Abstract—Demand bidding program (DBP) is recently adopted in practice by some energy operators. DBP is a risk-free demand response program targeting large energy consumers. In this paper, we consider DBP with the application in hotel energy management. For DBP, optimization problem is formulated with the objective of maximizing expected reward, which is received when the amount of energy saving satisfies the contract. For a general distribution of energy consumption, we give a general condition for the optimal bid and outline an algorithm to find the solution without numerical integration. Furthermore, for Gaussian distribution, we derive closed-form expressions of the optimal bid and the corresponding expected reward. Regarding hotel energy, we characterize loads in the hotel and introduce several energy consumption models that capture major energy use. With the proposed models and DBP, simulation results show that DBP provides economics benefits to the hotel and encourages load scheduling. Furthermore, when only mean and variance of energy consumption are known, the validity of Gaussian approximation for computing optimal load and expected reward is also discussed.

Index Terms—Building energy management, demand bidding, demand response, hotel energy management.

I. INTRODUCTION

Several existing works on smart grid focus on energy management in home environment [1]–[3]. On the other hand, the issue of smart grid integration into building environment is still largely unexplored. The role of buildings in smart grid was discussed in [4]. The paper elaborates several challenges such as multi-scale monitoring and control, occupancy sensing, data collection and management, and optimizing the operation of HVAC and IT equipment. In [5], a virtual building simulation platform together with model predictive control (MPC) was proposed. The MPC applies pre-cooling and peak load shifting which achieve the objective of economics saving under time-of-use pricing. A very recent work investigating smart grid with office building environment appears in [6]. Under real-time pricing scheme, the proposed scheduling at the device level provides significant economic savings in both with and without renewable energy unit. The results were obtained under living lab environment and take into account occupants’ satisfaction. Another recent work addresses the battery design for buildings under uncertainties in solar radiation and demand profiles [7]. The problem was solved by the scenario tree method, which is a tool from stochastic optimization.

In this paper, we are interested in the application of smart grid within lodging industry, especially the hotel industry. Our motivation is the fact that hotels are among the most energy intensive building category (after food services, shopping malls and hospitals) [8]. In the U.S. alone, the energy expenditure in the hotels reaches $4 billion annually [9]. Any successful attempt in reducing the energy consumption in hotels leads to a significant total amount of saving nationwide.

Unlike other types of commercial buildings, hotel energy management presents its own unique challenges. First, energy consumption in guest rooms is normally in complete control by the occupants. Second, any attempts to control energy use in the guest rooms shall not compromise guest comfort. This presents a dilemma between saving energy cost and losing customer satisfaction. Third, utilities may apply time-of-use tariff that is not optimal for hotel energy use patterns [10]. In addition, several other concerns for lodging industry to adopt smart grid technologies were discussed in [10]. It seems rather obvious that smart grid for hotel energy management needs much further research.

Future smart grid integrates demand response, where loads play major roles in optimizing energy consumption patterns. A study in [11] concluded that hotel is an excellent provider of spinning reserve. Preliminary testing suggested that up to 27% to 34% of loads can be curtailed depending on outside temperature [11]. Real-time pricing (RTP) (hourly pricing) with manual operation in response was studied in [12]. It was concluded that there was a substantial cost benefit in RTP but manual operation was labour intensive.

Demand bidding program (DBP) is one type of demand response. It has been recently adopted in practice by Southern California Edison (SCE) and Pacific Gas and Electric Company (PG&E). DBP attracts large energy consumers to participate and encourages them to reduce their energy use by setting their own target. The customer is free to choose a bidding value in terms of the amount of energy reduction. If the actual amount of energy saving conforms to certain requirement, the customer will be rewarded. On the other hand, if the customer fails to reduce the energy according to the requirement, there is no financial penalty. This risk-free feature of DBP attracts interest of hotel managers since normally the energy consumption in a hotel is highly variable. Its dependency on occupancy rate (number of rooms booked) and other uncertainties such as weather condition, causes the hotels to hesitate in participating in other demand response programs which require strict commitment.
In this paper, we discuss the DBP that is currently used in practice and formulate the corresponding mathematical optimization problem. Specifically, the problem is to determine the optimal bid that maximizes the expected reward subject to requirement of the operator. We provide a general condition for the optimal bid for a general distribution of energy consumption. Instead of numerical integration, this condition allows us to determine the optimal bid by using simple numerical method such as one-dimensional search algorithm. The general algorithm to compute the optimal bid is outlined. For the case of energy consumption that follows Gaussian distribution, we derive closed-form expressions for the optimal bid and expected reward, which can be easily computed without using numerical integration or optimization.

Note that the term “demand bidding” is typically referred in purchase allocation problem in electric energy market [22]. On the other hand, demand bidding for electric consumers is relatively new. These two types of demand bidding are quite different in terms of features and purposes. Demand bidding in energy market consists in competition among bidders, incurs high risk, and aims to acquire energy. In contrast, demand bidding for consumers involves no competition, no risk, and attempts to reduce energy consumption of large consumers.

