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Power capacity profile estimation for activity-based residential loads

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Abstract: This paper proposes a framework to determine day-ahead capacity profiles that account for the stochastic demand generated by user behavior in smart buildings. The user selects a level of capacity per time frame in the context of flexible time-and-level-of-use pricing. We generate the consumption scenarios by aggregating historical data. We also present two approaches to determine the required capacity given the demand. In the first approach, we solve a two-stage optimization model under the assumption that the start time probability distributions of the loads are known. In the second approach, we use a greedy-type algorithm that analyzes a set of previous consumption profiles to estimate future capacity requirements. We report experiments to validate the proposed approaches.

Keywords: Smart buildings, power demand, residential load sector, user behavior, activity-based loads, stochastic optimization

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1 Notation

Sets	
$t \in T$	Set of time frames in horizon.
$m \in M$	Set of loads.
$i \in I$	Set of scenarios.
$j \in J$	Set of intervals of the cost step function for the lower tariff.
$q \in Q$	Set of intervals of the cost step function for the higher tariff.
Scenario generation	
P_m	Power consumption of load m (kW).
L_m	Duration of load m (h).
X_m	Start/arrival time frame of load m.
ρ	Significance threshold for the scenario elimination.
Optimization parameters	
K_t^0	TOU tariff in time frame t (/kWh).
K_{jt}^L	Lower tariff in interval j in time frame t (/kWh).
K_{qt}^H	Higher tariff in interval q in time frame t (/kWh).
K_t^F	Booking cost in time frame t (/kWh).
C_{jt}^L	Capacity lower bound in interval j in time frame t for the lower tariff (kW).
C_{qt}^H	Capacity lower bound in interval q in time frame t for the higher tariff (kW).
Pr_{it}	Probability of scenario i in time frame t.
D_{it}	Demand for scenario i in time frame t.
Optimization variables	
x_{ijt}^L	Electricity consumption at lower tariff in scenario i, time frame t, and interval j (kWh).
x_{iqt}^H	Electricity consumption at higher tariff in scenario i, time frame t, and interval q (kWh).
c_{jt}	Booked capacity in time frame t and interval j (kW).
$\bar{c}_{qt}$	Auxiliary variable to identify the higher tariff interval q in time frame t.
ϕ_{jt}	$\begin{cases} 1 & \text{Capacity in time frame } t \text{ belongs to interval } j \text{ for the lower tariff} \\ 0 & \text{Otherwise} \end{cases}$
δ_{qt}	$\begin{cases} 1 & \text{Capacity in time frame } t \text{ belongs to interval } q \text{ for the higher tariff} \\ 0 & \text{Otherwise} \end{cases}$
Heuristic	
N	Number of days in Γ.
$\Gamma \in \mathbb{R}^{N \times \lvert T \rvert}$	Historical load consumption.
S	Number of time segments.
$\bar{S}(n)$	Number of time segments in iteration n.
α	Number of iterations with a constant $\bar{S}(n)$.
β	Stopping criterion.

2 Introduction

The increasing development of smart grids (SG) creates potential benefits and challenges for utilities, consumers, and society in general. An SG allows information flow among all the participants [1], supporting better decisions that ensure the stability, reliability, and economic viability of the system.

In this context, the consumers (end-users) become decision-makers and can contribute to the grid performance. This user participation is achieved through demand response (DR) programs [2], which are designed to encourage consumers to change their consumption preferences in a way that is beneficial for the grid, normally in exchange for compensation.

DR programs include incentive-based programs, where the consumer commits to reducing consumption over a determined period of time under prespecified conditions.

In pricing DR programs, the utility offers a variable tariff, expecting that the user will react by shifting load to cheaper periods. If the users do not shift they pay more to meet their energy requirements. These pricing policies normally reflect the aggregated peak of demand and therefore the utility's generation costs.

They are mostly oriented to customers in residential and commercial sectors and have particular potential in smart buildings [3], where the end-users can seek to benefit while meeting the grid requirements.

The residential and commercial sectors have a specific set of characteristics that must be taken into account. First, the demand is driven by a large number of end-users with low individual consumption. Second, the consumption is triggered by the user behavior, which may be (highly) stochastic.

