Distributed Scheduling Of Demand Resources In A Congested Network

Jhi-Young Joo and Marija Ilić
Department of Electrical and Computer Engineering
Carnegie Mellon University
Pittsburgh, Pennsylvania 15213
Email: {jjoo, milic}@ece.cmu.edu

***Abstract*—This paper proposes a distributed method to schedule supply and flexible demand in a congested network, accommodating diverse benefits of end-users. We look at two different time horizons to schedule supply and demand; a day ahead and an hour ahead, which we refer to as day-ahead and real-time clearing. For day-ahead clearing, we decompose the system-level problem and solve it in an iterative way to schedule supply and flexible demand over multiple time steps. However, after the day-ahead quantities are cleared and the actual consumption/production is to occur sooner, we use moving-horizon functional clearing. We show an application of this framework to the IEEE 30-bus test system with a large number of various air conditioning loads. The experiment shows effectiveness of the methods in managing congestion and in coping with unexpected conditions such as a rise in the weather temperature.**

I. Introduction

This paper concerns scheduling flexible demand resources a day or shorter ahead of operation. The goals are 1) to satisfy the diverse needs of a large number of end-users, 2) to schedule resources in a way that it manages congestion of the power network, and 3) to cope with unexpected conditions for consumption such as a higher weather temperature than forecast. We schedule generation and demand resources over multiple time horizons, taking into account the unique inter-temporal dynamics of each resource. This work is a direct extension of [1], with linearized network constraints added.

In order to solve this problem accounting for the individual dynamics and consumption preferences of a large number of end-users, we solve this problem in a distributed way. This not only allows us to solve otherwise a large problem more manageably, but keeps the information of each supply and demand unit more private while enabling their choices. An early formulation of a similar approach for supply/demand active participation in congestion management can be found in [2]. In this work multi-lateral trading for energy is unbundled from the delivery provision and pricing. The conditions for distributed participation of demand and supply resources in congestion management are fundamentally based on the same primal-dual decomposition of optimization with quadratic performance objectives and linear constraints as in this work. There has also been much literature on distributed optimization of power systems, e.g. most recently [3]. Our focus is on the information exchange framework that aligns with the market rules and privacy concerns in managing congestion while accounting for the end-users' various preferences and dynamics over multiple time steps.

To schedule resources a day ahead of operation after decisions for unit commitment have been made, we take into account the individual inter-temporal dynamics of each resource including flexible demand. For this reason, we apply iterative dual decomposition of the system-level problem. In this framework, the system condition is represented by the locational marginal price and sent to each supply/demand entity to calculate their own optimum with respect to their inter-temporal dynamics and consumption preferences. Locational marginal prices are updated and new price signals are sent to each entity to iterate this procedure until the global constraints of the system-level problem are satisfied.

Since the conditions of the system and/or the supply and demand units can change after they are scheduled a day ahead of operation, we also allow adjustment of the scheduled amount of energy an hour ahead of actual operation. The system operator obtains the price sensitivities and specified ranges of power by demand/supply entities and converts them into their cost/benefit function [4]. The price sensitivity is calculated by optimizing over several time steps ahead, and the specified quantity limits for the next time step is specified by each entity. The system operator clears the optimum for the next time step only, within the quantity limits of each entity. Each supply/demand entity realizes the dispatch and moves onto the next time step to repeat the whole procedure.

Since functional clearing does not require many iterations of communication, it is more suitable for communication in a faster time scale. Also, by applying functional clearing over a moving horizon, new information, on either the system conditions or the local entity, can be effectively incorporated in scheduling. Especially, we explore a situation where a transmission line can be congested if we do not have flexible demand resources, and when the weather temperature rises higher than what was forecast when the day-ahead amounts were scheduled. Our real-time clearing framework is able to handle this difficult situation in our example discussed in Section IV.

