

Characterizing the Benefits and Limitations of Smart Building Meeting Room Scheduling

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Abstract—Automated building meeting assignment attempts to save meeting room energy by more intelligently assigning meetings to the available rooms. While this approach has shown good potential for particular conditions, it relies on time-consuming building simulations or model based algorithms that do not scale well to larger problems, and fails to account for important building energy factors. We present a new approach to applying and understanding meeting scheduling based on building power characterization. We determine the key factors affecting the building energy consumption with respect to the meeting assignment, and develop an energy savings model. Using this model, we show how meeting room, meeting schedule, and weather related parameters affect the energy savings potential of smart meeting scheduling. We further identify the situations where smart meeting room assignment algorithms would give significant energy savings, and where simple assignment algorithms would suffice. We also demonstrate that the incorporation of key modeling parameters greatly improves modeling accuracy over prior approaches.

Index Terms—Energy Savings Model, Meeting Room Scheduling, Smart Buildings, Algorithms, Optimization

I. INTRODUCTION

Buildings significantly impact worldwide energy use and the consumption of fossil fuels. In the U.S., buildings constitute 40% of the nation’s energy consumption, with 74% of this energy coming from fossil fuels [1]. This energy is projected to grow by 20% by 2035 [2]. Since about half of a building’s energy consumption is for Heating, Ventilation, and Air Conditioning (HVAC), dynamic control and optimization of the HVAC systems, and encouraging occupants to take energy friendly actions, have been the subject of intense research.

One such way to affect the occupant behavior is by automatically assigning meetings to the rooms to reduce the overall HVAC energy consumption. The meeting room assignment problem is NP-complete [3], and is conventionally performed on a first-come, first-served basis. The typical “algorithm” matches the size of the meeting to the capacity of the available rooms. However, there are many possible assignments, great differences in their energy usage, and many factors that affect the meeting room energy consumption.

As a result, a number of automated smart meeting scheduling algorithms have been proposed [3], [4], [5], [6], [7], [8], [9]. These approaches range from simple greedy and backtracking searches [4], [5] to smarter Mixed Integer Linear Programming (MILP) formulations [6], [7], [8], [9]. These schemes have shown great potential for particular meeting

room properties, meeting schedules, and building models. However, it is unclear from previous work how different characteristics impact the achieved energy savings, and in what situations a simple assignment algorithm will suffice, or a smarter one proves worthwhile.

In this paper, we develop an abstract analytical energy model that captures the critical parameters that impact meeting room scheduling energy savings. Using this model, we characterize how meeting room, meeting schedule, building, and outside weather parameters impact the potential energy savings. We show how the model predicts when the conditions exist for significant energy savings using smart meeting room scheduling, and when it is not worthwhile. We further demonstrate through EnergyPlus simulations the intuition derived from our model, and how the addition of key modeling parameters improves the accuracy in estimating energy savings over prior models.

The rest of this paper is organized as follows. The meeting room assignment problem is presented in Section II, followed by a building power characterization study in Section III. Section IV describes our proposed energy model. Section V shows the key parameters affecting meeting scheduling energy savings and presents situations where simple algorithms would suffice. Section VI compares the accuracy of our model with respect to prior energy models. Finally, we discuss related research in Section VII and conclude in Section VIII.

II. MEETING ROOM ASSIGNMENT

Given a set of meetings and available rooms, the overall objective of meeting room scheduling is to allocate rooms to the meetings such that the HVAC energy to condition the rooms is minimized while maintaining the desired set temperature when a room is occupied (*Active*). Between meetings when the room is unoccupied, the set temperature is lowered to a *Sleep* temperature¹.

Let R and M be the set of n rooms and m meetings, respectively. For an i^{th} meeting $M_i \in M$, $M_i.st$, $M_i.et$, $M_i.size$, and $M_i.room$ represent, respectively, the start time, end time, meeting size, and the room where M_i is assigned. Initially, $M_i.room = \phi$. For a j^{th} room $R_j \in R$, $R_j.cap$ denotes its

¹Since it takes time to heat a room, the transition from *Sleep* to *Active* set temperatures occurs some time before the start of the meeting. Similarly, since occupants may linger at the end of a meeting, the transition from *Active* to *Sleep* at the scheduled meeting end time is delayed.

TABLE I
KEY VARIABLE DEFINITIONS.

n	Number of rooms
m	Number of meetings
$R_j.cap$	Capacity of a j^{th} room
$M_i.st$	Start time of an i^{th} meeting
$M_i.et$	End time of an i^{th} meeting
$M_i.size$	Size of an i^{th} meeting
r_j	Room size ratio of room R_j with respect to the smallest room
occ_j	Occupancy of room R_j
$occ_{j,A}$	Occupancy of R_j under assignment A
$\beta_{j,t}$	Ratio of sleep to active power for room R_j at timestep t
$\gamma_j(occ_j)$	Ratio of the active power of a partially occupied room R_j with respect to its full occupancy
η_t	Energy savings at timestep t
η	Net energy savings
τ	Time until the room temperature naturally drops to T_{lower} during a meeting gap
t_o	Offset time
\mathbb{T}	Total time over which energy is measured
T_s	Set temperature
T_r	Room temperature
$T_{r,a}$	Room temperature during active state
$T_{r,sl}$	Room temperature during sleep state
T_o	Outdoor temperature
T_{upper}	Upper set temperature
T_{lower}	Lower set temperature
$X_{i,j}$	Boolean variable that is <i>true</i> if meeting M_i is assigned to room R_j
$X_{i,j,t}$	Boolean variable that is <i>true</i> if meeting M_i is assigned to room R_j at timestep t
$Y_{A,j,t}$	Boolean variable that is <i>true</i> if room R_j is occupied at timestep t under assignment A
A_j	Set of meetings assigned to room R_j
\mathbb{S}_j	Number of effective meetings assigned in room R_j
$P_{a,j,t}$	Active power of room R_j at timestep t
$P_{sl,j,t}$	Sleep power of room R_j at timestep t
$P(T_s, T_r, T_o, occ)$	Power function, which depends on set temperature, room temperature, outdoor air temperature and room occupancy
$E_{a,j}$	Active energy of room R_j
$E_{sl,j}$	Sleep energy of room R_j
$E_{ov,j}$	Overhead energy of room R_j
$E_j(A_j)$	Energy of room R_j , which is a function of set of meetings assigned to room R_j

capacity. The room assignment problem is formulated as an optimization problem, described below.

