Why TESLA Works: Innovative Agent-based Application Leveraging Schedule Flexibility for Conserving Energy

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ABSTRACT

This paper presents TESLA, an agent-based application for optimizing the energy use in commercial buildings. TESLA's key insight is that adding flexibility to event/meeting schedules can lead to significant energy savings. TESLA provides two key contributions: (i) three online scheduling algorithms that consider flexibility of people's preferences for energy-efficient scheduling of incrementally/dynamically arriving meetings and events; and (ii) an algorithm to effectively identify key meetings that lead to significant energy savings by adjusting their flexibility. TESLA was evaluated on data of over 110,000 meetings held at nine campus buildings during eight months in 2011–2012 at the University of Southern California (USC) and the Singapore Management University (SMU), and it indicated that TESLA's assumptions exist in practice. This paper also provides an extensive analysis on energy savings achieved by TESLA. These results and analysis show that, compared to the current systems, TESLA can substantially reduce overall energy consumption.

Categories and Subject Descriptors

I.2.11 [**ARTIFICIAL INTELLIGENCE**]: Distributed Artificial Intelligence

General Terms

Algorithms, Experimentation, Human Factors

Keywords

Energy, Sustainable Multiagent Building Application, Energy-oriented Scheduling

1. INTRODUCTION

Reducing energy consumption is an important goal for sustainability. Thus, conserving energy in commercial buildings is important as it is responsible for significant energy consumption. In 2008, commercial buildings in the U.S. consumed 18.5 QBTU, representing 46.2% of building energy consumption and 18.4% of U.S. energy consumption [5, 11]. This energy consumption is significantly affected by a large number of meetings or events in those buildings. Furthermore, a recent study shows that meeting frequency in commercial buildings is significant and continues to grow [4]. In 2001, U.S. Fortune 500 companies are estimated to have held 11 million formal meetings daily and 3 billion meetings yearly.

Energy-oriented scheduling can assist in reducing such energy consumption [7, 15, 19]. Although conventional scheduling techniques compute the optimal schedule for many meetings or events while satisfying their given requirements (i.e., computing a valid schedule) [8, 13], they have not typically considered energy consumption explicitly. More recently, there have been some trials to conserve energy by consolidating meetings in fewer buildings [2, 3]. In particular, Portland State University consolidated night and weekend classes, which are previously scattered across 21 buildings, into five energy efficient buildings. By doing this, they reported that electricity consumption was reduced by 18.5% (78,000 kWh) in the autumn compared to the previous three-year average. Similarly, Michigan State University consolidated classes and events into fewer buildings on campus, and energy reductions in the seven buildings ranged from 2–20%, saving $16,904. However, these efforts have been decided manually, and no underlying intelligent system was used.

Motivated by this prior work, we describe TESLA (Transformative Energy-saving Schedule-Leveraging Agent), an innovative agent-based application for optimizing the use of facilities in commercial buildings. TESLA's key insight is that adding flexibility to meeting schedules can lead to significant energy savings. TESLA provides two key contributions. First, it provides three scheduling algorithms — myopic, predictive non-myopic, and full-knowledge

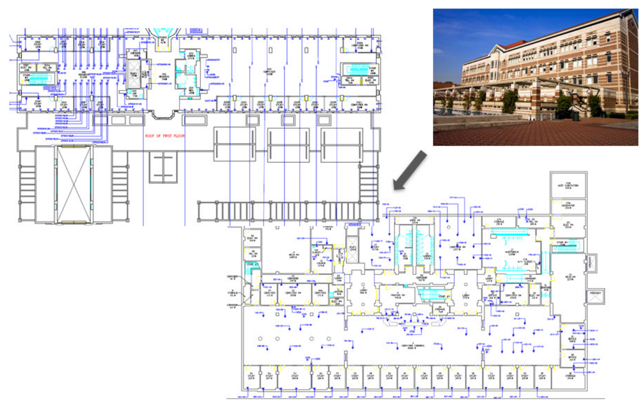


Figure 1: The actual research testbed (library) at USC

This paper extends our AAMAS main track paper [9]. New content includes: (i) an extensive analysis on energy savings achieved by TESLA (Section 5); (ii) energy saving results based on a different prediction heuristic for the predictive non-myopic method (Section 4.1.2); and (iii) energy saving improvements when to simultaneously identify multiple key meetings (Section 4.1.3). To accommodate this new content, we abbreviate the exposition of some of the findings of the main track paper including human subject experiments.

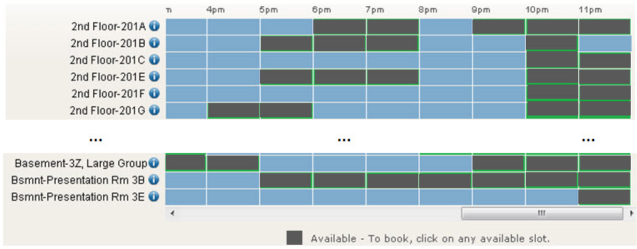
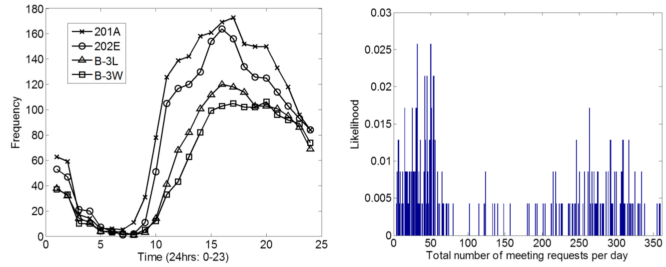


