SIMULATING HUMAN BEHAVIOUR AND ITS IMPACT ON ENERGY USES

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ABSTRACT

Although recent studies suggest that occupant behaviours change the energy use in buildings, few have explained the causal relationship between behaviour and energy performance. This paper aims to define building occupant behaviours that have implications for overall building energy performance. As a start, a comparison of the internal loads in response to the dynamic occupant schedule was conducted in EnergyPlus to illustrate that the uncertainties of occupant behaviour can be an important factor of building energy consumption. In addition, a simulation process that could potentially help to account for dynamic occupant behaviour is proposed.

INTRODUCTION

Building simulation programs are becoming increasingly advanced, and much effort has been spent on increasing their prediction accuracy. One of the most frequent criticisms of simulation capabilities found in the literature is the lack of consideration for human behaviour and its feedback in the simulation programs (Zimmermann, 2006; Crawley et al., 2008; Malkawi, 2004).

Some of the limitations that lead to this oversight are due to the complexity and uncertainties of human behaviour (Khotanzad et al., 1995; Mahdavi et al., 2001), and logistical limitations due to computational power and data storage (Somaranthne et al., 2005).

Currently, the most common ways to account for human behaviour and/or feedback are occupancy and operation schedules. However, in order to capture the dynamic characteristics of an actual operational building, and thus enhance the robustness of the building energy simulation programs, human behaviour and behavioural impact on energy use are essential components in future simulation development (Hoes et al., 2009; Rijal et al., 2007; Dusée, 2004).

The objective of this research is to connect the behavioural feedback into the building energy simulation program to increase the prediction (simulation) accuracy, with the aims of enhancing its capability to maximize/optimize energy efficiency.
such deterministic schedules that are based on historical data, while emulating the actual (dynamic) schedules of an actual operating building.

The two essential prerequisites of the greater human behaviour research are identifying the occupant behaviours in an operating building and quantifying the behavioural information into the building energy simulation program. This paper mainly presents the ‘Dynamic Schedule’ as a methodology, because it addresses the latter by way of manipulating operation schedules (occupancy, lighting, equipment, and HVAC schedules), where the schedules ultimately reflect the load changes as a result of particular occupant behaviour. This is based on the assumption that occupant behaviours identified in the buildings have distinct internal load associated with them. For example, if a behavioural intention of using a personal fan is anticipated, an increase in the equipment load can also be expected, and thus, the changes are made to the equipment schedule to reflect this load difference.

METHODOLOGY

Identifying specific occupant behaviours in an operating building is the precursor to making good use of the ‘Dynamic Schedule’. These behaviours can be obtained through the behaviour measurement methods (Fishbein et al., 2010), which will eventually be incorporated into the ‘Dynamic Schedule’ process (examples of the behaviours that have the highest probable occurrences in an office environment during the summer/hot months are obtained through a preliminary survey: opening windows, using a personal fan, adjusting blinds, lights, clothing level, and the thermostat).

A detailed process of the ‘Dynamic Schedule’ is outlined in Figure 1. The objective of the process is to simulate both a realistic occupancy – e.g., a routine meeting, class/training, etc – and the different occupant behaviours (as identified earlier), which are neglected in current simulation practices, to calculate the impact of behaviours on building energy use.

‘Schedule Generation’ explains how various occupant behaviours and occupancies are collected and quantified so that their load changes are interpreted in terms of the operation schedules (occupancy, lighting, equipment, and HVAC schedules). The collective schedules (occupancy, lighting, and HVAC schedules listed under ‘Schedule Generation’ in Figure 1) are estimations that are generated by methods explained later. ‘Schedule Population’ refers to transferring this input information, or generated schedules, into the building energy simulation programs. This basically takes the generated schedules and translates them into simulation syntax (or language). ‘Schedule Population’ can be a one-time event, or ‘Initial Input,’ prior to running the simulation. In other words, year-round schedule input information can be defined and used to simulate annual building energy consumption – this is demonstrated in the ‘CASE STUDY’ section. To achieve the dynamic aspect in the process, the means to feed in a real-time schedule is in the future works. The goal of the ‘Real-time Feedback’ is to allow a third-party simulation process to dynamically change the input information within the building energy simulation program. The need for this component is more evident when the need for schedules of behavioural observations other than occupancy and the demand for “what-if” scenarios increase – e.g., unexpected schedule changes, increased behaviour in certain months, etc.

