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UNLOCKING DEMAND RESPONSE AT THE BUILDING LEVEL: A DISTRIBUTED ENERGY OPTIMISATION APPROACH

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ABSTRACT

In this paper, we propose a distributed optimisation approach based on Alternating Direction Method of Multipliers to optimise building energy consumption, reduce energy bills, and adopt demand response (DR) schemes at the building level by exploiting building flexibility. Different optimisation models are proposed to represent the types of flexibility offered by building devices and to incorporate DR incentives. The evaluations of the approach show significant energy cost saving and prove the feasibility of DR adoption.

Keywords: building energy optimisation, distributed optimisation, demand response, flexibility

1. INTRODUCTION

Demand response (DR) presents considerable potentials for customers and utilities from financial benefits to system reliability. Traditional building management systems, however, are not ready to adopt the DR schemes. The objective of this paper is to incorporate DR in building energy optimisation.

A building may contain a significant number of devices. Each device possesses its own dynamic constraints and objectives. Performing an optimisation in such a context over a time horizon entails dealing with a large number of variables, making it computationally impractical to solve in a centralised manner [1]. The work in [2], [1], and [3] show the application of distributed optimisation methods to solve the optimal power flow problem. Advances in decomposition methods such as alternating method of multipliers (ADMM) [4] have been applied to solve the optimisation of energy flow due to their robustness and privacy-preserving features. In this paper, we propose an ADMM-based distributed approach to solve the building energy optimisation to reduce energy bills and enable participation to DR programs, while respecting device and user constraints.

2. CONTEXT

In this work, we define device flexibility as the deviation of consumption or generation of a device that is allowed to be carried out. Devices are categorised, based on their flexibility, into three types: shiftable-volume (i.e., require a certain amount of energy within a given time interval), shiftable-profile (i.e., its consumption can be scheduled within a given time interval, but its profile must be satisfied), and sheddable (i.e., its consumption can be shed at a cost).

The flexibility provided by the devices is exploited to participate in different DR schemes. A customer subscribing to a DR program receives a set of DR requests customised based on their consumption and generation. DR programs can be categorised into price-based and incentive-based. Price-based programs provide customers with time-varying energy tariffs. Incentive-based programs offer direct payments to customers to change their consumption patterns upon request.

In the context of this work, a price-based program is specified as a list of energy prices for the next 24 hours. Incentive-based programs consist of two types of requests: load shedding (i.e., emergency DR) and load shifting. The requests are expressed with regard to the base consumption. The base consumption represents the expected consumption of the customer without participating to any DR programs.

A load shedding request is expressed by a deviated consumption, which is the target consumption after shedding, a deviation duration, which corresponds the period where the shedding is to be executed, and an incentive for shedding, denoted as p_{shed}.

A load shifting procedure consists of deviation (i.e., shift the required amount of consumption from the base consumption) and recovery (i.e., consume the shifted amount in addition to the base consumption). A load shifting request is thus expressed by a deviated consumption, a deviation duration, a recovery duration, and an incentive for shifting, denoted as p_{shift}.

3. PROBLEM DEFINITION

Optimising energy flow in such a network of devices is to minimise the network objective function subject to the constraints of each device in the network. We model such a network as an energy coordination network [1] composed of a set of $terminals\ T$, a set of $devices\ D$, and a set of $nets\ N$. A terminal models a transfer point through which the energy flows between a device and a net. A net represents an exchange zone that constrains the energy schedules of its associated devices. Each device and each net is associated with a set of terminals.

Each terminal $t \in T$ has an associated energy flow schedule $p_t = (p_t(1), \dots, p_t(H)) \in \mathbb{R}^H$ over a time horizon $H \in \mathbb{N}^+$ (e.g., 24 hours). Then, $p_t(\tau)$ where $\tau \in [1, H]$ is the amount of energy consumed ($p_t(\tau) > 0$) or generated ($p_t(\tau) < 0$) by device d in time period τ through terminal t, where t is associated with d.

For each device $d \in D$, we use 'd' to refer to both the devices and the set of terminals associated with the device. Each device $d \in D$ has a set of energy schedules denoted by $p_d = \{p_t \mid t \in d\}$, possesses a set of $|d|$ terminals, and has an objective function f_d: $\mathbb{R}^{|d| \times H} \longrightarrow \mathbb{R}$. Then, $f_d(p_d)$ is the cost of operating device d according to the schedule p_d. Every device has a set of constraints $\mathcal{C}_d$ which p_d must satisfy.