Figure 2: The current room reservation system at the testbed building



(a) Meeting frequency data

(b) Distribution of total meeting requests per day

Figure 3: Real data analysis

optimization — that consider *flexibility* of people's preferences for energy-efficient scheduling of incrementally/dynamically arriving meetings and events. In this work, flexibility specifically refers to the number of options made available by the scheduling constraints in terms of starting time, locations and the deadline before committing to the finalized schedule details. Second, using the predictive non-myopic method, TESLA presents an algorithm to effectively identify key meetings that could lead to significant energy savings by adjusting their flexibility. To validate our work, we have used a public domain simulation testbed [11] with details in our testbed building and validated this simulation. Just within this testbed building, our results show that, in a validated simulation, TESLA is projected to save about 250 kWh of energy (roughly $17K) annually. If this pilot is successful, TESLA can offer energy saving benefits to all commercial buildings where meetings affect energy usage. While our paper in the AAMAS main track [9] discusses TESLA in more detail, this paper focuses on providing an extensive analysis on energy savings achieved by TESLA. Readers are referred to read [9] for a more technical description and full results.

The rest of the paper is organized as follows: In Section 2, we describe our testbed buildings along with real data from those buildings. In Section 3, we describe the TESLA agent system and scheduling algorithms at the heart of it. Section 4 provides evaluations of each of our algorithms using real-world meeting and energy data indicating that TESLA could potentially provide significant savings in overall energy consumption. Section 5 discusses why TESLA works in detail by providing an extensive analysis on energy savings. Section 6 discusses a number of approaches for handling energy-aware scheduling and emphasizes how different TESLA is. We conclude this paper in Section 7.

2. RESEARCH TESTBED

2.1 Educational Building Testbed

Our system is to be deployed in an educational building. Figure 1 shows the testbed building for TESLA's deployment and the floor plans of 2^{nd} and basement floors. It is one of main libraries at the University of Southern California and has been designed with a building management system. It hosts a large number of meetings (about 300 unique meetings per regular day) across 35 group study rooms. Each study room has different physical properties including different types and numbers of devices and facilities (e.g., video conferencing equipment, computer, projector, video recorder, office electronic devices, etc.), room size, lighting specification, and maximum capacity (4 – 15 people). This building operates these study rooms 24 hours a day and 7 days a week except on national holidays. The temperature in group study rooms is regulated by the facility managers according to two set ranges for occupied and unoccupied periods of the day. HVAC (Heating, Ventilating, and Air Conditioning) systems always attempt to reach the pre-set temperature regardless of the presence of people and their preferences in terms of temperature. Lighting and appliance devices are manually controlled by users.

In this building, meetings are requested by users by a centralized online room reservation system (see Figure 2). In the current reservation system, no underlying intelligent system is used; instead, users reactively make a request based on the availability of room and time when they access the system. While users make a request using the system, they are asked about additional information including the number of meeting attendees and special requirements. Reservations can be made up to 7 days in advance.

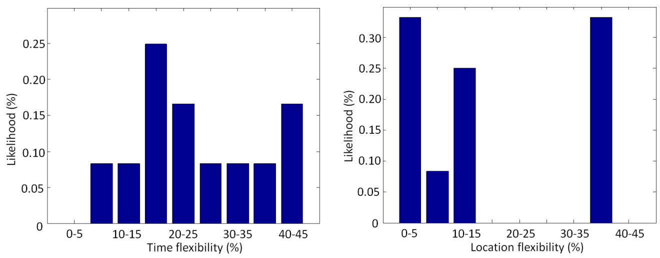
Given the significant number of meetings per day and the centralized online meeting reservation system, it provides a good environment to test various energy-oriented scheduling techniques to mitigate energy consumption. TESLA's goal is to enable users to input flexibility in their scheduling request, to identify key scheduling requests, and use this information in algorithms that can provide energy-efficient schedules to effectively conserve energy in commercial buildings. To evaluate TESLA, we have built upon a simulation testbed using real building data [11] and validated with real-world energy data.[1] This validated simulation environment is used to evaluate TESLA with real meeting data. In addition, we also test TESLA on buildings at the Singapore Management University as described below.

2.2 Data Analysis

In collaboration with building system managers, we have been collecting data specifying the past usage of group study rooms, which are collected for 8 months (January through August in 2012) at USC. The data for each meeting request includes the time of request, starting time, time duration, specified room, and group size. The data set contains 32,065 unique meetings, and their average meeting time duration is 1.78 hours.

Figure 3(a) shows the actual meeting frequency (y-axis) over time (24 hours, x-axis) of sampled 4 locations (out of 35 rooms). Figure 3(b) shows the probability distribution over total meeting requests per day. The x-axis of the figure indicates the total number of meeting requests per day (ranging from 0 to about 350) and the y-axis shows how likely the system will have the given number of total meeting requests (x-axis) on one day. One can see that the probability of having 50 or fewer meetings is 42.92% and the probability of having 250 or more meetings is 30.04%. These are used to estimate the model of future meetings in our algorithm that will be presented in Section 3.2.