II. DEMAND BIDDING PROGRAM

Independent system operator (ISO) introduces a demand bidding program (DBP) to encourage large energy consumers in order to reduce energy consumption [15]. Only the consumers whose maximum demand reaches a certain threshold is able to participate. DBP is a risk-free program that rewards the participants when they reduce their energy consumption below the mean value during some hours on the day of demand bidding event (DBE). There is no penalty when the participants are not able to reduce their energy according to the bid (except compromising their own comfort if any). Reward may be in terms of monetary credit for future payment.

In this program, there may be several constraints on how the reward is computed. For example, the amount of actual energy reduction must fall between certain percentages of the bid amount. There may also be a minimum bid requirement during any hours of the event. Nevertheless, it is still an attractive program since only minimum investment is in installing a smart meter with the ability to communicate with the ISO.

Bidding can be done on-line and customized by two bidding options. Manual bids allow the consumer to choose a bidding amount for a specific bidding event. Standing bids allow the consumer to bid once and apply it to future bidding events. DBP is a risk-free program that rewards the participants when they reduce their energy consumption below the bid (except compromising their own comfort if any). Reward may be in terms of monetary credit for future payment.

Proposition 1: The optimal bid is independent of the monetary reward, 
\[ r_t \]. This seems a bit surprising but in fact 
\[ r_t \] is given constant for each hour and can be factored out of the integral. Anyway, 
\[ r_t \] will affect the value of expected reward eventually.

Observation 1: The optimization in (1) is separable for each period. So, the optimal bid can be found for each period (hour) separately.

Observation 2: The optimal bid is independent of the monetary reward, 
\[ r_t \]. This seems a bit surprising but in fact 
\[ r_t \] is given constant for each hour and can be factored out of the integral. Anyway, 
\[ r_t \] will affect the value of expected reward eventually.

A. Proposed Formulation

The optimization problem is formulated to select the bid (amount of reduction) that maximizes the expected reward:

\[
\max_{t \in T_{DBE}} \sum_{t \in T_{DBE}} \int_{m_t - b_t}^{m_t - b_t + p} (m_t - x_t) r_t f(x_t) dx_t, \tag{1}
\]

where

- \( b_t \) : bid amount at hour \( t \)
- \( f(x_t) \) : probability distribution function of total hotel energy consumption \( x_t \) during hour \( t \)
- \( m_t \) : mean energy consumption during hour \( t \) without load scheduling
- \( r_t \) : monetary reward per unit of energy reduction
- \( T_{DBE} \) : demand bidding event hours
- \( p, q \) : maximum and minimum amount of reduction eligible to receive reward.

In the above formulation, the parameters that are given by the ISO are \( r_t, T_{DBE}, p, q \); \( b_t \) is chosen by the hotel. \( f(x_t), m_t \) are defined by the behaviour of hotel energy usage.

Note that the above optimization can be applied with and without load scheduling. With load scheduling, \( f(x_t) \) will be the respective probability distribution function of hotel energy consumption with load scheduling. In addition, it should be emphasized that \( b \) is independent of \( f(x_t) \). Our attempt is to obtain an optimal \( b \) regardless of \( f(x_t) \). There is no recursive effect in the formulation.

\[ \text{Proposition 1:} \quad \text{The optimal bid, } b^*, \text{ satisfies the condition} \]

\[ p^2 f(m_t - b^* \cdot p) \equiv q^2 f(m_t - b^* \cdot q). \tag{3} \]
TABLE I
DETERMINATION OF THE OPTIMAL BID USING BISECTION METHOD

<table>
<thead>
<tr>
<th>Require: ( p, q, \sigma_n^2 ) from ISO where ( \sigma_n^2 ) is the minimum bid required if any ( b_{\text{prev}} ) keeps the bid in the previous iteration. ( f(x) ), ( m ) from energy consumption statistics. ( \epsilon ) a small number greater than zero. ( b_{\text{max}} ) the maximum bid that the hotel can support.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Set ( b_{\min} = 0 ), ( b_{\text{prev}} = 0 ). Compute ( b = \frac{b_{\min} + b_{\text{prev}}}{2} ).</td>
</tr>
<tr>
<td>2. while ( b_{\text{prev}} - b \geq \epsilon ) do</td>
</tr>
<tr>
<td>3. if ( p^2 f(m - b - \cdot p) &gt; q^2 ) then</td>
</tr>
<tr>
<td>4. ( b_{\text{prev}} = b ).</td>
</tr>
<tr>
<td>5. else</td>
</tr>
<tr>
<td>6. ( b_{\text{max}} = b ).</td>
</tr>
<tr>
<td>7. end if</td>
</tr>
<tr>
<td>8. Compute ( b_{\text{prev}} = b, b = \frac{b_{\min} + b_{\text{max}}}{2} ).</td>
</tr>
<tr>
<td>9. end while</td>
</tr>
<tr>
<td>10. if ( b &gt; b_{\text{min}} ), then</td>
</tr>
<tr>
<td>11. ( b^* = b ).</td>
</tr>
<tr>
<td>12. else</td>
</tr>
<tr>
<td>13. ( b^* = b_{\text{eq}} ).</td>
</tr>
<tr>
<td>14. end if</td>
</tr>
</tbody>
</table>