The set of all energy schedules associated with a net $n \in N$ is denoted by $p_n = \{p_t \mid t \in n\}$. Each net n has a set of $|n|$ terminals and an objective function f_n: $\mathbb{R}^{|n| \times H} \longrightarrow \mathbb{R}$. Nets encode an energy balance condition, denoted as $\mathcal{C}_n$, formally:

$$\sum_{t \in n} p_t(\tau) = 0, \qquad \forall \tau \in [1, H],\ \forall n \in N$$

Provided an energy coordination network, we define the optimisation problem as follows:

$$\begin{aligned} & min_{p\ \in \mathbb{R}^{H \times |T|}} \sum_{d\ \in D} f_d(p_d) + \sum_{n\ \in N} f_n(p_n) \\ & subject\ \ to \quad p_d \ \in \mathcal{C}_d, \quad \forall d \in D \\ & \qquad\qquad\qquad p_n \ \in \mathcal{C}_n, \quad \forall n \in N \end{aligned}$$

4. DISTRIBUTED OPTIMISATION ALGORITHM

To solve the optimisation problem, we employ ADMM algorithm over a given energy coordination network. The cost functions and constraints of devices vary according to their types, which are presented in the following section. ADMM iteratively solves the problem until the convergence is reached. In each iteration, ADMM performs the following steps:

Step 1: Device-minimisation step (executed in parallel among devices)

$$\forall d \in D,$$
$$p_d^{k+1} = argmin_{p_d \in \mathcal{C}_d} \left(f_d(p_d) + \frac{\rho}{2} \left\| p_d - \dot{p}_d^k + \nu_d^k \right\|_2^2 \right)$$

Step 2: Net-minimisation step (execute in parallel among nets)

$$\forall n \in N,$$
$$\dot{p}_n^{k+1} = argmin_{p_n \in \mathcal{C}_n} \left(f_n(p_n) + \frac{\rho}{2} \| p_n - p_n^k - \nu_n^k \|_2^2 \right)$$

Step 3: The prices (scaled dual variables) update (executed in parallel among nets)

$$\forall n \in N, \qquad \nu_n^{k+1} = \nu_n^k + (p_n^{k+1} - \dot{p}_n^{k+1})$$

First, each device computes in parallel its best response to the price and energy requested by nets (i.e., computing its optimal variables locally). Second, each net, upon receiving the offers from all the devices connected to it, checks if the convergence has been reached. If there is no convergence, nets compute new requests for the devices considering the devices' previous offers and send the new request to the devices. Third, nets update the scaled dual variables. (refer to [1] for further details)

5. OPTIMISATION MODELS AND DEMAND RESPONSE

Device optimisation models capture device flexibility and incorporate the energy tariffs from price-based DR as well as the incentives from incentive-based DR.

5.1 External tie

An external tie (ET) [1] represents a connection of the building to an external source of energy. Transactions with ET consist in pulling energy from the source or injecting energy to the source. The cost function of ET is formally defined as follows:

$$f_{ET}(\tau) = \begin{cases} p_{ET}(\tau) < 0, & P^{exp}(\tau) \cdot p_{ET}(\tau) \\ p_{ET}(\tau) = 0, & 0 \\ p_{ET}(\tau) > 0, & (P^{imp}(\tau) + p_{shift}(\tau)) \cdot p_{ET}(\tau) \end{cases}$$

where $p_{ET}(\tau)$ is the amount of pulled or injected energy at a given time period τ, P^{imp} import energy price, and P^{exp} export energy price. Price-based DR (i.e., import energy tariffs) is considered in the model as P^{imp}. The incentive for load shifting p_{shift} is also incorporated in the model. The positive value of p_{shift} incentivises reduction of consumption, while the negative encourages consumption. $p_{ET}(\tau)$ in each transaction is constrained by a specified limit P^{max}, formally:

$$|p_{ET}(\tau)| \leq P^{max}, \qquad \tau = 1, \ldots, H$$

5.2 Shiftable-volume load

A shiftable-volume load (SVL) [1] has a zero cost function. Its first constraint ensures that the required consumption E is satisfied within a time interval between the earliest time period A and the latest D:

$$\sum_{\tau=A}^{D} p_{load}(\tau) = E$$

where $p_{load}(\tau)$ models the consumption of SVL at a given time period τ. Second, the energy consumption in each time period is constrained by a specified limit L^{max}:

$$0 \leq p_{load} \leq L^{max}$$

5.3 Shiftable-profile load

A shiftable-profile load (SPL) has a zero cost function. SPL encodes a hard constraint requiring the consumption p_{load} to be within the given interval between time period A and D, formally:

