Simulation-based Optimization of Energy Consumption and Discomfort in Multi-Occupied Offices Considering Occupants Locations and Preferences

Shide Salimi[1], Zheng Liu[2], Amin Hammad[3]
[1]Ph.D. Student, Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, Email: sh_sa@encs.concordia.ca
[2]M.Sc. Student, Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, Email: l_zhe28@encs.concordia.ca
[3]Prof. Department of Concordia Institute for Information Systems Engineering, Concordia University, Montreal, Email: hammad@ciise.concordia.ca

Abstract

Among the factors affecting the energy consumption of buildings, occupancy-related factors are the least understood due to the uncertainty and complexity associated with them. As a result, there is a rise in this area of research focusing on the effect of occupants (e.g., their location, behaviour, etc.) on buildings' energy consumption. Focusing on office buildings, researchers have suggested several occupancy monitoring techniques in order to minimize the energy usage of existing office buildings. However, a limited number of studies have been conducted to consider proper sensing techniques to distinguish between different occupants in multi-occupied offices and to apply local control to adjust the lighting and HVAC systems based on the occupancy information. This research proposes a simulation-based multi-objective optimization of the energy consumption in office buildings considering occupants' locations and preferences. The objective functions are minimizing the energy consumption and the occupants' discomfort hours simultaneously by applying local control of the Heating, Cooling, and Air Conditioning (HVAC) system. A case study is presented to demonstrate the feasibility of the proposed method.

Introduction

Buildings are responsible for 30-40% of the total global energy use (United Nations Environment Programme, 2007), and a similar percentage of the greenhouse gas (GHG) emissions (Yudelson, 2010). Many research studies investigated the most important factors affecting the buildings' energy consumption. According to Yu et al. (2011), among the factors influencing the total building energy consumption, building occupants' preferences and activities could have high positive or negative impacts on energy conservation. Occupants' behaviours are driving factors causing large discrepancies in the building energy usage even between similar buildings with the same function and located at similar locations. In addition, due to the uncertain and complex nature of the occupants' preferences, occupants' profiles are recognized as one of the most significant sources of uncertainty in energy simulation programs (Hong and Lin, 2014).

There are basically three main sectors investigated by researchers from energy efficiency point of view including commercial, residential, and other sectors. Offices constitute the largest portion of the commercial sector and are the focus of this research, which is limited to offices within university buildings. The main energy consumer systems in offices are the HVAC and lighting systems, which are responsible for 33% and 25% of the total energy consumption, respectively (Nguyen and Aiello, 2013).

Focusing on office buildings, most of the energy is consumed during the working hours due to the occupants-related effects (Masoso and Grobler, 2010). Lights are often set to produce more light than necessary and HVAC systems are set based on the peak occupancy regardless of actual room usage. Therefore, occupants' presence and preferences have an important effect on the buildings' energy consumption, which should be considered as accurately as possible when dealing with the buildings' energy usage models. However, it is also important to satisfy the occupants at an acceptable level (Hong and Lin, 2014; Lindén et al., 2006; Mahdavi et al., 2008). The emphasis of the importance of this subject can also be seen in the recent trend of the industry towards more occupancy-related technologies since people spend majority of their time in buildings (more than 80%) (Lawrence Berkeley National Laboratory, 2016).

This research proposes a simulation-based multi-objective optimization model of the energy consumption in office buildings considering occupants' locations and preferences. The objective functions are minimizing the energy consumption and the occupants' discomfort hours simultaneously by applying local control of the HVAC system. Local control actions include, but are not limited to, adjusting the lighting and HVAC systems based on the occupancy satisfaction and information. The occupants' preferences and their location can be collected by conducting surveys and using location-tracking technologies, respectively. In this research, it is assumed that there is a fixed number of users with assigned seats within each office room. Offices that have singular occupancy are not considered in this study. Furthermore, the offices should be big enough so that multiple zones in the same space can have different set points to satisfy different occupants.