Proof: Use the formula from ([19], 0.410),

\[
\frac{d}{da} \int_{\psi(a)}^{\varphi(a)} f(x, a)dx = \left( \frac{d\varphi(a)}{da} \right) \int_{\psi(a)}^{\varphi(a)} f(x, a)dx - \left( \frac{d\psi(a)}{da} \right) \int_{\psi(a)}^{\varphi(a)} f(x, a)dx + \int_{\psi(a)}^{\varphi(a)} \frac{d}{da} f(x, a)dx,
\]

with \( f(x, a) = f(x, \varphi(a) - m - b \cdot q, \psi(a) - m - b \cdot p) \). Setting the derivative to be zero and arranging the terms will arrive at the result.

Corollary 1: Since we have \( q < p \), it follows that

\[
f(m - b^* \cdot q) > f(m - b^* \cdot p).
\]

Therefore, for an optimal bid to exist, there must exist two points on the \( f(x) \)-curve on the left of \( m \) such that the line joining them has a positive slope.

Corollary 2: If \( f(x) \) is non-increasing for all \( x < m \), there is no optimal bid.

In practice, \( f(x) \) is typically unknown. Therefore, an empirical distribution from measurement might be used instead. One approach might be to measure occupancy independent load and occupancy dependent load separately for a given occupancy rate or a range of it. We might also take seasonal variations (date of year) into account in the measurement. Once we have large enough data for a given occupancy and/or date of year, one can estimate the required distribution of total energy consumption using a statistical method.

Since there is no closed form expression for an empirical \( f(x) \), optimization can be done numerically. However, rather than performing numerical integration in (1) with a trial optimal bid, with Proposition I, we can determine a solution by a simple search method as described in Table I. This can be done easily as it involves only one-dimensional optimization variable.

The bisection method in Table I will yield a global optimal point if there is a single solution that satisfies (3). So, one might want to plot the left hand side and right hand side of (3) with respect to \( b^* \) to see if there are more than one intersection. If there exist such points, we know roughly the candidate solution of \( b^* \). Then, the bisection method can be applied by appropriate range restriction. Once we obtain the accurate candidate of \( b^* \), we can substitute them back into (2) and choose the optimal bid.

In many cases, the energy consumption in a building can be suitably modeled by a Gaussian distribution according to the measurement [20]. In particular, Gaussian distribution provides a good fit during high load hours [20]. For \( f(x) \) a Gaussian distribution, we can derive the following closed-form optimal bid and expected reward.

**Theorem 1:** For \( x \sim N(m_n, \sigma_n^2) \) and a given \( \bar{m} \), the optimal bid is found to be

\[
b^* = \frac{\bar{m} - m_n + \sqrt{(\bar{m} - m_n)^2 + \frac{4(p + q)\sigma_n^2}{p - q} \ln \left( \frac{\bar{m}}{q} \right)}}{p + q}.
\]

Proof: Substitute

\[
f(x) = \frac{1}{\sqrt{2\pi}\sigma_n^2} e^{-\frac{1}{2}\frac{(x - m_n)^2}{\sigma_n^2}} \text{ in (3)}
\]

Rearranging the terms and solving the obtained quadratic function result in the optimal bid. (Note that two solutions are obtained from solving. Choose the positive \( b^* \).)

**Theorem 2:** For \( x \sim N(m_n, \sigma_n^2) \) and a given \( \bar{m} \), the expected reward, \( \zeta^* \), at the optimal bid is found to be

\[
\zeta^* = \left( \bar{m} - m_n \right) \left( \operatorname{erf}(u) - \operatorname{erf}(v) \right) + \frac{\sigma_n}{\sqrt{2\pi}} \left( e^{-u^2} - e^{-v^2} \right),
\]

where \( u = \frac{\bar{m} - m_n - b^* - p}{\sqrt{2\sigma_n^2}}, \quad v = \frac{\bar{m} - m_n - b^* - q}{\sqrt{2\sigma_n^2}} \) and \( \operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \) is the error function.

