Les Cahiers du GERAD ISSN: 0711–2440

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G–2019–16

February 2019

La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2019
– Bibliothèque et Archives Canada, 2019

The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

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A framework for peak shaving through the coordination of smart homes

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February 2019
Les Cahiers du GERAD
G–2019–16

Abstract: In demand–response programs, aggregators balance the needs of generation companies and end-users. This work proposes a two-phase framework that shaves the aggregated peak loads while maintaining the desired comfort level for users. In the first phase, the users determine their planned consumption. For the second phase, we develop a bilevel model with mixed-integer variables and reformulate it as a single-level model. We propose an exact centralized algorithm and a decentralized heuristic. Our computational results show that the heuristic gives small optimality gaps and is much faster than the centralized approach.

Keywords: Demand response aggregation, smart grid, decentralized approach, smart home, bi-level programming, peak shaving

Acknowledgments: This work is supported by a full scholarship from CNPq-Brazil.

1 Introduction

One of the challenges for an electricity generation company (GENCO) is the variability in the demand. It may try to influence customers to change their consumption to fit a desired load shape via, for example, demand–response (DR) programs. Such programs generally offer incentives for consumption adjustment. Reviews of DR are available in [1, 2, 3, 4, 5], and [6] reports its recent applications worldwide in the residential sector.

Individual residences make only a small contribution to the overall DR strategy. An aggregator acts as an intermediary between a group of users and a GENCO [7], and a GENCO may itself act as an aggregator [6].

High peak demands have a negative impact on the reliability and stability of the power grid, so the GENCO wants a consumption curve that is as flat as possible [1, 8]. When a price-based DR is used, consumers respond to price signals by moving their demand to a cheaper period, which creates new rebound peaks [9]. Moreover, for domestic electric water heaters, price-based DR alone is not enough to change the user behavior to favor the GENCO [10].

Incentive-based DR programs avoid new peaks and increase user participation. They pay customers to shift and/or reduce their consumption for a given time period. Direct load control (DLC) is common in the residential sector, and curtailable load (CL) is more appropriate for larger consumers [6]. However, consumers have reported that the incentives were insufficient and their comfort levels were impacted [11]. Moreover, DLC incurs a computational burden and leads to privacy issues [12].

We consider the following question: what incentive should be paid to maximize the social welfare while maintaining an acceptable level of comfort?

The organization of this work is as follows. Section 2 presents a literature review and our contributions. Section 3 introduces the mathematical models and the two algorithms. Section 4 discusses the computational results, and Section 5 provides concluding remarks.

2 Related work

According to [13], the existing literature on distributed methods for DR can be classified into two categories. The first consists of simplified models with continuous variables [12, 14, 15, 16]. The second category consists of more realistic mixed-integer models that consider inter-temporal device couplings. A similar classification is possible for models: more detailed models increase the user's profit while maintaining the desired comfort level. This work uses the appliance models from [17], so it belongs in the second category, in contrast to studies that consider simplified models or do not use specific appliance models (e.g., [8, 12, 18, 19, 20]).

There are at least two strategies for decreasing peak load while satisfying consumers. The first is to treat the DR problem as a single-level social welfare maximization problem (SWMP) by finding a trade-off between cost and/or a utility discomfort function for the consumers and a utility function for the GENCO (income, community's comfort, etc.). Lu et al. [21] classify SWMP methods into three types:

1. Single-objective optimization [22]: it considers either the users goal or the GENCO goal but not both;
2. Weighted sum multiobjective optimization [11, 12, 13, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35]: its limitation is the need to choose weights;
3. Pareto-front multiobjective optimization [36, 37, 38, 39]: it may have lower scalability because of the time to construct an approximation to the Pareto front or use simplified models to reduce the CPU time.

The second strategy, which we use, is a bilevel formulation with the upper level representing the GENCO (the leader) and N lower levels representing N electricity consumers (the followers). Linear bilevel problems are $\mathcal{NP}$-hard [40], so they are often reformulated.

A bilevel problem can be reformulated as a single-level mixed-integer linear program (MILP) [41, 42, 43, 44] using the Karush–Kuhn–Tucker (KKT) conditions [40]. However, this is not possible if a lower-level problem has discrete variables, as in our work. It is also possible to use a Stackelberg game process in which the upper and lower levels are solved iteratively until equilibrium is reached. This approach is used by [12, 19, 45, 46, 47], and [48], but they do not consider CL or specific appliance models for users. In addition, some of these studies use the weighted-sum approach [12, 19].

