0.2 \cdot N_{100-500}(\mathbf{x}) + 0.4 \cdot N_{3000}(\mathbf{x})}{27}\right] \qquad 6$$

where N_T is the number of hours when the room air temperature was above 28°C, N_{IAQ} is the number of hours when the CO_2 concentration was above 600 ppm, N_{100} is the number of hours when the illuminance level was under 100 lx, $N_{100-500}$ is the number of hours when the illuminance level was between 100 and 500 lx, and N_{3000} is the number of hours when the illuminance level was above 3000.

RESULTS AND DISCUSSION

In this paper, a GA based solution is proposed to schedule blind position, HRU and window opening while maintaining occupants' visual, thermal and IAQ comfort. The artificial lighting is automatically dimmed based on the illuminance level at a reference point. The GA minimizes an objective function i.e. the sum of heating, lighting and HRU energy consumption. The paper uses three different performance metrics to evaluate IAQ, visual and thermal comfort i.e. UDI for visual comfort, indoor air temperature more than 28°C for thermal comfort and CO_2 concentration for IAQ.

To evaluate the relative performance of the GA, we also run different reference case simulations in both summer and winter weather conditions. The summer reference cases results are shown in Figure 2. These simulations were performed on a day with highest cooling load, with window fully open and HRU switched off throughout the day. Only blind schedules were changed to either blind fully lowered (Figure 2- A) or blind fully retracted (Figure 2- B). In both cases, the indoor air temperature closely follows the outdoor air temperature except at the beginning of the occupied period. In both these cases, the boiler was switched ON as the indoor air temperature was lower than the heating set-point temperature. The room CO_2 concentration is also nearly the same; however as can be seen in (Figure 2- B), the case with blinds fully retracted has lower CO_2 concentration as compared to the case with blinds fully down. As the slat angle are fixed to 5 deg, which limits air entering into the classroom. The high transmittance (sum of beam and diffuse radiation rates) from south façade window is during the early part of the afternoon. As expected, minimum lighting energy consumption was used for blind fully retracted case (Case B). To minimize the negative impact of excessive daylighting, the GA should adjust the blind position.

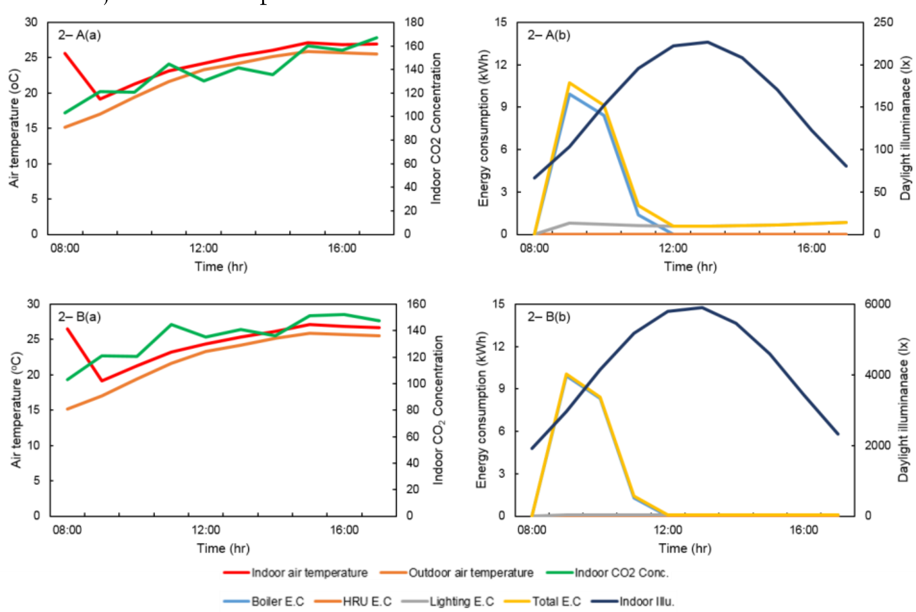

Figure 2 Summer reference cases: 2- A(a)- Hourly indoor and outdoor air temperatures, CO_2 concentration for summer reference Case A, 2- A(b)- Boiler, lighting, HRU and total energy consumption, and daylighting illuminance for Case A , 2- B(a)- Hourly indoor and outdoor air temperatures, CO_2 concentration for summer reference Case B, 2- B(b)- Boiler, lighting, HRU and total energy consumption, and daylighting illuminance for Case B.