$$\min_{A_1, \dots, A_n} \sum_{j=1}^n E_j(A_j) \quad (1)$$

$$\text{where } M_i \in A_j \text{ if } M_i.room = R_j$$

subject to:

- Timing

$$M_i.st < M_i.et \leq M_k.st < M_k.et \quad (2)$$

$$\forall j \text{ and } \forall i \neq k \text{ with } M_i.room = M_k.room = R_j$$

- Capacity

$$M_i.size \leq R_j.cap \quad (3)$$

$$\forall M_i.room = R_j$$

The objective is to determine a meeting assignment to rooms that minimizes the total HVAC energy over all meeting rooms

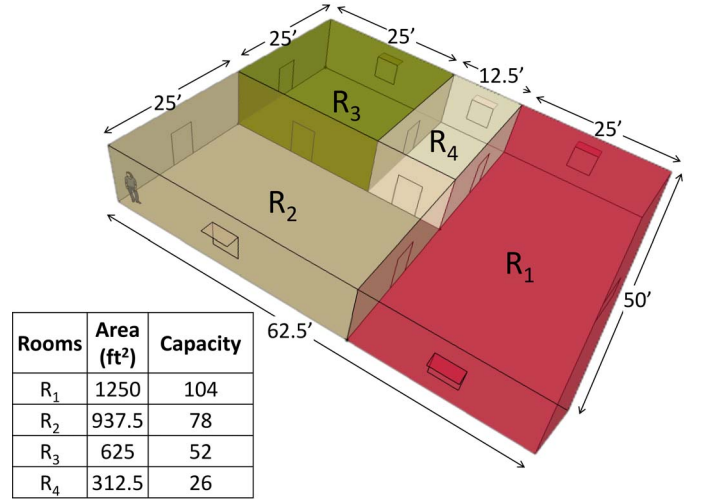


Fig. 1. Layout of the simulated building.

while maintaining thermal comfort (set temperature objectives). Here, E_j denotes the energy of room R_j , and the set A_j contains the meetings assigned to room R_j . The assigned meetings must be free from timing conflicts (meetings do not overlap within the same room) and capacity mismatches (an assigned meeting does not exceed the room capacity).

III. BUILDING POWER CHARACTERIZATION

The analytical model that we develop is based on understanding how various factors impact meeting room scheduling energy savings. In this section, we characterize the building power behavior, and identify the key factors that affect the energy savings. We first describe our modeling infrastructure and then present results from the characterization experiment.

A. Modeling Infrastructure

Modeling and energy characterization is performed using the Department of Energy's building energy simulation software EnergyPlus version 8.2 [10]. The layout is designed using the Google Sketchup Tool [11]. The construction material for building surface and fenestration are exported from an existing large office template, and lighting and electrical equipment usage are assumed to be on throughout the day to minimize its effect on HVAC energy. Each room maps to a unique thermal zone, and is controlled by an individual zone-level thermostat. The HVAC control system uses the default *IdealLoadsAirSystem*. We assume negligible building infiltration and enable Demand Controlled Ventilation to maintain occupancy comfort with minimum energy expense. To meet the thermal comfort and indoor air quality, we maintain a minimum outdoor airflow of 5 cfm per person and 0.06 cfm per square feet of room area as per ASHRAE's 2010 ventilation standards [12].

The layout of the simulated building is shown in Figure 1. The building contains four rooms of different sizes and capacities. We eliminate other spaces (offices, hallways, etc.) from the layout in order to focus on the meeting room energy savings. Room capacities are computed by assuming twelve

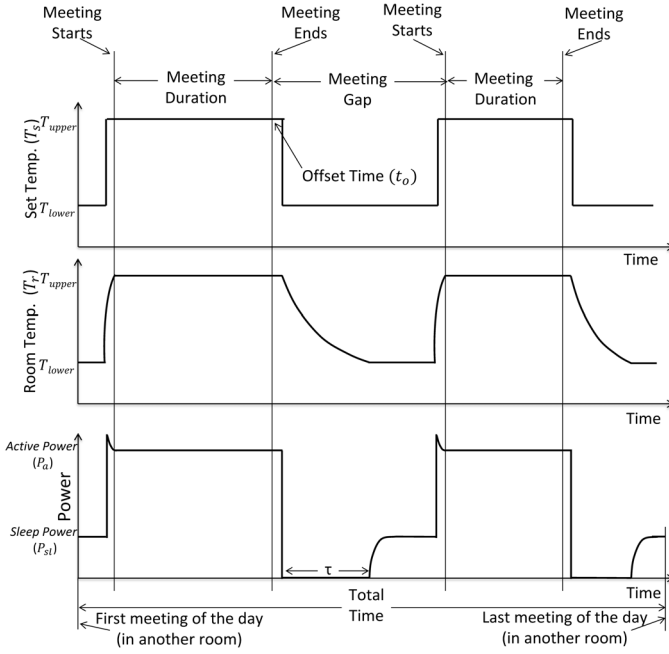


Fig. 2. Depiction of the HVAC power behavior for meeting rooms with *Active* and *Sleep* setpoint temperatures.

square feet of area per person for a theatre style room [13]. We evaluate heating energy during the winter in Minneapolis (from January 28th to February 1st).

B. HVAC Power Characterization

In this section, we discuss the results of several experiments that inform the construction of our energy model. Figure 2 shows the general power behavior of a meeting room operating using *Active* and *Sleep* setpoint temperatures. When a room is occupied (*Active*), the heating setpoint is increased to T_{upper} (21°C in our experiments). Between meetings when a room is unoccupied, or when a room is no longer needed for the day, the heating setpoint is lowered to the *Sleep* setpoint, T_{lower} (15.6°C in our experiments). A room in *Sleep* begins transitioning to *Active* an offset time, t_o , prior to the start of a meeting so that the building occupants are comfortable when the meeting begins². Similarly, when there is no subsequent meeting, the setpoint is lowered t_o minutes after the conclusion of the meeting in case occupants linger in the room.

When the setpoint is increased from T_{lower} to T_{upper} , the room temperature takes t_o to reach the setpoint. The power, however, shows a spike before settling down to a steady value. This is because the HVAC control uses room temperature as feedback. On changing the setpoint, the controller observes a large error in the room temperature and the setpoint, and thus expends high energy to mitigate this error. As the room temperature reaches the setpoint, the error reduces and the power settles to a non-zero value. The power is non-zero because it maintains the room at T_{upper} while bringing in and conditioning outside air to maintain acceptable indoor air

²We experimentally verified that $t_o = 15$ minutes is sufficient time to condition the room to a comfortable thermal state.

