ARTICLE IN PRESS

Applied Energy xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Microgrid to enable optimal distributed energy retail and end-user demand response

Ming Jin [a,b], Wei Feng [b,*], Chris Marnay [c], Costas Spanos [a]

[a] Electrical Engineering and Computer Sciences Department, University of California, Berkeley, CA 94720, USA
[b] Energy Technologies Area, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA
[c] Trottier Institute for Sustainability in Engineering and Design, McGill University, Montreal, Canada

HIGHLIGHTS

- Retail rate modeling to enable distributed energy adoption in a microgrid.
- Comprehensive energy (electricity, heating, cooling) dispatch to connect end user demand response (DR) with wholesale market.
- Dynamic pricing to provide equal access to energy for customers with different levels of affordability at a community scale.
- Mechanism design to promote DR engagement while delivering mutual benefits for stakeholders.

ARTICLE INFO

Article history:
Received 2 April 2017
Received in revised form 10 May 2017
Accepted 12 May 2017
Available online xxxx

Keywords:
Microgrid
Demand response
Energy pricing
Unit commitment
Distributed energy resources
Rate design

ABSTRACT

In the face of unprecedented challenges in environmental sustainability and grid resilience, there is an increasingly held consensus regarding the adoption of distributed and renewable energy resources such as microgrids (MGs), and the utilization of flexible electric loads by demand response (DR) to potentially drive a necessary paradigm shift in energy production and consumption patterns. However, the potential value of distributed generation and demand flexibility has not yet been fully realized in the operation of MGs. This study investigates the pricing and operation strategy with DR for a MG retailer in an integrated energy system (IES). Based on co-optimizing retail rates and MG dispatch formulated as a mixed integer quadratic programming (MIQP) problem, our model devises a dynamic pricing scheme that reflects the cost of generation and promotes DR, in tandem with an optimal dispatch plan that exploits spark spread and facilitates the integration of renewables, resulting in improved retailer profits and system stability. Main issues like integrated energy coupling and customer bill reduction are addressed during pricing to ensure rates competitiveness and customer protection. By evaluating on real datasets, the system is demonstrated to optimally coordinate storage, renewables, and combined heat and power (CHP), reduce carbon dioxide emission while maintaining profits, and effectively alleviate the PV curtailment problem. The model can be used by retailers and MG operators to optimize their operations, as well as regulators to design new utility rates in support of the ongoing transformation of energy systems.

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1. Introduction

The transition from an economy that relies heavily on fossil fuels to one that is powered primarily by renewable energy has been accelerating in recent years, bolstered by mounting concerns over climate change and falling prices of solar and wind energy [1]. However, the grid is being destabilized by penetration of volatile, distributed renewable resources [2]. Furthermore, grid resilience and rapid self-recovery in the face of natural disasters and malicious attacks are extremely necessary features [1,3].

Driven by the evolution of technologies and markets, there is a fundamental push across the industry to update utility rate structures as the existing tariff becomes less and less efficient [2]. Meanwhile, the emergence of electricity retail services enables customers to choose providers [4]. Increased competition exposes retailers to greater risks, while not necessarily reducing customers' bills [4]. Clearly, a systematic strategy for rate design and resource management is central to the ongoing transformation of the system.

* Corresponding author at: Energy Technologies Area, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA.

E-mail addresses: jinming@berkeley.edu (M. Jin), WeiFeng@lbl.gov (W. Feng), ChrisMarnay@lbl.gov (C. Marnay), spanos@berkeley.edu (C. Spanos).

http://dx.doi.org/10.1016/j.apenergy.2017.05.103
0306-2619/Published by Elsevier Ltd.

Nomenclature

$\alpha^t_{\min}$, $\alpha^t_{\max}$	min/max DR loads (8)
$\boldsymbol{d}_t$	building demands at time t
β^{DR}_t	fixed DR incentive at time t
$\boldsymbol{p}_t$	retail rates (electric/heat/cooling) at time t
$\boldsymbol{x}_t$	forecast features at time t
$\boldsymbol{x}_t$	generator dispatch plan at time t
ξ_t	set of uncertain variables at time t
$\boldsymbol{z}_t$	storage SOC at time t
$\cdot^{\mathrm{curt}}$, $\cdot^{\mathrm{critic}}$	curtailable, critical loads
$\cdot^{\mathrm{ref}}$	reference loads/prices
$\cdot_b$	building index $b \in \{1, \ldots, B\}$
$\cdot_t$	time index $t \in [0, T]$
$\epsilon_{t,b}$	elasticity coefficient for building b at time t
λ_{env}	environmental-tradeoff parameter
B	number of buildings in the microgrid
E	electric power/energy
f^{Rev}, $\cdot^{\mathrm{Ope}}$, $\cdot^{\mathrm{Env}}$	revenue, operational, and environmental costs (P0)
H	heating power/energy
Q	cooling power/energy
T	time horizon
CHP	combined heat and power
COP	coefficient-of-performance
MG	microgrid
MIQP	mixed integer quadratic programming
NG	natural gas
RMSE	root mean squared error
SOC	state of charge

This paradigm shift can be further driven by demand response (DR) by the institution of time-differentiated retail pricing, e.g., time-of-use (TOU) and real-time pricing (RTP), which reflect fluctuating wholesale prices and explore end-user demand flexibility [4–8]. Currently, RTP is most popular in the wholesale market, while being experimented on a few sites like the Illinois Power Company on the retail side. However, with the increasing penetration of internet-of-things (IoT) devices [9,10] and occupancy-aware building controls [8,11], buildings' responsiveness can be significantly enhanced through automated services [12,13]. Thus, study on DR at the retail level that finds its optimal pricing scheme and relationship with local distributed energy resources adoption and operation becomes increasingly important [12].

On the supply side, the division of the grid into productive subsystems, microgrids (MGs), that integrate distributed generation (DG) and storage to serve local demand, has been proposed to increase manageability, energy efficiency, and resilience [14–16]. The rapid development of integrated energy systems (IESs), which exploit the synergistic potential of thermal and electrical provision, is crucial for flexibility enhancement, carbon dioxide (CO_2) reduction, and renewable integration [3]. Nevertheless, in places like Jilin province, in northeastern China, about 89% of the total wind power curtailment is caused by operating conventional CHP at full load to satisfy high heat demands and lack of curtailable supply [3].

The central task for a retailer with generation capacity is thus to design energy rates and operate the facility to gain profits and preserve system stability. Previous works on MG operation often treat it as a non-profit entity that does not price its energy output, which confines its application to campuses and other situations where the total bill is paid by the MG owner [6,14,17–24]. As a result, DR in a MG is limited to contracts [24] or a mutual agreement where the MG operator has central control over DR-enabled loads [12,18,25]. This often requires the integration of advanced communication infrastructure and might raise security and privacy issues [26,27]. Furthermore, the scope is predominantly within electricity provision [24,25,28,29], rather than exploiting synergies of IESs. We focus on future smart MG with time-differentiated pricing on the retail side and propose a **M**icrogrid **R**etailer **P**ricing and **O**peration strategy with **D**emand response, or MR-POD (Fig. 1). Our key contributions are as follows:

- Modeling of the MG with integrated energy provision and renewable resources, plus the formulation of optimal rate design and MG dispatch under uncertainty

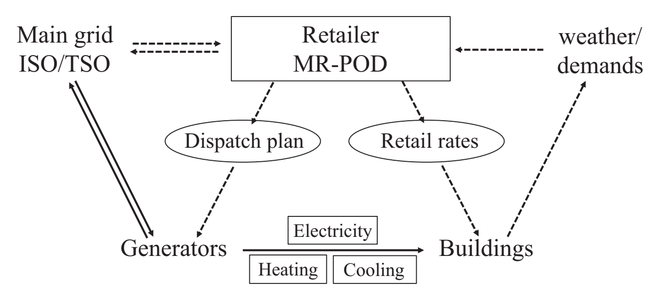

Fig. 1. Schematic of the proposed method, showing communication links (dashed lines) and energy links (solid lines), where planning is conducted day ahead. ISO/TSO: independent/transmission system operator.

- Design of pricing and DR incentive mechanisms that promote customer benefits, retailer competitiveness, and DR effectiveness
- Evaluation of the model on real datasets, demonstrating about 6% profit gain with reduced customer bills and improved system reliability for optimally designed RTP compared to daily rates

The rest of the paper is organized as follows. Previous works are surveyed in Section 2, with an emphasis on MG modeling and dispatch, DR, and optimal rate design. Section 3 discusses the retailer model, including problem formulation, the MG pricing mechanism, and energy demand and supply. Section 4 deals with operation under uncertainty, which includes the forecasting methodology, and the DR incentive mechanism. A schematic overview of the proposed MR-POD method is shown in Fig. 1, where the dispatch plan and retail rates are optimized for the generators and buildings day ahead (Section 3), while considering the forecasted operating conditions as well as DR objectives (Section 4). The dataset and implementation are discussed in Section 5, followed by scenario analysis (Section 6) and a case study for environmentally conscious operations with DR for PV over-generation (Section 7). Conclusions are drawn in Section 8.

2. Related work

Microgrids with demand response capabilities have emerged as a key feature of the ongoing transformation of the energy system towards high renewable penetration. This section focuses on three aspects of the proposal: MG modeling and dispatch, demand response, and optimal rate design.

2.1. MG modeling and dispatch

Previous work has been undertaken on modeling high-level system design for MGs to study their profitability and optimal technology selection [16,20,22,23,30].

The dispatch of MG has been attempted through a variety of approaches, including mixed integer linear programming (MILP) [31], dynamic programming [30], simulated annealing [6], particle swarm optimization [23], evolutionary algorithms [22], game theoretic agent-based formulations [14], and power routing among clusters of MGs [32]. Ommen et al. [19] conducted an empirical comparison of LP, MILP, and non-linear programming (NLP), and concluded that MILP is the most appropriate model from the viewpoints of accuracy and runtime. In comparison, our formulation of the dispatch problem as MIQP also *addresses the uncertainty in renewable generation and the flexibility in demand that facilitates DR*.

2.2. Demand response

Demand response (DR) is becoming a cost-effective balancing resource in power systems [33]. According to the US Department of Energy, DR is "a tariff or program established to motivate changes in electric usage by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity usage at times of high market prices or when grid reliability is jeopardized" [2]. There are mainly two groupings of DR programs: price-based DR and incentive-based DR, with the key difference that the former offers customers time-varying or localized prices, while the latter grants fixed or time-varying payments under specific contracts [34]. This study focuses on the design of rate signals for price-based DR, whose efficacies have been empirically examined in several studies [34].