Proof: Compute

\[
\int_{\bar{m} - b^* - q}^{\bar{m} - b^* - p} f(x)dx = \int_{\bar{m} - b^* - p}^{\bar{m} - b^* - q} f(x)dx - \int_{\bar{m} - b^* - p}^{\bar{m} - b^* - q} f(x)dx
\]

with \( f(x) = \frac{1}{\sqrt{2\pi}\sigma_n^2} e^{-\frac{1}{2}\frac{(x - m_n)^2}{\sigma_n^2}} \). The first term can be written into the error function format and using the fact that \( \int_{-\infty}^{x} e^{-t^2} dt = \frac{1}{\sqrt{\pi}} \). The second term can be determined by using the result from the first term. The second term is found to be \( -(\sigma_n)/(\sqrt{2\pi}) (e^{-u^2} - e^{-v^2}) - (m_n/2) \operatorname{erf}(v) - \operatorname{erf}(u) \). Combining these terms results in the Theorem.

**Corollary 3:** Without load scheduling, \( \bar{m} - m_n = 0 \), the optimal bid in (6) reduces to

\[
b^* = \frac{4\sigma_n^2}{p^2 - q^2} \ln \left( \frac{p}{q} \right).
\]

**Corollary 4:** Without load scheduling, \( \bar{m} - m_n = 0 \), the expected reward in (7) reduces to

\[
\zeta^* = \frac{\sigma_n}{\sqrt{2\pi}} \left( e^{-\frac{1}{\sqrt{2\sigma_n^2}} \ln(\frac{\bar{m}}{q})} - e^{-\frac{1}{\sqrt{2\sigma_n^2}} \ln(\frac{\bar{m}}{p})} \right).
\]

Substituting \( b^* \) from (8), the expected reward results in

\[
\zeta^* = \frac{\sigma_n}{\sqrt{2\pi}} \left( e^{-\frac{1}{\sqrt{2\sigma_n^2}} \ln(\frac{\bar{m}}{q})} - e^{\frac{1}{\sqrt{2\sigma_n^2}} \ln(\frac{\bar{m}}{p})} \right).
\]
Now we can notice an interesting effect of $\sigma_n$, which reflects the variation of energy consumption. The above results illustrate that a larger $\sigma_n$ results in a higher optimal bid and a higher expected reward.

The above result motivates us to propose an alternative way to compute the optimal bid. When only mean and variance of energy consumption are available, possibly from real measurement, we might assume the distribution to be Gaussian with the corresponding parameters. Then, we can apply the closed form expressions in the above theorems without using numerical optimization.

In summary, to our knowledge, the proposed approach is the only one to solve for an optimal bid for the considered DBP. The strength of the proposed approach lies in its simplicity in computation. The bi-section method is well-known to converge very fast. In addition, when Gaussian distribution is assumed, the alternative approach is even simpler to compute from a closed-form expression.

Requirements of practical implementation of DBP is included in the document provided by the ISO. In addition to Internet access, the hotel must purchase an approved smart meter capable of recording usage in 15-minute intervals [15]. For the algorithm, one approach might be to implement it on a software running on a PC. The software is informed about the bidding event, computes the bidding value and automatically inputs the bidding value on the ISO service.

III. LOAD CATEGORIES IN A HOTEL

Energy in a hotel is often obtained from a combination of sources: electricity, gas and diesel. In this paper, however, we will only consider the energy source to be from electricity.

Some types of loads in the hotel are dependent on how many guest rooms are booked and occupied. Therefore, dependence on occupancy is one of the criteria to characterize loads. Energy consumption of occupancy dependent loads increases as the number of guests increases. On the other hand, given the fixed infrastructure of the hotel (space, total number of rooms, etc.), energy consumption of occupancy independent loads does not change in a normal operation. However, it may still be varied randomly according to other uncertainties such as outside temperature, seasonal variations, etc.

In addition, some types of loads can be scheduled. Therefore, we can consider loads as either schedulable or non-schedulable. The schedulable loads are those whose operation can be advanced or postponed without compromising the utility.

From the above discussion, we characterize loads in a hotel into four categories.

1) Occupancy independent and schedulable: The loads in this type are flexible and are not likely to have strong impact to the guest comfort. For example, these may include lighting in some areas, water pumps/lighting in the garden, air-condition setting in the common area, swimming pool, etc.

2) Occupancy dependent and schedulable: The loads in this category reflect the activities directly related to guests and are flexible enough to be shifted. For example, laundry and house keeping, kitchen activities such as dish washing fall into this category.

3) Occupancy independent and non-schedulable (so-called base load): This type of load is fixed with a given hotel infrastructure. This may include refrigerator in a common facility, vending machines, computers, networking and IT equipment, security system, control room, lighting, etc.

4) Occupancy dependent and non-schedulable: This includes vertical transports, cooking activities, and everything in the guest rooms such as air-condition, shower, refrigerator, etc.

To avoid compromising the guest comfort, no schedulable loads exist in the guest rooms.