There are various models that consider user behavior. The model presented in [4] determines consumption profiles based on the aggregation of individual loads, the number of people in the housing unit, and their activity profiles. In a similar way, [5] uses a Markov-chain Monte-Carlo model to compute the activity profiles in order to estimate realistic load profiles for a wide variety of housing units. The approach presented in [6] uses logistic and Poisson regression to model the correlational and consistency elements of the shared activities of multiple inhabitants in a household.

The characterization framework in [7] analyzes the controllable demand and its potential savings for users participating in an energy management system. Similarly, the approach in [8] estimates consumption profiles by fitting probability density distributions over a historical set for single and multiple housing units.

The importance of a consumption-aware user is discussed in [9]. This survey includes elements such as potential energy savings, activities with higher potential impact, and the availability of information and automation in the building.

There are various strategies for integrating the end-users into the grid decisions. In demand-side management approaches, e.g., [10], [11], and [12], the user preferences are typically hard constraints and are met while optimizing the energy consumption or peak reduction. In other cases there is a negotiation process. Multi-objective optimization is used in [13] to balance the energy costs and thermal comfort. The user behavior is considered during the process of setting prices in [14]. In this case a bilevel optimization approach is used to find a trade-off between the revenue obtained by the energy provider and the user dissatisfaction.

Different pricing policies are assessed in [15] and [16] to explore the effect on user participation and grid performance. A pricing policy that considers user behavior facilitates the user's integration into the SG decisions.

In this article we propose a framework to determine day-ahead capacity profiles that account for the stochastic demand generated by the user behavior. In this framework the user books a level of capacity per time frame in the context of flexible time-and-level-of-use (TLOU) pricing. This pricing policy is an extension of that presented in [17]. We generate the consumption scenarios by aggregating the individual historical data for each activity load. We also present two approaches to determine when to book power and how much to book to satisfy the demand. First, we propose a two-stage optimization model that minimizes the cost. Second, we propose a heuristic algorithm that uses a set of previous consumption profiles to estimate future capacity requirements.

The use of capacity profiles gives savings for the users and provides the grid with more information about the operation of the system. One of the main features of this work is that the users do not manage their consumption to follow a fixed cost profile; instead, the utility adjusts the costs to the user preferences while considering the grid requirements.

This article is structured as follows: the proposed approaches are described in Section 3, the experimental results and analysis are presented in Section 4, and the conclusion is given in Section 5.

3 Proposed framework

Our framework is based on the concept of a capacity profile. A capacity profile allows us to establish a trade-off between user energy requirements and peak-oriented grid decisions. Our framework estimates capacity profiles considering the user behavior and a dynamic cost scheme. The consumer books a maximum level of consumption per time frame, providing the grid with information in advance and receiving energy below that level at a discounted price. The utility uses this information for planning purposes and is able to charge a higher price if the user exceeds the specified level.

A challenge of this type of decision-making is the proper representation of user behavior. The appropriate capacity depends on the demand. We represent the demand as a stochastic parameter derived by aggregating consumption over all the user's activities.

3.1 Flexible TLOU cost structure

Time of use (TOU) pricing is widely implemented for the residential sector. Under TOU the price depends on the time of day. Figure 1 shows the time windows for off-peak, mid-peak, and on-peak tariffs specified by the Independent Electricity System Operator of Ontario (Canada).

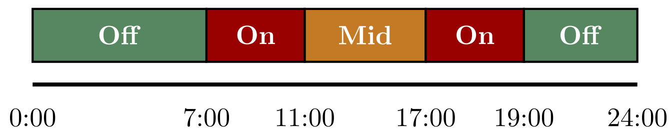

Figure 1: Ontario IESO TOU periods in winter.

We use a cost structure that includes another dimension: the price depends on the level of consumption in each time frame. For a specified power limit, consumption up to this limit is charged at a lower tariff, and consumption above this limit is charged at a higher tariff. This time-and-level-of-use pricing was implemented in [17], where the tariffs and capacity limits were set by the utility or the grid operator. In the approach presented in this article, the tariff depends on the capacity level booked by the user in each time frame. The utility provides a set of tariffs and capacities from which the consumer can choose. Figure 2 shows the possibilities for the lower tariff; this step function has $| J |$ segments, and the TOU tariff is represented by the parameter K_t^0. Note that all the possible tariffs are $\leq K_t^0$. Selecting $c_t^2 > c_t^1$ allows a cheaper tariff $K_t^{L_2} < K_t^{L_1}$. The higher tariff for consumption above the limit is represented by the function in Figure 3. This step function has $| Q |$ segments, and the possible tariffs are $\geq K_t^0$. In this case booking a lower capacity implies a cheaper tariff.