[1] Energy validation results can be found here: `http://teamcore.usc.edu/junyounk/TESLA-sp.pdf`



(a) Time flexibility (b) Location flexibility

Figure 4: Diversity of people's flexibility

We conducted an online survey to understand the flexibility of meeting attendees, and analyzed their profile including the details of their meeting requests and their flexibility in terms of time and locations considering their real constraints. Figure 4 shows the distribution of the time and location flexibility. The x-axis shows the discretized flexibility level [2] and their corresponding frequency in percentage is provided on the y-axis. People reported varied levels of time and location flexibility. The average time flexibility was 25.34% and their responses fell in a range of 9.86% and 42.86%. The average location flexibility was 16.05% and its range was 0 to 38.24%.

While evaluating TESLA, we also consider another data set containing over 80,000 meetings that have been collected for three months in 2011 from over 500 conference/meeting rooms across eight buildings at SMU, which gives us a sense regarding how TESLA will handle energy-oriented scheduling problems in large buildings.

3. TESLA

3.1 Application Architecture

TESLA is a goal-seeking (to save energy), continuously running autonomous agent. TESLA performs on-line energy-efficient scheduling while considering dynamically arriving inputs from users; these dynamic inputs makes the scheduling complex and TESLA needs to learn a predictive model for users' inputs and preferences. More specifically, TESLA:

- takes inputs (i.e., preferred time, location, the number of meeting attendees, etc.) from different users and their proxy agents at different times (Sections 2 & 3.1)
- autonomously performs on-line energy-efficient scheduling as requests arrive while balancing user comfort (Section 3.2.1)
- autonomously, on own initiative, interacts with different users based on identified problematic key meetings in order to minimize bother cost to users and persuades them to change meeting flexibility (Section 3.2.2)
- bases its non-myopic optimization on learned patterns of meetings (Sections 3.2.1 & 4)

TESLA communicates with other users or their proxy agents, who have the corresponding meeting attendees' preference and behavior models with a certain level of adjustable autonomy [14]. Proxy agents communicate on behalf of meeting attendees with TESLA. Meeting requests are the information we get from the interface of TESLA. TESLA may also communicate with proxy agents to adjust the given meeting flexibility of key meetings to compute energy-efficient schedules. TESLA focuses on minimizing unnecessary interactions by detecting a small number of key meetings while negotiating with people to adjust their flexibility.

[2] 0–100%; 0%: no flexibility, 100%: full flexibility. A formal definition will be presented in the next section.

3.2 Algorithm

The objective of this work is to come up with energy efficient schedules in commercial buildings with a large number of meetings while considering (i) flexibility in meeting requests over time, location and deadline; and (ii) user preferences with respect to energy and satisfaction. To account for these two constraints, we provide two types of algorithms, which are at the heart of TESLA. First, we provide algorithms that compute a schedule for known and predicted meeting requests which have flexibility in time, location and deadline. Second, based on the schedule obtained, we provide algorithms that detect meeting requests which if modified (to increase flexibility) can result in significant energy savings.

3.2.1 Scheduling algorithms

Before describing our scheduling algorithms, we formally describe the scheduling problem. Let T represent the entire set of time slots available and L represent the set of available locations each day. A schedule request r_i is represented as the tuple: $r_i =< a_i, T_i, L_i, \delta_i, d_i, n_i >$, where: a_i is the arrival time of the request, $T_i \subset T$ is the set of preferred time slots for the start of the event and $L_i \subset L$ is a set of preferred locations. d_i is the deadline by which the time and location for the meeting should be notified to the user, δ_i is the duration for the event and finally, n_i is the number of attendees.

The flexibility of the meeting request r_i, α_i, is a vector of three values: $< \alpha_i^T, \alpha_i^L, \alpha_i^d >$.

- α_i^T: time flexibility of meeting i (%). $\alpha_i^T = \frac{|T_i|-1}{|T|-\delta_i} \times 100$ ($|T| > \delta_i$; i.e., $|T|$ is 24 hours per day). Given only one time slot ($|T_i| = 1$), $\alpha_i^T = 0$ and all available time slots ($|T_i| = |T| - \delta_i + 1$), $\alpha_i^T = 100$. For example, assuming that people give T_i = 4–7pm on Monday and its meeting time duration is 2 hours, then α_i^T = (4-1)/(24-2) $\times$ 100 = 13.64(%).
- α_i^L: location flexibility of meeting i (%). $\alpha_i^L = \frac{|L_i|-1}{|L|-1} \times 100$ ($|L| > 1$). Given only one location slot ($|L_i| = 1$), $\alpha_i^L = 0$ and given all available locations ($|L_i| = |L|$), $\alpha_i^T = 100$.
- α_i^d: deadline flexibility of meeting i (%). $\alpha_i^d = \frac{d_i - a_i}{d_i^* - a_i} \times 100$, where d_i^* is the latest notification time (e.g., midnight on the meeting day) ($d_i^* > a_i$). $0 \leq \alpha_i^d \leq 100$

Given a set of requests, R, we provide a mixed integer linear program (MILP) to compute a schedule that minimizes the overall energy consumption (and will be used in our algorithms below). Here is the notation that will be employed in the MILP:

- $x_{i,l,t}$ is a binary variable that is set to 1 if meeting request r_i is scheduled in location l starting at time t.
- $E_{i,l,t}$ is a constant that is computed for a meeting request r_i if it is scheduled in location l at time t using the HVAC energy consumption equations.
- C is a constant that indicates the reduction in energy consumption because of scheduling a meeting in the previous time slot.