In this paper, we consider energy consumption value with a resolution of one hour time slot. The energy consumption at any hour depends strongly on whether guests are present in the room. Thus, guest checking in and out times need to be taken into account. We assume that the guest check-in and check-out times are uniformly random within given intervals of each day. Let us denote check-in and check-out time of room $i$ as $t_{in}(i)$ and $t_{out}(i)$, respectively. They are uniformly distributed over $T_{chk-in}$, $T_{chk-out}$, respectively.

IV. ENERGY CONSUMPTION MODELS

According to the survey and existing research, major energy consumption in a hotel consists of space heating/cooling, water heating for a shower in guest rooms, lighting, catering, laundry, lifts, swimming pool [13], [14]. Among these, space heating/cooling is the most energy consuming part of all. To capture energy use of different activities, we divide them to two parts: guest room energy consumption and common area energy consumption.

Notations:

- $i$ is the room index.
- $t$ is the (hour) index.
- $n_{guest}(i)$ is the number of guests in room $i$.
- $N_{room}$ is the number of rooms in use.
- $c(\cdot)$ represents a constant energy value of the appliance ($\cdot$).

A. Guest Room Energy Consumption

Energy consumption in guest rooms has a direct impact on guest comfort. Therefore, many first-class hotels may let guests have complete control of the energy use. Nevertheless, whenever the guests are not present in the room after check-in, the hotel could save energy in the room by, e.g., turning off light and TV, reducing the temperature setting of the air-conditioner, etc. Here, we assume that energy use in guest rooms occurs from check-in time for the current day to check-out time of the next day, i.e., we consider a single-night stay model for all rooms.

1) Air conditioner: Guests have complete control of the temperature setting in the guest rooms according to their preference. On the other hand, the hotel might enforce a limited range of temperature setting. Thus, we model the temperature setting, $T_{set}(i)$, as a uniform random variable with minimum and maximum values:

$$T_{set}^{\min} \leq T_{set}(i) \leq T_{set}^{\max}. \quad (11)$$

Once the temperature is set, we assume that it does not change during the guest stay period. Let us denote $T_{c}(i, t)$ as the room temperature and $T_{amb}(i, t)$ as the ambient temperature. The control for air conditioner follows a simple logic from [17] as follows: When $T_{c}(i, t) > T_{set}(i)$, the cooling system is switched on. When $T_{c}(i, t)$ is less than $T_{set}(i)$ by a margin $\Delta_{T}$, the cooling system is switched off. Otherwise, the cooling system maintains the same state. Let $\tau$ be the time index for thermostat operation, which has a finer resolution than $t$. Let us denote $z(\cdot, \tau)$ to be...
a binary control variable representing turning on (1) or off (0) the cooling system. Thus,
\[ z_a(i, \tau) = \begin{cases} 
0, & T_e(i, \tau) < T_{set}(i) - \Delta \tau \\
1, & T_e(i, \tau) > T_{set}(i) \\
z_a[i, \tau - 1], & \text{otherwise}
\end{cases} \] (12)

For the above control, we need to consider room temperature dynamics which can be modeled as
\[ T_e(i, \tau) = T_e(i, \tau - 1) + k_{th}(T_{mib}(\tau) - T_e(i, \tau - 1)) + k_{human} n_{guest}(i)(T_{human} - T_e(i, \tau - 1)) + k_{eff}^a T_{aircon}^a, \] (13)

where \( k_{th}, k_{human} \) are the thermal characteristics of the building and human, respectively. \( k_{eff}^a \) is the thermal efficiency of the air-conditioner, which is a negative quantity. \( T_{aircon}^a \) is the temperature gain when the cooling system is turned on. The total energy consumption of air conditioner per guest room at hour \( t \) is
\[ x_{aircon}(i, t) = \sum_{\tau \in t} z_a(i, \tau) \cdot e_{aircon}^a, \] (14)

where \( e_{aircon}^a \) is energy consumption when the thermostat is turned on during any period \( \tau \). To save energy, the air conditioner of each room is turned on from the check-in time and turned off at the check-out time. Thus, the \( t \) in (14) follows \( t_{in}(i) \leq \tau \leq t_{out}(i) \).

2) Water Heating System: Due to flexible temperature setting, the energy consumption of water heating system for a shower is assumed to be a uniform random variable with minimum and maximum values. The energy consumption per room depends on how many guests are staying in the room,
\[ n_{guest}(i) \cdot e_{shower}^m \leq x_{shower}(i, t) \leq n_{guest}(i) \cdot e_{shower}^M. \] (15)
The shower time is assumed to be random over some hours in the morning and evening, \( T_{shower} \). We assume that each guest uses the shower once in the morning and once in the evening.

3) Refrigerator: Similar to air conditioner, the refrigerator is turned on and off at check-in time and turned off at check-out time. Here, the energy consumption of refrigerator is assumed to be constant.
\[ x_{fridge}(i, t) = e_{fridge}, \quad t_{in}(i) \leq \tau \leq t_{out}(i). \] (16)

4) Coffee maker: Coffee maker generates high energy consumption for a short period of time. Its operation further increases peak energy consumption in the morning. For simplicity, the usage time is assumed to be within the wake-up hour. Its energy consumption is modelled as
\[ x_{coffee}(i, t) = e_{coffee}, \quad t \in T_{wakeup}. \] (17)

where \( e_{coffee} \) is a binary random variable with \( p_{coffee} \) the probability of usage and \( T_{wakeup} \) is set of wake-up times.