As for the operation of MG with DR, De Jonghe et al. [28] developed an elasticity-based operational and investment model to determine the optimal generation mix. Ghatikar et al. presented a model for customer distributed energy resource (DER) optimization and participation in grid transactions, which was deployed at a real test site [12]. Amini et al. [35] introduced multi-agent modeling in load management to enable self decision-making capabilities. Patteeuw et al. [36] proposed an integrated modeling of DR with electric heating systems coupled to thermal energy storage systems. Kim and Giannakis [25] considered a DR problem entailing a set of devices/subscribers whose operating conditions are modeled using mixed-integer constraints. However, these studies only focus on the electricity system, and assume central coordination of loads. The MOD-DR model proposed by Jin et al. [18] explores the efficiency of coupling electricity and thermal energy provision. On the other hand, the MG operator is assumed to be a *non-profit entity* that performs DR through utility maximization, while the current approach focuses on*retailers who own distributed generation system and can price the energy for profits and DR*.

2.3. Optimal rate design

Smart pricing plays a vital role in DR to increase system reliability, reduce generation costs, and lower consumers' bills [37]. To determine the consumer response, price-elastic load models were proposed [38,39], where the elasticity is often estimated using panel data [40,41]. Kamyab et al. [7] formulated the pricing problem as two noncooperative games for suppliers and customers, and demonstrated increased profits and payoffs. Kim and Norford [8] proposed a price-based DR framework to assist commercial buildings in devising a beneficial strategy for exploiting the thermal energy storage resources inherent in building structures via the optimal operation of variable speed heat pumps. Doostizadeh and Ghasemi [42] examined a day-ahead (DA) RTP scheme to maximize retailer profits while considering demand elasticity and benefits to consumers. Methods based on mixed-integer stochastic programming to determine the optimal sale price of electricity and the electricity procurement policy of a retailer have been proposed in [24,29]. However, these works only focus on electricity supply and profit maximization for the retailer without providing DR incentivization to enroll customers in the programs, which are often voluntary in practice.

Differentiated from the previous studies, our key proposal, MR-POD is aimed at *providing guidance on optimal MG operation and pricing on a district level with integrated energy provision*. By leveraging the efficiency of energy coupling and demand flexibility, the model provides a cost-effective and grid-cooperative strategy in a competitive and uncertain market.

3. MG retailer model

The MG dispatch and retailer pricing with DR problem is formulated within an optimization framework. Key components, including the MG generator and building loads, are shown in Fig. 2, where flows of cash, energy, and information within the MG are illustrated.

3.1. Problem formulation

The key problem MR-POD solves is: "How should energy prices be set and the microgrid operated to maximize retailer profit while satisfying building demand and grid requirements?". Two prominent factors are involved:

- *Price elasticity* of loads for individual buildings under the DR scheme
- *Uncertainty and fluctuation* of energy demand, electricity and thermal tariffs, and weather conditions

Price elasticity refers to the change in energy demand in response to a change in product price [34,43], which can be used by the retailer to estimate peak demand reduction potential, and provision of ancillary services to the grid. The uncertainty aspect, inherent for all planning problems, is addressed by forecasting, as discussed in Section 4.1.

The basic MR-POD problem is formulated by (Fig. 3):

$$\max_{\{\boldsymbol{x}_t,\boldsymbol{p}_t\}_{t=1}^T} \sum_{t=1}^{T} f_t^{\mathrm{Rev}}(\boldsymbol{d}_t,\boldsymbol{p}_t) - f_t^{\mathrm{Ope}}(\boldsymbol{x}_t,\boldsymbol{z}_t,\xi_t) - \lambda_{env} f_t^{\mathrm{Env}}(\boldsymbol{x}_t,\boldsymbol{z}_t)$$
$$\text{s.t. } \boldsymbol{x}_t \in \mathcal{X}_t(\boldsymbol{z}_t,\boldsymbol{d}_t,\xi_t), \boldsymbol{d}_t \in \mathcal{D}_t(\boldsymbol{p}_t), \boldsymbol{p}_t \in \mathcal{P}_t, \forall t = 1,\ldots,T \quad \text{(P0)}$$

where $\boldsymbol{x}_t$ is the dispatch proposal at time t, which includes variables in three categories: *generation* from on-site power plants, *storage charging/discharging*, and *grid import/export*. The energy demand of buildings, $\boldsymbol{d}_t$, is a function of retail prices and DR incentives, $\boldsymbol{p}_t$, determined by MR-POD. The state variable, $\boldsymbol{z}_t$, captures the state-of-charge (SOC) of the storage as governed by the previous state and any actions. The uncertain quantities, e.g., solar irradiation Irr_t and electricity price c_t^{grid}, are summarized in ξ_t.

Objective function. Driven by both economic gains and environmental consciousness, the retailer tries to maximize its profit,

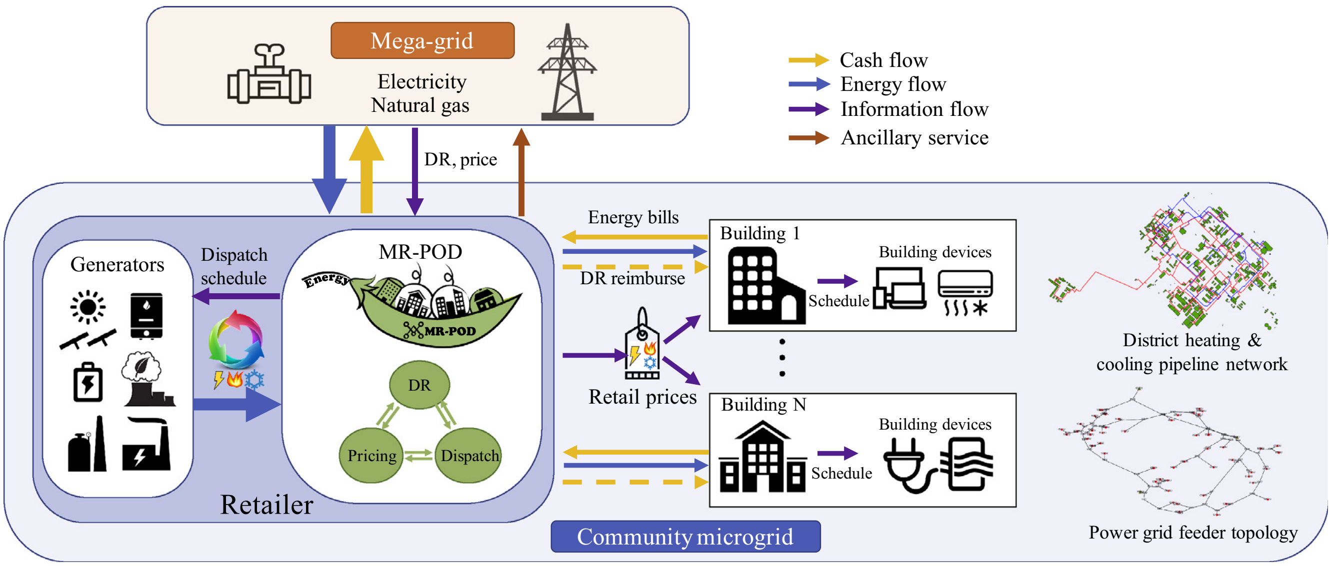

Fig. 2. Overview of the retailer model, incorporating generator dispatch and energy retailing.

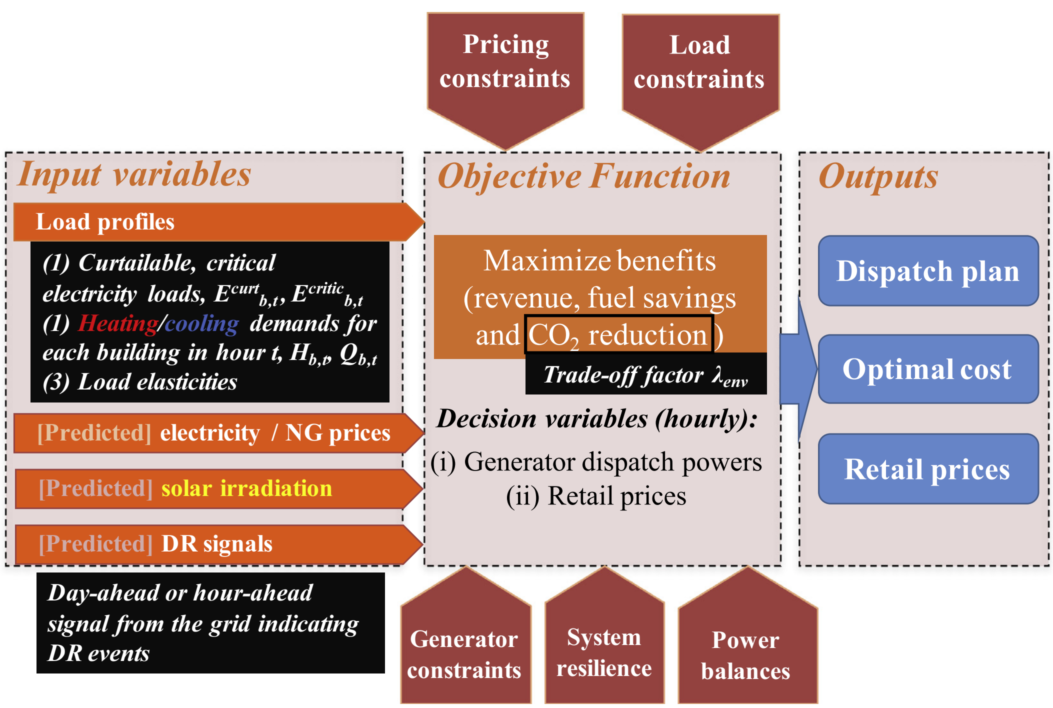

Fig. 3. Illustration of the optimization framework of MR-POD.

$f_t^{\text{Rev}}(\boldsymbol{d}_t, \boldsymbol{p}_t) - f_t^{\text{Ope}}(\boldsymbol{x}_t, \boldsymbol{z}_t, \xi_t)$, and at the same time, minimize its environmental impact, $f_t^{\text{Env}}(\boldsymbol{x}_t, \boldsymbol{z}_t)$. The revenue collected by selling energy to buildings, $f_t^{\text{Rev}}(\boldsymbol{d}_t, \boldsymbol{p}_t)$, depends on retail prices $\boldsymbol{p}_t$ and building loads $\boldsymbol{d}_t$. This is a *quadratic function* of the retail prices $\boldsymbol{p}_t$, since the building demand $\boldsymbol{d}_t$ depends linearly on the price as in (6). The operational cost, $f_t^{\text{Ope}}(\boldsymbol{x}_t, \boldsymbol{z}_t, \xi_t)$, is the expenditure on fuel imports net of any revenue from energy sold back, in addition to maintenance expenses for facilities with on-site personnel.