In order to further explain the ‘Dynamic Schedule’
(in particular, the ‘Schedule Generation’ process in Figure 1), one of the occupancy schedules – routine office meetings – was selected as a representative behavioural element (Figure 2). It primarily focuses on generating meeting schedules by way of a probabilistic process, as is commonly the case when making predictions of behavioural uncertainties (Malkawi et al., 2004); (Sokolowski et al., 2009). The following explains the process in depth (the methods explained here can be applied to all the collective schedules that may appear in ‘Schedule Generation’ in Figure 1):

- The simulation cycle consists of sub-cycles, e.g., ‘Weekday’, ‘Weekend’, ‘Holiday’, and one or more ‘Custom’ schedules (denoted as “1” on Fig 2), which is determined in advance as decisions on the simulation cycle and the occupant size are made by the user. This part is mostly done in the individual building energy simulation program.

- The meeting schedules are automatically generated by defining the four decision variables (rectangle symbols in “3” of Fig 2): 1) single meeting duration, 2) time of the day for a single meeting, 3) specific day of the week for a single meeting, and 4) the number of meetings in a week. The statistical algorithm (diamond symbol in “3” of Fig 2) will follow a stochastic process to predict the probability of the decision variables.

- The ‘Schedule Conversion’ is the most important part of the process, helping to reconfigure the generated schedules into the language of the building energy simulation programs (denoted as “2” on Fig 2). This involves two sub-tasks. First, the data structure of the generated schedules needs to match the data structure of the simulation program of choice, hence, ‘Program Specific’. On that note, it would be convenient if the users work with an open-source simulation program (e.g., EnergyPlus) that enables users to customize the simulation process. Second, the conversion must take into consideration the difference in the magnitude of meeting weights (frequencies) for every single day – or ‘Frequency Weight’ (see below for details).

Applying the weights for different days has significant importance because the changes in the internal load (and energy consumption) due to schedules can vary depending on the specific time, e.g., from diurnal and seasonal effects. Moreover, the need to accommodate different sub-cycles defined in Figure 2 is resolved by generating individual schedules that reflect adequate weights – for example, more weight for weekdays than for holidays or weekends. In the end, the goal is to increase the simulation accuracy by emulating the real world schedule patterns.

The ‘Frequency Weight’ process calls for a schedule prediction model that generates these weights. However, trying to replicate the exact daily schedule is hardly possible, especially when an actual schedule history is not readily available. Therefore, the objective of the schedule prediction model will be to replicate the same mean value, the same spread from minimum to maximum, and the same number of days to mimic the actual schedules. The specifics of the schedule prediction model follow the methods suggested by Degelman (Malkawi et al., 2004); with the input of mean frequency and standard deviation, the cumulative distribution function (CDF) of the simulated schedules (from “3” of Fig 2) will provide an acceptable estimation of the real schedules. Figure 3 is an example of the schedule prediction model for routine meetings in offices, or the CDF of daily operating schedule between 5am and 9pm. The x-axis is the time of the day, and y-axis shows the normalized occupancy.
occupancy normalized based on an average daily occupancy of 0.38 (from the suggested office occupancy in ASHRAE Standard 90.1-2004, ranging from 0 to 1). The results are from a sample size of \( n=100 \); \( m \) indicates the average frequency of 1, 3, 6, 9 and 12 meetings per day. Although these numbers are deterministic, the results cover 95\% of all probable occupancies (confidence interval level of ±0.8). In order to replicate future schedules, the weight will be the user inputs of mean frequency \( m \) and the standard deviation (\( \delta \)) of the frequencies (refer to Degelman’s methods for approximating the \( \delta \)). The weights can be specified for a day, a week, or a month depending on the preferences of the user.

The next section of the paper covers a simulation case study that reflects the methods presented here. The study presents how the dynamic schedule can result in increased simulation accuracy for building energy consumption.

**CASE STUDY**

The case study is an execution of the ‘Schedule Generation’ process outlined in the previous ‘METHODOLOGY’ section (or dynamic schedule generation), using EnergyPlus. The case study is divided into two sections. The first section presents a description of the case study and an example run-through of the ‘Schedule Generation’ process. The next section discusses the simulation model and the results comparing the actual and the simulated data.

(1) Description of the case study

Figure 4 is a representation that visualizes the outcome of the dynamic schedule generation in Figures 1 and 2. Figure 4-(a) presents five different daily schedules for occupancy. Each square block in the ‘Daily Schedule’ represents the fraction of occupancy in the given space, ranging from 0 to 1.