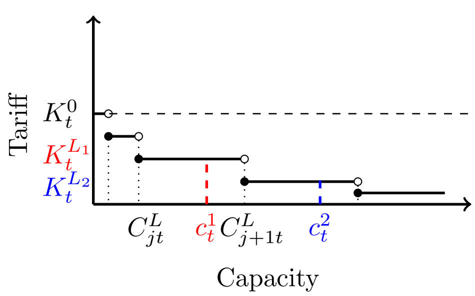

Figure 2: Lower energy tariff as a step function of the booked capacity.

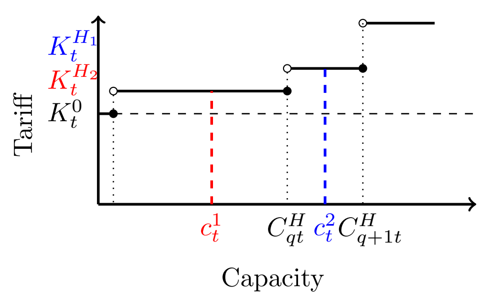

Figure 3: Tariff for consumption above limit as a step function of the booked capacity.

Additionally, we introduce a booking fee K_t^F per power unit that is paid in advance by the user. Determining the capacity is thus a nontrivial decision. Booking a higher capacity c_t^2 will give a cheaper $K_t^{L_2}$ and a more expensive $K_t^{H_2}$ as well as a higher booking cost $K_t^F c^2$.

3.2 Scenario generation

We assume that the start of each load follows a normal distribution. The duration and the level of consumption of each appliance are deterministic parameters.

The aggregation of individual loads can result in numerous scenarios since each time t has $\sum_{m=1}^{|M|} \binom{|M|}{m}$ possible consumption levels obtained from the possible arrivals of the loads. Including zero consumption, we have for each time frame $\sum_{m=1}^{|M|} \binom{|M|}{m} + 1 = \sum_{m=0}^{|M|} \binom{|M|}{m} = 2^{|M|}$ possible consumption levels.

The arrival distribution of each load m is discretized over $\mid T \mid$ time frames, and the probability that load m starts in time frame t is denoted $Pr(X_{mt} = 1)$.

We also need to consider the load durations, so we define the probability that load m is active in time frame t as:

$$Pr(\tilde{X}_{mt} = 1) = \sum_{t-L_m}^{t} Pr(X_{mt} = 1),$$

which is the accumulated probability over the duration of the load. Finally, we compute the probability that scenario i occurs in time frame t as

$$Pr_{it} = \prod_{m \in i} Pr(\tilde{X}_{mt} = 1) \prod_{m \notin i} (1 - Pr(\tilde{X}_{mt} = 1)),$$

where we aggregate the loads m of scenario i. Depending on the parameters of the distribution and the load durations, some of the scenarios can have near-zero probabilities. We remove the scenarios with a probability $< \rho$, where ρ is a significance threshold defined by the decision-maker. The more concentrated the loads are over a set of time frames, the more scenarios can be discarded from this set. Thus, each time frame t can have a different number of scenarios (i.e., $I(t)$).

3.3 Two-Stage stochastic optimization model

We estimate the capacity by solving a two-stage optimization problem [18]. In the first stage the user determines the capacity required per time frame. The second stage takes into account the cost of meeting the demand and the costs associated with the decision. The objective function (1) includes the booking cost, the expected cost of consumption at the lower tariff, and the expected cost of consumption at the higher tariff.