5) Miscellaneous: This category includes lights, television, personal devices belonging to guests such as laptop, cell-phone charger, and other undefined devices that may cause fluctuation in energy consumption in the guest room. This type of energy consumption is assumed to be a Gaussian random variable with a constant mean and variance for all time slots and guest rooms. It is nonzero only when the guests are not sleeping.
\[ x_{misc}(i, t) \sim \mathcal{N}(m_{misc}, \sigma_{misc}^2), \quad t \in [t_{in}(i), t_{out}(i)] \] (18)

where \( T_{misc} \) is the sleeping hours and \( \mathcal{N}(m_{misc}, \sigma_{misc}^2) \) is a Gaussian distribution with mean \( m_{misc} \) and variance \( \sigma_{misc}^2 \). The total energy consumption of guest rooms is thus
\[ x_{guest}(t) = \sum_{i=1}^{N_{room}} (x_{aircon}(i, t) + x_{shower}(i, t)) + x_{fridge}(i, t) + x_{coffee}(i, t) + x_{misc}(i, t). \] (19)

B. Common Area Energy Consumption

Common areas are the places such as lobby, corridor, restaurant, laundry, where energy consumption supports the operation of the hotel. It has less impact to guest satisfaction than the energy use in the guest rooms. Therefore, the hotel manager can take advantage of schedulable loads when the hotel participates in a demand response program. Followings describe major loads in the common area.

1) Air conditioner: We will use the same air conditioner model and dynamics as in the guest rooms, with the difference in the detailed parameters. The \( n_{guest}(i) \) in (13) is replaced by \( N_{staff} \) and the temperature setting is fixed at 26°C. The air conditioner is turned on only from 6 a.m. to midnight. We write the energy consumption of this part as \( x_{aircon}^{common}(t) \).

2) Light: We assume fixed energy consumption for lighting during daytime and another fixed value during nighttime. Thus,
\[ x_{light}(t) = \begin{cases} 
\epsilon_{light}^n, & t \in [6 \text{ a.m.}, 6 \text{ p.m.}] \\
\epsilon_{light}^d, & t \in [6 \text{ p.m.}, \text{midnight}] 
\end{cases}. \] (20)

3) Base loads: As mentioned previously, the base loads cover equipment and device that have fixed energy consumption during the operation. Their total energy consumption is modeled as a constant value:
\[ x_{base}(t) = \epsilon_{base}. \] (21)

4) Garden: The energy consumption in the garden includes water pump operating normally in the morning and in the evening.
\[ x_{garden}(t) = \epsilon_{garden}, \quad t \in T_{garden}. \] (22)

\( T_{garden} \) is the pump operating hour.

5) Kitchen: The probability of guests having meal at each hour is denoted by \( p_{room} \), where the first element of the vector corresponds to 1 a.m. The energy consumption in this category is divided into catering and cleaning parts. Both parts are a function of the number of guests. The energy for catering includes meal preparation which cannot
be shifted. The cleaning part, however, is schedulable. The energy consumption for catering is

\[ \eta_{\text{meal}} = \text{meal/10 kWh/meal/guest} \]

where \( \theta \) is a binary random variable, equal to one when the guests of room \( i \) eat at the restaurant at time \( t \) and zero otherwise. Similarly, the energy consumption for cleaning is modelled similar to catering with the parameters for “meal” replaced by “clean.” The cleaning time is assumed to be delayed by one hour from the catering time by default. In addition, we also include the overhead energy used in the kitchen by \( \eta_{\text{kitchen staff}} \) during the meal times. The total energy consumption in the kitchen is thus

\[ x_{\text{kitchen}}(t) = x_{\text{meal}}(t) + x_{\text{clean}}(t) + x_{\text{overhead}}(t). \]

(25)

6) Laundry: The energy consumption of laundry is a function of total number of rooms booked. It is flexible to be scheduled when needed. The washing machine is assumed to run during \( T_{\text{laundry}} \) hours. The energy consumption is

\[ x_{\text{laundry}}(t) = N_{\text{room}} \cdot \eta_{\text{laundry}}, \quad t \in T_{\text{laundry}}. \]

(26)

7) Elevator: The elevator used is assumed to concentrate around check-in and check-out times. It is also a function of total number of rooms booked. The number of elevator per room, \( n_{\text{lift}}(i, t) \), is a uniform random variable over \( N_{\text{lift}} \). The energy consumption is

\[ x_{\text{lift}}(t) = \sum_{i=1}^{N_{\text{room}}} n_{\text{lift}}(i, t) \cdot \eta_{\text{lift}}(i, t), \quad t \in \{ t_{\text{in}}(i), t_{\text{out}}(i) \}. \]