On top of the former commonly adopted economic incentives [18,24,25,28,29], the environmental impact, $f_t^{\text{Env}}(\boldsymbol{x}_t, \boldsymbol{z}_t)$, measured by the amount of carbon dioxide (CO_2) emissions, is incorporated to encourage the use of renewable energy and natural gas in favor of grid electricity.[1] Through the parameter λ_{env} controlling trade-offs such as a carbon tax,[2] MR-POD is able to offer guidance to balance the economic and environmental benefits for the retailer.

Constraints. There are two main groupings of constraints in MR-POD related to pricing and operation. The pricing constraints $\boldsymbol{p}_t \in \mathcal{P}_t$, which will be discussed in Section 3.2, ensure regulatory

[1] Based on the statistics from the U.S. Energy Information Administration, electricity generated from coal (0.98 $kgCO_2$/kW h) emits more carbon dioxide than that generated from natural gas (0.55 $kgCO_2$/kW h). Since coal combustion accounts for 71% of CO_2 emissions of the grid electricity while natural gas only accounts for 28%, it is cleaner to generate electricity from natural gas than import from the grid in the U.S.

[2] For example, a carbon tax of \$0.026/$kgCO_2$ is levied in Denmark, while the tax is \$0.131/$kgCO_2$ in Sweden [44].

compliance, market competitiveness, and customer satisfaction. The operation constraints, as detailed in Section 3.3, include (1) power balance between load and generation, $\boldsymbol{x}_t \in \mathcal{X}_t(\boldsymbol{z}_t, \boldsymbol{d}_t, \xi_t)$, for *heating, cooling, and electricity*, (2) feasibility for dispatch variables $\boldsymbol{x}_t$ and storage states $\boldsymbol{z}_t$ delineated by the generation and storage technologies, e.g., CHP partial loads, PV output, and storage charge/discharge rate limits, (3) the building load identity $\boldsymbol{d}_t \in \mathcal{D}_t(\boldsymbol{p}_t)$, based on the price elasticity model, (4) system resilience requirements, as prescribed in either the cap on the total imported power from the grid [22,25,45], or the spinning reserve limits on the storage resources [22,45], as well as (5) DR targets like peak load reduction, which can be achieved through energy price setting.

Due to the involvement of integer variables like discrete on/off decisions for CHP and charging/discharging for storage, in addition to quadratic coupling between prices and building loads, the resulting problem requires mixed integer quadratic programming (MIQP) (see Fig. 3).

3.2. MG energy pricing

The key to a sustainable pricing policy should align the incentives of the retailer, its customers, and its regulators, and ensure reliability, customer equity, and social welfare maximization [4,46,47]. In the following, we introduce the guiding principles of day-ahead rate setting for electricity ($\boldsymbol{p}_t^E$), heating ($\boldsymbol{p}_t^H$), and cooling ($\boldsymbol{p}_t^C$) services (Fig. 4).

Time-differentiated rate structure. While the DA prices of RTP can vary from hour to hour, TOU typically has three levels corresponding to off-, mid-, and on-peak hours, i.e., $\boldsymbol{p}_{t_1}^E = \boldsymbol{p}_{t_2}^E$ if t_1, t_2 are in the same time group. To avoid "response fatigue" due to price variation [48], it is enforced that the hourly price change and the difference between average rates of off-, mid-, and on-peak are limited,

$$\left|\boldsymbol{p}_t^E - \boldsymbol{p}_{t+1}^E\right|, \left|\frac{1}{n_{\text{mid}}}\sum_{t\in\text{mid}}\boldsymbol{p}_t^E - \frac{1}{n_{\text{off}}}\sum_{t\in\text{off}}\boldsymbol{p}_t^E\right|, \left|\frac{1}{n_{\text{on}}}\sum_{t\in\text{on}}\boldsymbol{p}_t^E - \frac{1}{n_{\text{mid}}}\sum_{t\in\text{mid}}\boldsymbol{p}_t^E\right| \leqslant \delta^{\text{diff}}, \tag{1}$$

where $n_{\text{off}}, n_{\text{mid}}, n_{\text{on}}$ are the sizes of each group, and δ^{diff} is capped at 0.1\$/kW h for electricity.

Rate competitiveness. Both hourly and daily average limits are imposed on thermal and electricity rates:

$$r_t^{\min} \leqslant \boldsymbol{p}_t^E \leqslant r_t^{\max}, \quad r_{\text{avg}}^{\min} \leqslant \frac{1}{24} sum_{t=1}^{24} \boldsymbol{p}_t^E \leqslant r_{\text{avg}}^{\max} \tag{2}$$

where typical values of $r_t^{\max}$ and $r_{\text{avg}}^{\min}$ are 0.3\$/kW h and 0.05\$/kW h, respectively, while $r_t^{\min}$ and $r_{\text{avg}}^{\max}$ can be chosen as the forecasted wholesale market tariff/the flat rate in the area to protect the retailer/customers. Further, to hedge consumers against high prices, the K-factor is introduced, K, as the upper bound on the ratio between the bills under the new rate $(\boldsymbol{p}^E, \boldsymbol{p}^H, \boldsymbol{p}^Q)$ and the flat rate $(p_{\text{flat}}^E, p_{\text{flat}}^H, p_{\text{flat}}^Q)$:

$$\sum_{t=1}^{24}(\boldsymbol{p}_t^E E_{t,b} + \boldsymbol{p}_t^H H_{t,b} + \boldsymbol{p}_t^Q Q_{t,b}) \leqslant K \sum_{t=1}^{24}(p_{\text{flat}}^E E_{t,b} + p_{\text{flat}}^H H_{t,b} + p_{\text{flat}}^Q Q_{t,b}), \quad \forall b \in \{1, \ldots, B\} \tag{3}$$

where $E_{t,b}, H_{t,b}, Q_{t,b}$ are the electricity/heating/cooling loads of building b. Setting the K-factor less than one implies that the new rates will reduce customers' bills relative to the incumbent utility. But, this would often result in a loss of profits for the retailer. A K-factor slightly larger than one allows more flexibility, and can, interestingly, lead to a win-win situation in tandem with the DR mechanism (Section 4.2).

Integrated energy coupling. The co-existence of multiple energy vectors in the system indicates the potential coupling between electricity and thermal loads. For a hypothetical consumer with a heat pump, competitive thermal rates could make it more cost-effective to purchase thermal energy from the retailer than self-generate(Fig. 4):

$$\boldsymbol{p}_t^H \leqslant \frac{\boldsymbol{p}_t^E}{\text{COP}^H}, \quad \boldsymbol{p}_t^Q \leqslant \frac{\boldsymbol{p}_t^E}{\text{COP}^Q} \tag{4}$$

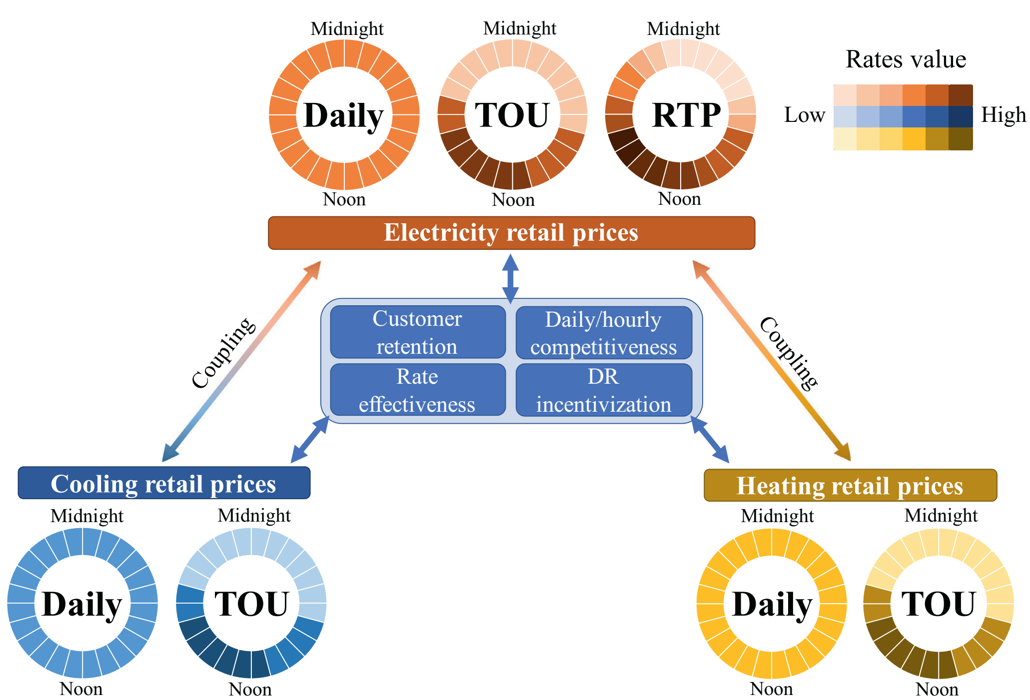

Fig. 4. Overview of the pricing strategy, including the time-differentiated rates structure and energy price coupling.

where $\mathrm{COP}^H, \mathrm{COP}^Q$ are the coefficients of performance (COP) for heat pumps, which can be as high as 4 for some commercial brands.

DR effectiveness. It is desirable to shape the loads during DR events, such as for peak load reduction, which can be incorporated in rate optimization, as detailed in Section 4.2. The key is to differentiate the price elasticity of demands, as discussed in the following section.

It is worth mentioning that electricity rates often include the commodity costs, transmission/distribution infrastructure charges, and public purpose programs, such as energy efficiency and low-income subsidies, which can be either fixed or variable [4]. Demand charges are also sometimes applied on maximum demand over a certain time. This study focuses on variable operational costs that arise from generation and fuel imports, though it could be combined with other fixed charges in practice.

3.3. Energy demand and supply

The effectiveness of price setting depends on the price sensitivity of energy demands. The load profiles of buildings in a MG, such as in residential and commercial buildings, hospitals, and public services, can be characterized as critical or curtailable loads [49].

Critical load. For electricity usage in data centers and ICUs of hospitals, for example, it is of utmost importance that critical loads are satisfied, i.e.,

$$E_{t,b}^{\mathrm{critic}} = E_{t,b}^{\mathrm{critic}} \tag{5}$$

where $b \in \{1, \ldots, B\}$ for a building within the community, and t denotes an hourly time step.