The simulations were performed for a day with highest cooling load and it was expected that the GA should find an optimum solution, which does not use HRU and provides fresh air requirements by opening the windows. The GA should also close the blind in order to reduce the negative impact of daylighting (solar radiation), which can increase the indoor temperature and hence thermal discomfort. However, closing the blinds will increase lighting energy consumption. The GA performed nearly the same as described, as it did not utilize HRU throughout the day (Figure 3(d)). The window was left open throughout the day to meet the ventilation requirement and also maintaining the indoor air temperature and CO_2 concentration within the comfort range as shown in Figure 3- (a). Only lighting energy was consumed during this day, and the GA tried to maintain the UDI within the comfortable range i.e. (100 lx to 3000 lx). However, it is worth pointing out that the optimization problem tackled in the paper is complex in nature as it considers different comfort metrics. The GA closed the blind (either fully or partially) three times during the day, this happened when the daylighting illuminance reached a high value. The window blind was left retracted during the late afternoon as the sun was shining on west façade, this reduced the lighting energy consumption.

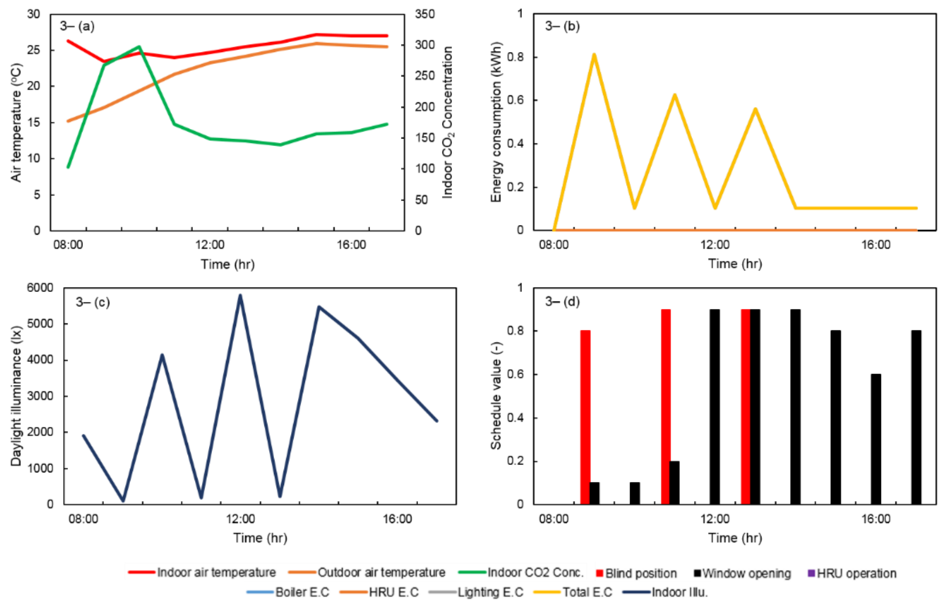

Figure 3 Summer GA case: 3- (a)- Hourly indoor and outdoor air temperatures, CO_2 concentration, 3- (b)- Boiler, lighting, HRU and total energy consumption, 3- (c)- daylight illuminance, 3- (d)- Optimized schedules for window opening, blind and HRU

Two different reference cases were also simulated for a winter day (a day with highest heating load). In these cases, the window was closed (to reduce draught and thermal discomfort), ventilation requirements were met by utilizing HRU and with blind fully opened and closed. In both these reference cases, the boiler was used during early hours of the day to meet indoor air temperature set-point. The case with blind fully retracted used less energy as it benefited from daylighting to meet lighting requirements and reduce heating load. The daylight illuminance for the second case (Figure 4- B(b)) is higher and exceeded the recommended values for most of the day. In both cases, the CO_2 concentration is maintained within the acceptable range (<600ppm) by the HRU.

On the highest heating load day (Jan), the GA tried to close the window blind during different hours of the day, which was not expected as far as energy savings are concerned (Figure 5- (d)). The ideal case would have been to allow solar energy to enter the space, which will reduce the heating load. However, the GA closed the blind to reduce visual discomfort as the daylighting illuminance was exceeding 3000 lx value. The GA solution also minimized the use of heating energy consumption as compared to reference cases. This also switched OFF HRU during the early part of the day (saving energy consumption), this resulted in a higher concentration of CO_2 during that time as shown in Figure 5- (a). This is not recommended as a CO_2 concentration value of 2000ppm could result in 'general drowsiness'. The GA did not know about these severe outcomes and tried to minimize energy consumption at the cost of CO_2 concentration.

The optimized schedules save 37% energy as compared to reference case A (blind fully closed) and 13.7% as compared to reference case B (blind fully retracted).