Literature Review

The intelligent use of energy within buildings is a recent trend of research and is the target of Building Energy and

Comfort Management (BECM) systems (Nguyen and Aiello, 2013). These control systems aim to keep a trade-off between minimizing the energy cost and usage while maximizing the occupants' satisfaction (Yu, 2010). However, current buildings' control practices are unable to fully achieve these goals. This means applying more cost-efficient strategies usually results in reducing the occupants' satisfaction and even productivity. The BECM system comprises HVAC system, lighting, hot water, and electricity control (Nguyen and Aiello, 2013; Singhvi et al., 2005). As mentioned in the Introduction section, occupants' location and preferences have large impacts on energy consumption within the building; therefore, carefyl management of these parameters could leat to about 33% saving in energy usage (WBCSD, 2009).

Some researchers investigated the effect of the application of different kinds of control on the energy usage of buildings and their interaction with occupants' location and preferences. From heating and cooling points of view, HVAC control systems usually work based on the maximum occupancy regardless of the actual room state (e.g., occupied or not in use). Considering that HVAC systems consume about 50% of the total generated electricity in the U.S. (Erickson and Cerpa, 2010), smart control of HVAC systems based on the occupancy information and predicted usage patterns could lead to a significant energy saving. Researchers tried to control HVAC systems using different kinds of technologies.

In order to have a more detailed model capturing the occupants' interactions with the HVAC and lighting systems, IT devices, etc., some researchers used wireless camera networks, different wireless sensor networks (e.g., passive infrared (PIR) motion detector, door sensors, contact sensors), etc., to gather data pertinent to the occupants' behaviour and location. They investigated the energy savings that result from reaching to the maximum efficiency of the HVAC systems within office buildings (Padmanabh et al., 2009; Erickson et al., 2009; Agarwal et al., 2010; Newsham and Birt, 2010; Marchiori and Han, 2010; Schoofs et al., 2011; Azar and Menassa, 2012; Nguyen and Aiello, 2013; Hong and Lin, 2014; Schakib-Ekbatan et al., 2015).

On the other hand, simulation programs for estimating the buildings' energy consumption are mostly based on deterministic profiles of the occupants (Duarte et al., 2013). However, the poor ability of these programs to simulate based on the stochastic occupants' profiles results in big discrepancies between the results of a building energy usage from the simulation and the actual energy consumption (Hong & Lin 2014). Therefore, there is a need to consider the probabilistic modelling of occupant location and preferences within building energy simulation programs based on Poisson or Markov processes. Research works that are done by Yamaguchi et al., 2003; Wang et al., 2005; Dodier et al., 2006; Haldi and Robinson, 2008; Page et al., 2008; Hawarah et al., 2010; Dong & Lam 2011; Wang et al., 2011; Chang and Hong, 2013; Wang & Ding 2015; Feng et al., 2015 are some examples in this area. In order to have more detailed occupancy model, Hong et al. (2015) focused on energy-related building occupants' behaviours and suggested an ontology called DNAS (Drivers, Needs, Actions, and Systems) framework. To represent the proposed DNAS framework in an interoperable language, the same group used an XML schema, titled 'occupant behaviour XML' (obXML) to capture the data syntax and structure and present them in a standardized way (Hong, et al., 2015; Hong, et al., 2015).

From optimization point of view, a limited number of research studies has been conducted using optimization algorithm. More specifically, Yu (2010) used Genetic Programming (GP) to find the occupants' behaviors in five different single occupied offices using motion sensors. Although, they mentioned that the number of state changing is high in the period of data they used, the distributions of occupancy have very low probabilities for an office building. Furthermore, they did not consider shared spaces in their research and the effect of proposed occupancy models on the operation of building systems. Fesanghary et al. (2012) used harmony search algorithm (HS) to perform multi-objective optimization on a typical single-family house to investigate the effect of using different envelope parameters on the building energy consumption. The main problem with the HS algorithm is the selection procedure of new set of design variables in each run. The new values are selected either randomly or using the best obtained values so far. This makes the calculation time long in order to converge to local optimum solutions. In addition, they did not consider occupancy profiles in their research.

Based on the literature, efforts are being made to apply different strategies in order to minimize energy waste considering the factors affecting the buildings' energy consumption while maintaining or increasing the occupants' comfort level. However, previous occupancy models, which predict the presence of the occupants to control the HVAC and lighting systems, did not consider local control strategies. Local control strategies combine the spatiotemporal variations of the space usage and the occupants' preferences. Thus, new models should be developed to optimize energy usage by providing detailed simulation models considering local control and occupants' preferences and probabilistic location profiles in order to be able to distinguish between different occupants in multi-occupied offices.