Constraints (2) and (3) ensure that the booked capacity belongs to one of the intervals of the step functions for both tariffs. Constraints (4) and (5) set the lower and upper bounds for each interval of the step functions. We introduce the auxiliary variable $\bar{c}_{qt}$ for the capacity in the higher-tariff step cost function. Constraint (6) establishes the relationship between the capacity and the auxiliary variable.
Constraints (7) and (8) impose the lower-tariff consumption and the demand satisfaction, respectively, for each scenario. Finally, constraints (9) and (10) are the nonnegativity and binary constraints.

$$\min \sum_{t \in T} \sum_{j \in J} K_t^F c_{jt} + \sum_{t \in T} \sum_{j \in J} \sum_{i \in I(t)} Pr_{it} K_{jt}^L x_{ijt}^L + \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I(t)} Pr_{it} K_{qt}^H x_{iqt}^H \tag{1}$$

subject to

$$\sum_{j \in J} \phi_{jt} = 1 \qquad \forall t \in T \tag{2}$$

$$\sum_{q \in Q} \delta_{qt} = 1 \qquad \forall t \in T \tag{3}$$

$$\phi_{jt} C_{jt}^L \le c_{jt} \le \phi_{jt} C_{j+1t}^L \qquad \forall j \in J \mid j <\mid J \mid -1, t \in T \tag{4}$$

$$\delta_{qt} C_{qt}^H \le \bar{c}_{qt} \le \delta_{qt} C_{q+1t}^H \qquad \forall q \in Q \mid q <\mid Q \mid -1, t \in T \tag{5}$$

$$\sum_{j \in J} c_{jt} - \sum_{q \in Q} \bar{c}_{qt} = 0 \qquad \forall t \in T \tag{6}$$

$$x_{ijt}^L \le c_{jt} \qquad \forall i \in I(t), j \in J, t \in T \tag{7}$$

$$\sum_{j \in J} x_{ijt}^L + \sum_{q \in Q} x_{iqt}^H \ge D_{it} \qquad \forall i \in I(t), t \in T \tag{8}$$

$$x_{ijt}^L, x_{iqt}^H, c_{jt}, \bar{c}_{qt} \ge 0, \qquad \forall i \in I(t), j \in J, q \in Q, t \in T \tag{9}$$

$$\phi_{jt}, \delta_{qt} \in \{0, 1\} \qquad \forall j \in J, q \in Q, t \in T \tag{10}$$

In the model the capacity requirements are computed by time frame; in a more realistic scenario the grid operator could assign capacity profiles over a longer horizon of consumption. In the context of TOU we can identify several time windows (groups of time frames) with the same price (for example, off-peak, mid-peak, and on-peak tariffs). Given a set Ω of time windows, we could enforce the same capacity for the time frames in the same time window by adding constraint (11):

$$c_{jt} = c_{jt'} \quad \forall j \in J, \quad t, t' \in \tau^{\omega} \mid t \neq t', \quad \omega \in \Omega \tag{11}$$

where $\tau^{\omega} \subset T$ is a subset of time frames. This modification to the original model will be explored in Section 4.

3.4 Heuristic approach

Figure 4 shows two possible realizations of the capacity (dashed red line) required to operate two loads in some time frame. Booking the complete area will be costly if the total booking cost is greater than the savings associated with the cheaper tariff.

The approach presented in this section reduces the area under the dashed red line by using information about which time frames are more likely to receive loads. This consumption information is contained in the matrix $\Gamma \in \mathbb{R}^{N\times|T|}$ for a set of N previous days. We use the data in Γ to split the horizon into several segments S and then to allocate a capacity c_t to each time frame.

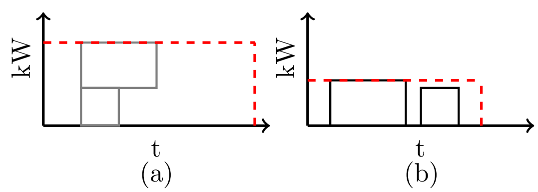

Figure 4: Capacity profile area reduction.

First, we identify several contiguous submatrices in Γ by clustering time frames based on proximity and consumption. Each submatrix contains either only time frames with no consumption (columns of zeros) or columns with some consumption over the historical set. Equation (12) shows Γ for three days and six time frames; we can identify four segments: columns 1, 2–3, 4–5, and 6.

$$\Gamma = \begin{pmatrix} \mathbf{0} & 0 & \lambda & \mathbf{0} & \mathbf{0} & 0 \\ \mathbf{0} & \epsilon & 0 & \mathbf{0} & \mathbf{0} & \lambda \\ \mathbf{0} & 0 & \eta & \mathbf{0} & \mathbf{0} & 0 \end{pmatrix} \tag{12}$$

After this identification we discard the time frames where loads are not expected based on the historical data.