- $e_{i,l,t}$ is a continuous variable that corresponds to the energy consumed because of scheduling meeting i in location l at time t. The value of this variable is affected based on whether there is a meeting scheduled in the previous time slot $(t-1)$. $e_{i,l,t} = x_{i,l,t} \cdot E_{i,l,t} - \sum_{i' \in R \setminus \{i\}} x_{i',l,t-1} \cdot C$.[3]
- $S_{i,l,t}$ is an value that indicates the satisfaction level obtained with users in meeting request r_i for scheduling the meeting in location l at time t. B is a threshold on the satisfaction level required by users.
- M is an arbitrarily large positive constant.

$$\min \sum_{t \in T} \sum_{l \in L} \sum_{i \in R} e_{i,l,t} \tag{1}$$

s.t.

$$e_{i,l,t} = x_{i,l,t} \cdot E_{i,l,t} - \sum_{i' \in R \setminus \{i\}} x_{i',l,t-1} \cdot C, \quad \forall i \in R \tag{2}$$

$$\sum_{t \in T}^{l \in L} x_{i,l,t} \cdot S_{i,l,t} \geq B, \qquad \forall i \in R \tag{3}$$

$$\sum_{i \in R} x_{i,l,t} \leq 1, \qquad \forall l \in L, t \in T \tag{4}$$

$$\sum_{i' \in R \setminus \{i\}} \sum_{t'=t}^{t+\delta_i-1} x_{i',l,t'} \leq M(1 - x_{i,l,t}), \forall l \in L, i \in R, t \in T \tag{5}$$

$$x_{i,l,t} \in \{0,1\}, \qquad \forall i \in R, l \in L, t \in T \tag{6}$$

The objective of the MILP above is finding the optimal assignment of meeting requests to locations and time slots that is characterized by the solution, $x^*_{i,l,t}$ in order to minimize energy consumption. The constraint (2) is for computing energy consumption considering the back-to-back meeting effect. The constraint (3) is for checking if the computed schedule maintains the given comfort level B. The constraints (4) and (5) are the allocation restrictions that for each assignment slot, only one meeting can be scheduled considering the given time duration of meeting.

We now define specific disjoint sets of meeting requests, R that will enable us to characterize two type of scheduling algorithms, where t is time to schedule a given set of requests, R.

- $R^S(t) = \{i : d_i = t \text{ and } a_i \leq t\}$: a set of requests that have to be scheduled at time t
- $R^A(t) = \{i : d_i < t \text{ and } a_i < t\}$: a set of requests that were assigned before time t
- $R^K(t) = \{i : d_i > t \text{ and } a_i \leq t\}$: a set of known future requests, which arrived before time t, but will be scheduled in the future
- $R^U(t) = \{i : d_i > t \text{ and } a_i > t\}$: a set of unknown future requests

The MILP is the core of the three scheduling algorithms, and the algorithms call the MILP formulation using the function GETMINENERGYSCHEDULE(R) on the actual input R and provide different results as described below.

Myopic optimization algorithm: We have the myopic optimization algorithm, which obtains a schedule by making the following function call: GETMINENERGYSCHEDULE($R^A(t) \cup R^S(t) \cup R^K(t)$). A schedule and energy consumption are obtained without accounting for future unknown meetings.

Predictive non-myopic optimization: We have a predictive optimization method that minimizes expected reduction of energy over possible unknown meetings. Let U be a set that contains various possibilities of unknown meeting requests (obtained by analyzing previous meeting data such as the one in Figure 3(b)) that could arise in future times. More specifically, we have a probability distribution over the possible number of total meeting requests per day (shown in Figure 3(b)). Then, the likelihood that k more meetings will arrive on the same day, $p^U(k)$, is computed considering that we currently have s meetings so far. For those k future meeting requests in U, we generate random request tuples (specifically, T_i & L_i) based on the distribution over the assignment spots as shown in Figure 3(a). A predictive optimization approach thus solves the following optimization problem:

$$\min_{\mathbf{x}} \sum_{U \in \mathbb{U}} p^U \cdot GetMinEnergySchedule(R^A(t) \cup R^S(t) \cup R^K(t) \cup U)$$

Full-knowledge Optimization: As a benchmark algorithm for comparison purposes, we provide the full-knowledge optimization method. In this method, assuming that the entire set of meeting requests R is given, which is ideal, we compute the final schedule using the MILP used in the myopic optimization technique. The performance comparison results will be provided in Section 4.1.

3.2.2 Identifying key meetings

The scheduling agent computes the optimal schedule considering the given flexibility of meetings. It can obtain more energy-efficient schedules by relaxing those constraints.

We provide an algorithm that finds key meetings that can reduce significant energy consumption if made more flexible.