Research Methodology

The proposed framework is comprised of running simulation model within optimization module. In order to achieve the objectives of minimizing energy consumption as well as the occupants' discomfort hours, energy prediction models via simulation tools are used in selecting the most optimized settings for energy consuming systems considering occupants' locations and preferences.

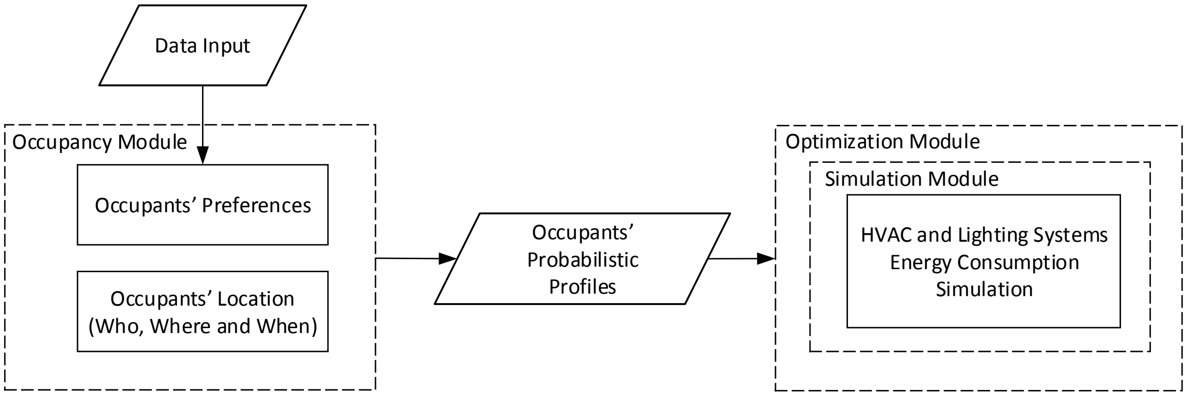

Figure 1: Proposed method main modules.

There are many factors determining the accuracy of the occupants' probabilistic profiles including the duration of the occupants' presence and their locations in building spaces, and their preferences. New real-time location systems (RTLSs) can provide the former data while the latter data can be collected by a simple questionnaire. The proposed method consists of three main modules as illustrated in Figure 1. There are several steps within each module which are explained in detail in the following sections.

Occupancy Module

The first module is used to determine the occupants' probabilistic profiles based on their location and preference data. Hourly occupant's location as well as the desired changes to the settings of the HVAC and lighting systems are recorded to find the spatiotemporal patterns of the occupant preferences with respect to these systems. An RTLS and a survey are used to collect data regarding the occupants' location and their preferences, respectively.

The survey approach is selected since asking the occupants about their preferences is the best way to have a clear understanding about the occupants' satisfaction criteria. In addition, RTLSs are able to detect occupants' location and are becoming cheaper and easier to implement. Input data should be analysed in order to produce occupants' probabilistic profiles. The RTLS can be used to track the locations of the occupants at a certain frequency. The captured location data can be used to create a customized dynamic profile for each occupant to fit the actual pattern of that specific occupant. There are different kinds of RTLSs used by researchers to gather data regarding the occupants' location. For instance, Zhen et al. (2008), Spataru and Gillott (2012), and Li et al. (2012) deployed RFID technology to detect number of occupants and occupancy duration. Masoudifar et al. (2014) utilized ultra-wideband (UWB) RTLSs to find the information pertinent to the occupants' location.

After collecting the occupancy data, post processing analysis is required to find periods of absence, presence, breaks, and other occasional variations in the occupants' profiles. The lighting and HVAC systems should be adjusted to reflect the variations in daily occupants' profiles.

Simulation-based Optimization Modules

The optimization module uses the occupants' probabilistic profiles to optimize the defined objective functions. The optimization genetic algorithm (GA) (Holland, 1973) starts with creating the initial population of size N in the first generation. The input variables to the optimization are occupants' preferences and the combined probabilistic occupant profile for each zone in the space from the points of view of the HVAC and lighting systems. The HVAC and light set points of each zone in the office spaces of the building are randomly varied within their pre-defined ranges to create the members of the population.