Curtailable load. Apart from critical loads, demands like heating, cooling, ventilation, and lighting usually fall as the energy price increases. A consumer's sensitivity to price changes is measured by the coefficient of elasticity, ϵ, which indicates a ϵ% change in energy demands due to a 1% change in price. The curtailable load, therefore, is modeled as:

$$E_{t,b}^{\mathrm{curt}} = E_{t,b}^{\mathrm{curt,ref}} \left(1 + \epsilon_{t,b} \underbrace{\frac{p_t^{\mathrm{E}} - p_t^{\mathrm{E,ref}} + \beta_t^{\mathrm{DR}}}{p_t^{\mathrm{E,ref}}}}_{\%\text{ change in price}} \right) \tag{6}$$

where $\epsilon_{t,b}$ is the elasticity coefficient for building b at time t, $E_{t,b}^{\mathrm{curt,ref}}$ is the curtailable load under the price $p_t^{\mathrm{E,ref}}$, which usually corresponds to historical data [39,40,43].

The elasticity coefficient $\epsilon_{t,b}$ is typically negative, indicating the reciprocal relationship between demand and price; its value depends on (1) time of the day: the load is usually more price responsive during on-peak than off-peak hours [2], (2) rate structures: it is found that loads under TOU rates are less elastic than those under RTP rates [40], and (3) planning horizon: the elasticity is usually greater in the long-run when customers can react to a price increase by purchasing more energy efficient appliances [40,50]. For instance, the elasticity of electricity demands for residential buildings in the US ranges from -0.20 to -0.35 in the short-run, and -0.30 to -0.80 in the long-run [41]. Differentiated from more complex non-linear models based on logarithm or potential [38], the linear model simplifies the optimization and is also more accurate and reliable [38]. We focus our attention on*own-price elasticity*, which limits the influence of price on demands in the same time period, since it is sufficient for capturing how customers adjust their consumption to price changes [34].

As for the supply side, we consider an integrated energy system to satisfy the buildings' electric and thermal loads. By exploiting synergies and complementarities of various energy vectors, this approach can improve energy efficiency, reduce CO_2 emissions, and facilitate renewable integration [3]. Apart from CHP and conventional thermal generators like electric/natural gas/absorption chillers/boilers and heat pumps, renewable resources like solar thermal and photovoltaics (PV) are included in the retailer's facility to harness solar energy and reduce carbon footprints. Electric and thermal storage with dynamic charging/discharging behaviors are available to enable smooth operation and exploit time-shifting opportunities. Maintaining a minimum amount of stored energy, typically 5% of the total capacity, i.e., state-of-charge (SOC), is referred to here as the *spinning reserve requirement* [22,45]. Modeling details can be found in [18].

4. MG operation strategy

This section introduces MG planning under uncertain market and weather conditions, as well as the DR incentivization scheme.

4.1. Planning under uncertainty

Using MR-POD for strategizing, the operator can optimize the energy dispatch and retailing in five critical steps (Fig. 5): Before the actual day of dispatch (*day 0*), data related to weather, energy demands, and MG status are acquired from installed sensors and meters (*step 1*); this is used to predict and estimate key quantities such as DR potentials, renewable energy, and electricity wholesale tariffs (*step 2*). Based on the prediction, MR-POD produces the optimal dispatch plan and retail rates (*step 3*), which are announced to generation facilities and consumers (*step 4*). The plan is executed on the actual day of dispatch (*day 1*), and repaired to adjust to unaccounted for fluctuations in demand and renewable generation (*step 5*).

Prediction of uncertain variables. Methods for solar and load forecasting can be grouped into data-driven or model-based methods [51]. Weron [52] recently conducted a comprehensive review of price prediction approaches. Specifically, we employ the "forecast combination" method based on ordinary least squares (OLS[c]), which combines M forecasts from a committee of predictors, $\hat{y}_{m,t}$, according to

$$y_t^{\mathrm{OLS}} = c_{\mathrm{OLS}} + \sum_{m=1}^{M} w_m \hat{y}_{m,t} \tag{7}$$

where constant c_{OLS} and weights $\{w_m\}_{m=1}^{M}$ are learned from past performance of the forecasts [52,53]. Its performance is shown to be superior among an array of candidates for solar and tariff prediction [18].

Generator dispatch and energy retailing. As with electricity market bidding, upon receiving predictions on *day 0*, the retailer performs MR-POD optimization to prepare a day-ahead (DA) dispatch plan and its energy retail rates and announces them to the generation facility and building owners. The original dispatch proposal is amended for actual execution on *day 1* by exploiting the cheapest sources/destinations of energy immediately available, e.g., storage (if any) or grid, to maintain the power balance.

Setting the DA retail rates is common practice, such as the DA RTP tariff used by the Illinois Power Company, pilots in California, Idaho, and New Jersey, and the three-level TOU pricing in Ontario, Canada. And it reaps several benefits [48]. First, the DA prices like RTP can best reflect the costs of energy procurement incurred by the retailer. Also, it can handle exceptional days, for instance, by declaring DA CPP when the forecasted loads are high. Importantly, it allows consumers sufficient time to schedule their consumption, while not being "fatigued" by hourly rate changes [54].

Please cite this article in press as: Jin M et al. Microgrid to enable optimal distributed energy retail and end-user demand response. Appl Energy (2017), http://dx.doi.org/10.1016/j.apenergy.2017.05.103

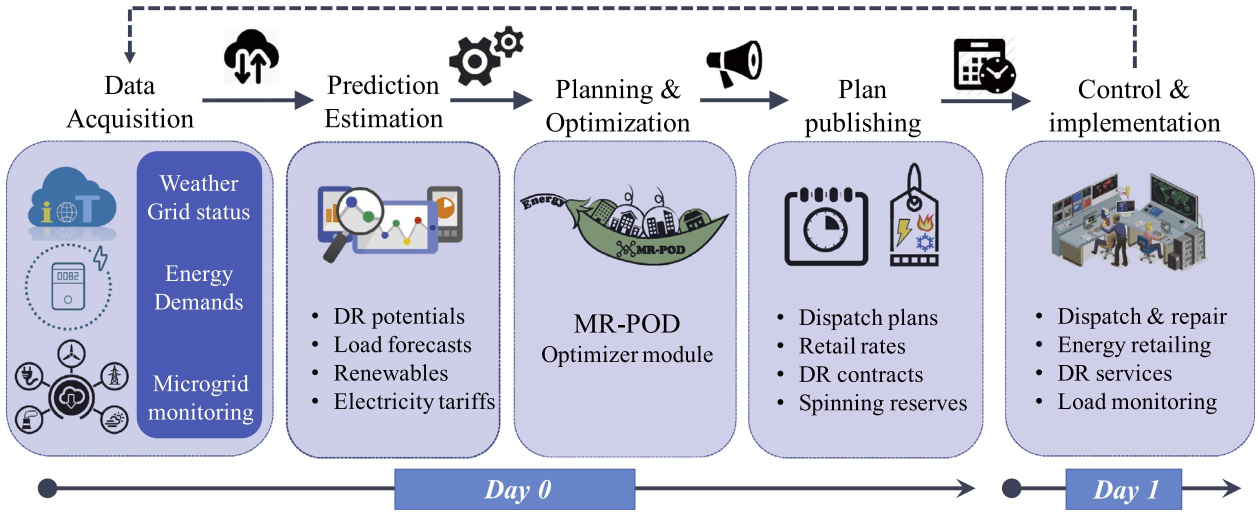

Fig. 5. System overview of MR-POD, illustrating key components: data acquisition, estimation and prediction, planning and optimization, and control and actuation.

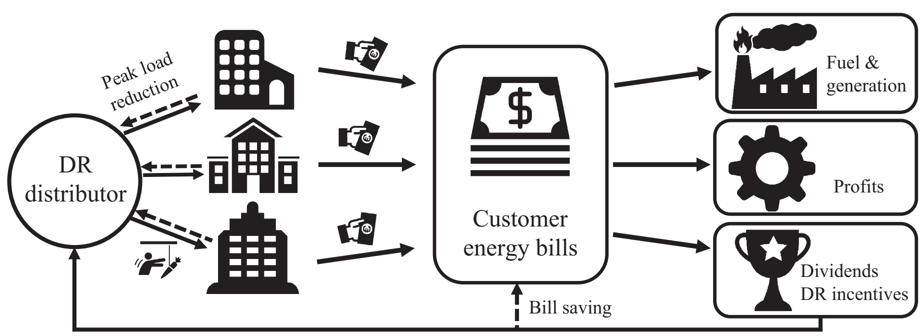

Fig. 6. The mechanism of DR incentivization with performance-based dividends, which uses a portion of the retailer's profits as rewards to buildings based on their peak load reduction performance.

4.2. DR incentivization

Time-differentiated rates bring about changes in customers' energy consumption by differentiating prices during peak and off-peak hours. The targeted change patterns, or load shaping, are described by:

$$a^t_{\min} E^{\text{curt,ref}}_{t,b} \leqslant E^{\text{curt}}_{t,b} \leqslant a^t_{\max} E^{\text{curt,ref}}_{t,b} \quad (8)$$

where $a^t_{\min}$ and $a^t_{\max}$ are design parameters indicating the ranges of actual loads when the retail rates are in effect; for instance, normal load conditions typically correspond to $a^t_{\min} = 0.85$ and $a^t_{\max} = 1.1$ [42], while load reduction requires $a^t_{\min} < a^t_{\max} < 1$. Occasionally, in response to unusual events, the retailer can employ additional incentive/penalty terms, β^{DR}_t, in tandem with the regular retail rates to induce further changes in loads, as predicted by the curtailable load model (6).

While the success of DR relies on customer engagement, in practice, interest in switching to RTP rates wane due to a lack of financial incentives and increased exposure to market volatility [55]. One viable strategy is to motivate DR participation by offering guarantees of energy bill reduction. As discussed in Section 3.2, this can be achieved by dictating the "K factor" to be less than one when setting the rates (P0); however, experiments show that this strategy often yields inefficient pricing, and even leads to a significant loss of profits for the retailer.

Our proposal (Fig. 6) allows an initial increase in customer energy payments, but later compensates the customers with performance-based dividends, which serve several purposes: (1) alignment of the financial interests of stakeholders; (2) incentivization of DR; (3) protection of customers, e.g., low-income families, by reducing their bills.

The performance-based dividends are calculated relative to a baseline, which is usually the flat rate pricing. First, assuming baseline loads, any increase in energy bills due to RTP is compensated. This ensures non-increasing bills for customers who opt for RTP over flat rates. Second, a share of retailer's total fuel cost savings is distributed among DR participants. The amount that each building receives is proportional to its contribution to total peak load reduction of the community, though it is possible to factor customer type and income levels into the distribution weights.[3] As ancillary services are usually scheduled by the ISO a day ahead and called upon as needed on short notice, the scheme is able to introduce added flexibility to MG load responses, thus improving services to the grid [55].