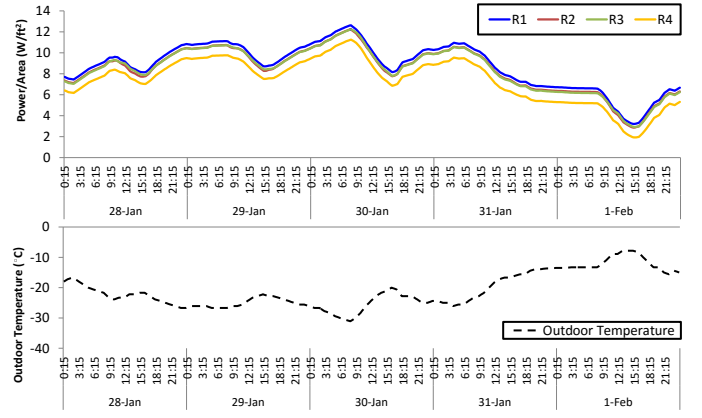


Fig. 3. Active power per unit area of the different rooms, and outdoor air temperature, over a five day period.

quality. After t_o minutes have passed from the scheduled end of the meeting, the room is assumed to be empty, and thus the heating setpoint is reduced to T_{lower} . Thus, the HVAC system shuts down so that the room temperature naturally decays towards T_{lower} , with zero HVAC power. This time of zero power, τ , depends on outdoor weather, how long the room has been warmed up (thermal state), and building heat loss characteristics. After time τ , the HVAC controller turns on to maintain the room temperature at T_{lower} .

The intuition derived from this characterization permits constructing an analytical energy model that relates to the meeting and room specifications, as well as building and environmental conditions.

1) *Active Power*: Active power (P_a) is the HVAC power of a zone when it is occupied and set to the T_{upper} setpoint. We evaluated a number of factors that affect the active power.

Room Capacity: We evaluate the active power of each of the four meeting rooms in order to understand the relationship between active power and room capacity and the effect of outside temperature. In our experiments, the HVAC system maintains the T_{upper} setpoint temperature throughout the day over a five day period with full occupancy. Figure 3 shows the heating power per unit room area for each of the rooms during different periods of the day. The ratio for the different rooms is very close, which indicates a linear relationship between room area and active heating power. We observe that room R_4 has a slightly lower ratio, which we experimentally determined was due to R_4 being a small room that experiences lateral heat transfer from neighboring rooms because of our particular building layout, where R_4 has three walls adjacent to other rooms. This results in R_4 expending less W/ft^2 than the other rooms. From Figure 3, as expected, the active power increases with colder weather, and vice-versa. This is because more heating energy is needed to warm up the colder outdoor air brought in to maintain the indoor air quality. Note, however, that all the rooms respond similarly to the changes in outdoor temperature.

Room Occupancy: With Demand Controlled Ventilation, more outdoor air is brought in during periods of high occupancy in

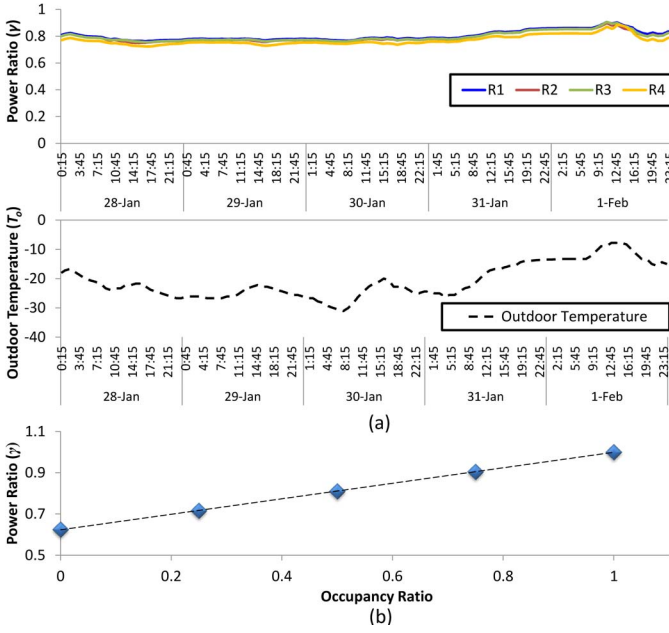


Fig. 4. (a) Effect of room size and outdoor temperature on γ for half occupancy. (b) Effect of partial occupancy on active power.

order to maintain acceptable indoor air quality. As a result, higher occupancy requires more heating power to heat the outdoor air. We explore the effect of partial occupancy on the heating power as a function of room size and outdoor temperature. We define γ as the ratio of the active power of a partially occupied room to a fully occupied one. Figure 4(a) shows γ at half occupancy for the different room sizes. As expected, γ is less than one, but the effect of both room size and outside temperature is small. Figure 4(b) further shows that active power per unit area increases linearly with occupancy, since more outside air is required to maintain acceptable indoor air quality.

2) *Sleep Power*: Sleep power is the HVAC power to maintain the room temperature at T_{lower} during periods of no occupancy. During this period, the desired set temperature is lowered as is the outdoor airflow, which can significantly reduce the heating power.

We define β as the ratio of the sleep to active power, and we explore the effect of room size and outdoor temperature on this parameter. Figure 5 shows the value of β for the four rooms throughout the five day period. Here, we model the *Sleep* power through the five day period (with the set temperature at T_{lower} throughout) and the *Active* power (with the set temperature at T_{upper}), and then take the ratio. As expected, β is less than one since sleep power is smaller than active power. Moreover, the value of β is inversely proportional to the outside temperature. The reason for this behavior is that the HVAC power is roughly proportional to the difference in the room and outside air temperatures. Thus, as the outside temperature increases, the change has a greater effect on reducing required *Sleep* power compared to *Active* power. Furthermore, β is relatively independent of room size,

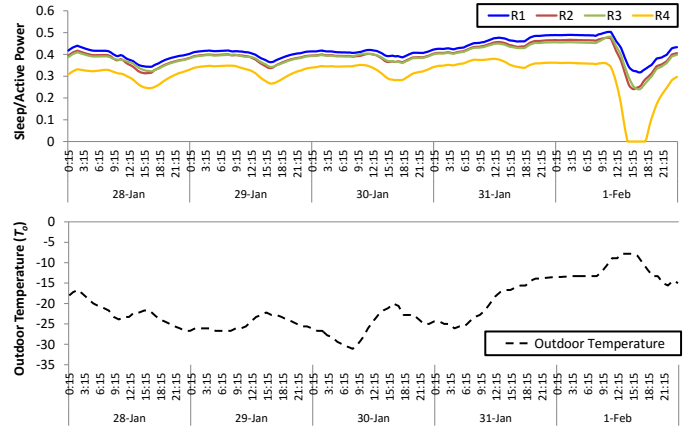


Fig. 5. Effect of room size and outdoor temperature on the sleep to active power ratio (β).

except for R_4 . This is because of lateral heat transfer from shared walls.