The ‘Base-1’ refers to the schedule used in the test suite Case CE100 as described in ANSI/ASHRAE Standard 140-2007. The ‘Base-2’ refers to that of a typical office space as described in ASHRAE Standard 90.1-2004. The first two schedules are for comparison purposes as they represent the most commonly used schedules adopted in simulation studies. The following schedules, ‘Schd-1’, ‘Schd-2’, and ‘Schd-3’, are selected samples generated by the process proposed in this paper, reflecting the daily meeting patterns. Daily schedules are then converged into a ‘Weekly Schedule’ shown in Figure 4-(b). As mentioned earlier, the first two weekly schedules in Figure 4-(b) are deterministic with no intention of value changes in the simulation model: ‘Base-1’ and ‘Base-2’ are schedules constructed based on ANSI/ASHRAE Standard 140-2007 and ASHRAE Standard 90.1-2004, respectively. ‘Option-1’ to ‘Option-3’ (boxed in a dotted line) are the more realistic occupant schedules that reflect the weekly meeting patterns. Note that the accuracy of the predictions (or meeting occurrences) made by the dynamic schedule generation process depends solely on the statistical algorithm and the site-specific factors that are unique to individual buildings. This paper will dismiss the effort trying to define a robust algorithm, but focus on establishing a foundation that would facilitate a gamut of algorithms later.

Figure 5 is a class diagram that delineates the process of dynamic schedule generation, its population, and the conversion into the building energy simulation program. This is intended for any commercial programming language, so that the information generated from the previous step can be converted into the syntax/codes used by the building energy simulation program. As an object-based programming, the ‘Meeting Schedule’ model consists of the following class functions:

![Figure 4 Daily and weekly schedule generated by the ‘Schedule Generation’ process](image-url)
• Schedule Initialization: This part uses the *schedule prediction model* (Fig 3) to generate daily schedules that represent the meeting patterns (this will eventually expand to other occupant behaviours mentioned in the ‘METHODOLOGY’ section).

• Default Settings: This is a predefined library of the baseline schedule, ‘No Work Day’ schedule, etc that are part of the algorithm used in the previous ‘Schedule Initialization’ class. For example, the baseline for this particular case study is from the ASHRAE Standards, but options to customize or optimize it as needed are available.

• Schedule Allocation: This class allocates the generated dynamic schedules according to the characteristics of the simulation calendar (particular year the user is trying to simulate). For example, it will match the schedules for weekdays, weekends, holidays, etc. The schedules populated are basically 0 to 1 occupancy for every hour of the day, stored in a CSV (comma-separated values) format.

• Translator: If all the class functions up to this point are generic, the ‘Translator’ class requires unique attention as different building energy simulation programs run on dissimilar program syntax. For example, in order to apply an alternative schedule in EnergyPlus, one needs to substitute an existing schedule, such as weekly, into three separate schedules – the schedule for the room with meetings, the schedule for the room where people vacate to attend the meeting, and the schedule for rest of the hours that is not affected by meetings.

• Calendar Initialization: This takes the schedules populated by the ‘Translator’ class and rewrites and/or reconfigures the building energy simulation program of choice to run on newly generated schedules.

(2) Simulation model and results

Based on this process, the schedule generated by the dynamic schedule generation process is compared to both the actual and ASHRAE schedules for validation. This study is conducted in EnergyPlus using a simulation model that includes a simple mechanical system, adopted from the CASE CE100 of ANSI/ASHRAE Standard 140-2007, which is a standard method for testing and evaluating EnergyPlus models (Henninger et al., 2010):

• The basic test building is a rectangular 48m² single zone (8m wide × 6m long × 2.7m high) with no interior partitions and windows.

• The building is a near-adiabatic cell with cooling load driven by user specific internal gains.

• Simple unitary vapour compression cooling system with air-cooled condenser and indoor evaporator coil, 100% convective air system, and no outside air or exhaust air.

• There is a non-proportional-type thermostat, heating is always off, and cooling is on if the zone air temperature > 22.2°C.

• The simulation case runs for a three-month period, with results report only for February. A constant outdoor dry-bulb temperature is set at 22°C.
Due to the limitations of the model, the simulation results fall short of representing the whole-building energy performance. Nevertheless, the model is sufficient for comparing different schedule settings, because it is sensitive to the changes of the internal load caused by the different schedules.

