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Energy management for a commercial building microgrid with stationary and mobile battery storage

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ABSTRACT

This paper investigates the Demand Side Management (DSM) in a commercial building microgrid with solar generation, stationary Battery Energy Management System (BESS) and gridable (V2G) Electric Vehicle (EV) integration. Taking into consideration of a comprehensive pricing model, we first formulate a deterministic DSM as a mixed integer linear programming problem, assuming perfect knowledge of the uncertainties in the system. A two-stage stochastic DSM is further developed that addresses the stochastic nature in solar generation, loads, EV availabilities and EV energy demands. The proposed DSMs are validated with real solar generation, loads, BESS and EV data using sample average approximation. Detailed case studies show that the stochastic DSM outperforms its deterministic counterpart for cost saving for a wide range of prices, though at the expense of higher computational time. Computational results also demonstrate that moderate number of EVs helps to cut down the overall operation cost, which sheds light on the benefit of future large scale EV integration to smart buildings.

1. Introduction

1.1. Motivations

Future smart buildings will incorporate an increasing renewable generation, dispatch units and storage devices, switching from traditional dumb consumptions to distributed and regulated counterparts. With continuous increase in Electric Vehicles (EVs) and solar penetrations for more than a decade [1,2] unregulated EV charging together with intermittent solar generation are posing additional challenges on supply-demand balancing in smart buildings.

Microgrids represent a vision for distributed generations and consumptions, enhancing the robustness of power grid and creating new ways of utilizing sustainable energy resources [3]. Facilitated by recent advances in Demand Side Management (DSM), renewable generation and loads are managed in response to variations in the price signal [4,5]. Coupled with the target of cutting down overall operational cost, DSM collaboratively addresses peak shaving and load shedding with physical and human comfort constrains [6–8].

The integration of EVs to households and commercial buildings is creating new challenges as well as opportunities [9,10]. Combined with fluctuations in renewable generation, EVs' randomness in arrival and departure time, State-of-Charge (SoC) and energy demands, all add up to introduce larger uncertainties to the system. The emergence of EVs with Vehicle-to-Grid (V2G) capability has also restructured EVs' role from heavy loads to small-sized distributed virtual generators [11–13]. Hence, the DSM design in households and commercial buildings has been a subject of significant ongoing research.

1.2. Literature review

Previous research on DSM in households and commercial buildings has primarily focused on deterministic optimizations [14–17]. Two studies of DSM on a household with one EV and solar generation reported peak shifting with price incentives [14,15]. Mixed integer linear programming optimization is used in both the papers to achieve minimum operation cost. Chabaud et al. [16] modeled a grid-connected residential building with renewables and battery storage, which confirmed the importance of energy storage device and diversity of renewable generation in cost saving. Furthermore, Shi et al. [17] studied the optimal energy management of

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Nomenclature

Sets, indices and naming rules
$H \in \mathbb{Z}$ horizon of a day
$s \in \mathbb{Z}$ scenario index
$\tau \in \mathbb{R}$ duration of the timeslot
$\boldsymbol{\xi}, \boldsymbol{\nu} \in \mathbb{R}^H$ uncertainty set of solar generation and load
$\boldsymbol{\zeta}_i \in \mathbb{R}^H$ uncertainty set of energy demand of EV i
$\boldsymbol{\delta}_i \in \mathbb{Z}^H$ uncertainty set of availability of EV i
$\mathbf{1}, \mathbf{0} \in \mathbb{Z}^H$ 1 and 0 column vector
$\boldsymbol{X}_s \in \mathbb{Z}^H/\mathbb{R}^H$ parameter/variable $\boldsymbol{X}$ in scenario s

Parameters
$\boldsymbol{c}^{\mathrm{DA}} \in \mathbb{R}^{1\times H}$ day-ahead energy sell and buy price
$\boldsymbol{c}^{P} \in \mathbb{R}^{1\times H}$ real-time penalty price
$\boldsymbol{p}^{\mathrm{solar}} \in \mathbb{R}^H$ solar generation power
$\boldsymbol{p}^{\mathrm{load}} \in \mathbb{R}^H$ building load power
$\underline{p^{\mathrm{grid}}}/\overline{p^{\mathrm{grid}}} \in \mathbb{R}$ minimum/maximum allowed $\boldsymbol{p}^{\mathrm{DA}}$
$\underline{P^{\mathrm{DA}}_{\mathrm{step}}}/\overline{P^{\mathrm{DA}}_{\mathrm{step}}} \in \mathbb{R}$ minimum/maximum allowed $\boldsymbol{p}^{\mathrm{DA}}$ step variation between consecutive timeslots
$\overline{P^B_c}/\overline{P^B_d} \in \mathbb{R}$ maximum allowed BESS charging/discharging power
$P^B_{c,\mathrm{lim}}/P^B_{d,\mathrm{lim}} \in \mathbb{R}$ BESS charging/discharging high power region limitation
$\boldsymbol{h}^B \in \mathbb{Z}^{H\times H}$ ancillary matrix for calculating cumulative energy of BESS
$\eta^B_c/\eta^B_d \in \mathbb{R}$ charging/discharging efficiency of BESS
$\underline{\mathrm{SoC}^B}/\overline{\mathrm{SoC}^B} \in \mathbb{R}$ BESS minimum/maximum SoC
$\mathrm{SoC}^B_I/\mathrm{SoC}^B_F \in \mathbb{R}$ BESS initial/final SoC
$\underline{P^{E,i}_c}/\overline{P^{E,i}_c} \in \mathbb{R}$ minimum/maximum charging power of EV i
$\underline{P^{E,i}_d}/\overline{P^{E,i}_d} \in \mathbb{R}$ minimum/maximum discharging power of EV i
$\boldsymbol{\sigma}^{E,i} \in \mathbb{Z}^H$ availability matrix of EV i
$\underline{\mathrm{SoC}^{E,i}}/\overline{\mathrm{SoC}^{E,i}} \in \mathbb{R}$ minimum/maximum allowed SoC of EV i
$\boldsymbol{h}^{E,i} \in \mathbb{Z}^{H\times H}$ ancillary matrix for calculating cumulative energy of EV i
$\eta^{E,i}_c/\eta^{E,i}_d \in \mathbb{R}$ charging/discharging efficiency of EV i
$\mathrm{SoC}^{E,i}_I/\mathrm{SoC}^{E,i}_F \in \mathbb{R}$ initial/final SoC of EV i