In this study, the objective functions are the occupants' discomfort and energy consumption, which should be minimized simultaneously. The occupants' discomfort related to the room temperature is defined as the difference between the desirable set point for the HVAC system and the actual zone temperature to provide pleasant work area for the occupants. Another discomfort factor is the amount of lighting provided for each occupant. Therefore, the occupants' discomfort objective function is a combination of these two factors.

The local control of the HVAC and lighting systems set points should be applied within the simulation model in order to reflect the occupants' preferences. Based on the selected values of these variables in each simulation run, the objective functions of the optimization engine are calculated. After calculating the fitness values of all members of the population, the selection, crossover, and mutation operations are performed on the entire population. This procedure is repeated for all members of the population in all generations until the convergence criterion is met or a specified number of generations is reached. Figure 2 illustrates this procedure. The optimal results obtained from running the integrated framework of the simulation-based optimization are used to control the setting of the HVAC and lighting systems considering a trade-off between occupants' satisfaction and the energy consumption.

Implementation and Case Study

In this paper, only the effect of HVAC system control is investigated in the case study. An open office space

(962.36 m^2) with multiple zones is modelled in DesignBuilder software (DesignBuilder, 2016) as shown in Figure 3. The zoning is used to assign different occupancy schedules for each zone in order to be able to apply the local control for HVAC system based on different types of activities in each zone. These zones are created using virtual partitions to separate open spaces without having physical boundaries that could affect the energy consumption of the space.

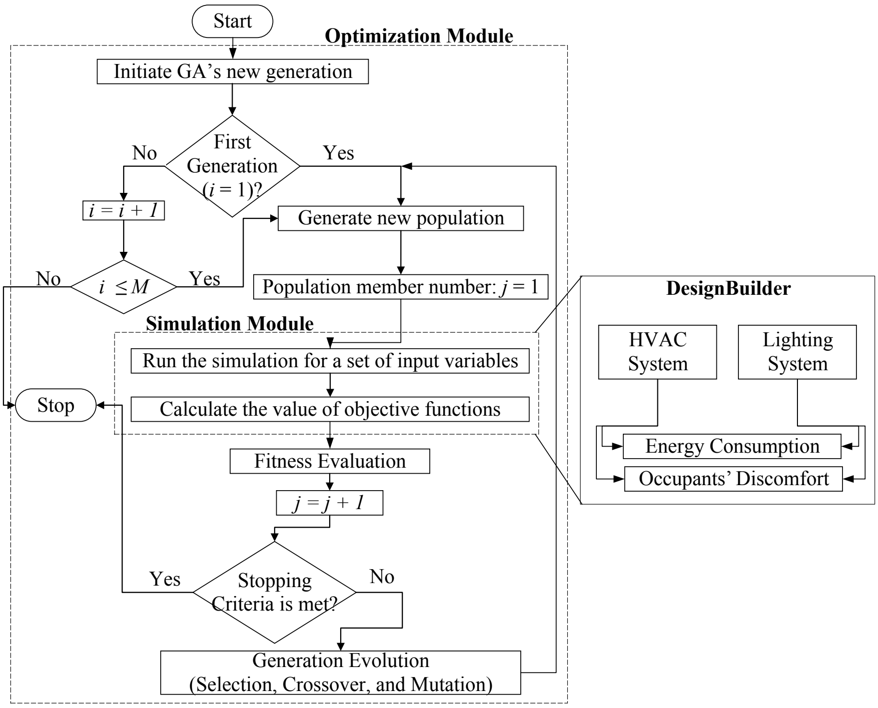

Figure 2: Integration of optimization and simulation modules.

In this study, minimizing discomfort hours (all clo), which is the total discomfort hours when winter or summer clothes are worn (ASHRAE 55, 2004) and minimizing energy consumption are the two objective functions. Therefore, the cooling and heating set point temperatures and cooling and heating operation schedules are defined as the optimization variables. Table 1 shows these variables along with their specified ranges or options. These ranges are selected based on the occupants' preferences. The cooling and heating set back temperatures are set as 37.2 ℃ and 12.8 ℃, respectively, for unoccupied periods for all zones according to the ASHRAE 90.1-2007 recommendations (ASHRAE, 2007).