5. Experimental setup

This section presents the data for solar irradiation, building loads, and energy prices. We also specify six (6) campus scale

[3] For instance, if the bill for a customer enrolled in RTP is $92 but would be $90 under the flat rate, then he would be compensated by $2 to bring down the bill. If, in addition, the building contributes 50 kW out of 1000 kW of total peak load reduction of the community, and the cost savings of the retailer is $200, then, with a sharing rates of 0.5, an additional $5 rebate will apply, leading to a reduced bill of $85.

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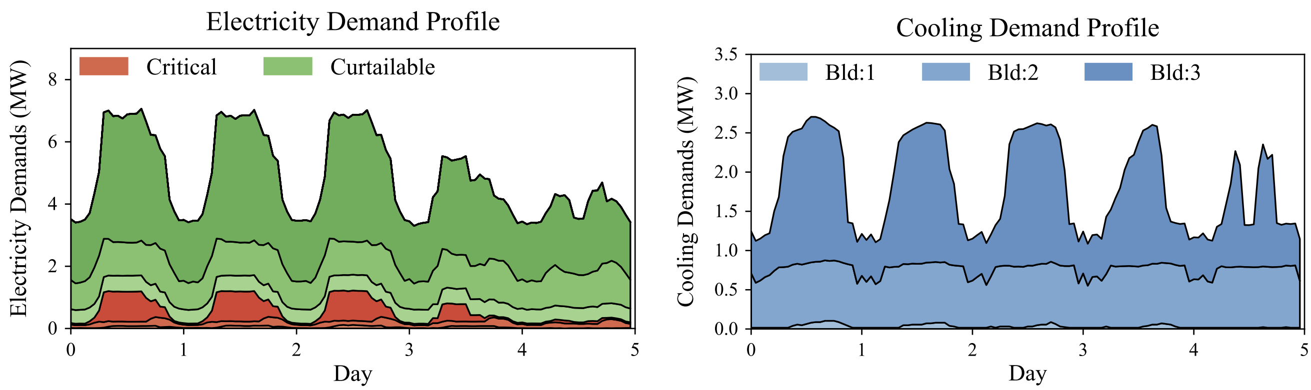

Fig. 7. Electricity load profiles (left), which display the critical loads (red) and curtailable loads (green), for three buildings (different shadings). Cooling demands (right) for the buildings in a stacked plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Building elasticity parameters for off-peak hours (12 am–7 am, 7 pm–12 am), mid-peak hours (7 am–11 am, 5 pm–7 pm), and on-peak hours (11 am–5 pm) in the summer period, where cooling loads are dominant.

	Off-peak			Mid-peak			On-peak		
	Elec.	Heat	Cool	Elec.	Heat	Cool	Elec.	Heat	Cool
B1	−.1	−.2	−.2	−.3	−.3	−.3	−.46	−.4	−.4
B2	−.12	−.22	−.2	−.32	−.35	−.3	−.48	−.45	−.4
B3	−.15	−.24	−.2	−.34	−.4	−.3	−.5	−.5	−.4

MGs with different generators to serve three buildings with electricity, cooling and heating.

5.1. Dataset

Solar irradiation. The TMY3 dataset [56] is queried for the Global Horizontal Irradiance (GHI) index.[4] in Oakland, California (Fig. 9) to determine PV outputs.

5.1.1. Building loads

The load data is retrieved from the Open Energy Information (OpenEI) for a research facility (Bld:1),[5] a large hotel (Bld:2), and a commercial building (Bld:3).[6] During the period of study, i.e., May, the thermal loads are predominantly for cooling (Fig. 7). The elasticity parameters (Table 1), prudently derived from [2,41,42], differentiated responses in off-/mid-/on-peak hours and building types.

Electricity and gas prices. The electricity spot price is accessed from the National Grid Online Database[7] and adapted to be similar to the California wholesale market and to reflect the time of use rates (Fig. 8). The natural gas price, which according to the U.S. Energy Information Administration[8] experiences less fluctuations throughout the month, is assumed to be at a constant level of 0.03$/kW h.

5.2. MG specification

We have prototyped six (6) MGs with different generation capacities (Table 2). MG1 is considered as the baseline, which imports electricity from the grid and provides heating and cooling energy by a NG boiler and an electric chiller. The aim of the rest of the prototypes is to study the effects of energy storage (MG2 vs. MG1), renewables (MG3 vs. MG1), CHP and absorption chiller (MG5 vs. MG4), and grid imports (MG6 vs. MG5) on operations.

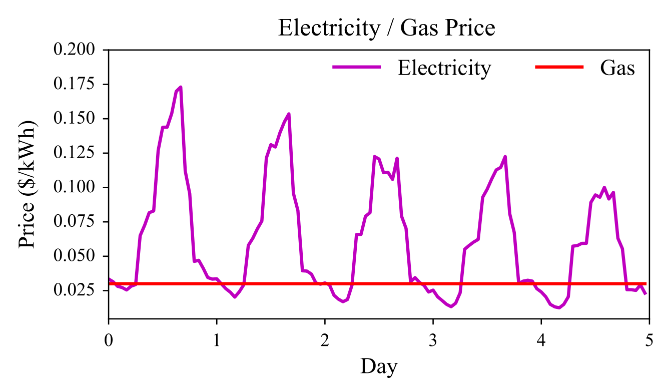

Fig. 8. Electricity and natural gas tariffs, where the spark spread is mainly driven by the daily fluctuation of electricity prices. Data sources: see Footnotes 7 and 8.

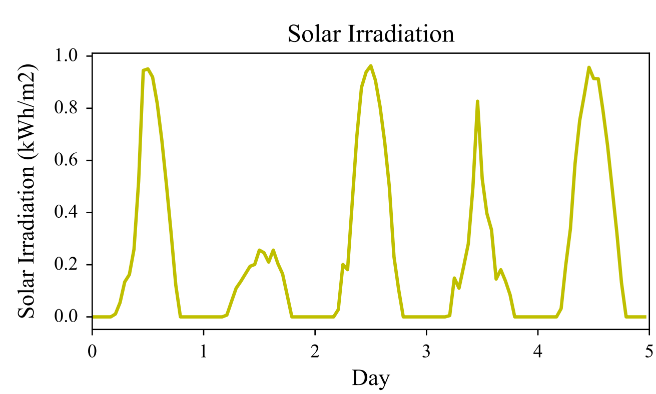

Fig. 9. Solar irradiation measured by the GHI index (kW h/m^2) on several days of the study period, which clearly exhibits diurnal patterns.

[4] GHI, measured in 1 kW h/m^2, is the total amount of direct and diffuse solar radiation received on a horizontal surface during the 60-min period.
[5] NREL RSF Measured Data 2011, accessed: 10/2016.
[6] OpenEI Load Profiles, accessed: 10/2016.
[7] National Grid Online Database, accessed: 10/2016.
[8] U.S. Energy Information Administration, accessed: 10/2016.

Table 2
MG specifications. The storage capacities follow the format of heating storage/cooling storage/electric battery. Four discrete CHP plants are considered. The modeling and specifications of generator technologies can be found in [18]. For those MGs with grid imports, they can also function as islands.

	NG boiler	Electric chiller	Storage	PV	Solar thermal	Absorption chiller	CHP	Grid import
MG1	5 MW	10 MW						Yes
MG2	5 MW	10 MW	1/1/4 MW					Yes
MG3	5 MW	10 MW		1.5 MW	.75 MW			Yes
MG4	5 MW	10 MW	1/1/4 MW	1.5 MW	.75 MW			Yes
MG5	5 MW	10 MW	1/1/4 MW	1.5 MW	.75 MW	10 MW	1.5/2/3/4 MW	Yes
MG6	5 MW	10 MW	1/1/4 MW	1.5 MW	.75 MW	10 MW	1.5/2/3/4 MW	No

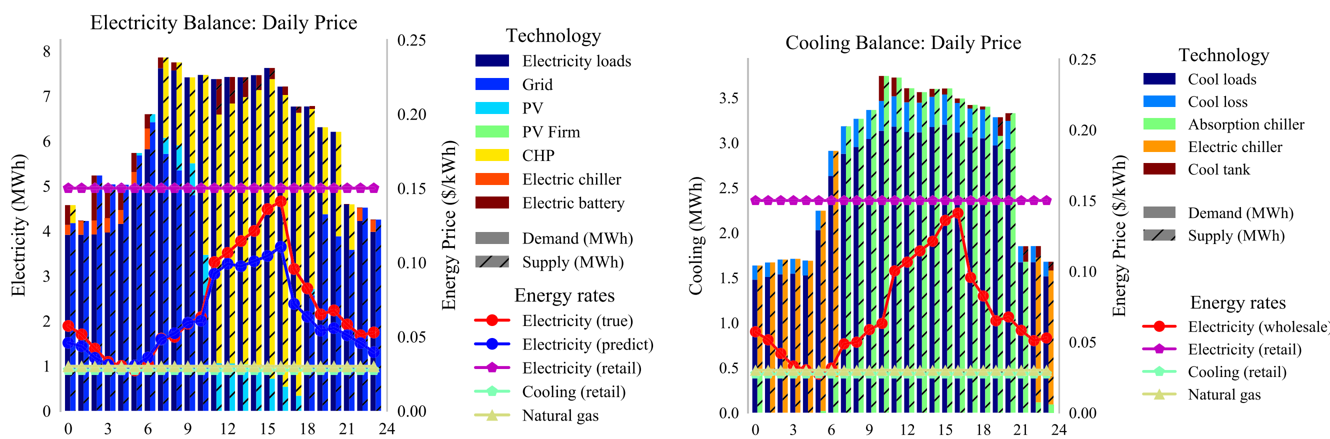

Fig. 10. Electricity and cooling balances with daily flat rates. The graph also shows the forecasted and true wholesale price, as well as the natural gas rates. Since the experiment is conducted during the summer, the heat balance is not shown due to insignificant loads.

The core MIQP programs (P0) are built in Python and solved by Gurobi. The following experiments are performed on a MacBook with a 2.8 GHz Intel Core i7 CPU and 16 GB RAM memory.

6. Scenario analysis

This section studies the impact of optimal dispatch and pricing on system economy and reliability. First, the scenario without DR is examined with fixed retail rates (Section 6.1). The DR option is enabled in Section 6.2 by jointly optimizing rates and dispatch.

6.1. Energy dispatch and uncertainty effect

This section demonstrates the optimal energy dispatch planning of MR-POD while keeping retail prices fixed. Several observations can be made about the energy dispatch plan (Fig. 10) for MG4, which includes CHP, storage, and PVs: (1) the predicted spot price follows the trend of the true spot price[9]; as a result, (2) the battery takes advantage of its variation by charging during the night (off-peak) and discharging during the afternoon (on-peak); also, (3) CHP and the absorption chiller are dispatched for electricity and cooling generation to exploit the spark spread.