We now investigate the effect of room size and outdoor temperature on τ , the time for the room temperature to decay to T_{lower} when the HVAC system is turned off. Figure 6 shows the power relative to the *Active* power over a two day period (blown up for clarity) and room sizes when meetings are periodically assigned for a time period followed by a time gap with no assigned meetings. Our results for the full five day period show that τ varies widely with outdoor temperature, from 5 minutes to an hour. It also varies across different rooms. A longer τ results in less sleep power, since the HVAC system can be shut down for longer periods during meeting gaps. Furthermore, we observe a power spike when the setpoint is increased to T_{upper} , due to the large temperature error observed by the HVAC controller. While our model currently ignores this power spike, we later show in Section VI that our accuracy is still very high.

IV. ANALYTICAL ENERGY MODEL

In this section, we present an energy model derived from the building power characterization. The model estimates the *Active* energy when a meeting is scheduled, the *Sleep* energy when no meeting is scheduled, and the *Overhead* energy during transitions. Before we present the individual models for each of these energy phases, we review some of the key variables. The complete list can be found in Table I.

A. Key Variable Definitions

Let $X_{i,j,t}$ be a Boolean variable that indicates that room R_j is assigned to meeting M_i at timestep t . When $X_{i,j,t} = true$, it indicates meeting M_i is assigned to room R_j , i.e., $M_i.room = R_j$. At timestep t , variable $\beta_{j,t}$ is the ratio of sleep to active power of R_j when it is fully occupied, i.e., $occ_j = R_j.cap$. It is a function of room temperature (T_r) and the outdoor air temperature (T_o), and is formally defined in Equation (4). Note that $\beta_{j,t}$ is zero during the meeting gaps for a decay time

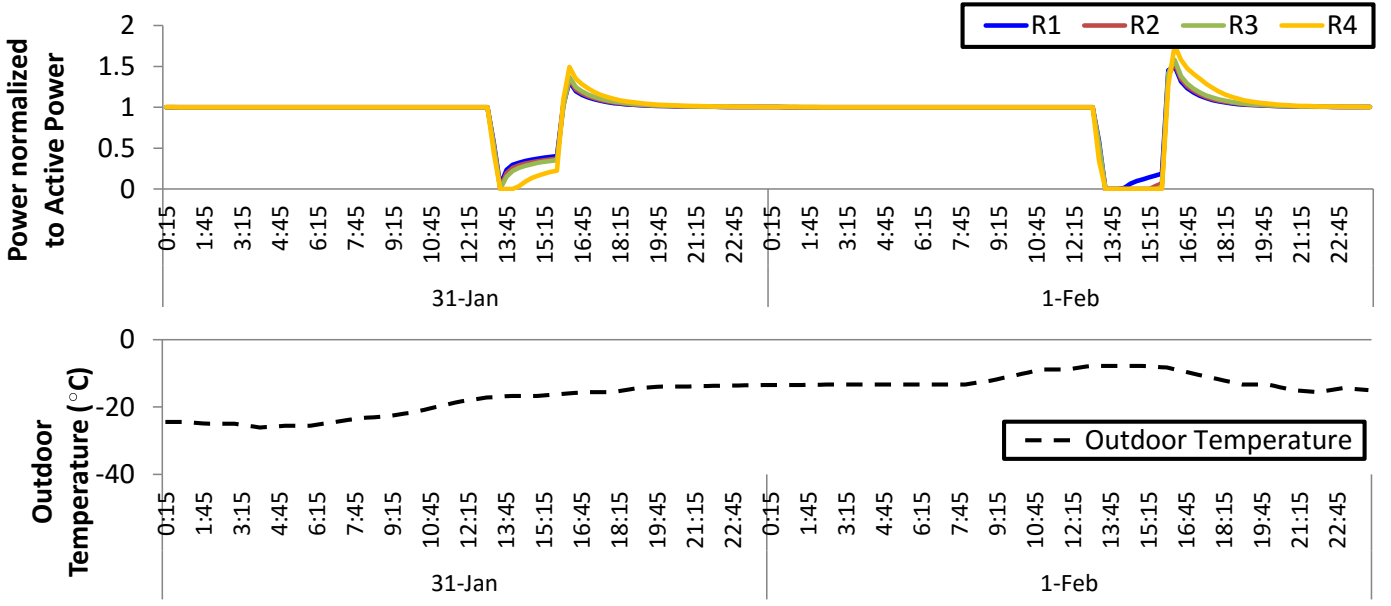


Fig. 6. Sleep-to-active power ratio during meeting gaps.

of τ when the room temperature is greater than the lower set temperature.

$$\beta_{j,t} \triangleq \begin{cases} \frac{P_{sl,j,t}}{P_{a,j,t}} = \frac{P(T_{lower}, T_{r,sl}, T_o, 0)}{P(T_{upper}, T_{r,a}, T_o, R_j.cap)}, & \text{if } T_{r,sl} \leq T_{lower} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

We also define γ_j in Equation (5) as the ratio of the active power when room R_j is partially occupied with occupancy occ_j compared to the active power when it is fully occupied. As γ_j and occ_j are linearly related, we employ a linear regression model and use the slope and intercept from Figure 4(b).

$$\gamma_j(occ_j) \triangleq \frac{P(T_{upper}, T_{r,j}, T_o, occ_j)}{P(T_{upper}, T_{r,j}, T_o, R_j.cap)} \quad (5)$$

B. Active Energy

From the building power characterization, the active power at timestep t is a function of room capacity and occupancy. At full occupancy, the active power is proportional to the room capacity. For less than full occupancy, the active power is expressed as Equation (6).

$$P_{a,j,t} \propto \gamma_j(occ_j) \times R_j.cap \quad (6)$$

The active energy of a room j is the sum of its active power over the total time \mathbb{T} , and is proportional to the capacity of R_j times the total duration of all the meetings assigned to it. Here, $X_{i,j}$ is a Boolean variable, which is *true* if meeting M_i is assigned to room R_j .

$$\begin{aligned} E_{a,j} &= \sum_{t=0}^{\mathbb{T}} P_{a,j,t} \\ &\propto R_j.cap \times \sum_{i=1}^m X_{i,j} \times \gamma_j(M_i.size) \times (M_i.et - M_i.st) \end{aligned}$$