(27)

8) Miscellaneous: This part covers other types of energy use in the common area. We assume that the energy consumption is a Gaussian random variable with the same variance but different means between daytime and nighttime.

\[ x_{\text{misc}}(t) \sim \mathcal{N}\left(m_{\text{day/night}}, \sigma_{\text{misc}}^2\right). \]

(28)

In summary, the energy consumption in the common area is

\[ x_{\text{common}}(t) = x_{\text{meal}}(t) + x_{\text{clean}}(t) + x_{\text{kitchen}}(t) + x_{\text{laundry}}(t) + x_{\text{lift}}(t) + x_{\text{misc}}(t), \]

(29)

and the total hotel energy consumption is the summation,

\[ x_{\text{hotel}}(t) = x_{\text{guest}}(t) + x_{\text{common}}(t). \]

(30)

V. RESULTS AND DISCUSSIONS

We consider a hypothetical hotel with a known number of rooms under reservation, which is 100 rooms. The number of guests in a room is a random variable with the guest profile probability \( p_{\text{g}} \), where \( p_{\text{g}}(n) \) is the probability of a room having \( n \) guests. The common area parameters are summarized in Table II. The schedulable loads are only cleaning part of kitchen activities and laundry. With load scheduling, the energy consumption \( x_{\text{clean}}(t) \) is removed from (25) and \( x_{\text{laundry}}(t) \) in (26) is not included. The probability of guests having meal at each hour is set to be

\[ p_{\text{meal}} = [0 \ 0 \ 0 \ 0 \ 0 \ 0.2 \ 0.4 \ 0.3 \ 0 \ 0.01 \ 0.02 \ 0.02 \ 0.01 \ 0 \ 0 \ 0.04 \ 0.06 \ 0.06 \ 0.04 \ 0 \ 0]. \]

(31)

\( p \) defined above implies \( T_{\text{breakfast}} = \{ 7 \text{ a.m.} \} \), \( T_{\text{lunch}} = \{ 12 \text{ a.m.} \} \), \( T_{\text{dinner}} = \{ 7 \text{ p.m.} \} \).

The guest room parameters are summarized in Table III. The shared parameters are summarized in Table IV. We perform ten thousand simulation runs to obtain the empirical distribution of the energy consumption computed by the MATLAB function \textit{kdsdensity}.

Demand bidding program follows that of Southern California Edison (SCE) [15]. The minimum bid is required at 30 kWh/hour. The DBP event starts anytime from 12 p.m. to 8 p.m. The participant must bid for at least two consecutive hours during the
DBP event in order to receive reward. The reward is paid when the actual energy is reduced from the mean between 50% and 200% of the bid amount. The payment is 50 cents per 1 kWh reduction minus the hourly price of energy set by California ISO (CAISO) which can be downloaded from [16]. We take the LMP/DAM price data on 7 August 2012 as an example. On the DBP event day, the hotel that applies load scheduling shifts all schedulable loads away completely from the DBP event.

Fig. 1 shows the mean energy consumption in terms of guest rooms, common area and total. The common area has a very low energy consumption between 1 a.m.–5 a.m., during which most hotel staffs do not work. On the contrary, the guest room energy is still active during the night period due to operation of air-conditioner. Two peaks occur in the guest room energy from guest activity in the morning and evening. This characteristic is also evident in the literature [20], [21]. On the other hand, during daytime, most guests are outside the hotel and the total energy consumption is low.

Fig. 2 shows the expected reward as a function of bid at 2 p.m. There is a bid amount of energy reduction that achieves maximum expected reward regardless of scheduling. Even without scheduling, the hotel may participate in the DBP and expect to gain some rewards if the bid amount is chosen properly. Without scheduling, the optimal bid is slightly less than 30 kWh while that with scheduling is above 30 kWh. Therefore, to follow the minimum bid requirement, the hotel may bid at 30 kWh although it is not the optimal point. On the other hand, with scheduling, the hotel can bid at the optimal bid. The expected reward is almost double with scheduling.

The maximum expected reward is shown in Fig. 3. This plot is obtained with the optimal bid that is not less than 30 kWh. Otherwise, the bid is set at 30 kWh and the reward is computed. The expected reward obtained with scheduling is almost double to that without scheduling during the period when the optimal bid is greater than the minimum bid requirement. Suppose the DBP event starts from 12 p.m. and ends at 8 p.m. The total expected reward on this day with and without load scheduling are $26.6, $54.5, respectively.

Fig. 4 illustrates the difference of optimal bid (•) and expected reward (◦) when Gaussian approximation is applied. It is apparent that Gaussian approximation is highly accurate during nighttime (from 7 p.m. to 7 a.m.). This is the time when rooms are occupied with guests and energy consumption from guest

Fig. 1. Energy consumption in guest rooms, common area and total.