Occupancy Schedules

The density of the occupants in this open office space is considered as 0.1 people/m^2. A hypothetical occupancy schedule is defined based on data collection that was conducted over one week where the identity and location of the occupants in a multi-occupied office were captured using UWB RTLS (Liu et al., 2016). Table 2 shows the extended occupancy schedules for the four zones during a year. The text-based *Compact Schedule* is used in DesignBuilder to define the occupancy schedule of each zone and for different days of the week. These schedules are used to calculate the internal loads that affect the energy consumption by the HVAC system.

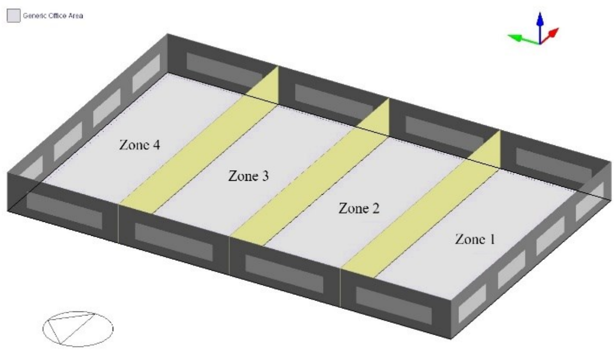

Figure 3: DesignBuilder simulation model.

Table 1: Optimization variables

Variable	Min (℃)	Max (℃)	Increment (℃)	Options	Target Objects
Four Cooling set points	23	26	0.5	-	Each Zone
Four Heating set points	18	23	0.5	-	Each Zone
Cooling operation schedule	-	-	-	9	All Zones
Heating operation schedule	-	-	-	9	All Zones