II. Formulation and Methodology

The system objective can be formulated as the sum of every individual entity's objectives subject to the global constraints

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and the individual inter-temporal dynamics and constraints.

$$\underset{P_{G_i},P_{D_j},x_j}{\text{maximize}} \sum_{t=1}^{T}[\sum_{i=1}^{N_G} -C_i(P_{G_i}(t)) + \sum_{j=1}^{N_D} B_j(P_{D_j}(t), x_j(t))] \tag{1a}$$

$$\text{subject to } \sum_{i=1}^{N_G} P_{G_i}(t) = \sum_{j=1}^{N_D} P_{D_j}(t) + P_{D_{\text{in}}}(t) \quad \forall t \tag{1b}$$

$$|H\{C_g P_G(t) - C_d(P_D(t) - P_{D_{\text{in}}}(t))\}| \preceq F(t) \quad \forall t \tag{1c}$$

$$|P_{G_i}(t+1) - P_{G_i}(t)| \leq R_i \quad \forall i, t = 0, \cdots, T-1 \tag{1d}$$

$$x_j(t+1) = a_j x_j(t) + b_j P_{D_j}(t) + \Theta_j(t) \quad \forall j, t = 0, \cdots, T-1 \tag{1e}$$

$$P_{G_i}^{\min}(t) \leq P_{G_i}(t) \leq P_{G_i}^{\max}(t) \quad \forall i, t \tag{1f}$$

$$P_{D_j}^{\min}(t) \leq P_{D_j}(t) \leq P_{D_j}^{\max}(t) \quad \forall j, t. \tag{1g}$$

where t denotes the discretized time step set to be an hour in this work. Supply entities are indexed with $i = 1, \cdots, N_G$, and demand entities with $j = 1, \cdots, N_D$. The energy produced by i-th entity at time step t is $P_{G_i}(t)$ while the energy consumed by j-th entity is named $P_{D_j}(t)$. $P_{D_{\text{in}}}(t)$ denotes the part of system demand that is not elastic, i.e., unresponsive to the price. $C_i(\cdot)$ and $B_j(\cdot)$ denote the cost and benefit functions of the i-th supply entity and j-th demand entity, respectively. x_j is the state of end-user j's linear dynamic system that is governed by electricity consumption P_{D_j}. H is the power transfer distribution factor (PTDF) matrix of the network, and $F(t)$ is the transmission limits at time step t. C_g (C_d) is a supply (demand) connection matrix with binary elements 0 and 1 in the dimension of (the number of buses except the slack bus)-by-N_G (N_D). (1d) and (1e) define the inter-temporal dynamics of each supply/demand entity's power output/consumption with exogenous parameters denoted as Θ.

The objective function (1a) is the sum of objectives of the individual entities, and the constraints (1d)-(1g) can be separated with respect to each entity's problem. The *complicating* global constraints that include variables from multiple entities are (1b) and (1c). The Lagrange multiplier associated with constraint (1b) gives the uniform price throughout the system, and the one with constraint (1c) is the congestion cost at each bus. If there is no congestion, the system has a uniform price for all the buses. Moreover, the uniform price without congestion is the same as the price in a setting where one does not consider the network topology and simply matches the demand and supply.

We assume that variables P_{G_i} and P_{D_j} are continuous, and the cost/benefit functions are smooth convex/concave functions. The dynamics of the supply and demand entities in Equations (1d) and (1e) are linear, and are discretized in accordance with the system/market operation rules. We assume that only the loads that respond to the system price can be modeled as (1e). Therefore, we differentiate between the demand entities that are controllable and not, and treat the uncontrollable load (or inelastic demand) as an exogenous parameter. Moreover, the end-user's system dynamics is governed not only by the electric energy that she consumes but by her preferences. An end-user's system has a possibly time-varying desired state, which is driven by her electricity consumption. This way an end-user's benefit can be more clearly stated as the proximity to the desired state.

A. Day-ahead clearing

Using Lagrange relaxation of Problem (1) with the global constraints (1b)-(1c) and decomposing the problem by each demand unit j [5] with only the relevant terms regarding the unit j, the problem of an individual demand unit j will be [1], [6]

$$\underset{P_{D_j}}{\text{maximize}} \sum_{t=1}^{T}[B_j(P_{D_j}(t), x_j(t)) - \lambda(t) P_{D_j}(t) + \overline{\mu}_j^T(t) H_j P_{D_j}(t) - \underline{\mu}_j^T H_j P_{D_j}(t)] \tag{2a}$$

$$\text{subject to (1e) and (1g).} \tag{2b}$$

$\mu_j \geq 0$ is the congestion prices at the buses where demand unit j is located, and H_j is the column of H that corresponds to demand entity j. μ is a vector that has the length equal to the number of the buses that the entity is connected to minus the slack bus since the power transfer distribution matrix H is defined to be of size, (the number of lines)-by-(the number of buses excluding the slack bus). H_j is also a vector with the same length as μ_j that includes only the elements related to the entity j and the lines connected to it. The problem of an individual supply entity i can be formulated in exactly the same way.

