Distributed Energy Resource Integration by Dispatch and Retail Optimization

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***Abstract*—While distributed energy resource (DER) integration plays a key role in energy system transformation, it also raises issues of efficiency and reliability. The study exploits flexibility in integrated energy provision and end-user elastic demand to develop an optimal dispatch and energy retail strategy. By modeling DERs such as photovoltaics, combined heat and power, and energy storage, an optimization problem is built to maximize retailer profit while reducing environmental impact. An optimal strategy of dispatch and energy retail is obtained, which satisfies DER physical constraints and electrical and thermal energy balance. The method is evaluated in two case studies: the first investigates the influence of energy retail rates on system efficiency and reliability, and the second examines a mitigation strategy to address oversupply risk due to high renewable penetration. The study provides a framework for incorporating DERs and enable end-user demand response in the future energy retail market.**

***Index Terms*—Distributed energy resource, optimal dispatch, energy retail, smart grid, optimization**

I. Introduction

Distributed energy resources (DER) are small-scale power sources, such as storage and renewable generation, that can be aggregated to meet local demand. DER integration plays a vital role in facilitating ongoing energy system transformation. For instance, in California, key initiatives include [1]:

- Promote renewable power to provide 50% of retail electricity by 2030
- Institute policies to increase distributed generation
- Reduce greenhouse gas emissions to 1990 levels

In the paradigm shift of DER-grid integration, several challenges emerge, such as security and reliability issues caused by voltage rise and renewable power oversupply [1], [2].

To address these challenges, local productive sub-systems like microgrids (MGs) are adopted to improve manageability, energy efficiency, and resilience [3], [4]. The emergence of *energy retail* service enables time-differentiated rates and demand response by end users. Furthermore, as buildings become intelligent agents capable of detecting occupant activities and automatically controlling major loads like heating, ventilation, and air conditioning (HVAC) and lighting [5], demand flexibility has become an increasingly important energy resource [4].

Existing works on DER dispatch often treat the system operator as a non-profit entity who does not sell energy, thus confining microgrid applications to campuses or community-owned generation facilities [3], [4], [7], [8], [9], [10], [11], [12], [13], [14]. Demand response (DR) has been investigated on the transmission side, but is often limited to contracts [14] or direct load controls [4], [15], [16], relying on advanced two-way communication and raises privacy concerns [17], [18].

Differentiated from prior studies, this work promotes DER integration by *exploiting synergies in integrated energy provision and unlocking demand flexibility potential in energy retail* (see components "optimal dispatch" and "optimal energy retail" in Fig. 1). We focus on future smart grid with time-differentiated pricing on the retail side and DERs for local energy production. Key contributions include:

- Modeling of DERs, such as solar panels and combined heating and power, for integrated energy provision
- Development of DER dispatch and energy retail optimization to enhance system efficiency and retailer profit
- Demonstration of time-differentiated rates to improve system efficiency, and dispatch/retail optimization to mitigate renewable power oversupply risk

The rest of the paper is organized as follows. DER dispatch and retail optimization is discussed in Section II. Section III investigates the influence of retail rate structures on system efficiency and a system-wide solution to oversupply mitigation in case studies. Conclusions are drawn in Section IV.

II. DER dispatch and retail optimization

This section focuses on the optimization approach based on DER and demand flexibility modeling, where a practical implementation strategy is also discussed.

A. Problem overview

To support local energy consumption, DER integration should ensure system reliability and efficiency while respecting physical dynamics. The main challenges include:

- Stochasticity and variability of renewable resources
- Coupling of electrical and thermal energy provision
- System-wide balancing due to weather and user activity

Opportunities arise from power facility digitization and building modernization, allowing online generation monitoring and control, and consumer automated response to price signals. Key aspects of our proposal include:

- Storage planning to smooth demand/supply valley/peaks and exploit grid tariff arbitrage opportunities
- DER dispatch to promote synergy between electrical and thermal energy provision

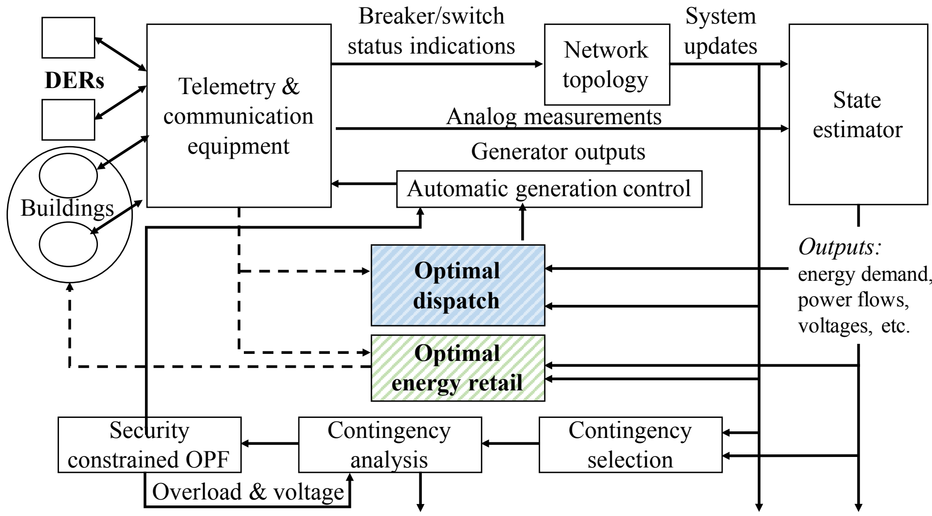

Fig. 1. Power system overview (adapted from [6]), illustrating the key components of optimal dispatch and energy retail for DER integration.