$$p_{load}(\tau) = 0 \ , \qquad \tau = 1, \ldots, (A-1)$$

$$p_{load}(\tau) = 0 \ , \qquad \tau = (D+1), \ldots, H$$

Its second constraint ensures that the consumption profile matches the required profile p_{req}, formally:

$$\bigcup_{\tau=A}^{D-\delta} \Big(p_{load}(\tau) = p_{req}(1)\Big) \cap \Big(p_{load}(\tau+1) = p_{req}(2)\Big) \cap \ldots \cap \Big(p_{load}(\tau+\delta-1) = p_{req}(\delta)\Big)$$

5.4 Sheddable load

The cost function of a sheddable load (SL) [1] considers the inconvenience from the shedding p_{inc} and the DR incentive for shedding p_{shed}, formally:

$$f_{SL}(\tau) = (p_{inc}(\tau) - p_{shed}(\tau)).(p_{baseload}(\tau) - p_{load}(\tau))$$

where $p_{shed}(\tau) \geq 0$ and $p_{baseload}(\tau)$ is the expected consumption and $p_{load}(\tau)$ is the consumption after shedding. The consumption in each time period must satisfy the following constraint:

$$0 \leq p_{load}(\tau) \leq p_{baseload}(\tau) \ , \qquad \tau = 1, \ldots, H$$

6. EVALUATIONS

The evaluations are conducted on a case study of a prosumer building with a connection to an energy supplier (ET) and a PV. The time horizon for the experiments is 24 hours divided into 96 time periods (TP) of 15-minute interval. For a 24-hour predicted consumption of the building, we use the consumption data from UK Elexon [1]. In each scenario, the fixed consumption represents a certain percentage of the overall consumption, and a certain percentage is considered flexible (i.e., shiftable loads). PV production is based on the data from one of our projects. To simulate price-based DR, we use the two-banded ToU tariffs from EDF[2] consisting of peak price (0.158 €/kWh) and off-peak price (0.11 €/kWh). For incentive-based DR, we generate DR requests based on the consumption of the scenarios as the requests are consumer-specific.

6.1 Reduction of energy bills & price-based DR

In this evaluation, we experiment with four scenarios, with varying percentages of flexibility (i.e., 0%, 20%, 50%, and 100%) proportional to the total consumption of the building. Figure 1 shows the energy imported for each of the scenarios. The imported energy is the energy pulled from the supplier via ET.

In the first scenario (*Import baseline*), we suppose all the consumption is fixed. Thus, the algorithm is unable to optimise the consumption based on the energy tariffs. For other scenarios, the algorithm schedules the flexible consumption in the off-peak periods as much as possible. The imported energy during peak period between TP 29 (i.e., 7:00) and TP 91 (i.e., 23:00) decreases as the flexibility increases, with no import when the flexibility reaches 100%. Energy bills are the consequence of importing energy. Figure 2 shows reduction in energy bills as the flexibility increases. In the best-case scenario, in which all the consumption can be shifted, the reduction reaches over 20%. In a more realistic scenario[3] (i.e., 20% flexibility), there is a decrease of roughly 5%.

6.2 Load shedding

This evaluation investigates the feasibility of the proposal in participating to load shedding requests. We experiment with different inconvenience p_{inc} and incentive p_{shed} values. Figure 3 demonstrates the results. We simulate a request to shed the consumption such that the imported energy between TP 5 and TP 14 is reduced to 3 kW. Providing p_{shed} that compensates p_{inc}, we obtain the desired result (*Import shed*). In reality, a user may find load shedding at a certain time more acceptable than at others. Therefore, the inconvenience

[1] Non-domestic unrestricted customers (https://www.elexon.co.uk/knowledgebase/profile-classes/)

[2] An energy supplier in France

[3] Different studies have shown that around 10-20% of demand can be time-shifted [5]

level also varies accordingly. To simulate this, we conduct another experiment with varying convenience levels by increasing inconvenience value in TP 8 to 10. Since the incentive cannot compensate the inconvenience between TP 8 and 10, no shedding is carried out in that period (shown as *Import varying inconveniences*).