C. Sleep Energy

Sleep power is expressed as β times the active power of a room when fully occupied. β determines the degree of energy savings when conditioned at a lower set temperature, and depends on room temperature and outside weather conditions. Equation (8) shows this relationship.

$$\begin{aligned} P_{sl,j,t} &= \beta_{j,t} \times P_{a,j,t} \\ &\propto \beta_{j,t} \times R_j.cap \end{aligned} \quad (8)$$

Equation (9) shows the sleep energy formulation.

$$\begin{aligned} E_{sl,j} &= \sum_{t=0}^{\mathbb{T}} P_{sl,j,t} \\ &\propto R_j.cap \times \sum_{t=0}^{\mathbb{T}} \overline{X_{i,j,t}} \times \beta_{j,t} \end{aligned} \quad (9)$$

D. Overhead Energy

Every transition between *Active* and *Sleep* incurs *Offset* overhead to ensure thermal comfort requirements. Before a meeting starts, the overhead is incurred to condition the room before occupants arrive. At its conclusion, the overhead is incurred to keep the room conditioned for lingering occupants. To model the overheads, we compute the number of switching activities and multiply by the energy overheads. During these periods, the room is assumed unoccupied. Equation (10) formulates the energy from this overhead.

$$E_{ov,j} \propto \mathbb{S}_j \times \gamma_j(0) \times R_j.cap \times (2 \times t_o) \quad (10)$$

Here, \mathbb{S}_j represents the number of *effective meetings* assigned to room R_j . If two meetings are scheduled back to back with no gap, these two meetings can be simply considered as one (7) longer effective meeting.

E. Room Energy

The energy of a room R_j is the sum of active energy ($E_{a,j}$), sleep energy ($E_{sl,j}$), and the overhead energy ($E_{ov,j}$).

F. Energy Savings

In this section, we describe the calculation of energy savings using the energy model. We first show a simple example, and then the general case.

1) *An Illustrative Example:* Using the building layout of Figure 1 with $n = 4$ rooms, we consider assignments A and B , with B as the baseline. If $E_j|_A$ represents the room energy of R_j under assignment A , and $E_j|_B$ for assignment B , the energy savings η_t at timestep t is given by

$$\eta_t \triangleq 1 - \frac{\sum_{j=1}^n E_j|_A}{\sum_{j=1}^n E_j|_B} \quad (11)$$

Assume in this example that for a given timestep t , assignment A keeps room R_4 occupied with occupancy $occ_{4,A}$ and all other rooms unoccupied. Baseline B maintains R_1 with occupancy $occ_{1,B}$ while keeping the rest of the rooms unoccupied. In this case, $occ_{1,B} = occ_{4,A}$ and η_t is expressed as:

$$\begin{aligned} \eta_t &= 1 - \frac{E_{1,sl} + E_{2,sl} + E_{3,sl} + E_{4,a}(occ_{4,A})}{E_{1,a}(occ_{1,B}) + E_{2,sl} + E_{3,sl} + E_{4,sl}} \\ &= 1 - \frac{\beta_{1,t}E_{1,a} + \beta_{2,t}E_{2,a} + \beta_{3,t}E_{3,a} + \gamma_4(occ_{4,A})E_{4,a}}{\gamma_1(occ_{1,B})E_{1,a} + \beta_{2,t}E_{2,a} + \beta_{3,t}E_{3,a} + \beta_{4,t}E_{4,a}} \end{aligned} \quad (12)$$

Also, since the active energy at full occupancy is proportional to the room capacity, we can write

$$\eta_t = 1 - \frac{\beta_{1,t}R_1.cap + \beta_{2,t}R_2.cap + \beta_{3,t}R_3.cap + \gamma_4(occ_{4,A})R_4.cap}{\gamma_1(occ_{1,B})R_1.cap + \beta_{2,t}R_2.cap + \beta_{3,t}R_3.cap + \beta_{4,t}R_4.cap} \quad (13)$$

Dividing both the numerator and denominator in Equation (13) by the smallest room capacity $R_4.cap$, we get

$$\eta_t = 1 - \frac{\beta_{1,t}r_1 + \beta_{2,t}r_2 + \beta_{3,t}r_3 + \gamma_4(occ_{4,A})r_4}{\gamma_1(occ_{1,B})r_1 + \beta_{2,t}r_2 + \beta_{3,t}r_3 + \beta_{4,t}r_4} \quad (14)$$

Here, r_j is the room capacity ratio of R_j relative to a smallest room capacity. This formulation permits the use of relative rather than absolute room size as energy parameters when applying the model to new scenarios.

2) *General Case:* Equation (15) shows the energy savings η_t at timestep t of a generic room occupancy situation for assignments A and B . Here, variable $Y_{A,j,t}$ is a Boolean variable, which is *true* if room R_j is occupied with occupancy $occ_{j,A}$ under assignment A at timestep t .

$$\eta_t = 1 - \frac{\sum_{j=1}^n [\beta_{j,t}r_j \overline{Y_{A,j,t}} + \gamma_j(occ_{j,A})r_j Y_{A,j,t}]}{\sum_{j=1}^n [\beta_{j,t}r_j \overline{Y_{B,j,t}} + \gamma_j(occ_{j,B})r_j Y_{B,j,t}]} \quad (15)$$

The net energy savings, η , over total time \mathbb{T} is given by

$$\eta = 1 - \frac{\sum_{t=1}^{\mathbb{T}} \left[\sum_{j=1}^n \{ \beta_{j,t}r_j \overline{Y_{A,j,t}} + \gamma_j(occ_{j,A})r_j Y_{A,j,t} \} \right]}{\sum_{t=1}^{\mathbb{T}} \left[\sum_{j=1}^n \{ \beta_{j,t}r_j \overline{Y_{B,j,t}} + \gamma_j(occ_{j,B})r_j Y_{B,j,t} \} \right]} \quad (16)$$

Therefore, apart from the meeting assignment vector Y , energy savings η_t at any timestep t depends on the sleep to active power ratio (β), the room capacity ratio (r), and the number of rooms (n). We illustrate in the Section V how these factors affect the energy savings.

V. ANALYZING THE ENERGY SAVINGS OF MEETING ROOM SCHEDULING

In this section, we apply our model to understand how various factors impact the potential energy savings achievable with smart meeting scheduling. We then illustrate when smart energy saving algorithms are useful, and when simple methods suffice.