Algorithm 1 IDENTIFYKEYMEETINGS (**R**)

```
1: U ← ∅
2: {Initialize a set of key meetings}
3:
4: for all I ⊂ 2^R do
5:     {R is a set of requests.}
6:     if ISPROBLEMATIC (I) then
7:         U ← U ∪ I
8:
9: return U
```

Algorithm 1 describes the overall flow of the algorithm. We first initialize a set that will contain key meetings identified by our algorithm (line 1). For each subset of the power set of meeting requests R, we then tell whether or not the current meeting set I is a problematic key meeting set by relying on Algorithm 2 (line 6).

Algorithm 2 recursively tells if the given meeting set I is problematic. The meeting set I is detected as a key meeting set only if the expected energy savings of meeting requests in I are monotonically increasing and show higher energy improvements than the given threshold value. To handle this, we first compute the expected energy savings of the meeting set I when its flexibility level is changed from the initial level α_I to the desired level α'_I assuming the other meetings' flexibility levels are fixed (line 1). The expected energy saving value of meeting set I, $V_I = (E_{\alpha_I} - E_{\alpha'_I})/E_{\alpha_I}$

[3] $e_{i,l,t}$ gets affected by a meeting in the previous time slot in the same location. This is because adjacent meetings affect the indoor temperature, which makes HVACs operate differently to maintain the desired temperature level.

Algorithm 2 IsProblematic (I)

1: $V_I \leftarrow$ CalExpEnergySavings(α_I, $\{\alpha'_{I,1}, \ldots, \alpha'_{I,k}\}$)
2: $\{\alpha_I$ is an initially given flexibility of meetings in I, and $\alpha'_{I,k}$ is one of the desired flexibility options for meetings in I.$\}$
3:
4: **if** $|I| = 1$ **then**
5:     **if** $V_I > \tau$ **then**
6:         **return** TRUE
7:     **else**
8:         **return** FALSE
9: **else if** $|I| > 1$ **then**
10:     **for all** $i \in I$ **do**
11:         **I'** $\leftarrow$ **I**$\backslash\{i\}$
12:         $V_{I'} \leftarrow$ CalExpEnergySavings($\alpha_{I'}$, $\{\alpha'_{I',1}, \ldots, \alpha'_{I',k}\}$)
13:         **if** $V_I - V_{I'} > 0$ **then**
14:             **return** IsProblematic (I')

($0 \leq V_I \leq 1$), where E_{α_I} is the current total energy consumption with the given level of flexibility α_I, and $E_{\alpha'_I}$ is the reduced total energy consumption if the meeting set I's flexibility is changed to one of k possible options, $\alpha'_{I,k}$, while others keep their given flexibility levels. In this work, we consider a heuristic for setting the threshold value to tell whether or not the current meeting set I is problematic: a fixed single threshold value τ (line 5; e.g., 0.4 as a universal threshold).

4. EMPIRICAL VALIDATION

We evaluate the performance of TESLA and experimentally show that it can conserve energy by providing more energy-efficient schedules in commercial buildings. The experiments were run on Intel Core2 Duo 2.53GHz CPU with 8GB main memory. All techniques were evaluated for 100 independent trials and we report the average values.

4.1 Simulation Results

4.1.1 Does flexibility help?

As an important first step in deploying TESLA, we first verified if the agent could save more energy with more flexibility while scheduling given meeting and event requests. To that end, we compared energy consumption of three different approaches using the real-world meeting data mentioned in Section 2.2: (i) the current benchmark approach in use at the testbed building; (ii) a random method that randomly assigns time and location for meetings; and (iii) the optimal method using the full-knowledge optimization technique described in Section 3.2.

Figure 5 shows the average daily energy consumption in kWh computed based on schedules from the three algorithms above. In the figure, the consumption is the amount of energy consumed based on the past schedules obtained from the current manual reservation system, which shows a very similar performance to the random approach. The optimal method assuming the full amount of flexibility (i.e., 24 hours for α^T, 35 rooms for α^L and delay the deadline before which the final schedule should be informed for α^d) achieved statistically significant energy savings of 48.08% compared to the current energy consumption at the testbed site (t-test; p < 0.01), which is equivalent to annual savings of about \$17,600 considering an energy rate of \$0.193/kWh [1] and CO_2 emissions from the energy use of 5.5 homes for one year.