By comparison (Table 4, "Daily" columns), given the same revenue from customer bills, MG1–or the baseline–earns the least profit, whereas MG5 brings in the most profit, which exceeds MG6 that operates in "island-mode". This illustrates the energy cost reduction offered by storage, renewables, and CHP, which is in alignment with our previous findings [18].

The uncertainty effect of solar and electricity prices is studied by collating the daily profit loss with the forecasting error[10] (Fig. 11). We can see that there is a positive correlation between profit loss and forecasting error. Since the dispatch of CHP relies on accurate prediction of the spark spread, the effect of wholesale spot price forecasting error is more pronounced for MG5 than both MG2 and MG4. This result is in alignment with the findings from [31]; however, their studies incorporated the situation with only electricity loads and no distributed generation capacity, and the forecasting errors were simulated from a noise model rather than derived for state-of-the-art predictors.

6.2. Optimal retail pricing strategies

The central question in this section is: "How can the retailer strategize its operation and retailing to promote mutual benefits for its customers and the grid".

Firstly, we investigate the benefits of time-differentiated rate structures with elastic building loads (Table 1) and practical-oriented pricing constraints (Table 3). The DA electricity and thermal rates are evaluated over a month during the summer, as illustrated in Fig. 12 for MG4 and Fig. 13 for MG5 (which differ by the installation of CHP plants), where the monthly average and 90% confidence interval of the retail prices and true/predicted spot prices are shown. While the optimal RTP and TOU rates share similar trends, RTP exhibits more flexibility for accommodating hourly fluctuations in loads and spot prices. Prices are relatively stable over the month, which reduces customers' risks of exposure to the wholesale market volatility. One crucial difference between the rate profiles of MG1 to MG4 and that of MG5 and MG6 is focused on the peak hours (see Figs. 12 and 13). For MGs that rely

[9] To reduce uncertainty in the spot market and solar irradiation, an OLS forecast combination scheme based on an array of forecasters (Gaussian process, support vector regression, multi-layer perceptron, etc.) is employed, which use a month of data for training and to make day-ahead predictions.

[10] The forecasting error is measured by the root mean squared error (RMSE), given by $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$, with y_i and $\hat{y}_i$ denoting the true and predicted values at time $i\in\{1,\ldots,n\}$.

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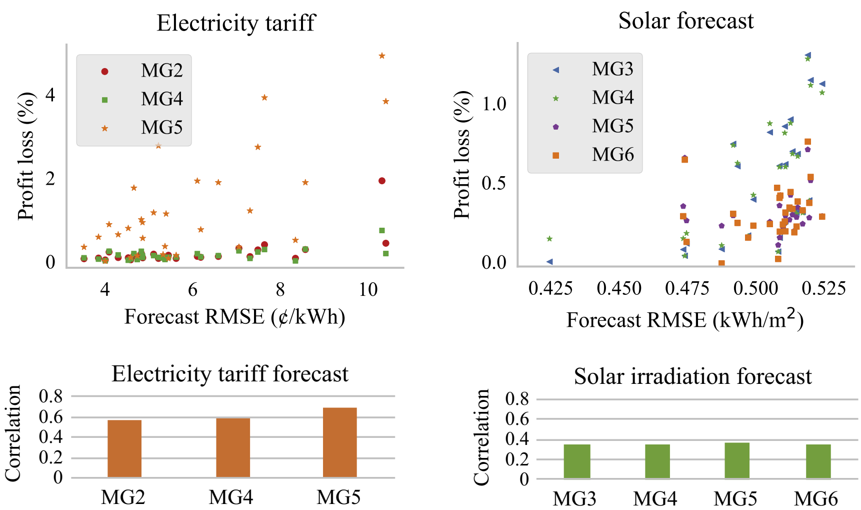

Fig. 11. Top panel: scatter plots of the profit loss against electricity tariff (left) and solar (right) forecast error. The baseline is an oracle that uses true electricity tariff and solar irradiation for dispatch and pricing. Bottom panel: Pearson correlation between profit loss and forecast error. A positive number closer to 1 occurs when the two random variables follow similar trend.

Table 3
Parameters of optimal rate design. Each parameter category is followed by the equation reference. For hourly rates limits, $\hat{y}_t^E$ is the predicted wholesale tariff at hour t. The unit for rates-related quantities is $/kW h.

	Electricity	Thermal
Hourly change cap (1)	$\delta_E^{\text{diff}} = 0.2$	$\delta_{H,Q}^{\text{diff}} = 0.1$
Hourly rates limits (2)	$r_t^{\max} = 0.3, r_t^{\min} = \min(0.05, \hat{y}_t^E)$	$r_t^{\max} = 0.05, r_t^{\min} = 0.01$
Daily rates limits (2)	$r_{\text{avg}}^{\max} = 0.15, r_{\text{avg}}^{\min} = 0.05$	$r_t^{\max} = 0.15/\text{COP}, r_t^{\min} = 0.01$
K factor (3)	$K = 1.2$ (unless otherwise specified)	
Energy coupling (4)	COP = 3.0 for both heating and cooling	
Reference rates (6)	$p_t^{E,\text{ref}} = 0.15$	$p_t^{H,\text{ref}} = 0.036, p_t^{Q,\text{ref}} = 0.028$
DR requirements (8)	$a_{\min}^t = 0.85, a_{\max}^t = 1.1$	
TOU groupings	off-peak: 7 pm–7 am, mid-peak: 7 am–11 am, 5 pm–7 pm, on-peak: 11 am–5 pm	
DR dividends	customer share 50% of retailer profits (Section 4.2)	

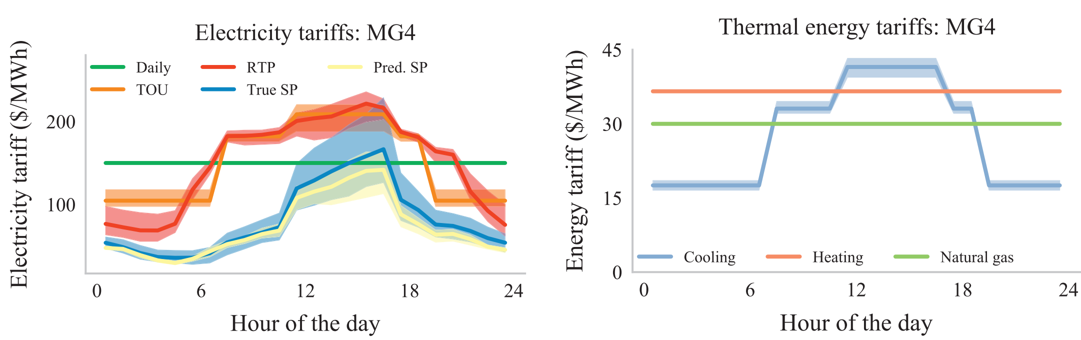

Fig. 12. Optimized electricity (left) and thermal (right) retail rates under different pricing structures (Daily, TOU, RTP) for MG4. The shading indicates 90% confidence interval. Both the predicted and true wholesale electricity tariffs are shown.

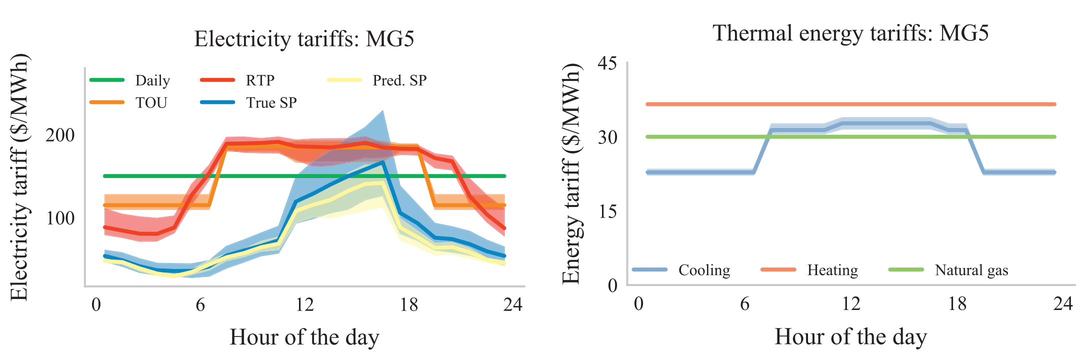

Fig. 13. Optimized electricity (left) and thermal (right) retail rates under different pricing structures for MG5.

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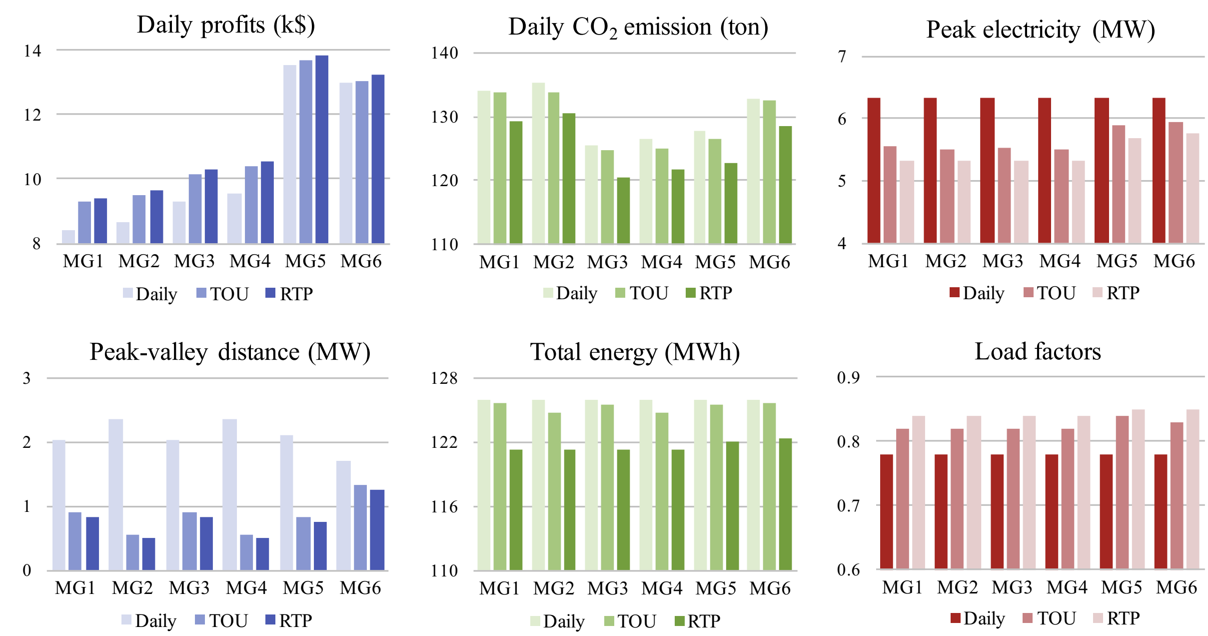

Fig. 14. Comparison of different dynamic rate structures (Daily, TOU, RTP) for MGs, based on the economic (daily profits), environmental (CO_2 emission, total energy), and reliability (peak electricity, peak-valley distance, load factors) indicators.