Our work is related to [49], which proposes a bilevel optimization problem to coordinate DR for a set of users. The service provider announces the load profiles to the householders. Each user then returns adjustments to its profile. This process is repeated until no further improvements are made. The objective function at the upper level minimizes the standard deviation between a current load and a target load, while the lower-level objective functions minimize the user costs. The optimization problem is solved in two steps. In the first step, the energy expenses of the individual customers are minimized. Then, for each user, a constraint that limits the user cost is added to the upper-level problem. The connection between our work and this framework is the use of the same constraint to reformulate the bilevel problem as a single-level one. However, our work differs in that it determines a personalized monetary incentive for each customer, uses specific models for home appliances, has cost minimization as the objective function for the GENCO, and executes each phase only once.

2.1 Contribution

We propose a scalable framework involving mixed-integer variables for the coordination of user consumption. It minimizes the user costs while maintaining their comfort and also minimizes the GENCO costs. Detailed appliance models are used. The framework is divided into two phases. The first phase minimizes the energy expenses of individual customers. In the second phase, the framework assumes that the users participate in a DR program and will accept requests that do not impact their cost or comfort. Thus, we propose a bilevel problem in which the upper level represents the GENCO and each lower-level problem is assigned to a customer. We reformulate this into a single-level problem as in [49]. We develop two algorithms: an exact centralized approach and a decentralized heuristic. The solution encourages the users, via monetary incentives (CL), to adopt a new consumption that minimizes the peak loads and the costs for the GENCO. No existing study has all of these features. Our framework can also be used for regulation review, for instance in Brazil, where the current DR program is not economically attractive for consumers [50].

2.2 Limitations

We do not consider personalized user tariffs for two reasons. First, current rules (e.g., in Brazil and Quebec) do not allow different tariffs for different customers in the same neighborhood. Second, such tariffs increase the complexity of the optimization model. If the tariff is a variable, then the model becomes nonlinear since the costs are products of the tariffs and the energy consumption, which is also a variable. We consider fixed tariffs and linear models.

3 Framework

This section presents the two-phase framework. In the first phase, each user finds its best consumption schedule and sends that information to the aggregator. In the second phase, the aggregator finds a solution that better coordinates the customers from the GENCO perspective.

3.1 User model

The set $\mathcal{N}$ represents the users. Their appliances and features [17, Table 1] are represented by the models from [17]. Each model schedules the energy consumption for one day in T time intervals indexed with t, with length Δ_t, and the appliances are grouped as follows:

- A: Set of electrical appliances;
- $A_I \subseteq A$: Set of appliances with uninterruptible operation;
- A_I^*: Set of tasks for appliances in A_I.
- $A_P \subseteq A$: Set of appliances with interruptible phases;
- A_P^*: Set of tasks for appliances in A_P;
- $A^* = \{A_P^* \cup A_I^*\}$: Set of tasks for appliances in A.

Let $\mathcal{X}$ be the space of all variables and $\Xi \in \mathcal{X}$ a solution. The functions f_c, f_t, f_u, and f_d represent, respectively, the total cost, the thermal discomfort, the usage-time discomfort, and the total discomfort:

- $f_c(\Xi) = \sum_{t \in T} \left(C_b^t - C_s^t + C_{CHP}^t \right) + C_{ev}$,
- $f_t(\Xi) = \sum_{t \in T} \sum_{a \in A} V_a^t$,
- $f_u(\Xi) = r_1 \left[\sum_{k \in A_p^*} \sum_{p=1}^{P_k} \Psi_{k,p} + \sum_{k \in A_I^*} \zeta_k \right] + r_2 \sum_{t \in T} \sum_{k \in A^*} U_k^t$,
- $f_d(\Xi) = \alpha_t f_t(\Xi) + \alpha_u f_u(\Xi)$

where C_b^t [\$] and C_s^t [\$] represent the cost at $t \in T$ of buying and selling energy, respectively, C_{CHP}^t [\$] is the combined heating power (CHP) operation cost at $t \in T$, C_{ev} [\$] is the fuel cost for a hybrid vehicle, V_a^t [^{o}C] is the discomfort related to the deviation from the target temperature of appliance a at $t \in T$, U_k^t [h] is the discomfort related to the deviation from the target time for task k at $t \in T$, ζ_k [h] is the discomfort related to the omission of task $k \in A_I^*$, $\Psi_{k,p}$ [h] is the discomfort related to the omission of phase p of task $k \in A_P^*$, P_k is the number of phases of task $k \in A_P^*$, $r_1 \in \mathcal{R}$ is the discomfort factor per task not performed, $r_2 \in \mathcal{R}$ is the discomfort factor per usage-time deviation, and α_t [discomfort/^{o}C] and α_u [discomfort/h] are discomfort factors.