4.1.2 Online scheduling methods with flexibility:

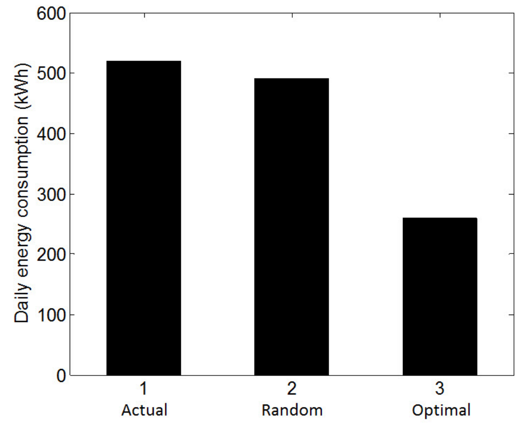


Figure 5: Energy savings

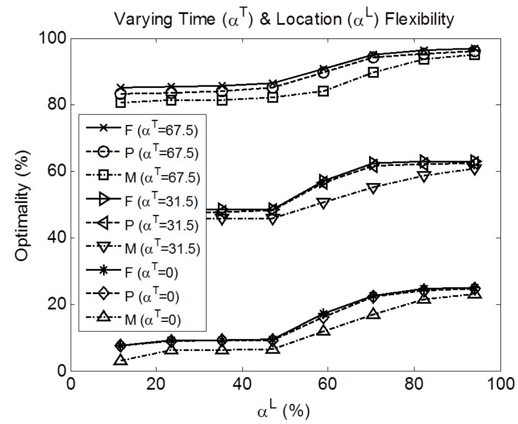


Figure 6: Energy savings while varying flexibility

We then compared solution qualities of the three scheduling algorithms in TESLA presented in Section 3.2.1. Figure 6 shows that how much each algorithm saves when compared to the optimal value (i.e., full-knowledge optimization assuming the full flexibility) while varying the time and location flexibility level (assuming 0% deadline flexibility). *The flexibility in our model represents a 3-dimensional space (time, location and deadline), which we have fully explored. Due to the limitation of space, however, we have only shown results with the deadline flexibility of 0%.*

The optimality is computed as follows: $(E_a - E_c)/(E_a - E_o)$, where E_a is the actual energy consumption without any flexibility, E_o is the optimal energy consumption, and E_c is the computed energy consumption using three different scheduling algorithms that we compare using the real meeting data.

Figure 6 shows the average optimality in percentage of each algorithm (M: myopic, P: predictive non-myopic and F: full-knowledge) while varying the location flexibility (α^L; x-axis) and time flexibility (α^T; each graph assumed the different amount of α^T as indicated in the legend). In the figure, for each pair of flexibility values (α^T, α^L), we report the average optimality in percentage (i.e., 100% indicates the optimal value, and 0% means that there was no improvement from the actual energy consumption). Thus, higher values indicate better performance.

As shown in the figure, as more flexibility is given to the system, the agent can compute schedules with less energy consumption. The gain in optimality from myopic to predictive non-myopic

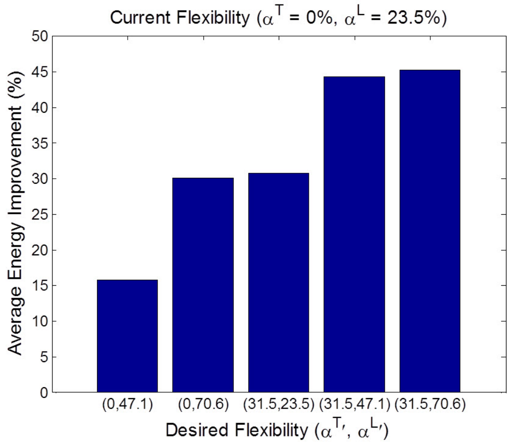


Figure 7: Average energy improvements (%)

is because the latter can leverage user flexibility to put a meeting in a suboptimal spot at the meeting request time to account for future meetings, yielding better results at the actual day of meetings. For example, a flexible meeting request can be moved away from a known popular time-location spot. We conclude that (i) the predictive non-myopic method is superior to the myopic method; (ii) the predictive non-myopic method performs almost as well as the full-knowledge optimization (about 98%)[4]; and (iii) the full flexibility is not required to start accruing benefits of flexibility.

In the real-world, it is hard to imagine that all people will simply comply to change their flexibility to achieve such optimality. Thus, we provided one additional result in [9] while varying the percentage of meetings that will have flexibility (p_f). Our main conclusions are: (i) if we increase p_f, we are able to achieve a higher optimality; and (ii) flexibility in a small number of meetings can lead to significant energy reduction. This motivates considering more intelligent identification of key meetings to change their flexibility (described in the next section). The same types of analysis are performed with another data set from SMU and results were presented in [9][5].

We investigated runtime comparisons of the three algorithms to verify the feasibility of our approaches to solve the real-world problem. The average runtime of the myopic optimization method was about 2 seconds, and the predictive non-myopic method was about 30 seconds.

4.1.3 Performance of identifying key meetings

We evaluated the performance of the algorithm to identify key meetings for energy reduction. In our tests, we selected 10 meetings and calculated the average energy savings if only one of these meetings changed their flexibility for each of the 10 selected meetings. This reflects an assumption that about 10% of people contacted will modify their flexibility.

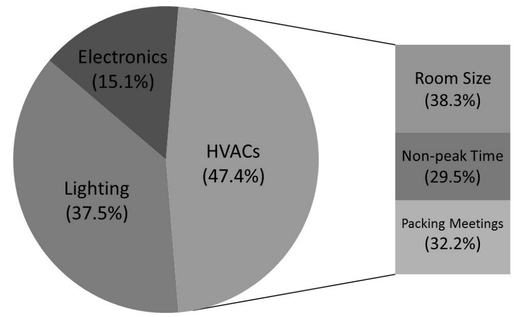


Figure 8: Energy savings by TESLA

Figure 7 shows the average energy savings as described for various flexibility transitions. In the figure, the x-axis shows the desired level of flexibility ($\alpha' = (\alpha'^T, \alpha'^L)$) and the y-axis indicates the average energy improvement assuming the initial flexibility $(\alpha^T, \alpha^L) = (0\%, 23.5\%)$ [6]. For instance, if flexibility of 10 key meetings are changed one by one from (0%, 23.5%) to (31.5%, 47.1%), the average energy savings improvement is 44.25%. As shown in the figure, the average energy improvement of the selected 10 key meetings is 33.21%, which is significant. An important interpretation of that results is that changing the flexibility of only one meeting (of 150 on average), when that one is from an appropriately chosen set, contributed to significant energy savings. We also tested how much we can save energy if we choose key meetings simultaneously rather than independently. For the same situation, if we choose 10 key meetings at the same time, the average energy savings were improved by 10.3% (i.e., 43.51% of energy savings). In the future, we will investigate another heuristic to set a feasible threshold value based on a learned profile of user likelihood of changing meeting flexibility.