Second, we compute the capacity profile by assigning the average consumption for each time frame. We must decide the size of N before determining the capacity profile. Too few days (rows) in Γ could result in insufficient information. On the other hand, increasing the number of days may not add significant information or could introduce rare events that do not represent typical user behavior. Experimentally we observe that as the number of days increases, the number of segments stabilizes because of the finite horizon. We continue including days and identifying segments until we have added β days without changing the number of segments. Algorithm 1 presents this process in detail.

3.4.1 Algorithm termination

We prove that Algorithm 1 terminates by proving the existence of an upper bound for $\bar{S}(n)$ and monotonically decreasing behavior after this maximum value has been reached.

Let z_t^n be a parameter indicating whether or not column t of matrix Γ at iteration n is an all-zero column:

$$z_t^n = \begin{cases} 1 & \text{If column } t \text{ is zero} \\ 0 & \text{Otherwise} \end{cases}$$

Algorithm 1 Capacity profile for activity-based loads

Initialization

- $n = 0$ Iteration number (i.e., days added)
- $\alpha = 0$ Number of iterations with the same number of segments

Obtain number of segments

```
while α < β do
    n ← n + 1
Add a row to Γ
Compute S̄(n) by identifying the number of intervals in Γ
    if S̄(n) = S̄(n − 1) then
        α = α + 1
    else
        α = 0
    end if
end while
N ← n
S ← S̄(n)
```

Compute profile

$c_t \leftarrow (\sum_{n=1}^{N} \Gamma_{n,t})/N \quad \forall \quad t \in T$

We can determine the number of segments via:

$$\bar{S}(n) = y(n) + 1$$

where $y(n)$ is the number of transitions between zero and nonzero columns, and $\bar{S}(n)$ is an integer value in the interval $[0, \mid T \mid]$:

$$y(n) = \sum_{t=1}^{|T|-1} (z_t^n - z_{t+1}^n)^2.$$

Lemma 1 *There exists $S^{\max}$ such that $\bar{S}(n) \leq S^{\max}$ for a given horizon $\mid T \mid$.*

Proof. The maximum value for each pair $(z_t^n - z_{t+1}^n)^2 = 1$, so $y^{\max} \leq \mid T \mid -1$ and $S^{\max} \leq \mid T \mid$. Therefore, $S^{\max}$ exists. □

Lemma 2 *After $\bar{S}(n)$ reaches $S^{\max}$, $\bar{S}(n)$ is monotonically decreasing.*

Proof. We know that the number of rows in Γ increases at each iteration, so

$$z_t^{n+1} \geq z_t^n, \quad \forall \quad n = 1 \dots N, \quad \forall \quad t \in T.$$

If $z_t^{n+1} = z_t^n \quad \forall \quad t \in T$, then $y(n+1) = y(n)$ and $\bar{S}(n+1) = \bar{S}(n)$.

If there exists t such that $z_t^{n+1} > z_t^n$, then there exists a pair $(z_t^n - z_{t+1}^n)^2 = 0$, $y(n+1) \leq y(n) - 1$, and $\bar{S}(n+1) \leq \bar{S}(n) - 1$. □

Theorem 1 *Algorithm 1 terminates.*

Proof. Because $y \geq 0$ and $S \geq 0$, by Lemma 2 the algorithm must terminate. □

4 Experimental results

4.1 Stochastic optimization

We explore changing the number of loads, the standard deviation of the arrivals, and the concentration of the average arrival time (i.e., how close the arrivals are to each other). The first impacts the number of scenarios and the aggregated consumption level; the second and third affect the congestion over a time window. We denote the instances with $\Phi_{|M|\sigma\bar{x}}$ where $|M| = \{3, 5, 10\}$, $\sigma = \{0.5, 2, 4\}$, and $\bar{x} = \{1$: low, 2: medium, 3: high$\}$ concentrations of the arrival of the loads over similar time frames. Figure 5 shows the values for $\bar{x}$.