Let Θ_n be the set of variables related to appliances, machines and smart home components [51] not available for the user $n \in \mathcal{N}$ and $\Xi_n \in \mathcal{X}$ be the vector of variables for the user $n \in \mathcal{N}$, which contains real and binary variables. The vector Ξ_n can be used as an entry of the functions defined above considering that for all $i \in \Theta_n$, $x_i = 0$ where $\Xi_n = [x_1, x_2, \ldots, x_i, \ldots, x_{|\mathcal{X}|}]$. Each user also imposes its own constraints, which specify the feasible region $\mathcal{F}_n \subseteq \mathcal{X}$. Thus, for each user $n \in \mathcal{N}$, we have the following MILP:

$$\min_{\Xi_n} \quad f_c(\Xi_n) \tag{1}$$

$$\text{s.t.} \quad f_d(\Xi_n) \leq D_n \tag{2}$$

$$\Xi_n \in \mathcal{F}_n \tag{3}$$

The objective function (1) minimizes the cost of user $n \in \mathcal{N}$. Constraint (2) limits the maximum discomfort D_n; this parameter can be set using multi-criteria decision analysis and multiobjective optimization (see [51]). Finally, (3) are the constraints that represent the flow conservation, the operation of the appliances, the pricing policies, and the energy limits. See [17] for details.

3.2 First phase

We use overbars ($\overline{x}$) to indicate quantities calculated in the first phase. In this phase, there is no coordination of the users or the DR, and the tariffs are known one day ahead. Each user $n \in \mathcal{N}$ solves Model (1)–(3) to find a scheduling plan with optimal cost $\overline{C_n}$. That cost and the desired load are returned to the aggregator.

3.3 Second phase

Let E_n^t [Wh] be the energy obtained from the grid at $t \in T$ by user $n \in \mathcal{N}$, β [\$] the cost for the hydro-power unit start-up, ω [W] a factor to convert β/ω into ramp-up/down cost per watt, $C_p^t \geq 0$ [\$] the energy production cost at $t \in T$, and $\kappa_n \geq 0$ [\$] the incentive paid to client n to change its consumption.

The GENCO goal is to maximize its profit. The revenue is considered to be the total amount of bills paid by customers, expressed as $\sum_{n\in\mathcal{N}} \overline{C_n}$. The cost has four components. The first is the cost incurred by the variability of the total energy produced for a given horizon, which may be related to the ramp-up and ramp-down costs. The second is that of the energy production. The third is the CL incentive given to customers. The fourth is related to clients' injection of energy into the grid; this is included in the revenue.

The minimization of the total energy variance for the whole horizon is as follows:

$$\min_{E_n^t} \frac{1}{(|T|-1)} \sum_{t\in T} \left(\sum_{n\in\mathcal{N}} E_n^t - \frac{\sum\limits_{t_2\in T} \sum\limits_{n\in\mathcal{N}} E_n^{t_2}}{|T|} \right)^2 \tag{4}$$

The objective function (4) and Constraints (2)–(3) form a mixed-integer nonlinear problem, and even small instances are hard to solve. We instead use β/ω as an approximation for the ramp-up/down cost, use e_1^t and e_2^t as gap and surplus variables, and remove the constant ($|T|$-1) since it does not change the optimal solution. This allows us to reformulate (4) as a cost minimization of the total energy variance generated, which is locally an approximation of (4):

$$\min_{E_n^t, e_1^t, e_2^t} \frac{\beta}{\omega} \left(\sum_{t\in T} \frac{e_1^t + e_2^t}{\Delta_t} \right) \tag{5}$$

$$\text{s.t.} \left(\sum_{n\in\mathcal{N}} E_n^t - \frac{\sum\limits_{t_2\in T} \sum\limits_{n\in\mathcal{N}} E_n^{t_2}}{|T|} \right) + e_1^t - e_2^t = 0 \;\forall\; t \in T \tag{6}$$

If we aggregate the other costs, the GENCO objective function becomes:

$$\min_{\substack{E_n^t, e_1^t, e_2^t,\\ C_p^t, \kappa_n}} \frac{\beta}{\omega} \left(\sum_{t\in T} \frac{e_1^t + e_2^t}{\Delta_t} \right) + \sum_{t\in T} C_p^t + \sum_{n\in\mathcal{N}} \kappa_n \tag{7}$$

In the first phase, the aggregator can estimate the GENCO energy production cost as $\overline{C_p} = \overline{\sum_{t\in T} C_p^t}$ and the cost of variability as $\overline{R_c} = \overline{\beta/\omega \sum_{t=1}^{|T|} [(e_1^t + e_2^t)/\Delta_t]}$ if there is no DR.