Fig. 2. Expected reward as a function of bid at 2 p.m.

Fig. 3. Maximum expected reward at different hours.

Fig. 4. Difference of optimal bid and expected reward when Gaussian distribution is assumed. (a) No scheduling, (b) With scheduling.
rooms is dominant. On the other hand, during daytime, Gaussian approximation may under- or over-estimates the optimal bid and expected reward. During daytime, the energy consumption occurs mainly outside the guest rooms and the number of variables involved may not suffice for total energy to be well approximated by Gaussian distribution.

VI. CONCLUSION

The paper investigates demand bidding program (DBP) under the context of hotel energy management. Optimization problem of DBP is formulated with the objective of maximizing expected reward. A general condition for the optimal bid is given and closed-form expressions of the optimal bid and the corresponding expected reward are derived for the case of Gaussian distribution. It is shown that the DBP provides economic benefit to the hotel and encourages the hotel to schedule the loads.

REFERENCES


Poramate Tarasak (S’97, M’05) received the B.E. degree in electrical engineering from the Chulalongkorn University, in 1997, the M.E. degree in telecommunications from the Asian Institute of Technology (AIT), Pathumthani, Thailand, in 1999, and the Ph.D. degree in electrical engineering from the University of Victoria, Victoria, BC, Canada, in 2004. From 2004 to 2005, he was a Postdoctoral Fellow with the Department of Electrical Engineering and Computer Science, KAIST, Daejeon, Korea. From 2006–2013, he was a Research Fellow and a Scientist at the Institute for Infocomm Research, Singapore. Dr. Tarasak served as a TPC member for GLOBECOM 2013, 2012, ICC 2011 Workshop on HETNet, SmartGridComm 2012, PIMRC 2009, VTC Fall 2012, Fall 2011, Fall 2009. He was named as an Exemplary Reviewer for the IEEE WIRELESS COMMUNICATIONS LETTERS in 2012.

Chin Choi Chai (M’98) received the Ph.D. and B.Eng.(Hons.) Degrees, both in electrical engineering, from the National University of Singapore (NUS) in year 1999 and 1995 respectively. He was a recipient of the NUS Research Scholarship from 1995 to 1998. He has joined the Institute for Infocomm Research (formerly known as Center for Wireless Communications, NUS and Institute for Communications Research) in 1998, where he is presently a Scientist in their Smart Grid Programme. His research interest is in wireless MIMO relay, wireless fading channels, digital modulation and detection, transmission rate and power control, performance enhancement of cellular radio and spread spectrum systems, and smart grids.

Kwok Yuen Sam received the B.Eng. (EE) from NUS in 1995 and M.Eng. (Telecommunications) from RMIT in 1999. He joined IFR since then and have worked on a number of projects on wireless communications systems. This includes the investigation of the performance of turbo coding with blind channel estimation, participation in standardization activities in IEEE 802.15.4a/b, and investigation of the performance of modulation and coding schemes for UWB signalling and ranging. He has also worked on the design and implementation of meter reading and routing protocol of a multi-communications module used in smart metering applications. He is currently the deputy programme head of TV White Space Programme in IFR.

Ser Wah Oh (SM’05) obtained his B.Eng. from the University of Malaya, Malaysia and Ph.D. and M.B.A degrees from Nanyang Technological University (NTU), Singapore. He is currently the Head of TV White Spaces Programme at Singapore-based Institute for Infocomm Research (IFR) and Co-Director of IFR-Singapore Power Joint Lab. He is looking into application of TV White Spaces onto Smart Grid. He previously led a team to contribute to the FCC TV White Space trial in the USA, which helped FCC to open up TV White Space for unlicensed communications. He is also being appointed as a member of the Ministry of Communication and Information’s Infocomm Media 10-Year Masterplan working committee on Infrastructure. At the same time, he also served as Technical Adviser for Rohde & Schwarz and ConSOc Technologies. From 2005 to 2008, he concurrently held the position of Adjunct Assistant Professor in NTU. Prior to IFR, he was a Technical Manager at STMicroelectronics in charge of teams in Singapore and Beijing R&D Centers for 3 G WCDMA and TD-SCDMA physical layer development. He is also a recipient of the 2013 & 2012 WUN CogCom Best Paper Award in Practical Implementations and Trial and 2012 Ernst & Young Cash Prize Award as the Top MBA Graduate, the 2009 Institution of Engineers Singapore Prestigious Engineering Achievement Award, STMicroelectronics Corporate Excellence Team Award (Bronze), and IEEE ICT 2001 Paper Award. He served as General Chair, General Co-Chair, and other chairs and committees for various conferences and workshops. He was also invited to give a number of talks worldwide related to TV White Spaces and Smart Grid. He has published over 40 papers and held eight US patents with several pending.