When the dual variables are known, each entity can calculate its optimal consumption with respect to them by solving Problem (2). However, since the dual variables cannot be known to either the system operator or the entities, they need to be solved in an iterative way with the primal solutions of the individual entities without information of their objectives and constraints. In practical terms, the prices of electricity should be determined by communicating iteratively an estimate of the prices and the optima of each entity with respect to those prices.

With the subgradient method, the dual variables can be updated at each iteration with respect to the subgradient of the dual function. The subgradients are obtained from the local primal optima calculated with the dual variables evaluated at the previous iteration. Therefore, omitting (t) for simplicity since each equation applies to all t's, we have

$$\lambda^{(\nu+1)} = \lambda^{(\nu)} + \alpha_\lambda^{(\nu)}\{\sum_{i=1}^{N_G} P_{G_i}^\star(\lambda^{(\nu)}, \overline{\mu}^{(\nu)}, \underline{\mu}^{(\nu)}) - \sum_{j=1}^{N_D} P_{D_j}^\star(\lambda^{(\nu)}, \overline{\mu}^{(\nu)}, \underline{\mu}^{(\nu)}) - P_{D_{\text{in}}}\} \tag{3a}$$

$$\overline{\mu}^{(\nu+1)} = [\overline{\mu}^{(\nu)} + \alpha_{\overline{\mu}}^{(\nu)}[H\{C_g P_G^\star(\lambda^{(\nu)}, \overline{\mu}^{(\nu)}, \underline{\mu}^{(\nu)}) - C_d(P_D^\star(\lambda^{(\nu)}, \overline{\mu}^{(\nu)}, \underline{\mu}^{(\nu)}) - P_{D_{\text{in}}})\} - F]]^+ \tag{3b}$$

where ν denotes the iteration step, and $[\cdot]^+$ denotes the projection onto the nonnegative orthant. $\underline{\mu}$ can be updated in the same way as (3b) except that the sign of H will be negative. The conditions for this problem to converge to the global primal optimum are discussed in [1].

B. Real-time clearing

The price sensitivity of demand ρ_j given the reference price π_0 and demand $P_{D_j,0}$ is defined as

$$\rho_j = \frac{\Delta\pi}{\Delta P_{D_j}} = \frac{\pi' - \pi_0}{P'_{D_j} - P_{D_j,0}}. \quad (4)$$

Note that the price sensitivity of demand is specific to the reference price and the demand quantity. Prices π_0 and π' are given to the demand entity, and come from the system condition as described in Problem (1). In fact, π can be considered as $\pi_j = \lambda + \underline{\mu}_j^T H_j - \overline{\mu}_j^T H_j$, i.e., a locational marginal price of demand entity j that includes congestion costs.

We assume that the real-time clearance is done in an hourly interval, and the quantities of supply and demand are settled from the day-ahead clearing. Now we want to *adjust* the near-real-time energy consumption from the day-ahead settlement. We reiterate Problem (2) but with slightly different notations to account for the amount $P_{D_j}^{\text{DA}}$, which was the result of day-ahead clearing.

$$\underset{P_{D_j}^{\text{RT}}}{\text{maximize}} \sum_{t=1}^{T} \{B_j(P_{D_j}(t), x_j(t)) - \pi_0^{\text{RT}}(t) P_{D_j}^{\text{RT}}(t)\} \quad (5a)$$

subject to

$$x_j(t+1) = a_j x_j(t) + b_j\{P_{D_j}^{\text{DA}}(t) + P_{D_j}^{\text{RT}}(t)\} + \Theta_j(t) \quad \text{for } t = 0, \cdots, T-1 \quad (5b)$$

$$P_{D_j}^{\min}(t) \le P_{D_j}^{\text{DA}}(t) + P_{D_j}^{\text{RT}}(t) \le P_{D_j}^{\max}(t) \quad \forall t \quad (5c)$$