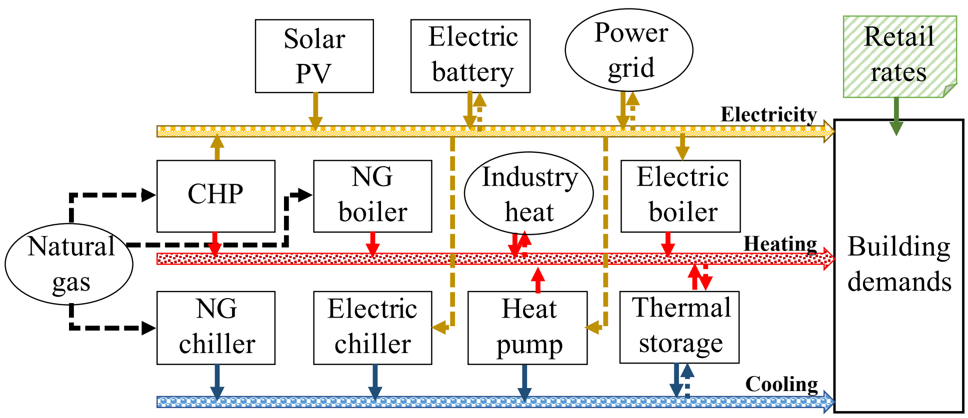

Fig. 2. Interaction of DERs in an integrated energy system to provide electrical and thermal energy through retail service.

- Retail rates optimization to enable demand flexibility as an energy resource

The central problem is therefore:

How to dispatch DERs and design retail rates to achieve efficient and reliable local energy provision?

B. Optimization framework

Consider a day-ahead (DA) planning scenario. The problem can be formulated in an optimization framework, whose inputs are either given (e.g., DER technology specification) or predicted (e.g., solar irradiation, wholesale tariff), and outputs include a dispatch plan and retail rates (see Table I for details).

The objective function to *minimize* includes:

- *Fuel cost* that arises from natural gas and electricity purchases from the wholesale market
- *Revenue* collected from building owners from energy retail (subtracted in the objective function)
- *Carbon dioxide (CO_2) emissions* weighted by a carbon tax or its equivalent to promote emission reduction

TABLE I
INPUT AND OUTPUT VARIABLES IN THE OPTIMIZATION ALGORITHM.

	Variable	Description
Input	DER parameters	specification of DER operation characteristics, e.g., efficiency, rated capacity
	building energy demands	predicted electrical/thermal hourly demands on dispatch day
	solar irradiation	predicted solar irradiation in the region
	electricity tariff	predicted grid tariff for actual dispatch day
Output	DER outputs	dispatch plan for DERs operation status and generation outputs for actual dispatch day
	grid exchange	import/export electricity from/to grid
	fuel imports	hourly natural gas imports
	retail prices	hourly end-user retail prices for electricity, heating, and cooling energy

The objectives are influenced by control variables, such as DER dispatch and retail prices, which are also optimization problem outputs (see Table I).

Constraints considered are as follows:

- *DER operational models* specifying input output relations, as determined by physical characteristics
- *Electrical and thermal energy balance* between supply and demand, including energy transfer among generators (e.g., electricity generated from PV is transferred to electric chiller to produce cold water, see Fig. 2)
- *Elastic building demands* that depend on retail prices
- *Pricing constraints* that specify the upper/lower limits of retail rates for competitiveness and legitimacy

The aforementioned constraints capture the complex dynamics of energy provision and retail, as shown in Fig. 2. Key components, such as DER modeling and elastic demand, are detailed below.

C. DER modeling

Combined heating and power (CHP). The coupling of power and heat production effectuated by CHP makes it economically viable; for instance, more than 99.7% of electricity in Danish energy system originates from CHP and renewables [10]. Thermal energy from burning natural gas in microturbines is converted to electricity. The remaining power, according to the heat-to-electricity ratio (HER), is recovered in part in heat recovery steam generators (Fig. 3). The partial load constraint is imposed in addition to the maximum capacity to comply with desirable operating conditions [10], [19], [20].