Table 2: Occupancy probabilistic schedules for four zones

<table>
<tr><th rowspan="2">Day of a Week</th><th colspan="2">Zone 1</th><th colspan="2">Zone 2</th><th colspan="2">Zone 3</th><th colspan="2">Zone 4</th></tr>
<tr><th>Period</th><th>Occupancy (%)</th><th>Period</th><th>Occupancy (%)</th><th>Period</th><th>Occupancy (%)</th><th>Period</th><th>Occupancy (%)</th></tr>
<tr><td rowspan="6">Monday</td><td>11:00-12:00</td><td>50</td><td rowspan="2">17:30-18:00</td><td rowspan="2">100</td><td rowspan="3">11:00-12:30</td><td rowspan="3">50</td><td rowspan="6">All Day</td><td rowspan="6">0</td></tr>
<tr><td>13:00-16:00</td><td>50</td></tr>
<tr><td>16:30-17:30</td><td>50</td><td rowspan="2">18:00-19:30</td><td rowspan="2">50</td></tr>
<tr><td>17:30-18:00</td><td>100</td><td rowspan="3">14:00-17:00</td><td rowspan="3">50</td></tr>
<tr><td>19:30-20:30</td><td>100</td><td rowspan="2">19:30-20:30</td><td rowspan="2">100</td></tr>
<tr><td>20:30-21:30</td><td>50</td></tr>
<tr><td rowspan="5">Tuesday</td><td>11:30-14:00</td><td>100</td><td>11:00-11:30</td><td>50</td><td rowspan="3">11:30-13:00</td><td rowspan="3">50</td><td>13:00-14:30</td><td>100</td></tr>
<tr><td>14:00-17:00</td><td>50</td><td>11:30-14:00</td><td>100</td><td>14:30-15:00</td><td>50</td></tr>
<tr><td>18:00-19:00</td><td>50</td><td>19:00-20:00</td><td>100</td><td>19:00-20:00</td><td>50</td></tr>
<tr><td rowspan="2">19:00-20:00</td><td rowspan="2">100</td><td rowspan="2">20:00-21:00</td><td rowspan="2">50</td><td rowspan="2">13:00-14:30</td><td rowspan="2">100</td><td>20:00-21:00</td><td>100</td></tr>
<tr><td>21:00-22:00</td><td>50</td></tr>
<tr><td rowspan="6">Wednesday</td><td>10:30-13:00</td><td>100</td><td>10:30-13:00</td><td>100</td><td rowspan="2">11:00-11:30</td><td rowspan="2">50</td><td rowspan="3">11:30-14:00</td><td rowspan="3">100</td></tr>
<tr><td>13:00-13:30</td><td>50</td><td>15:00-16:00</td><td>100</td></tr>
<tr><td>15:00-16:00</td><td>100</td><td>17:30-19:00</td><td>50</td><td rowspan="2">11:30-14:00</td><td rowspan="2">100</td></tr>
<tr><td>16:00-17:30</td><td>50</td><td>19:00-19:30</td><td>100</td><td rowspan="3">20:00-22:00</td><td rowspan="3">50</td></tr>
<tr><td>19:00-19:30</td><td>100</td><td rowspan="2">20:00-21:00</td><td rowspan="2">50</td><td rowspan="2">15:00-18:00</td><td rowspan="2">50</td></tr>
<tr><td>19:30-20:30</td><td>50</td></tr>
<tr><td rowspan="7">Thursday</td><td>09:30-10:00</td><td>50</td><td>10:00-11:30</td><td>100</td><td rowspan="2">12:00-13:00</td><td rowspan="2">100</td><td>12:00-13:00</td><td>100</td></tr>
<tr><td>10:00-11:30</td><td>100</td><td>11:30-12:00</td><td>50</td><td>15:00-16:00</td><td>100</td></tr>
<tr><td>12:00-13:30</td><td>100</td><td>12:00-13:30</td><td>100</td><td rowspan="3">15:00-16:00</td><td rowspan="3">100</td><td>16:00-16:30</td><td>50</td></tr>
<tr><td>14:00-15:00</td><td>50</td><td>13:30-14:00</td><td>50</td><td rowspan="2">16:30-18:00</td><td rowspan="2">100</td></tr>
<tr><td>15:00-17:00</td><td>100</td><td>15:00-17:00</td><td>100</td></tr>
<tr><td>18:00-18:30</td><td>100</td><td>17:00-18:00</td><td>50</td><td rowspan="2">16:30-18:00</td><td rowspan="2">100</td><td rowspan="2">18:00-19:00</td><td rowspan="2">50</td></tr>
<tr><td>18:30-19:00</td><td>50</td><td>18:00-18:30</td><td>100</td></tr>
<tr><td rowspan="5">Friday</td><td rowspan="3">11:00-13:00</td><td rowspan="3">50</td><td rowspan="3">13:00-14:00</td><td rowspan="3">100</td><td>10:00-11:00</td><td>100</td><td>09:30-10:00</td><td>50</td></tr>
<tr><td rowspan="2">13:30-15:00</td><td rowspan="2">50</td><td>10:00-11 :00</td><td>100</td></tr>
<tr><td>12:00-13:00</td><td>50</td></tr>
<tr><td rowspan="2">13:00-14:00</td><td rowspan="2">100</td><td rowspan="2">14:00-16:00</td><td rowspan="2">50</td><td rowspan="2">15:00-15:30</td><td rowspan="2">100</td><td>15:00-15:30</td><td>100</td></tr>
<tr><td>15:30-16:00</td><td>50</td></tr>
<tr><td rowspan="2">Saturday</td><td>15:30-17:30</td><td>50</td><td rowspan="2">13:00-15:00</td><td rowspan="2">50</td><td rowspan="2">All Day</td><td rowspan="2">0</td><td rowspan="2">All Day</td><td rowspan="2">0</td></tr>
<tr><td>19:00-20:30</td><td>50</td></tr>
<tr><td>Sunday</td><td>13:00-16:00</td><td>50</td><td>All Day</td><td>0</td><td>All Day</td><td>0</td><td>15:30-16:00</td><td>50</td></tr>
<tr><td>Holidays</td><td>All Day</td><td>0</td><td>All Day</td><td>0</td><td>All Day</td><td>0</td><td>All Day</td><td>0</td></tr>
</table>

*Time periods with no occupancy are excluded from this table.