Figure 6 compares the energy consumption of HVAC with a conventional simulation schedule (as suggested in ASHRAE 90.1-2004), an actual schedule referenced from an existing building\(^1\), and the dynamically generated schedule. The x-axis refers to three HVAC components that showed visible differences among the different schedules. The y-axis indicates the total energy consumption (in watts) for February. Note that while the actual schedule was manually constructed in EnergyPlus for each day of the week – a multiple input process – the schedule prediction model enables the user to mimic the actual schedule with a single input process (refer to weight in the ‘METHODOLOGY’ section) without redundancy.

Figure 7-(a) describes the outcome of all the schedules (n=100, mean=4.8 meetings per day, \(\delta=0.396\); mean and \(\delta\) from the actual schedule) generated for this case study, plotted as dots, using the ‘Dynamic Schedule’ method. The single line plot is the average of the generated schedules that was actually used in the simulation process (in accordance with the ‘Initial Input’, not ‘Real-time Feedback’, in Figure 1). Figure 7-(b) compares the occupancy for meetings of the simulated, ASHRAE, and actual schedule used in the case study. The simulated schedule appears to resemble the ASHRAE schedule more than the actual schedule because the baseline for the schedule prediction model used in the case study was the ASHRAE schedule. In addition, the schedule patterns shown in Figure 7-(b) are not representative of all the schedules throughout the simulation cycle. Nevertheless, the EnergyPlus simulation results using the three schedules reveal that the resemblance between the simulated and actual schedules is noticeable – in the end, the goal is increasing the prediction accuracy of the energy use, not obtaining the exact, unique schedule patterns.

The detailed simulation results and comparisons among the different schedules are summarized in Table 1. The first column of Table 1 refers to the x-axis described in Figure 6. Columns two to four list the total energy consumption, while the parentheses in the third and fourth columns depict the percent difference from the actual schedule simulation results. The last column delineates the percent increase in the accuracy of the dynamically generated schedule in comparison with the conventional ASHRAE schedule.

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\(^1\) Meeting schedules: Mon 1pm-9pm; Tue 9am-11am and 6pm-9pm; Wed 5pm-9pm; Thurs 9am-12pm, 1pm-3pm, and 6pm-8pm. Full occupancy assumed during meetings.
Many occupant behaviours in buildings – such as control of light, windows, blinds, etc – are predictable with the help of existing simulation capabilities. However, the ability to predict the behaviours that directly affect the fluctuation of an occupant’s microclimate, and thus influence the whole-building energy performance, are still lacking in recent studies. This paper presents a theoretical framework and methodology that are constructed towards quantifying the impact of human behaviours (both frequency and magnitude of behavioural uncertainties) on the whole-building energy performance.

The causality between the dynamic schedule, occupant behaviours, and the overall energy performance is still in its infancy. Nevertheless, the preliminary simulation case study informs, to some extent, the behaviour-energy relationship that will accredit our efforts to further pursue the research.

### DISCUSSION AND CONCLUSION

Based on the research process illustrated in Figures 1 and 2, this paper conducted a simple simulation case study to see how the building energy simulation program responds to the ‘Dynamic Schedule’ – both the methodology and literal sense of the dynamic meeting schedules. The results reveal the following findings:

- Any changes in the schedule (occupancy schedule in particular) are expected to cause noticeable changes in the overall energy consumption of the building.
- The ‘Dynamic Schedule’ process enables simulation users to simulate realistic occupancy (and potentially other occupant behaviours) that has impact on the internal load and energy consumption. The resemblance between the actual and the simulated data is more evident with the energy calculation results than with the patterns of the schedules themselves.
- Simulation results using the ‘Dynamic Schedule’ process showed up to 17% increased energy prediction accuracy compared to the industry’s standard schedule, which commonly references the ASHRAE Standards.

Although the case study yielded a generous superiority (17% increased prediction accuracy) over the current modelling approach (static), it used an oversimplified simulation model that lacks the robustness in mimicking true-life energy uses. As a next step, constructing a simulation model that accounts for realistic settings (exact weather data, complex geometry, etc.) is needed to optimize the ‘Dynamic Schedule’ process. In addition, to elaborate on findings more pertinent to human behaviour research, other behavioural influences must be identified and incorporated into the ‘Dynamic Schedule’ process.

### Table 1

<table>
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<th>Actual [kW]</th>
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<th>Dynamic [kW (DHF)]</th>
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<td>282.35 (-19.4%)</td>
<td>328.08 (-6.3%)</td>
<td>16.2%</td>
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### REFERENCES