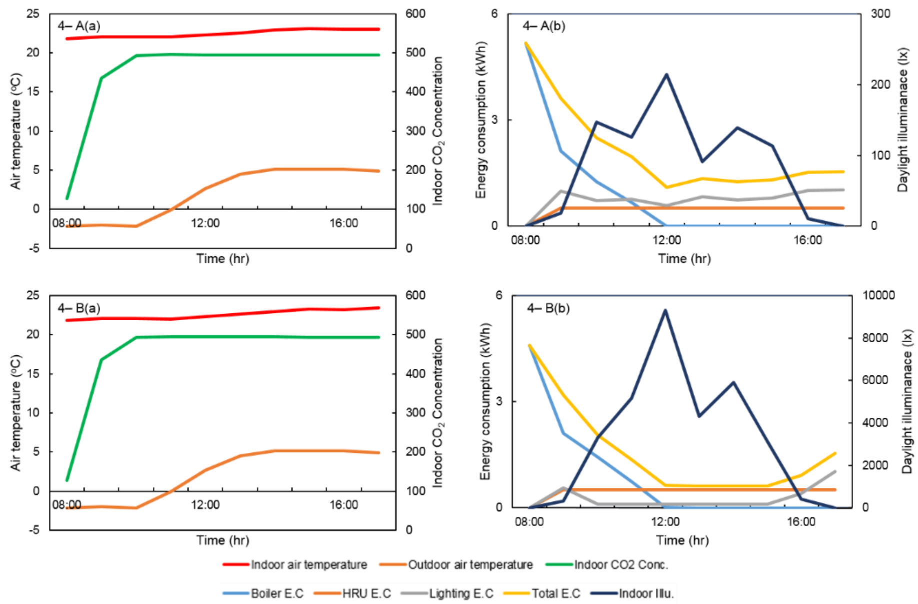

Figure 4 Winter reference cases:4- A(a)- Hourly indoor and outdoor air temperatures, CO_2 concentration for winter reference Case A, 4- A(b)- Boiler, lighting, HRU and total energy consumption, and daylighting illuminance for Case A , 4- B(a)- Hourly indoor and outdoor air temperatures, CO_2 concentration for winter reference Case B, 4- B(b)- Boiler, lighting, HRU and total energy consumption, and daylighting illuminance for Case B.

Figure 6 shows evaluation of the best fitness value for different runs. The optimization runs were limited to 45min on a 3 GHz Intel Core2 Duo PC with 4GB memory and performed approx. 2000 evaluations for both winter and summer test days. It is clearly shown in Figure 6 that even after 2000 evaluations the optimization results did not converge (found an optimum solution). The experiments were extended and optimization was carried out on a 2GHz Core i7 PC with 8GB memory for 10000 evaluations, which took 3 hours to complete. However, in both cases, the GA found an optimized solution at around 3000 evaluations, and it can be concluded that it is not recommended to run the optimization for more than 3000 evaluations (for this optimization problem). This also concludes that a powerful computer may be required to carry out optimization runs as the amount of time required for simulation tools to run 3000 evaluations is high, making them unsuitable for online or near real-time applications. Future research should, therefore, focus on developing a surrogate model to replace the simulation model. It is also worth mentioning that for highest cooling load day, the GA might have stuck in local minima, this needs to be further investigated. It is evident from the results that the GA performed better on both highest cooling and heating load days as compared to reference cases, the next step is to deploy this GA-based optimization scheduler in the school (PERFORMER project's pilot site) and evaluate its performance based on energy consumption, IAQ, thermal comfort and visual comfort. Due to the complex nature of the problem, the GA sacrificed one or more constraints in order to minimize energy consumption. It is also concluded that glare index will also be included in the problem formulation as high values of daylight illuminance can cause visual discomfort. It is also recommended to highly penalize an optimized solution with CO_2 values higher than 1000ppm as this could have negative effects on students' health and academic performance, even if this comes at the cost of energy consumption.