A. Understanding the Potential Energy Savings of Smart Meeting Scheduling

In this section, we show how varying the model parameters and meeting room situations impact the potential energy savings of smart meeting assignment. Specifically, we examine the sleep-to-active power ratio, the number of scheduled meetings, scheduling flexibility, and room size ratio.

1) *Sleep-to-Active Power Ratio:* We consider the building layout of Figure 1 and examine one meeting whose size equals that of the smallest room R_4 . To understand the potential energy savings achievable with smart meeting assignment, we assume that the baseline assigns the meeting to the largest room R_1 , while the smart algorithm assigns it to the smallest room R_4 . The unoccupied rooms in both cases are in the *Sleep* state.

Figure 7 shows that the energy savings increases as β decreases. For smaller β , the sleep power is relatively small compared to the active power, which yields higher savings from the use of the *Sleep* state for the three unoccupied rooms. Since the value of β depends on a number of factors, it serves as a proxy for various conditions. As shown earlier, more extreme weather conditions result in higher β ; thus, in these conditions, a lower relative energy savings would be expected compared to more moderate times of the year³. Moreover, room characteristics and building layout may significantly impact the value of β , and thus the expected savings.

2) *Number of Scheduled Meetings:* For a given number of rooms, increasing the number of meetings reduces the number that are unoccupied and in *Sleep* mode. This impacts the potential energy savings as shown in Figure 8. Here, we assume the same rooms R_1 to R_4 and that each scheduled meeting is the same capacity as the smallest room (R_4). The baseline algorithm assigns rooms in descending order of capacity (R_1 first) while the smart algorithm works in ascending order (R_4 first). As expected, the largest savings is achieved with a single meeting, since the smart algorithm puts the largest room in *Sleep* while the baseline chooses the smallest room. With all four rooms occupied, there is no benefit since all rooms are *Active* and have the same

³Note that our model only predicts *relative* energy savings. Depending on the conditions, the differences in *absolute* savings between different times of the year may be lower or higher.

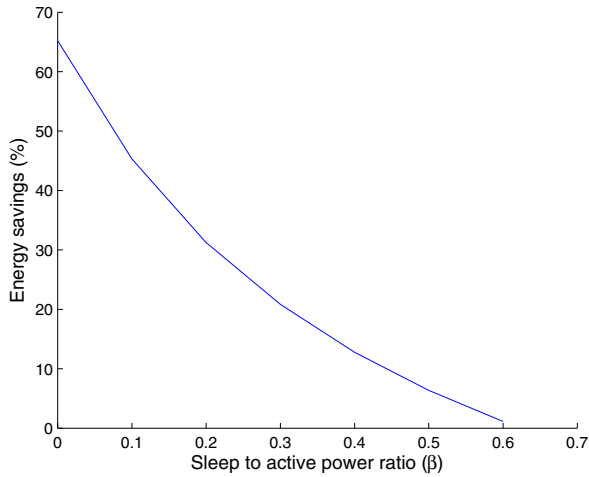


Fig. 7. Effect of sleep-to-active power ratio (β) on the meeting room energy savings. Here, we consider one meeting and report the relative energy savings for the building presented in Figure 1. The baseline algorithm assigns the meeting to the largest room, while the smart policy uses the smallest one.

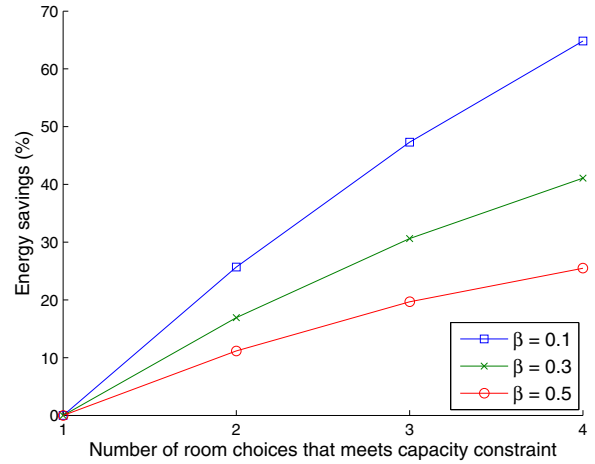


Fig. 9. Effect of scheduling flexibility on meeting room energy savings. Here, we consider one meeting with increasing occupancy and report the relative energy savings for the building presented in Figure 1. The baseline algorithm assigns the meeting to the largest room, while the smart policy uses the smallest room that can fit the meeting.

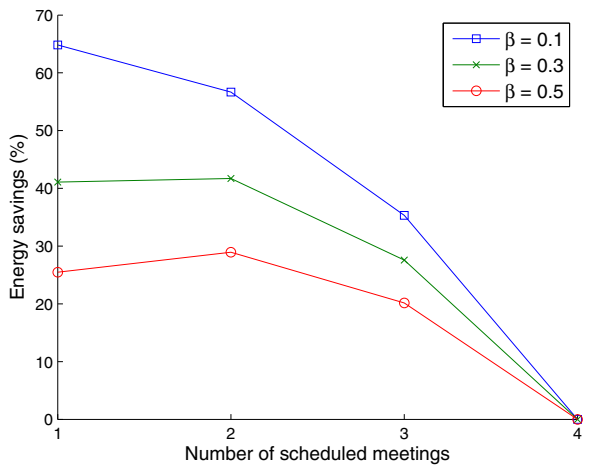


Fig. 8. Effect of number of scheduled meetings on meeting room energy savings. Here, we increase the number of meetings each of same size, and report the relative energy savings for the building presented in Figure 1. The baseline algorithm assigns rooms in descending order of capacity, while the smart policy assigns in ascending order.

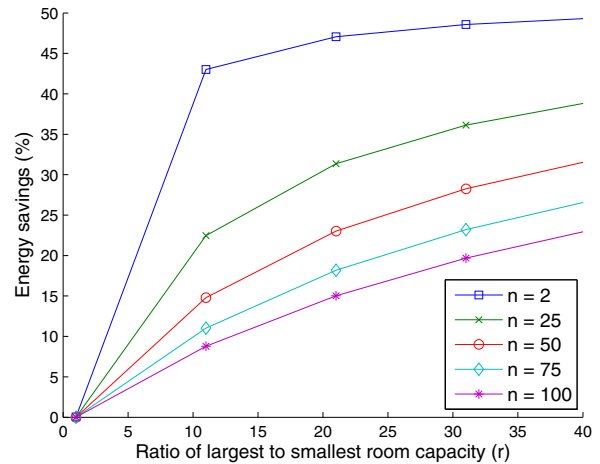


Fig. 10. Effect of number of rooms (n) and room size ratio (r) on meeting room energy savings for $\beta = 0.5$. Here, we consider one meeting, and assume a building of n rooms, of which $n - 1$ rooms are of equal size, and the last room is r times larger. The baseline algorithm assigns the meeting to the largest room, while the smart policy uses the smallest one.

occupancy. This demonstrates that offices that frequently use all or most of their rooms at the same time would expect lesser savings than those that simultaneously use fewer rooms.