Decision variables
$\boldsymbol{p}^{\mathrm{DA}} \in \mathbb{R}^H$ day-ahead buy and sell power
$\boldsymbol{p}^{P} \in \mathbb{R}^H$ real-time penalty power
$\boldsymbol{p}^B_c/\boldsymbol{p}^B_d \in \mathbb{R}^H$ BESS charging/discharging power
$\boldsymbol{\sigma}^B \in \mathbb{Z}^H$ binary BESS status indicating charging or discharging
$\boldsymbol{\sigma}^B_c/\boldsymbol{\sigma}^B_d \in \mathbb{Z}^H$ binary status indicating BESS operating in high power charging/discharging region
$\boldsymbol{p}^{E,i}_c/\boldsymbol{p}^{E,i}_d \in \mathbb{R}^H$ charging/discharging power of EV i
$\boldsymbol{\sigma}^{E,i}_c \in \mathbb{Z}^H$ binary status indicating EV i charging or discharging

Acronyms
BESS battery energy storage system
DSM demand side management
EV electric vehicle
KDE kernel density estimation
SAA sample average approximation
SoC state-of-charge
V2G vehicle-to-grid

residential units in a microgrid with a decentralized convex optimization method, which reduced computational time and preserved consumer privacy. These researchers assumed perfect knowledge of uncertainty and used deterministic optimization methods for DSM, without considering the loads, EVs and renewable generation's stochastic nature.

Much of the research in DSM has examined uncertainties caused by renewable generation and EVs with robust optimization [18–20]. Malysz et al. [18] considered uncertainties in loads and solar generation of a microgrid, and formulated the optimal control of a microgrid as a robust mixed integer linear programming problem. Bai et al. [19] evaluated a robust mixed integer quadratic programming optimization method for large scale V2G for EV aggregator taking into account EV instant power demand uncertainties. Zhang et al. [20] proposed distributed robust optimization algorithms for DSM with intermittent renewable generation in a microgrid. These methods addressed the uncertainties in the systems by estimating the worst case of the uncertainty sets, which might be conservative and resulted in high operational cost.

In [21,22], the wind generation uncertainties were modeled in a microgrid with probabilistic constrained stochastic programming. The operation cost minimizations were achieved with constraints of utilizing certain percentage of wind generation to meet minimum renewable utilization regulations. These papers considered the load and renewable uncertainties in the power grid, and addressed the stochastic behavior with uncertainty-aware stochastic optimization. However, these researchers did not consider how the randomness of EV's energy demands, arrival/departure time would interact with the intermittent renewable generation, which if managed improperly, will increase the burden of a microgrid.

Apart from the mixed integer linear programming, mixed integer quadratic programming and convex optimization used in deterministic optimization, robust optimization and stochastic optimization mentioned above, heuristic-based DSM has captured researcher's attention [23–25]. Adaptive neuro-fuzzy inference system [23], fuzzy logic [24], and θ-krill herd [25] are some of the examples of heuristic based DSM. Although heuristic based DSM allows operators to achieve multiple optimization goals at the same time, compared to traditional mixed integer linear programming, mixed integer quadratic programming and convex optimization, the heuristic methods cannot be solved with standard solvers and hence may result in longer computational time.

Together with many paper not cited, existing papers have made sound contributions to DSM in households, commercial buildings. However, existing research either failed to consider the effect of EVs' integration in DSM or did not capture uncertainties in renewable generation, loads and EV modeling. Furthermore, though DSM in households and commercial buildings shares some of the similarities, a commercial building typically has more EVs introducing larger uncertainties on demand side. Hence, DSM of a grid-connected commercial building with renewable generation and EVs needs to be reexamined in details.

1.3. Scope, contributions and organization

This paper jointly studies DSM in a commercial building microgrid with solar generation, building loads, Battery Energy Storage System (BESS) and EVs. We consider a comprehensive pricing model and targets at maintaining a low operation cost while utilizing solar generation, stationary BESS and mobile EV storage as much as possible. We first deduct a deterministic DSM and formulate it into a mixed integer linear programming problem. Taking into consideration the stochastic behaviors of solar generation, building loads and EVs, we further develop DSM with two-stage stochastic programming. Sample Average Approximation (SAA) Monte Carlo simulation is used to get numerical results of the proposed DSMs.