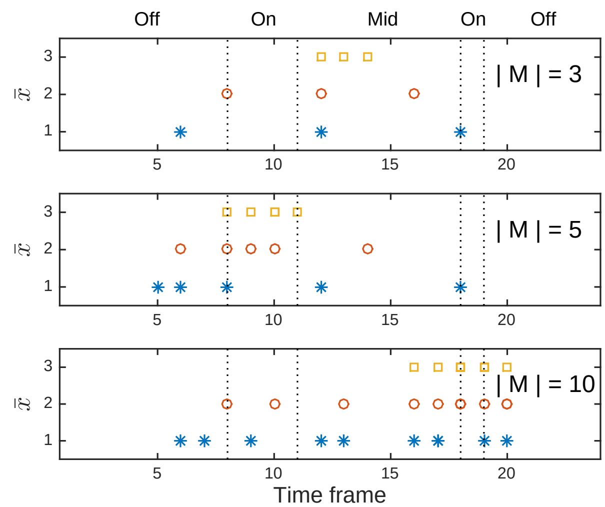

Figure 5: Concentration of load arrivals.

We observe that the activities become closer as $\bar{x}$ increases. They cluster in the mid-peak frames for $|M| = 3$, in the on-peak frames for $|M| = 5$, and spread over the evening for $|M| = 10$.

Table 1 shows the total cost and accumulated capacity c^{tot} over the horizon, obtained by solving the problem for all combinations of the parameters previously introduced as well as both versions of the model presented in Section 3.3: Model 1: Equations (1)–(10) and Model 2: Equations (1)–(11).

Table 1: Total cost () and total capacity (kWh) for the instances.

Instance	$\|M\|=3$				$\|M\|=5$				$\|M\|=10$			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Cost	c^{tot}	Cost	c^{tot}	Cost	c^{tot}	Cost	c^{tot}	Cost	c^{tot}	Cost	c^{tot}
$\Phi_{\|M\|0.5,1}$	142.7	12.3	147.5	5.0	158.6	13.6	164.3	5.0	217.8	23.8	242.3	3.0
$\Phi_{\|M\|1.0,1}$	147.0	11.5	149.0	5.0	159.4	11.5	161.7	5.0	226.3	21.5	240.5	3.0
$\Phi_{\|M\|2.0,1}$	149.6	7.5	149.8	5.0	161.6	7.5	161.8	5.0	232.5	16.0	236.8	8.0
$\Phi_{\|M\|0.5,2}$	171.2	12.3	186.5	5.0	181.6	13.3	193.9	23.0	271.8	22.7	276.6	20.0
$\Phi_{\|M\|1.0,2}$	172.1	11.5	179.8	5.0	184.9	12.2	190.2	23.0	267.5	21.3	268.6	20.0
$\Phi_{\|M\|2.0,2}$	169.0	7.5	170.5	0.0	188.2	10.5	189.4	14.0	255.2	16.5	256.1	11.0
$\Phi_{\|M\|0.5,3}$	141.8	15.3	149.7	24.0	190.0	19.4	207.6	16.0	237.3	23.0	254.7	14.2
$\Phi_{\|M\|1.0,3}$	147.4	14.8	151.6	24.0	193.3	20.8	204.0	16.0	223.7	24.0	236.9	12.0
$\Phi_{\|M\|2.0,3}$	161.7	14.5	162.7	12.0	194.8	16.5	199.4	16.0	212.2	24.5	220.2	12.0

We observe that none of the parameters or models has clear behavior with respect to the total capacity. A higher $|M|$ (i.e., higher total demand) does not always lead to the booking of more capacity. This counterintuitive behavior is repeated for σ, $\bar{x}$, and both versions of the model. At this point we need to consider the interaction of the parameters to understand how the optimization is working, since they determine the shape of the expected demand curve. Figures 6 and 7 give examples.

We change σ in Figures 6(a) and 6(b) while keeping the other parameters constant. For $\sigma = 0.5$ we obtain $c^{tot} = 13.3$. A higher $\sigma = 1.0$ flattens the expected demand curve, resulting in a lower $c^{tot} = 12.2$. Similarly, we change σ in Figures 6(c) and 6(d), this time with $\bar{x} = 3$. In this case we end up with a higher c^{max} for $\sigma = 1.0$. Although the demand curve is flattened, it is still high enough to make it economical to buy capacity in advance, due to the proximity of the different loads over time. We can see this clearly at $t = 13$, where the expected demand changes from 0.1 in 6(c) to 1.1 in 6(d).