Solving this problem gives the optimum $P_{D_j,0}^{\text{RT}\star}(t)$ for $t = 1, \cdots, T$, with a given set of price $\pi_0^{\text{RT}} = [\pi_0^{\text{RT}}(1), \cdots, \pi_0^{\text{RT}}(T)]^T$. By replacing π_0^{RT} in the problem with ${\pi'}^{\text{RT}} = [{\pi'}^{\text{RT}}(1), \pi^{\text{RT}}(2), \cdots, \pi^{\text{RT}}(T)]^T$and solving the problem again, we obtain ${P'}_{D_j}^{\text{RT}\star}(t)$ for $t = 1, \cdots, T$. Note that the price at only the next time step $t = 1$ is changed and the price at the other time steps are intact. Since we solve real-time functional clearing in a receding horizon, we calculate the price sensitivity of demand only for the next time step $t = 1$. Therefore, we obtain the price sensitivity of demand at the next time step $t = 1$ by taking only the first elements of the solutions $P_{D_j,0}^{\text{RT}\star}(1)$ and ${P'}_{D_j}^{\text{RT}\star}(1)$ and plugging them in (4). In our simulations, to account for the price sensitivity of demand for both price increase and decrease, we calculated three sets of different demand quantities with respect to the price, e.g., $P_{D_j,0}^{\text{RT}\star}(1)$, $P_{D_j,1}^{\text{RT}\star}(1)$, $P_{D_j,-1}^{\text{RT}\star}(1)$ with respect to π_0^{RT}, π_1^{RT}, π_{-1}^{RT}, and extrapolated the sensitivity by least-square estimation.

The price sensitivity of demand ρ_j is essentially the marginal benefit of end-user j, in the same way as the price sensitivity of supply is the marginal cost. Therefore, we can construct a benefit function $B_j(P_{D_j}) = \frac{1}{2}\rho_j P_{D_j}^2 + \beta_j P_{D_j}$ where β_j is the y-intercept of the marginal benefit function constructed with the slope as ρ_j [4]. $P_{D_j}^{\min}(1)$ and $P_{D_j}^{\max}(1)$ are calculated based on the current state $x_j(0)$ and the preference $x_{\text{set}}(1)$ so that the resulting $P_{D_j}^{\star}(1)$ as a result of dispatch does not violate the end-user j's preference at the next time step.

TABLE I: Profiles of generators in the system

Bus	Capacity (MW)	Ramp rates (%/min)	Cost($) coefficients 2nd order	Cost($) coefficients 1st order
1	150	3	0.02	2
2	60	5	0.0175	1.75
22	62.5	10	0.0625	1
27	48.7	40	0.00834	3.25
23	40	30	0.025	3
13	44.7	40	0.025	3

III. System configuration

The system studied here is based on the IEEE 30-bus test system [7]. Transmission line limits were added as in [8], but in order to make one line congested at the peak hour, the transmission limit of the line connecting bus 1 and 2 was reduced to 23 MW from the original value of 130 MW. The value of this limit was chosen so that the line is over the limit at the peak hour (hour 17), if the system demand was not scheduled or adjusted.

Since the test system does not include the specifics of the loads, we configure the flexible loads based on inference from available data. We chose air conditioners in residential premises as the flexible loads to be scheduled and adjusted with the generators in the system. In order to estimate the number of air conditioners for each load bus, first we obtained the number of residential air conditioning systems in Northwestern Power Coordinating Council (NPCC) region [10], including part of the PJM Interconnection and ISO New England areas, Ontario, and Maritimes, and the hourly load in the same region on August 8th 2007, which was the hottest day of the year. The numbers of residential air conditioners were obtained from [11], [12], and the load data was obtained from the websites of the regional transmission organizations (RTOs) in the region such as PJM Interconnection and ISO New England.

The test system only provides load data for a single time step. We calculated a 24-hour load profile at each bus in the test system based on the ratio of each hourly load to the maximum load of the day in the NPCC system. The number of residential air conditioners at each bus of the test system was calculated to be the same ratio of the number of air conditioners in NPCC system region to the system load values. We assumed that 10% of the central units and 1% of the window units are participating in our framework, to make the case more realistic. The number of total air conditioners calculated for each bus can be found in [6]. There are six generators in this 30-bus system. The profiles of these generators are shown in Table I.