The effect is more pronounced for smaller values of β where the potential savings while in *Sleep* mode is larger. Note how the energy savings increases slightly when moving from one to two meetings for the two larger values of β . This occurs because the energy difference between the two assignment policies reaches its maximum for two scheduled meetings, since no rooms are maintained at the same condition in both policies.

3) *Scheduling Flexibility*: To understand the effect of scheduling flexibility on potential energy savings, we consider a single meeting whose size is increased from the capacity of the smallest room (R_4) to the largest (R_1) and assume the same baseline and smart algorithms as before. As shown in Figure 9, as the size of the meeting increases, there are fewer choices (less flexibility) and the difference between the baseline and smart policies diminishes. Thus, if larger meetings tend to be scheduled over smaller ones, then the expected savings from smart scheduling would be expected to be smaller. Note also the effect of β : the relative improvement with maximum flexibility can vary by a factor of three.

Meeting Benchmarks		Avg. Sched. Mtgs.	Avg. Sched. Flex.	Graphical Representation of the Meetings
S Y N T H E T I C	10 continuous meetings with size 15 (10c_15)	Low [1]	High [4]	
	10 interval meetings with size 15 and 30 (10i_15_30)	Low [1]	Medium [3.5]	
	10 interval meetings with size 15 and 100 (10i_15_100)	Low [1]	Low [2.5]	
	9 meetings with size 15 and 90 (9m_15_90)	Low [1.6]	Low [2.6]	
	6 overlapping meetings with size 15 (6o_15)	Medium [2.4]	High [4]	
R A N D O M	8 randomly generated meetings (8r)	Low [1.7]	Medium [3.5]	
	12 randomly generated meetings (12r)	Low [1.9]	Low [2.8]	

Fig. 11. Meeting benchmarks. Each node represents a time slot, while the edges represent meeting name and [size].

4) *Unused Rooms and Room Size Ratio*: Finally, we examine the effect of the number of unused rooms and their relative size ratios on the energy savings. We assume n rooms, of which $n - 1$ are of equal size, and the last room is r times larger. For this experiment, we assume $\beta = 0.5$. We consider a single meeting where the baseline uses the largest room and the smart algorithm one of the other smaller rooms.

As shown in Figure 10, as n increases, the proportional amount of *Sleep* energy increases, which results in lower overall energy savings. On the other hand, as r increases so does the energy savings, since the differences in *Active* energy increases.

To summarize the findings of our model, the relative energy savings potential is highest when:

- the outside temperature is less extreme,
- the meeting scenarios have fewer simultaneously scheduled meetings and high scheduling flexibility, and
- when the building has rooms with large size ratios and the assignments leave fewer unusable rooms.

B. Validating the Model Intuition

In this section, we simulate different algorithms and benchmarks with the aim of validating the insights gained from our model. We show how the model predicts the trends seen from simulating actual meeting room schedules. We also identify the meeting cases where smart assignment algorithms

TABLE II
WEATHER SIMULATED WITH DIFFERENT β RATIOS.

	Outdoor Temp. Range ($^{\circ}$ C)	Range of β during gaps	Weather
Jan 30th	-31 to -21	0.18 to 0.34	Extreme
Feb 1st	-13 to -8	0 to 0.19	Less extreme
Apr 21st	0 to 1.1	0	Moderate

significantly improve upon simple algorithms, and when they are not worthwhile.

1) *Experimental Setup*: In order to demonstrate where smart assignment algorithms significantly improve upon simple assignment algorithms, we formulate the meeting room assignment problem as an MILP similar to that of Chai et al. [8]. We use our proposed energy model as the objective function from which we derive the least energy consuming meeting schedule. To represent the class of simple algorithms, we use *Random Assignment* as a practical baseline. For this algorithm, we average the energy over 30 randomly generated assignments, each meeting the capacity and timing constraints outlined in Section II. For each assignment, we use the EnergyPlus infrastructure described in Section III-A to find the relative energy savings.

We use the meeting benchmarks of Majumdar et al. [5] shown in Figure 11. We annotate each benchmark with its av-

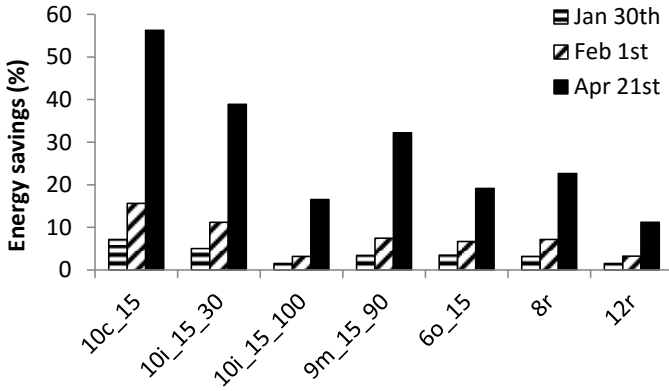


Fig. 12. EnergyPlus energy savings of MILP with respect to the *Random Assignment* baseline for different days and benchmarks.

erage number of scheduled meetings and scheduling flexibility. The formulas used to compute these two metrics are shown in Equations (17) and (18), respectively. To examine different β values, we simulate for three different days as shown in Table II. The energy values are computed from 7am to 7pm, and include the room energy of all the rooms of the building presented in Figure 1.

$$\text{Avg. Sched. Meetings} \triangleq \frac{\sum_{t=1}^T \# \text{ of meetings at } t}{T} \quad (17)$$

$$\text{Avg. Sched. Flex} \triangleq \frac{\sum_{i=1}^m \# \text{ of rooms that can hold } M_i}{m} \quad (18)$$

2) *Impact of Environmental and Meeting Conditions on Energy Savings*: Figure 12 shows the energy savings of MILP compared to *Random Assignment* for different benchmarks and days of the year. This figure validates a number of the insights gained from our model.

First, the effect of β is apparent by comparing the results from the different days of the year. *Apr 21st* with its very small β shows much higher energy savings than *Feb 1st* and *Jan 30th*. These latter two days incur more extreme winter, and thus spend relatively more *Sleep* energy during the meeting gaps, which significantly constrains the relative benefit of the smart MILP algorithm. This matches the basic intuition derived from Figure 7.