HVAC Operation Schedules

In order to be able to apply the proposed integration framework, the *Detailed HVAC* mode should be selected in DesignBuilder. *Simple HVAC Data* and *Detailed HVAC Data* are two types of data in this mode of HVAC system. Although the latter has more flexibility in terms of defining schedules for the heating and cooling set points, DesignBuilder optimization module is restricted to the Simple HVAC Data. Therefore, this type of data is used in this study. Among the nine cooling and heating operation schedules (Table 3), four of them (options 1-4) are probabilistic schedules for HVAC operation system. HVAC system is set to operate one hour before the earliest working start time of the occupants within one week (Table 2) for each zone and for each day of a week. The HVAC is turned off when all the occupants leave the room. In addition, deterministic operation options are shown as options 5-8. For these options, HVAC system works based on one schedule for all weekdays for each zone. This schedule turns on the HVAC one hour before the earliest working start time of the occupants within one week (Table 2). The last option in this table shows the case when the HVAC system works for 24 hours.

Using optimization gives the capability of testing optimization variables within their specified ranges to find out which combination of variables results in the optimal solutions; thus, optimization normally involves running a big number of simulations. Two settings are considered for the optimization algorithm in this study: 100 generations with population size of 20 and 200 generations with population size of 50. The results of the two runs are very close to each other; however, the former leads to slightly better solution, which is compatible with the DesignBuilder recommendation settings. Figure 4 illustrates the results of the optimization with setting of 100 generations and population size of 20. Out of total number of results, 3% of points are found as optimal solutions that make the Pareto front as demonstrated in Figure 4. Table 4 shows the summary of optimal solutions from discomfort and energy consumption points of view along with the values of the optimization variables.

According to Figure 4, it can be concluded that almost 11% of solutions (14 out of 129 optimal solutions), which are enclosed within an ellipse, are the most desirable solutions that correspond to trade-off between the total hours of discomfort and the total energy consumption. As shown in Table 4, the average discomfort hours and energy consumption associated with this area are about 125 hours and 143,660 kWh, respectively.

Table 3: Cooling and heating operation schedules

	Options 1-4	Options 5-8	Option 9
Type of Operation Schedule	Probabilistic	Deterministic	On 24 hours
One Schedule for Each Day of a Week	Yes	No	No
One Schedule for Weekdays	No	Yes	Yes
One Schedule for Weekends and Holidays	No	Yes	Yes

According to the U.S. Energy Information Administration (EIA), total electricity consumption of an office building with the total floor area of 1000 m^2 is about 250,000 kWh (U.S. Energy Information Administration, 2016). This shows that using the proposed framework results in promising, reliable and better solutions. There is a 43% improvement in energy consumption by applying the proposed method. The best cooling and heating set points are about 25°C and 22°C, respectively. These temperatures lead to the most desirable conditions from comfort and energy usage. In addition, options 6 and 1 are the best type of settings for the cooling and heating operations, respectively (for the last set of optimal solutions in Table 4). This shows that simpler schedules for HVAC operation system result in a trade-off between occupants' discomfort and energy consumption.

On the other hand, since there are many fluctuations in the occupancy schedules based on the options 1-4, it seems logical that although the HVAC operation schedules that follow the occupancy schedules lead to lower energy consumption, they result in fewer satisfied occupants. This is due to not having a stable indoor air condition (for the first set of optimal solutions in Table 4). In addition, option nine that corresponds to having the HVAC system on for 24 hours consumes the highest amount of energy (the middle set of optimal solutions).

Conclusions and Future Work

A simulation-based multi-objective optimization framework of the energy consumption in office buildings considering occupants' locations and preferences is proposed in this paper. The required steps to accomplish the framework are explained in detail. Running the simulation model for 100 generations with population size of 20 for each generation leads to the average discomfort hours and total energy consumption about 125 hours and 143,660 kWh, respectively. Expanding and generalizing the data collected over one week to a full year is the first limitation of this study. More long-term data collection is required to overcome this limitation. In addition, due to some restriction imposed by the software, such as number of design variables, using DesignBuilder could be considered as one of the limitations. Thus, more robust and flexible tool is required to make all changes to the simulation model's components possible.

For the future work, a cost-benefit analysis of the RTLS system will be done to justify the applicability of the location tracking system. In orer to apply better control startegies, the combination of HVAC and lighting systems' local control will be applied. The occupants' preferences can also be expressed using fuzzy sets, which helps to obtain more realistic energy consumption results by the simulation model. In addition, real-time optimization using short period simulation is considered as another future work.