A. Modeling flexible loads

An end-user's air conditioning system is modeled the same way as described in [13], as a linear time-invariant system with the indoor temperature as its state and the electricity consumption as its input. The expected weather temperature is assumed to be given every time step, and the insulation and efficiency factors are known parameters of the system dynamics. The dynamic equation for the air conditioning system is rewritten here.

$$x_j(t+1) = \varepsilon_j x_j(t) + (1-\varepsilon_j)(T_{\text{out}}(t) + \gamma_j P_j(t)) \quad \text{(6a)}$$

$$\text{subject to } P_{j,\min} \le P_j(t) \le P_{j,\max} \quad \forall t,\ \forall j \quad \text{(6b)}$$

where $x_j(t)$ is the indoor temperature at hour t of end-user j's building, $T_{\text{out}}(t)$ is the outdoor temperature at hour t, and $P_j(t)$ is the electric energy usage of the air conditioning system at hour t by end-user j. Parameters ε_j is an air inertia factor calculated from $e^{-\tau/TC_j}$ of end-user j, and γ_j is the steady-state temperature gain of end-user j. We have a total of 11,329 air conditioners to be scheduled along with 6 generators on a network with 30 buses and 42 lines. Therefore, we assign different parameters such as insulation and efficiency factors for each end-user j. We assume that the weather temperature, shown in Fig. 1a, is the same in the whole area for this network. The detailed procedure of obtaining the values of air conditioning system parameters can be found in [6].

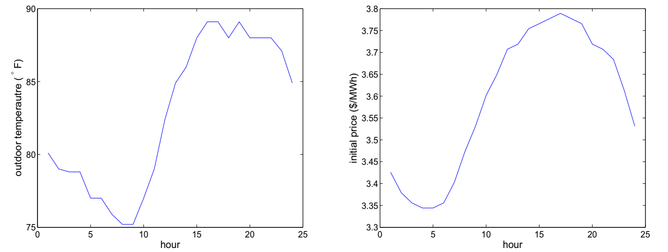
For the air conditioner models, we define the benefit of end-user j by consuming electricity as $B_j(P_{D_j}(t), x_j(t)) = -(x_j - x_{j,\text{set}})^T(x_j - x_{j,\text{set}})$ where $x_{j,\text{set}}$ is defined as the temperature set point of end-user j. Therefore, at each iteration in day-ahead clearing and at each time step in real-time clearing, an air conditioner model solves Problem (2) and Problem (5) respectively, subject to the local inter-temporal constraints (6). In the day-ahead clearing, by recalculating the optimal consumption with respect to the price at each iteration, the load effectively responds to the price. In the real-time clearing, the price sensitivity of demand is calculated directly by calculating consumption quantities from different sets of prices at the time step of interest.

IV. Simulation Results

Since the network is only congested at one line in our example, we use [14] to further simplify calculations of locational marginal prices. [14] shows that if only one line is congested in a network, the locational marginal prices at all buses can be calculated with respect to the price at one-end bus of the congested line and the congestion cost.

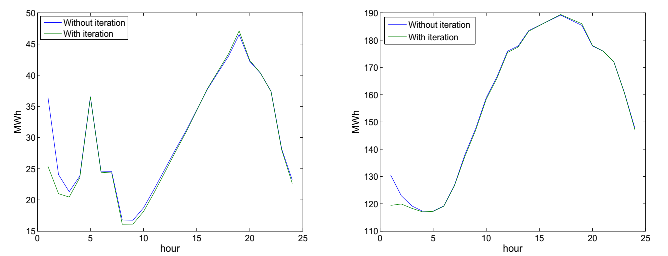
A. Day-ahead iterative clearing

The initial locational marginal prices (LMPs) for all buses to start the iteration were calculated based on the demand without any price-responsiveness and without any network constraints. This was to have a good initial value for the iteration. The resulting initial price over 24 hours is shown in Fig. 1b. Since we did not take the network equation in this calculation, all buses have the same price. After only 100 iterations, the system demand and supply match very closely; the mismatch of supply and demand is less than $1e-5$ at all hours except -0.0286 MWh at hour 17, which is the peak hour when a line is congested. Note that this iteration is done among a system operator, 6 generators, and more than 11,000 end-users, over a horizon of 24 time steps *accounting for* the intertemporal dynamics of the generators and the end-users' cooling systems.