The aggregator cannot increase the incentives. Let the "saved costs" be the amount that the GENCO saves using DR, which must be lower than the incentives spent. This can be modeled as follows:

$$\overline{R_c} - \frac{\beta}{\omega} \sum_{t=1}^{T} \left(\frac{e_1^t + e_2^t}{\Delta_t} \right) + \overline{C_p} - \sum_{t\in T} C_p^t \geq \sum_{n\in\mathcal{N}} \kappa_n \tag{8}$$

The aggregator goal is represented by the following optimistic bilevel problem with an upper level representing the GENCO and $|\mathcal{N}|$ lower levels representing the consumers:

$$\begin{aligned}
&\min_{\substack{E_n^t, e_1^t, e_2^t,\\ C_p^t, \kappa_n}} \ \frac{\beta}{\omega}\left(\sum_{t\in T}\frac{e_1^t+e_2^t}{\Delta_t}\right)+\sum_{t\in T}C_p^t+\sum_{n\in\mathcal{N}}\kappa_n && (9)\\
&\text{s.t.}\quad (6),(8)\\
&\qquad \forall\, n\in\mathcal{N}\quad \min_{\Xi_n} f_c(\Xi_n) && (10)\\
&\qquad\qquad\qquad \text{s.t.}\quad (2),(3)
\end{aligned}$$

In a bilevel optimization problem, the leader sets incentives/prices according to its goal, and the consumers respond based on their targets. The term "optimistic" means that if the lower-level problem has multiple optimal solutions, we choose the one most favorable to the upper-level problem. If the aggregator guarantees a discount or no cost increase, the customers can change their consumption to favor the GENCO. Thus, if the cost with DR for client $n \in \mathcal{N}$ is above $\overline{C_n}$, the GENCO must pay the extra cost with incentives. Therefore, we add constraints to protect users against cost increases:

$$\kappa_n \geq \sum_{t\in T}\left(C_b^t - C_s^t + C_{CHP}^t\right) + C_{ev} - \overline{C_n} \quad \forall\, n\in\mathcal{N} \tag{11}$$

The GENCO revenue is fixed in phase one. Thus, additional user costs are in fact costs for the GENCO, and C_b^t is replaced by C_p^t in (11). Moreover, we assume that the GENCO is not interested in paying for energy injected into the grid since $\pi < \nu < \lambda$ where π, ν, and λ are respectively the production cost per watt, the buying cost per watt, and the selling price per watt from the GENCO perspective. Hence, $C_s^t = 0$ for all $t \in T$ and the objective functions (10) are replaced by Constraints (12):

$$\kappa_n \geq \sum_{t\in T}\left(C_p^t + C_{CHP}^t\right) + C_{ev} - \overline{C_n} \quad \forall\, n\in\mathcal{N} \tag{12}$$

The final aggregator problem is then represented by the following single-level model:

$$\begin{aligned}
\text{(P)}\quad &\min_{\substack{E_n^t, e_1^t, e_2^t,\\ C_p^t, \kappa_n, \Xi_n}} \ \frac{\beta}{\omega}\left(\sum_{t\in T}\frac{e_1^t+e_2^t}{\Delta_t}\right)+\sum_{t\in T}C_p^t+\sum_{n\in\mathcal{N}}\kappa_n && (13)\\
&\text{s.t.}\quad (6),(8),(12),(2),(3)
\end{aligned}$$

3.4 Algorithms

We could solve (P) using commercial solvers, but a centralized approach has little scalability and privacy issues [3]. A decentralized approach improves scalability but not necessarily privacy since the model may be solved in a single machine. Ideally, (P) should be solved in a distributed way, with each user solving the problems associated with its consumption in its own home management system. This mitigates privacy concerns and improves scalability.

Let K (a divisor of $|\mathcal{N}|$) be the cluster size, S the heuristic solution, and UB an upper bound for the optimal value of (P). We propose a decentralized heuristic (DH): see Algorithm 1. If $K = 1$, DH can be used in a distributed mode.

4 Results and discussion

This section presents the results for the centralized approach (CA) and DH. We considered data from Belo Horizonte, Brazil. We set $\beta = \$140.50$ based on the average cost for a hydro-power unit start-up [52, Example 1], $\omega = 50\,\text{MW}$, and $\pi = 0.01\,\$/\text{KWh}$. The other parameters are set as in [17]. The solver is Cplex 12.8.