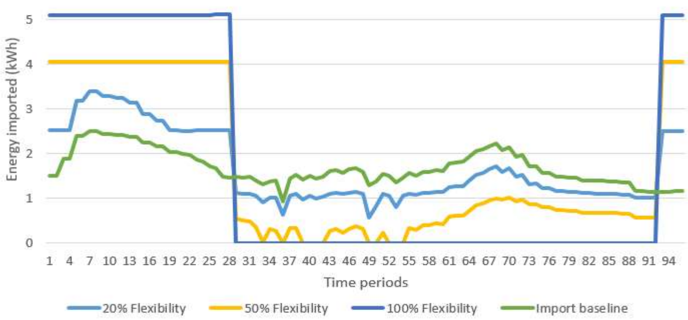

Figure 1 Energy imported for different amounts of flexibility

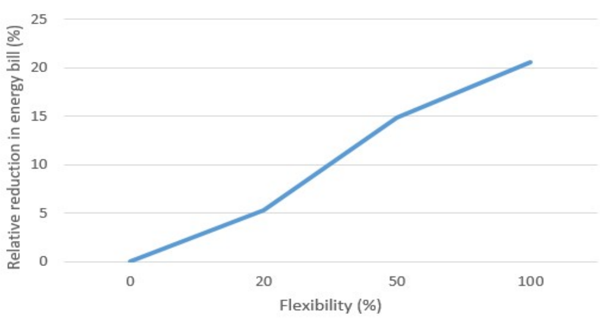

Figure 2 Reduction of energy bills

6.3 *Load shifting*

This evaluation aims at validating the feasibility in participating to load shifting requests. We simulate a request to shift 10% of the import from TP 1-28 (i.e., deviation duration - DD) to TP 56-75 (i.e., recovery duration - RD). The result is shown in Figure 4. To reduce the consumption in DD, we provide an incentive p_{shift} that compensates the energy price during that period. This actually encourages consumption, which is contradictory to the objective. However, we set the import limit P^{max} in DD to $Import\ baseline - 10\%$. Therefore, the consumption, though encouraged, will only reach the set limit. The same mechanism is applied in RD, except with the import limit of $Import\ baseline + 10\%$, to encourage the consumption of the shifted load.

7. DISCUSSION AND CONCLUSION

The evaluations included in this paper cover only the general and demonstrative cases due to the page limit. However, other more specific cases are also to be considered. For instance, one needs to consider the case where the request requires to shed or shift more consumption than the loads available to be shed or shifted. Furthermore, how the inconvenience and incentive are modelled and converted into the same scale and unity to include them in the device's cost function is a significant question to be addressed.

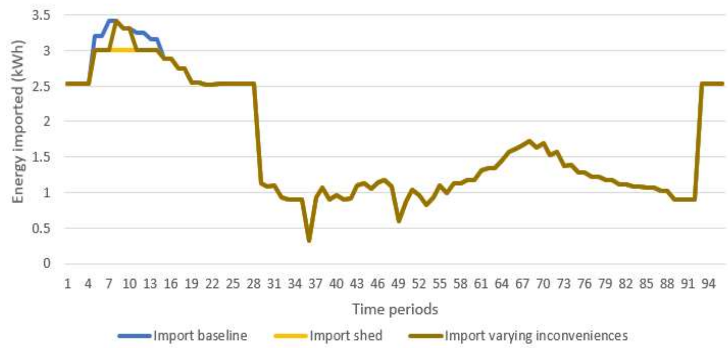

Figure 3 Load shedding

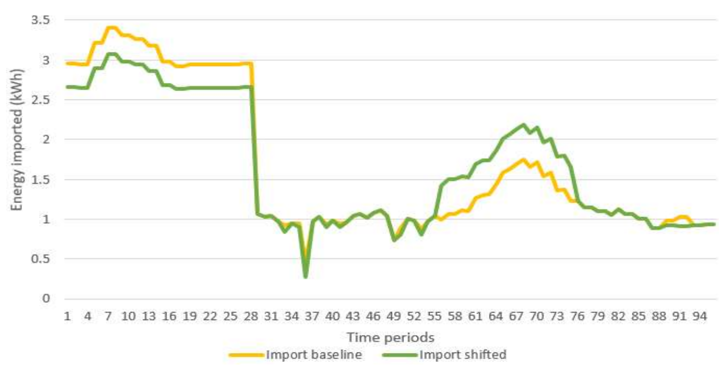

Figure 4 Load shifting

In conclusion, it has been shown that the proposed approach is able to reduce energy bills up to over 20% in the best-case scenario by exploiting the flexibility of consumption to benefit the off-peak price of the price-based DR. Device optimisation models incorporating incentives and inconveniences related to load shedding and load shifting have been shown to enable participation to different incentive-based DR requests.

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