(a) Outdoor temperature (b) The initial price for iterative clearing

Fig. 1: Outdoor temperature and the initial price



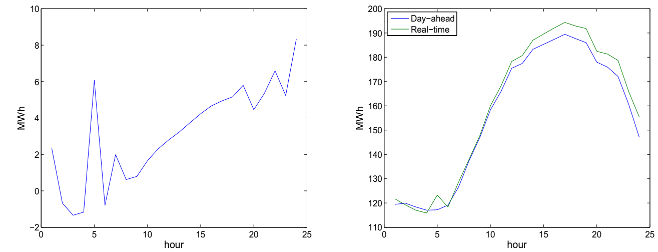
(a) Air-conditioning loads with and without iterative clearing (b) System load with and without iterative clearing

Fig. 2: Comparison of demand with and without iterative clearing

We compared the energy consumption of the end-users with and without iterative clearing with the system price. Assuming that the end-users only satisfy their temperature comfort without regard to the hourly price, we obtain the case of the demand irresponsive to the price. Fig. 2 shows the compared results. Over the 24-hour horizon, the loads scheduled with iterative clearing reduced the system load by 18.6 MWh, which is about 0.4% of the total energy demand. Since we set the end-users' temperature constraints as hard constraints, the amount of energy savings during the peak hours is minimal. The system operation can still benefit by scheduling demand a day of operation with iterative clearing, from having better information on how demand will behave. The resulting system price over 24 hours is shown in Fig. 4a. The congestion cost at hour 17 was ± 0.1294 \$/MWh on bus 1 and 2, respectively.

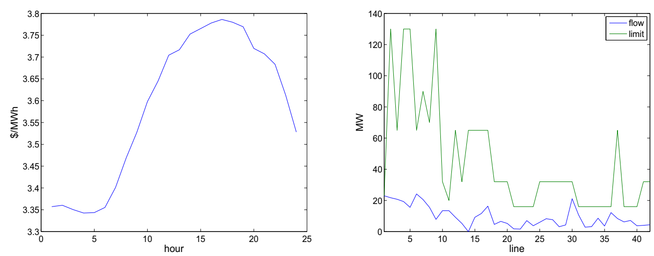
B. Real-time functional clearing

In order to account for an unexpected change from the day-ahead scheduling, we apply real-time functional clearing,



(a) Adjusted system demand from day-ahead clearing (b) Comparison of system demand

Fig. 3: Comparison of demand with day-ahead and real-time clearing (Note: real-time clearing had higher weather temperatures.)



(a) The resulting system price from iterative clearing (b) Transmission flows as a result of real-time functional clearing

Fig. 4: The resulting system price and transmission flows on the lines

with the outdoor temperature higher than assumed for day-ahead scheduling in Fig. 1a. Specifically, the temperature from 10 a.m. to 2 p.m. was higher by 1°F, and from 2 p.m. to midnight by 2°F. We applied the moving horizon method for functional clearing, with locational marginal prices as the input signal for suppliers and end-users to calculate their price sensitivity of supply/demand. The end-users' information on the price sensitivity of demand and consumption limits were aggregated by a load serving entity at each load bus, so that the system operator worked with 6 suppliers and 20 demand entities representing the end-users at their buses.

Fig. 3 shows the difference between the hourly system demand from day-ahead and real-time clearing. As a result of the higher temperature, the demand increased during the hotter hours. We can also observe that there is a small peak at hour 5. This is suspected to be a result of look-ahead optimization; since the price at hour 5 was the lowest, a lot of end-users consumed more energy to precondition their buildings at this hour. This implies that in order to avoid unexpected system peaks as a result of price-responsive demand adjustment, a way to *distribute* price signals is needed so that it can disperse concentration of energy consumption at hours with a low price.

Meanwhile, the resulting transmission at all lines are successfully limited within the bounds. Fig. 4b shows the absolute values of the transmission flows and limits in all lines.

V. Conclusion

We showed an effective framework to schedule flexible demand resources in a distributed way a day and shorter ahead of time. Day-ahead iterative clearing could efficiently schedule the generators and the end-users' systems including their vectorized inter-temporal dynamics and constraints. Real-time functional clearing was conducted for near-real-time adjustment of both demand and supply after the hourly supply and demand of each entity was cleared with day-ahead iterative clearing. Our framework could effectively manage congestion even in a condition where the weather temperature was higher than forecast at the time of day-ahead scheduling.

For future work, a way to eliminate secondary peak loads that occur in real-time adjustment needs to be studied. One of the ways to tackle this issue can be to devise a cooperative coordination among end-users. This framework can also be extended to include more complicated dynamics of loads, or a wider variety of heterogeneous loads and other system components such as storage.

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