We use the predictive non-myopic algorithm to identify key meetings, and we need to validate its accuracy. We checked the accuracy by directly comparing the meeting IDs of the key meeting set generated when using the predictive non-myopic and the full-knowledge optimization method. The average accuracy of our predictive method was over 93%, which supports that our detection algorithm is accurate.

5. ANALYSIS: WHY ARE THERE ANY SAVINGS DUE TO TESLA?

There are three major components that affect energy consumption in commercial buildings: HVACs (accounting for 35% of the entire energy consumption in commercial buildings), lighting (27%), and electronic devices (about 10%) [5]. TESLA focuses on these three energy consumers to save energy by computing energy-efficient schedules that exploit key factors that affect energy consumption of each building component. Figure 8 shows the percentage of energy savings per each energy consumer and factor in TESLA.

5.1 HVACs

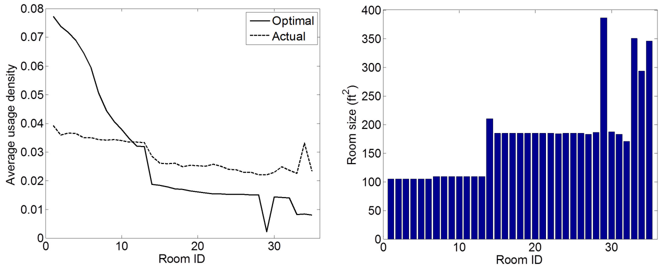
Key assumptions The following assumptions are made in TESLA:

- HVACs are centrally regulated by the university facility management team to satisfy two pre-defined temperature ranges: occupied time zone (8am to 6pm: 70–75F) and unoccupied time zone (rest of the hours: 60–80F).

[4] The average performance of the predictive non-myopic optimization depends on the prediction method of future requests. We, thus, additionally tested a more sophisticated prediction method considering the time factor that is one of key features determining the overall trend of requests (i.e., when the meeting requests arrive at the system to be scheduled; e.g., regular semester vs. summer/winter break). With this additional consideration, the predictive non-myopic method improved the overall performance of the predictive method by 1.1%.

[5] You can find the whole set of results here: `http://teamcore.usc.edu/junyounk/TESLA-sp.pdf`

[6] The full results are provided in [9].



(a) Average room usage density (b) Room size

Figure 9: **Energy saving analysis: room size**

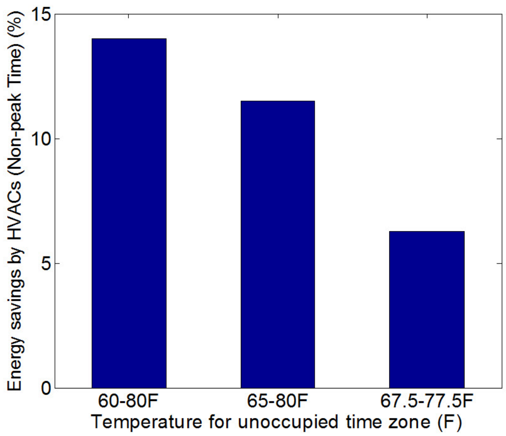


Figure 10: **Energy savings only by HVACs (Non-peak Time)**

- While optimizing schedules, the threshold of people's comfort level was set to 50%, which is a configurable parameter.

Factors impacting HVAC energy As shown in Figure 8, given the above assumptions, HVACs accounted for 47.4% of the overall energy savings. Numbers in the parentheses below indicate the amount of energy savings by each of the following three factors:

- Room Size: TESLA focuses on assigning meetings to smaller spaces while considering the number of meeting attendees, since a larger room requires more energy than a smaller room when occupied for the same amount of time (38.3%). Figure 9 shows the actual and optimal room usage density and the physical room size of the testbed building at USC. As shown in the figure, TESLA generates the schedule that uses 18.16% less space compared to the actual schedule, which clearly proves that TESLA provides more energy-efficient schedules by assigning meetings to smaller spaces.

- Non-peak Time: TESLA avoids the peak time in terms of energy and popularity considering the given constraints/flexibility. Since an unoccupied time zone requires less energy than occupied time zone when the same room is occupied for the same amount of time, TESLA focuses on assigning meetings under an unoccupied time zone as much as possible (29.5%). However, since an unoccupied time zone has a wider regulated temperature range, this optimization may cause a drop in the average comfort level of people, which may bring up a significant issue in a certain situation, although the amount of energy savings achieved by the non-peak time factor itself is less significant (i.e., 13.93%) compared to other factors. Thus, in Figure 10, we provide a result that shows how the non-peak time factor affects the overall energy savings (y-axis) while varying the unoccupied time zone temperature (x-axis). As shown in the figure, as we reduce a temperature range for an unoccupied time zone, the amount of energy savings by the non-peak time factor decreases, but TESLA can still achieve meaningful energy savings while satisfying the given comfort level constraint. Furthermore, TESLA provides a flexible architecture that allows people to configure the temperature value accordingly under different situations.