Table 4
Scenario analysis result summary. The reported daily values for the cost of generation, profits, and CO_2 emissions are averaged over 30 days period. Compared to the baseline model that uses flat daily retail rates (Section 6.1), the percentage differences are shown in the parenthesis. Graphical illustrations for other indicators, such as peak electricity and load factors, are shown in Fig. 14.

	Cost of generation (k$)			Profits (k$)			CO_2 emissions (ton)		
	Daily	TOU	RTP	Daily	TOU	RTP	Daily	TOU	RTP
MG1	11.9	11.0(−7.6%)	10.9(−8.4%)	8.4	9.3(+10.3%)	9.4(+11.9%)	134	133(−0.7%)	129(−3.7%)
MG2	11.7	10.8(−7.7%)	10.7(−8.5%)	8.6	9.5(+10.5%)	9.6(+11.6%)	135	134(−0.7%)	130(−3.7%)
MG3	11.0	10.1(−8.2%)	10.0(−9.1%)	9.3	10.2(+9.7%)	10.3(+10.8%)	125	124(−0.8%)	120(−4.0%)
MG4	10.8	9.9(−8.3%)	9.8(−9.3%)	9.6	10.4(+8.3%)	10.6(+10.4%)	127	124(−2.4%)	121(−4.7%)
MG5	6.8	6.6(−2.9%)	6.5(−4.4%)	13.5	13.7(+1.5%)	13.9(+3.0%)	128	127(−0.8%)	123(−3.9%)
MG6	7.3	7.3(0%)	7.1(−2.7%)	13.0	13.1(+0.8%)	13.2(+1.5%)	133	133(0%)	128(−3.8%)

on grid imports for electricity provision, the retail price *peaks along with the spot price* to reflect the increased cost of generation, while this increase in rates is absent for MGs that can use natural gas as an alternative source. Indeed, as is shown in the previous section, CHP is dispatched when the grid electricity is expensive (Fig. 10).

The economic and environmental impacts are assessed (Fig. 14 and Table 4), illustrating increased daily profits and reduced total energy and CO_2 emission.[11] To gain insights into the impact on MG-level efficiency, we study the measures of peak electricity usage, peak-to-valley distance and load factors, which indicate the average peak loads (11 am–5 pm), the difference between peak loads and valley loads (7 pm–7 am), and the ratio between the average loads and peak loads, respectively. The RTP scheme is shown to significantly bring down peak loads and peak-to-valley distance while raising the load factors, which lessens the burden of the MG to invest in peak capacity and improves resource management and system reliability. Above all, RTP is shown to improve the economics more significantly over the daily rates when CHP is not present, due to the substantial reduction in peak hour loads that lowers the cost of generation (see Table 4 for MG1–MG4).

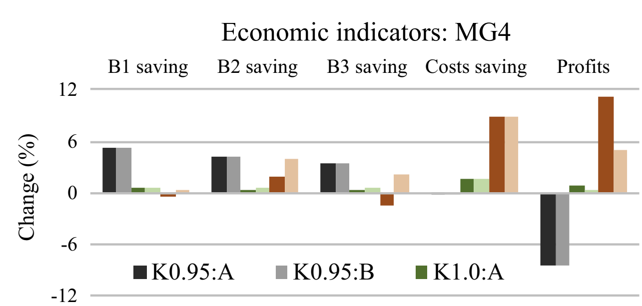

Fig. 15. Economic indicators of building bill savings, cost savings, and profits increase (percentage) for different K factors (0.95, 1.0, 1.2). Scheme A and B represent the indicators before and after the performance-based dividends are rewarded to each building (Fig. 6). With K factor of 0.95, while buildings can enjoy substantial bill savings, the retailer incurs a profit loss of −8%. By introducing more flexibility in rate setting, e.g., K factors of 1.2, both consumer bill savings and retailer profits will improve after the performance-based dividends.

Next, we evaluate the performance-based dividend strategy outlined in Section 4.2 to promote customers' participation in RTP and demand response. Three rate settings (K factors 0.95, 1.0, 1.2) are considered. Fig. 15 illustrates the percentages of customer bill savings, energy production cost saving, and retailer profit increase for MG4 before (denoted as A) and after (B) the dividend. Customers achieve the most significant bill saving under the

[11] The profit is calculated as the revenue minus the fuel cost, e.g., electricity from the grid or natural gas, which also include the dividends for the buildings due to DR. The total energy consumption includes daily electricity and thermal energy demands. The CO_2 emission is estimated from the use of grid electricity (0.98kgCO_2/kW h) and natural gas (0.55kgCO_2/kW h).

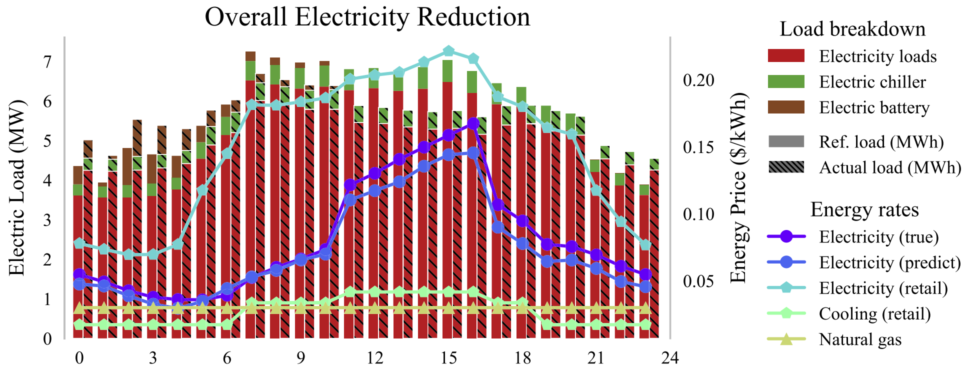

Fig. 16. Overall electricity reduction with RTP rates. During peak hours, the original thermal and electricity loads are reduced (shaded bars) due to the high rates, while some of the loads are shifted to off-peak hours.

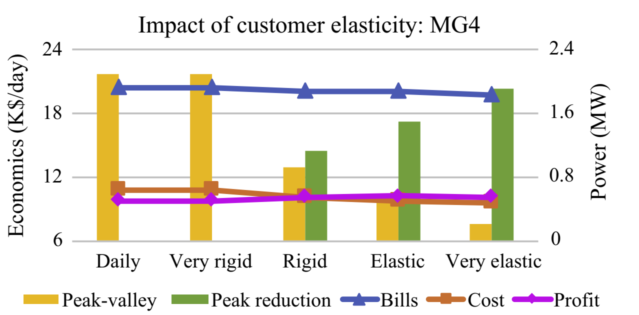

Fig. 17. The economic and system indicators for four different customer profiles (elastic, baseline: elasticity in Table 1, very elastic: elasticity is 2 times the baseline, very rigid: elasticity is 0, rigid: elasticity is 50% of baseline). The performance of the system with elastic demands under daily rates is identical to that with very rigid consumers under RTP. Both indicators are improved with the customers being more elastic.

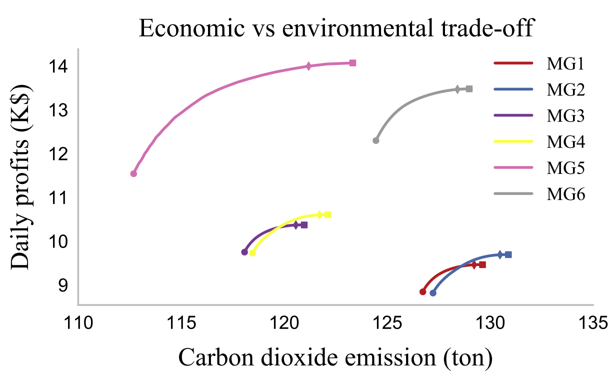

Fig. 18. The trade-off between daily profits and CO_2 emission in MG operations and pricing. The square, diamond, and circle markers indicate λ_{env} being 0, 40, and 1000 $/t$CO_2$e. Clearly, MG5 is at the Pareto frontier, which can achieve more profits with less emissions due to the capability of fuel switching.

price setting with K-factor of 0.95; however, the conservative pricing does not induce peak load shedding in order to reduce the retailer generation cost, causing a considerable loss of profits. On the contrary, by allowing more flexibility in pricing (K factor of 1.2), the time-differentiated rates become more effective to reduce peak loads (Fig. 16), whose benefits can be shared among buildings (1 to 5% bill saving) and the retailer (3 to 6% profit increase) through the dividend mechanism. Since most RTP programs in the U.S. are voluntary [48], this offers economic incentives for enrollment.

From the above results, customers with more elastic demands (B2 and B3) are more likely to save, since they tend to reduce more usage when the price is high. To assess the effects of energy load elasticity, four types of profiles are examined, namely, "very rigid", "rigid", "elastic", and "very elastic", which correspond to −100, −50, 0, 100% changes of elasticity parameters in Table 1 for all buildings.[12] There seems to be a positive correlation between the elasticity of customers and energy bill savings, retailer profit increase, and peak load reductions (Fig. 17), indicating the potential benefits of programs like openADR [57] that aim at improving responsiveness to price through building automation [12].

7. MG case study

Due to the increasing penetration of renewables and heightened environmental awareness, it is crucial to ensure economic and environmental viability and system stability. This section demonstrates the capability of MR-POD in addressing the following issues:

- *Case 1:* Environmentally aware pricing and operation
- *Case 2:* Demand response for PV over-generation

The operation of a clean MG that aims to reduce the environmental impact, such as that of greenhouse gas emissions, is often pursued as a positive externality for society. According to a recent report by the World Bank, about 40 national jurisdictions worldwide put a price on carbon, a.k.a. carbon tax, which spans from less than 1$/t$CO_2$e to 131$/tCO_2e [58]. Case 1 focuses on the design of environmentally aware pricing and operation strategies. More specifically, the cost of CO_2 emission can be considered by setting the λ_{Env} parameter in the optimization (P0), which acts as a "virtual carbon tax". The tradeoff between profits and carbon dioxide emission is demonstrated for different MG infrastructures (Fig. 18), which illustrates the *Pareto frontier* in a multi-objective optimization.