Figure 12 also shows the effect of the number of scheduled meetings and the scheduling flexibility predicted by the model in Figures 8 and 9. Benchmark *10c_15* achieves the highest energy savings since it has both few scheduled meetings and high flexibility. On the other extreme, benchmark *12r* has the second highest number of scheduled meetings and a relatively low scheduling flexibility; thus, the relative energy savings of MILP is very small, especially for higher values of β , making the merit of MILP difficult to justify. Benchmark *6o_15* also achieves very little savings due to its relatively high number of scheduled meetings. Thus, these results demonstrate how the basic intuition provided by the model (from Figures 8 and 9) help identify the situations where smart meeting scheduling

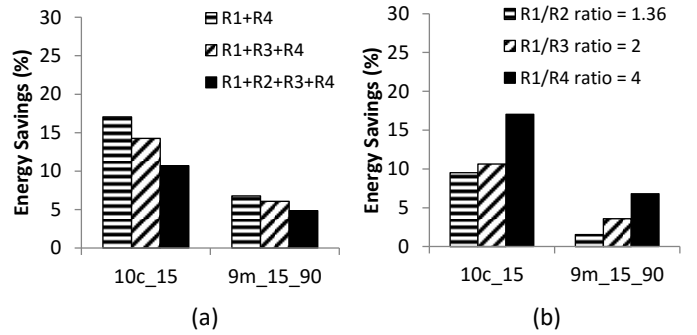


Fig. 13. (a) Effect of additional unused rooms on the energy savings. R_2 and R_3 are unused, while the meetings are assigned only to R_1 and R_4 . (b) Impact of room capacity ratios on energy savings with two available rooms.

algorithms would prove most useful, and situations where simple assignment algorithms are as effective as smarter ones.

The insights provided by the model are further demonstrated in Figure 13, which shows the variation in energy savings as the number of empty rooms increases, as well as the capacity ratios. We consider assigning meetings only to R_1 and R_4 for two of our benchmarks, one with a single meeting assignment and a second where up to two meetings may be simultaneously assigned. For Figure 13(a), we show the effect of adding unused rooms R_2 and R_3 on the overall energy savings. As predicted by Figure 9, as the number of unused meeting rooms (n in Figure 9) increases, the energy savings decreases due to the added *Sleep* energy.

For Figure 13(b), we assume two rooms and analyze the effect on the room capacity ratio (r in Figure 9). As predicted by Figure 9 and shown in Figure 13(b), increasing the ratio r increases the energy savings with the smarter MILP algorithm as there is more room for *Active* energy savings.

VI. COMPARISON WITH PRIOR MODELS

In this section, we compare the energy savings estimated by our model to that of EnergyPlus, and make a rough comparison with prior models. We simulate the meeting benchmarks from January 28th to February 1st, and report the energy savings from 7am to 7pm using MILP over the *Random Assignment* algorithm. Our *Weather and occupancy dependent* model uses values of $\beta = 0.4$, $\tau = 5$ minutes, and a γ that is linearly proportional to occupancy. The *Weather and occupancy independent* model is based on Kwak et al. [6], which assumes no energy during meeting gaps and is occupancy independent. We implement this model by setting $\beta = 0$, and $\gamma = 1$. Chai et al. consider extra energy consumption during meeting gaps, which can be modeled as sleep energy, but is occupancy independent. This *Weather dependent and occupancy independent* model is constructed by setting $\beta = 0.4$, $\tau = 5$ minutes, and $\gamma = 1$.

As shown in Figure 14, the *Weather and occupancy independent model* incurs a large error with respect to EnergyPlus, while adding weather dependency reduces the error. Our model, which takes into account both weather and occupancy

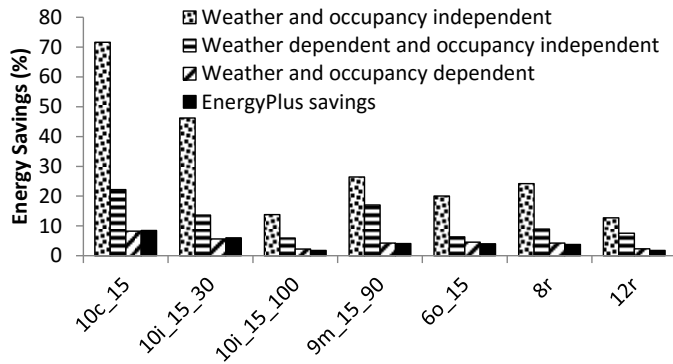


Fig. 14. Energy savings estimated by different models compared to EnergyPlus.

factors, closely matches EnergyPlus, with a maximum difference of 0.5% in energy savings. This result demonstrates how the additional parameters embedded in our model greatly improve modeling accuracy.

VII. RELATED WORK

The work by Pan et al. [4] is the first research to our knowledge that proposes intelligent meeting room assignment to reduce the building energy use. The authors use an energy-temperature correlation model and propose a greedy method to assign meetings to closely-sized rooms, which was demonstrated to be suboptimal [5]. They extend their work for minimizing building electric cost in a dynamic power market, and use EnergyPlus to model the thermal behavior of a building [3]. Majumdar et al. propose search algorithms using a combination of heuristics and EnergyPlus simulations [5], while Lim et al. use an RC network to model the building thermal behavior [7], [9].

A number of researchers use a MILP formulation to solve the meeting room assignment problem [3], [6], [7], [8], [9]. As the meeting room assignment problem is NP-complete [3], MILP based formulations do not scale well towards larger problems. We identify the meeting cases where MILP based assignment algorithms may be unnecessary compared to a simple random assignment.

Among the model based approaches, Kwak et al. propose an energy model that is independent of occupancy factors and considers no energy when a room is unoccupied [6]. Chai et al. consider the extra energy spent before a meeting is scheduled, but their energy model is occupancy independent [8]. We show that these assumptions impact model accuracy, while our more detailed model derived from building power characterization very closely matches EnergyPlus.

VIII. CONCLUSIONS

We present an abstract energy model that captures the key parameters that impact meeting room scheduling energy savings. Using this model, we characterize how various meeting, building, and weather parameters impact the potential energy savings. We further demonstrate how the model predicts when the conditions exist for significant energy

savings using smart meeting room scheduling, and when it is not worthwhile. We demonstrate through EnergyPlus simulations the intuition derived from our model, and how the addition of key modeling parameters significantly improves modeling accuracy.

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