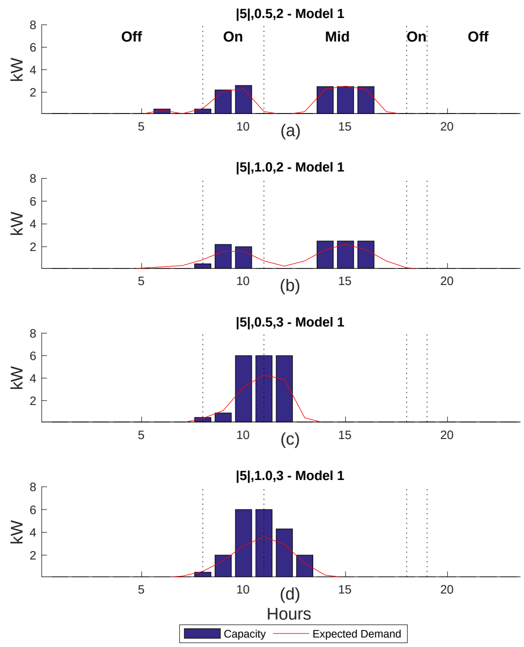

Figure 6: Example of effect of σ and $\bar{x}$ on c^{tot}.

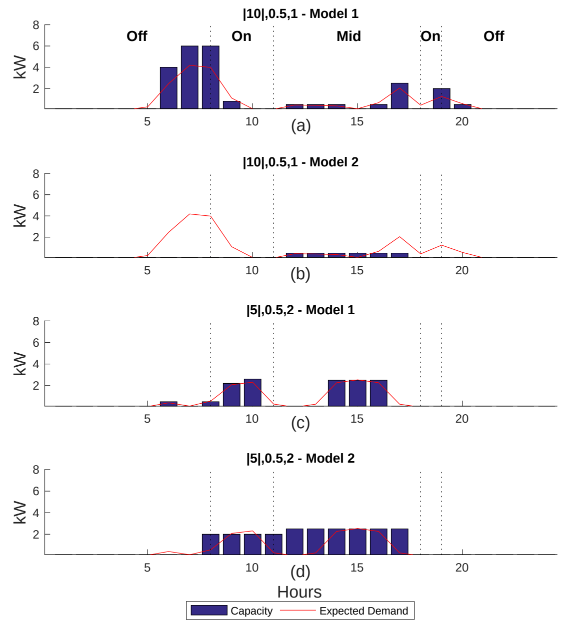

Figure 7: Example of the effect of negotiation frequency.

The selection of the negotiation frequency is represented in model 1 (each time frame) and model 2 (each time window). Figure 7 shows an example of this.

Figures 7(a) and 7(b) show the results of the model variations for the same instance. The hourly negotiation in 7(a) gives a higher c^{tot} than does the window negotiation from 7(b). The dispersed expected demand makes it inefficient to buy capacity for a full time window.

We observe opposite behavior in Figures 7(c) and 7(d). In this case, the way the expected demand curve fits the defined time windows will give a higher c^{tot} by negotiating at every time window.

Note that we are analyzing the conditions where the user chooses to buy more or less capacity, and we are not comparing the costs directly since the models are different. In every case, hourly booking is cheaper than booking for a complete window. The latter can be interpreted as a trade-off between simplicity for the utility and savings for the user.

4.1.1 Necessary condition for booking capacity

In Figures 6 and 7 we see that some time frames with an expected demand greater than zero do not have any capacity booked, even in an hourly negotiation policy.

We can compare the objective function (1) for a single time frame where it was better not to book instead of booking c (for simplicity we do not include the cost intervals from the step functions):

$$K^F 0 + \sum_{i \in I} Pr_i D_i K^0 < K^F c + \sum_{i \in I} Pr_i [x_i^L K^L(c) + x_i^H K^H(c)] \tag{13}$$

Because $D_i = x_i^L + x_i^H$, we can reorganize Equation (13) as

$$\sum_{i \in I} Pr_i [x_i^L [K^0 - K^L(c)] + x_i^H [K^0 - K^H(c)]] < K^F c, \tag{14}$$

where we find a clear relationship: *the net expected savings must be less than the fixed cost from booking capacity c*. The net expected savings are the savings from the lower tariff and the extra cost of consumption at the higher tariff. The optimization seeks a c that violates the condition in Equation (14). If such a c does not exist, it is optimal to retain the TOU pricing K^0.