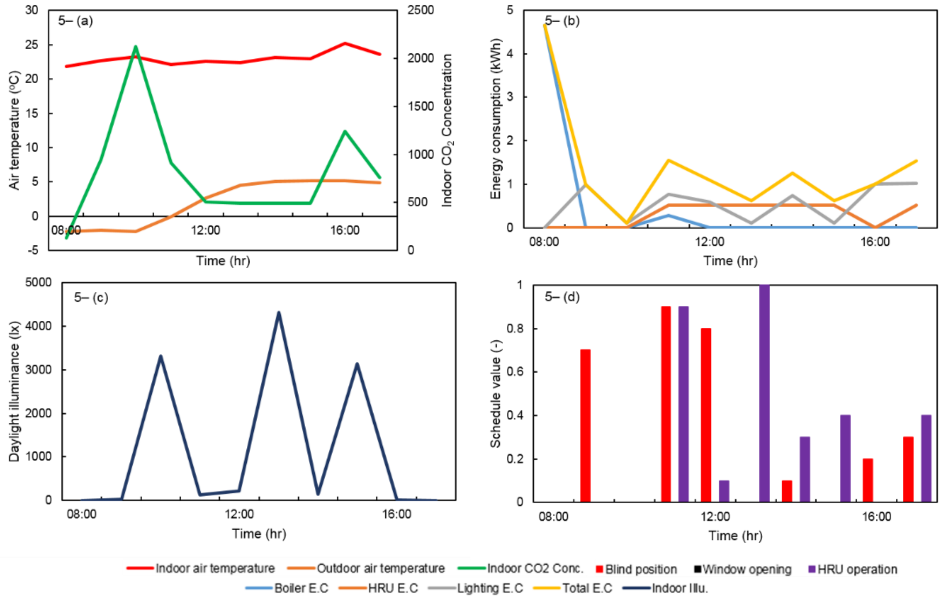

Figure 5 Winter GA case: 5- (a)- Hourly indoor and outdoor air temperatures, CO_2 concentration, 5- (b)- Boiler, lighting, HRU and total energy consumption, 5- (c)- daylight illuminance, 5- (d)- Optimized schedules for window opening, blind and HRU

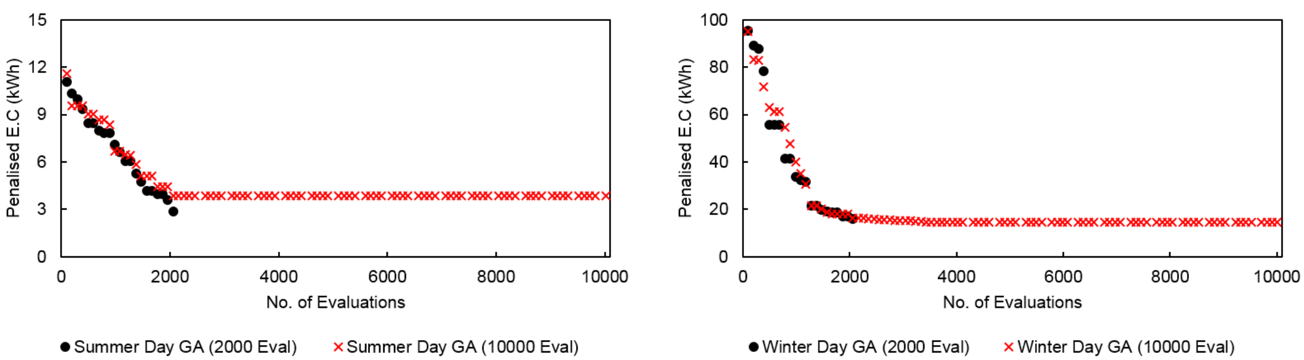

Figure 6 Best GA fitness values for different runs

CONCLUSION

The paper studies the schedule optimization of HRU, window opening and blind operation simultaneously by using a genetic algorithm to minimize the energy consumption (lighting, heating and ventilation) while maintaining thermal, visual and IAQ comfort within the acceptable ranges. UDI, CO_2 concentration and indoor air temperature were used as constraints in the optimization problem. The study uses EnergyPlus as simulation engine to perform daylighting and thermal simulations. Two different days (highest cooling and heating load days) were studied to evaluate GA performance against reference cases.

It was found that the GA-based solution performed better than the reference cases and minimized energy consumption on both days. It is acknowledged in the paper that the optimization problem is complex in nature as it is considering different aspects of occupants' comfort and the GA may have to sacrifice one or more constraints to minimize other constraints/objective function. This was clearly demonstrated on the highest heating load day, where

GA did not use HRU during the early part of the day to minimize energy consumption. However, this clearly has an impact on CO_2 concentration, which reached to a value of 2000ppm. The paper also highlighted directions for future work, the need of using a surrogate model (instead of simulation engine) is also stressed in the paper. The next step of the research is to deploy and test the performance of the proposed solution in the school building to evaluate its performance against energy consumption, thermal comfort, IAQ and visual comfort. It is recommended to penalize highly GA-based schedules with higher levels of CO_2 concentration. This problem could also be tackled by performing multi-objective optimization to find a better compromise between different criteria.

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