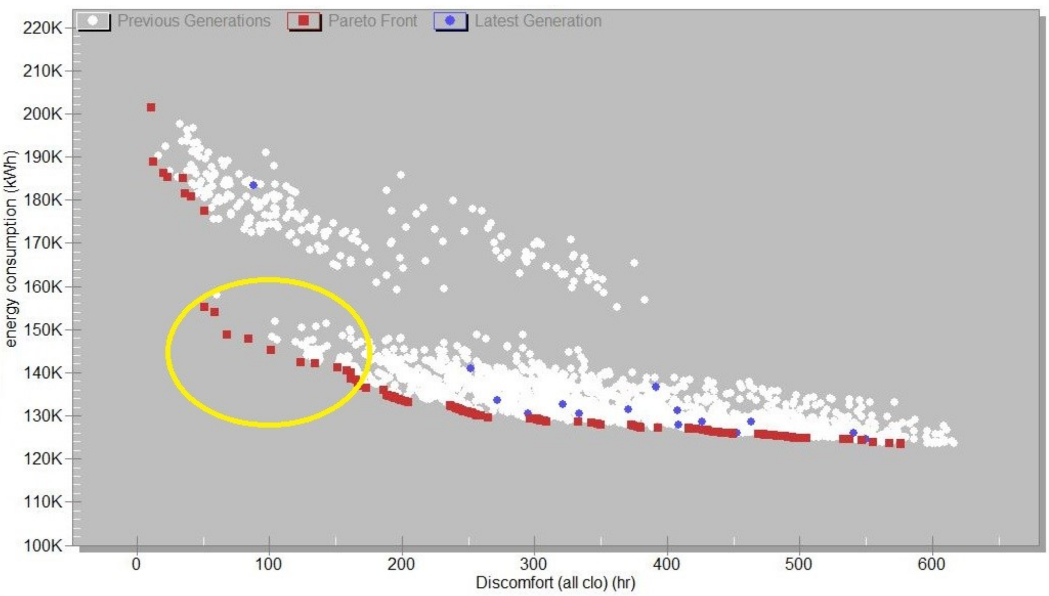

Figure 4. Optimization results

Table 4. Best optimal solutions from discomfort and energy consumption points of view

<table>
<tr><th colspan="3">Best Answers</th><th>Based on Energy Consumption Objective Function</th><th>Based on Discomfort Objective Function</th><th>Based on Both Objective Functions</th></tr>
<tr><th colspan="3"></th><th>Max. Discomfort, Min. Energy Consumption</th><th>Min. Discomfort, Max. Energy Consumption</th><th>Ellipse Area in Figure 4 (Average Values)</th></tr>
<tr><td rowspan="2">Objective Functions</td><td colspan="2">Discomfort (hrs.)</td><td>576</td><td>11</td><td>125</td></tr>
<tr><td colspan="2">Energy Consumption (kWh)</td><td>123,335</td><td>201,487</td><td>143,660</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td rowspan="10">Optimization Variables</td><td rowspan="4">Cooling Set Point (°C)</td><td>Zone 1</td><td>25.50</td><td>24.00</td><td>24.54</td></tr>
<tr><td>Zone 2</td><td>26.00</td><td>24.00</td><td>24.96</td></tr>
<tr><td>Zone 3</td><td>26.00</td><td>25.50</td><td>25.29</td></tr>
<tr><td>Zone 4</td><td>25.50</td><td>25.50</td><td>25.07</td></tr>
<tr><td rowspan="4">Heating Set Point (°C)</td><td>Zone 1</td><td>18.00</td><td>23.00</td><td>22.21</td></tr>
<tr><td>Zone 2</td><td>19.00</td><td>23.00</td><td>22.11</td></tr>
<tr><td>Zone 3</td><td>21.50</td><td>23.00</td><td>22.11</td></tr>
<tr><td>Zone 4</td><td>18.00</td><td>23.00</td><td>21.43</td></tr>
<tr><td>Cooling Operation Schedule</td><td>All Zones</td><td>Option 3</td><td>Option 6</td><td>Option 6</td></tr>
<tr><td>Heating Operation Schedule</td><td>All Zones</td><td>Option 3</td><td>Option 9</td><td>Option 1</td></tr>
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References

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