Because Equation (14) depends strongly on the tariffs, and the tariffs vary depending on the TOU, we observe different behavior for different time frames. We can see this situation in Figure 6(b), where the user buys capacity at $t = 8$, an on-peak period, and not at $t = 13$, a mid-peak period, despite the similar expected demands.

4.2 Simulation

In this section we implement a 180-day simulation corresponding to the period of the TOU winter tariff in Ontario. We generate each day's consumption randomly given the normal distributions from all the instances introduced in Section 4.1. We compare the total cost of the complete simulation for four different approaches: no booking of capacity, booking capacity based on the heuristic approach, and booking it based on our two optimization models.

In the first case, the user pays the TOU tariff originally offered by the utility. In the second case, the user determines the capacity profile with the heuristic value and accepts the K_t^L and K_t^H corresponding to the capacity value. Note that the heuristic does not take into account the cost. Finally, the two models determine both the capacity and the tariffs at the beginning of the simulation as optimal policies.

Figure 8 compares the costs of the 27 instances. The optimal hourly negotiation has the best performance for all the instances. As mentioned previously, time-window negotiation represents a trade-off between grid management and potential user savings, giving optimal values that are between the optimal hourly negotiation values and those of the no-booking policy for all the instances. Finally, in both models the average costs are similar to those in Table 1. In general terms the user achieves savings of up to 16% by using model 1 rather than TOU only.

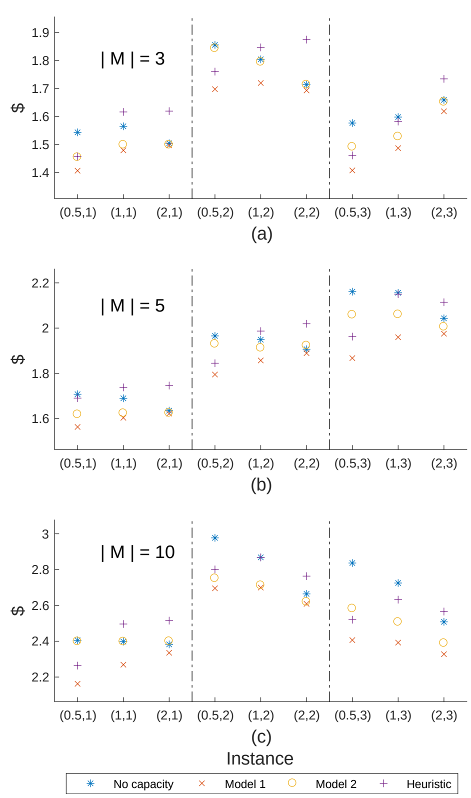

Figure 8: Average cost per day for the instances $(\sigma, \bar{x})$.

The heuristic approach works well in some cases, occasionally reaching values similar to those of model 2. The heuristic is useful in situations where insufficient information is available: it provides suboptimal solutions until the optimization model is ready (i.e., the distributions are known). It could also be helpful for transitions where the user behavior changes and the previous optimal solution is no longer appropriate.

We also observe that the heuristic has poor performance for some instances. These instances have the property that the optimal values for both models are close to the no-booking policy. In these cases, the optimization models either return a low capacity or the savings are not significant because of the shape of the expected demand curve, and the heuristic is not able to determine if booking is a good policy.

In general, the approaches perform better when it makes sense to buy capacity in advance. They could be used in combination with demand-side management to support a learning process (optimal consumption) and eventually give more benefits to the user.

5 Conclusion

We have proposed a new framework that allows end-users to profit from a novel flexible TLOU tariff in a DR context.

The framework starts with the generation of consumption scenarios by aggregating historical data. We have presented two approaches to help the user determine the required capacity given the demand. The first approach solves a two-stage optimization model under the assumption that the start time probability distributions of the loads are known. The second approach uses a greedy-type algorithm that analyzes a set of previous consumption profiles to estimate future capacity requirements.

The use of capacity profiles contributes to the expansion of DR in the residential and commercial sectors, allowing consumers to take advantage of lower prices and providing utilities with a tool that helps to compensate for the extra cost of matching generation and demand in congestion periods.

We have provided several scenarios and instances to validate the ideas underlying our approaches. An important aspect of this work is that we consider the user perspective, ensuring satisfaction and obtaining benefits in all the instances. The user does not change his/her preferences and always satisfies his/her energy requirements. The experimental results provide insight into how consumers can modify their expected demand curves to gain greater benefits.

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