- Packing Meetings: TESLA focused on packing meetings together in terms of the time interval between meetings in the same room. When a meeting ends, the room is conditioned to a pre-defined environment. This built-up thermal momentum can benefit later meetings scheduled in the same room in close proximity by reducing the number of changes of HVAC operations, which saves much more energy (32.2%).

5.2 Lighting

Key assumptions The following assumptions are made in TESLA:

- The standard nominal values were used for the lighting configuration in spaces.
- When the room was occupied, the full (100%) lighting level was considered.
- When the room was unoccupied, 0% lighting level was considered.

Factors impacting lighting energy As shown in Figure 8, given the above assumptions, the lighting sources accounted for 37.5% of the overall energy savings. The entire energy savings are caused by different room size; specifically, TESLA focuses on assigning meetings to smaller spaces while considering the number of meeting attendees, since a larger room requires more energy than a smaller room when occupied for the same amount of time (see Figure 9).

5.3 Electronics

Key assumptions The following assumptions are made in TESLA:

- Actual number of devices existing in each room was considered to calculate the correct energy consumption.
- When the room was occupied, 80% of the devices were used.
- When the room was unoccupied, 0% of the devices were used.

Factors impacting electronics energy As shown in Figure 8, given the above assumptions, the electronics accounted for 15.1% of the overall energy savings. The entire energy savings are caused by different room size; specifically, TESLA focuses on assigning meetings to smaller spaces while considering the number of meeting attendees, since a larger room requires more energy than a smaller room when occupied for the same amount of time (see Figure 9).

6. RELATED WORK

TESLA is different from previous work by focusing on comfort-balanced energy-efficient incremental scheduling and identifying key meetings for adjusting their flexibility in commercial buildings. Furthermore, as an innovative application for energy savings, TESLA is evaluated on real meeting data (over 110,000 meetings and events) that have been collected from more than 500 rooms in nine educational buildings at USC and SMU. This combination of research contributions sets our work apart from previous research.

Energy Systems and Scheduling: Stein *et al.* [16] introduced a novel online mechanism that schedules the allocation of an expiring and continuously-produced resource to self-interested agents with private preferences while focusing on the fairness using pre-commitment in smart grid domain, which is not directly applicable in commercial buildings. There has been another work focusing on scheduling of home appliances considering user preferences [7, 15, 19], which is different from ours as preference considerations in their work is limited and we handle scheduling in large-scale commercial buildings. More recently, there has been some work focusing on energy-aware scheduling in commercial buildings [12], which did not account for people's comfort. The authors only considered the HVAC systems and ignored other significant energy consumers such as lighting and electronics in commercial buildings while optimizing schedules based on the given *fixed* constraints.

Wainer *et al.* [17] presented a set of protocols for scheduling a meeting among agents that represent their respective user's interests and evaluated the suggested protocols while handling meeting scheduling problems. The objective in their work to find the optimal protocol to reach agreement among agents, which does not explicitly account for energy. Recently, there have been some other work considering meeting (re)location problems by exchanging messaging among agents [10, 11]. Although their work focused on minimizing energy consumption, they relied on the reactive scheduling and no flexibility model was considered.

There has been a significant amount of work done on online scheduling techniques to handle incremental requests considering temporal flexibility [8, 13]. Our work is different in focusing on energy-oriented scheduling in commercial buildings while allowing people to play a part in optimizing the operation in the building instead of managing the optimal resource allocation on buildings.

Social Influence in Human Subject Studies: In social psychology, there has been a significant deal of work to understand the correlation between social influence and persuasion. We leverage insights from social psychology in understanding and designing reliable and accurate human behavior models. Wood and Neal [18] have studied the potential of interventions to reduce energy consumption and they have shown that it is not only to change workplace energy consumption but also to establish energy use habits that maintain over time. Anderson *et al.* [6] have particularly investigated social influence in energy use behavior, which can be used for enhancing TESLA to effectively change people's preferences and energy behaviors to conserve energy.

7. CONCLUSION

The key contribution of this paper is not just our agent TESLA, but more importantly, TESLA's analysis of real-world data — 32,000 meetings from the University of Southern California (USC), and 80,000 meetings from the Singapore Management University (SMU) — to show the power of flexibility. TESLA's promise of energy savings is rooted in this real data, and illustration that significant energy savings may accrue not from imposing any complex interaction protocol on humans, but from a simple action of providing schedule flexibility. More specifically, TESLA provided two key contributions. First, it provided three online scheduling algorithms that consider the diversity of people's flexibility for energy-efficient scheduling of incrementally/dynamically arriving meetings and events. Second, it presented an algorithm to effectively identify key meetings that lead to significant energy savings by adjusting their flexibility while minimizing bother cost to people. In addition, this paper focused on explaining why TESLA works by providing an extensive analysis on energy savings achieved by TESLA. We showed that, compared to the current systems, TESLA can substantially reduce the overall energy consumption.

8. ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 1231001. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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