The results indicate that there is a limited range of trade-off for MGs with a single fuel source (MG1, 2, 3, 4, 6) that can only control through the price signal, as compared to MG5 that can also perform fuel switching. At a reasonable level of carbon taxes, or 40 $/t$CO_2$e, MG5 can substantially reduce CO_2 emissions while maintaining a high profit. As can be seen in Fig. 19, the use of an electric chiller and grid electricity is replaced by the absorption chiller and CHP at hours 11 pm-2 am, except during hours when the grid electricity price is relatively low to save generation cost. Indeed, the proportion of natural gas consumption significantly rises for

[12] For instance, the electricity elasticity for B1 during off-peak hours would be $-0.1*(1-0.5) = -0.05$ for a "rigid" profile, and $-0.1*(1+1) = -0.2$ for a "elastic" profile.

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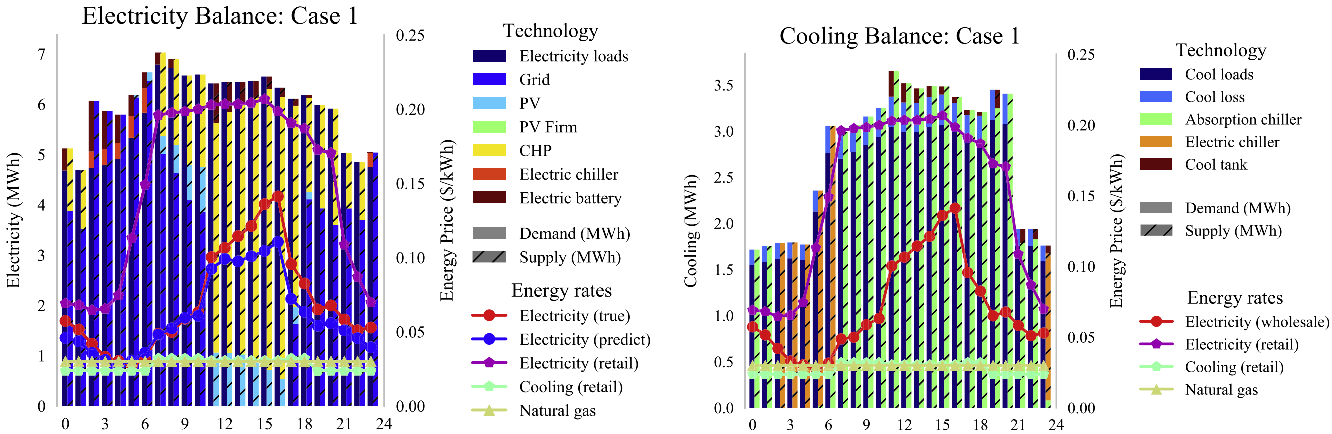

Fig. 19. Electricity and cooling balances with a reasonable level of carbon taxes at 40$/tCO$_2$e. For comparison, the plot is presented for the same day as in Fig. 10, which adopts a flat rate but does not include carbon tax equivalence in its operation.

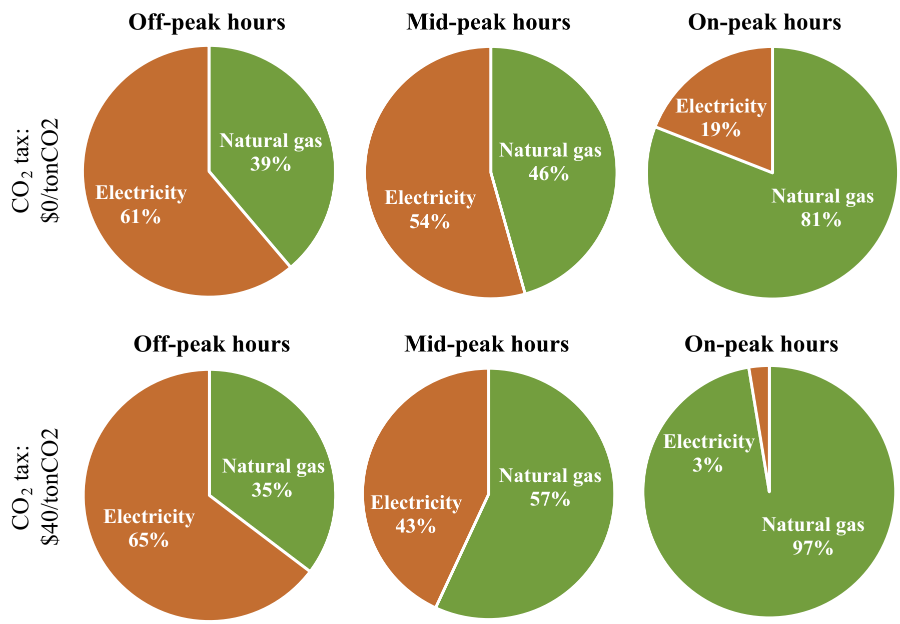

Fig. 20. Fuel mixing during off-, mid-, on-peak hours for a schemes with λ_{env} being 0 and 40$/tCO$_2$e. The latter results in more natural gas usage during mid- and on-peak hours for clean operations. However the usage of natural gas does not change significantly due to off-peak hours, due to the lower price of grid electricity.

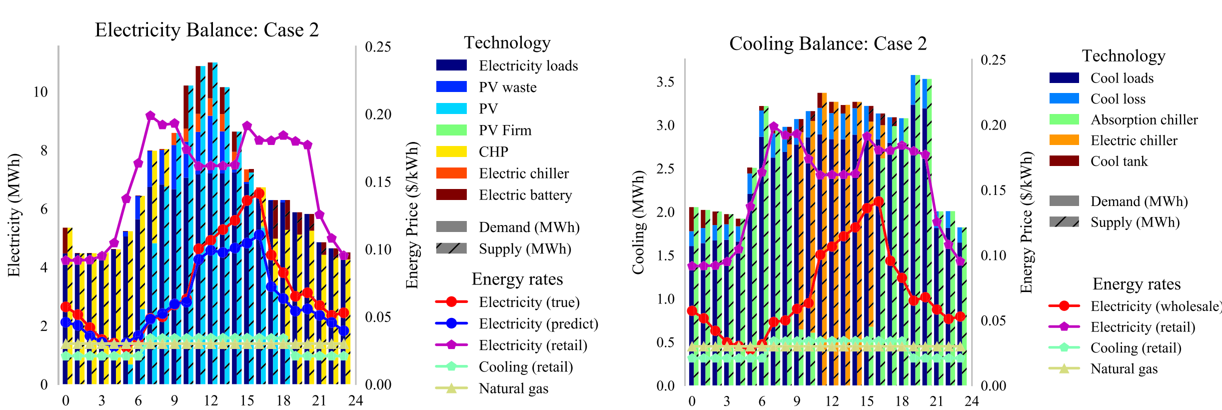

Fig. 21. Electricity and cooling balances under RTP. When there is a PV surplus during the noon, the rates are set lower to encourage flexible consumption while the storage is charged, which reduces the amount of PV curtailment.

environmentally aware operations during mid- and on-peak hours as the spark spread widens (Fig. 20).

By leveraging the natural gas fired, electricity powered devices, and renewable sources within a MG, it is possible to perform fuel switching as circumstances dictate. In particular, *Case 2* focuses on the problem of curtailed electric energy [59], when some of the renewable energy generation must be wasted to keep real-time power balance.

To simulate the case of PV over-generation, MG5 is assumed to have a high level of renewable generation (solar panels with 15 MW rated capacity). Consequently, the problem often arises during a sunny day, when the supply of electricity far exceeds the demand. However, due to the prediction of the event, the retailer can promptly respond by lowering the electricity rates to encourage consumption, in addition to coordinating the charging of battery to shift the excessive generation to the night, which avoids the destabilization of the system and reduces customer bills (Fig. 21). In light of the upward tendency of renewable adoptions, this illustrates the added flexibility of MG enabled by optimal coordination and retail rates setting.

8. Conclusion

In this study, an optimal strategy for energy dispatch and pricing is investigated, which is shown in experiments to promote energy efficiency and MG retailer profitability, bill savings for the customers, and demand response for the grid. Key findings of the study are:

Optimal rate design:

- Time-differentiated rates can be co-optimized with MG dispatch to reflect generation cost. For instance, electricity rates for a MG with CHP are much lower during peak hours than that without CHP, due to the prompt switching to natural gas (see Figs. 12 and 13).
- RTP demonstrates considerable potential in improving profits and load factors while reducing peak loads and environmental impact (Fig. 14 and Table 4). The benefits can be expected to accrue in the long run, as customers tend to adjust their consumption behaviors and make investments in energy efficient products [50].
- The variation of RTP and TOU rates across the month of evaluation is limited, as a result of the restrictions imposed by the pricing mechanism to ensure competitiveness and consumer protection (see Figs. 12 and 13 and Table 3).

Economic dispatch and DR:

- The most significant reduction in operational costs is brought by the CHP plant, which performs fuel switching by exploiting the spark spread when the electricity wholesale tariff is high (Table 4). Natural gas is effective for curbing CO_2 emissions, which can be incorporated in the objective as a trade-off with economic gains (Fig. 20).
- By incentivizing load curtailment during on-peak hours, the proposed DR scheme ensures both profitability and customer bill savings, which in turn encourages participation in DR programs (Fig. 17). In essence, as the retailer's incentives are changed to encourage consumers to conserve energy rather than sell it in ever-increasing amounts, a certain level of decoupling of rates and profits is achieved [47]. This can spur the use of clean and renewable energy resources, and enhance the MG's DR capability.

While energy retailing services provide consumers with more options, it is critical to ensure customer bill reduction, retailer risk management, and proper sharing of revenues among stakeholders [4]. Though retail choices can potentially extend the market penetration of dynamic pricing programs, a main barrier is the recovery of fixed costs for smart metering, communication and control systems. As for DR, the challenges of interoperability among stakeholders, and the security and privacy of customer data need to be addressed in future works [60].

With an increasing penetration of renewables and the advent of electric vehicles as mobile batteries, fundamental changes in utility rate structures are vital. Rate design, for example, can have a substantial impact on the deployment of customer-sited solar [46]. We plan to investigate game-theoretic pricing in future work for MGs with distributed energy resources such as rooftop solar panels and batteries owned by households.

Acknowledgements

This manuscript has been authored by authors at Lawrence Berkeley National Laboratory with the U.S. Department of Energy. This work is also supported by the Energy Foundation China, and the Republic of Singapore's National Research Foundation through a grant to the Berkeley Education Alliance for Research in Singapore (BEARS) for the Singapore–Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) program.

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