Algorithm 1 Heuristic DH

Input: $|\mathcal{N}|, K$
Output: UB, S
1: $UB \leftarrow 0$
2: Divide the users into $|\mathcal{N}|/K$ clusters
3: For each cluster c, create an instance I^c of (P)
4: Solve each I^c to optimality, obtaining the solution $\boldsymbol{x}^c$
5: Concatenate $\boldsymbol{x}^c$ for every cluster c into the vector S
6: Calculate UB using S in objective function (13)

Table 1 summarizes the results; we report CPU times for both CA and DH. The first column gives the number of users. The "gap" columns give the difference between the solution found and the optimal solution: gap $= (UB - Z^*)/UB$, where UB is the value found by DH and Z^* is the optimal value found by CA. If no time is given, CA could not solve the instance within 24 hours.

Table 1: Results.

$\|\mathcal{N}\|$	CPU time [s]			Gap [%]	
	CA	DH (K=1)	DH (K=10)	DH (K=1)	DH (K=10)
10	10.18	10.08	12.5	0.037	0
50	238.7	83	170.1	0.039	0.003
100	1000	146	410	0.042	0.005
300	8244	559	1245	0.046	0.006
500	12522	940	2084	0.045	0.006
1000	-	1882	4217	-	-
5000	-	24880	22696	-	-
8000	-	40221	39952	-	-
10000	-	50329	43966	-	-

CA can solve only small instances, which confirms the scalability issues. For $50 \leq |\mathcal{N}| \leq 500$, DH is faster than CA: the speed-up factors are between 2.87 and 14.74 for $K = 1$ and between 1.40 and 6.6 for $K = 10$. In terms of deviation from the optimal value, for $|\mathcal{N}| = 500$ the UB-LB is \$10. If a distributed approach is employed, i.e., $K = 1$, the CPU time improves since it is divided, approximately, by $|\mathcal{N}|$: see Table 2. Moreover, DH gives small optimality gaps.

Table 2: Estimated CPU time per user for $k = 1$ in a distributed implementation.

$\|\mathcal{N}\|$	10	50	100	300	500
Time [s]	1.008	1.66	1.46	1.86	1.88
$\|\mathcal{N}\|$	1000	5000	8000	10000	
Time [s]	1.88	4.98	5.03	5.03	

Our approach efficiently flattens the load profile: see Figures 1 and 2. Without coordination, near time 96, there is a large peak due to an increase in tariffs in the current time-of-use program. Hence, from the users' perspective, it is cheaper to use batteries and thermal storage. This behavior is undesirable from the GENCO perspective.

The peak-to-average ratio (PAR), which is given by

$$\text{PAR} = |T| \left(\max_t \left\{ \sum_{n \in \mathcal{N}} E_n^t \right\} \right) \left(\sum_{t \in T} \sum_{n \in \mathcal{N}} E_n^t \right)^{-1},$$

decreased from 2.06 without coordination to 1.17 in the DH solution for $|\mathcal{N}| = 10^4$ (an improvement of 43.2%). 2 figures avec minipage:

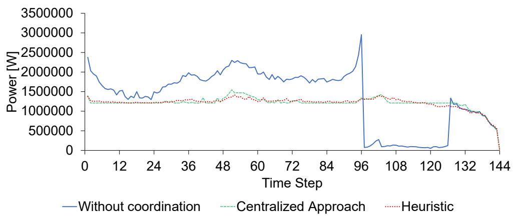

Figure 1: System load profile for $|\mathcal{N}| = 500$.

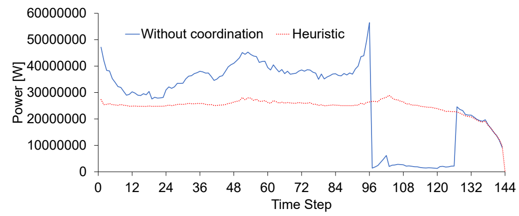

Figure 2: System load profile for $|\mathcal{N}| = 10^4$.

5 Conclusions

Price-incentive DR programs can create new rebound peaks. This increases demand variability and is undesirable from the GENCO perspective. We have proposed a framework that minimizes costs for both users and the GENCO, by shaving aggregated peak loads and maintaining the desired comfort level. The framework results in a formulation that can be solved in a centralized or decentralized way. Centralized methods have scalability issues, so we have presented a DH with a small optimality gap; it decreases the CPU time by a factor of up to 6.6 compared to the centralized approach. In addition, the DH can be used in a distributed mode if privacy is required.

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