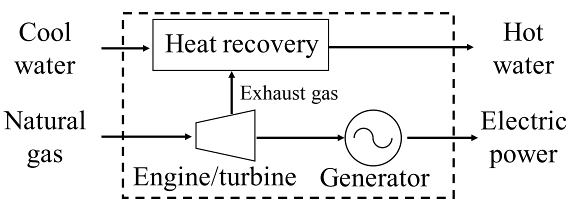

Fig. 3. Modeling of a CHP facility.

Electric, natural gas, and absorption chillers / boilers. Heat from a liquid is removed in a chiller via a vapor-compression or absorption refrigeration cycle, where the input energy can be electricity, natural gas, or heat from steam or hot water (Fig. 4). The coefficient-of-performance (COP) is the ratio between output cooling to input power, typically used to depict the conversion efficiency.

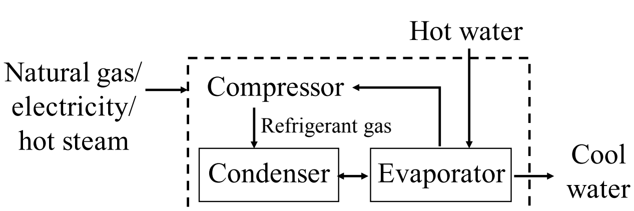

Fig. 4. Modeling of electric and natural gas chillers.

Electric and natural gas boilers are modeled similarly as chiller, that thermal energy is generated from sources of natural gas combustion or electric resistance heating (Fig. 5).

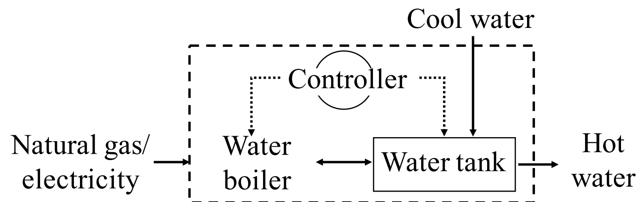

Fig. 5. Modeling of electric and natural gas boilers.

Heat pumps (HP) transport thermal energy from the source to the destination, which decouple the production constraints of the coproduced products while maintaining high energy efficiency [21]. The device can be engaged in either heating or cooling mode (Fig. 6). Additionally, the rated capacity and partial loads requirements are enforced. The effect of temperature difference between the source and destination, or "lift", on COP also needs to be assessed in practice.

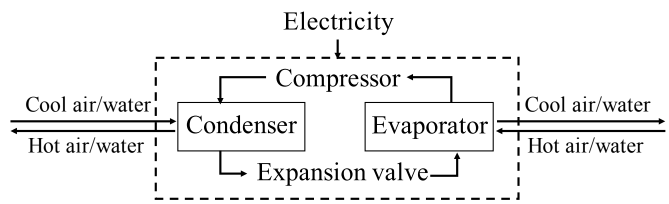

Fig. 6. Modeling of heat pumps.

Solar thermal and photovoltaics (PV) reduce carbon footprints, bringing about wide adoption. The output is modeled to be linearly proportional to the solar irradiation and limited by the production capacity (Fig. 7 and 8).

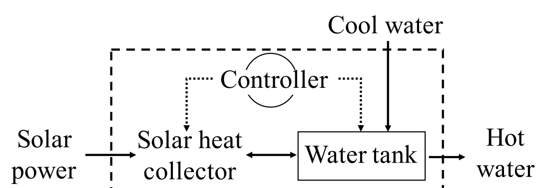

Fig. 7. Modeling of solar thermal.

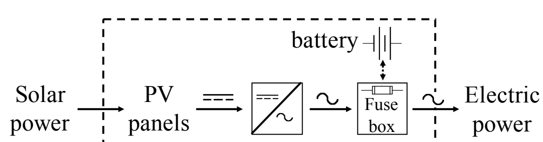

Fig. 8. Modeling photovoltaics.

D. Demand-side flexibility

Consider a community of residential, commercial, and public-service buildings. Energy demands can be broadly categorized as *critical* and *curtailable* loads.

Critical loads must be wholly served at all times. Most electric loads in hospital ICUs, data centers, and critical infrastructures cannot be reduced regardless of the retail price.

On the other hand, curtailable loads can be responsive to price signals. For instance, demand due to HVAC and lighting is curtailable. To characterize the flexibility, a demand elasticity is used, which measures the percentage of load reduction due to one percent of price increase. Several factors influence this parameter:

- Elasticity during on-peak hours is usually higher than that during off-peak hours [22]
- Loads under real time pricing (RTP) rates are more elastic than those under time-of-use (TOU) rates [23]
- Elasticity is usually greater in the long-run when customers can react to a price increase by purchasing more energy efficient appliances [23], [24]. 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 [25].

As energy demands are responsive to retail price, it can be an effective control signal to incentivize peak load reduction.

E. Practical implementation

The optimal dispatch and retail can be implemented as follows (see Fig. 9 for illustration):

1) Acquisition of data related to DER status (e.g., availability and operation conditions), predicted weather, energy demand, and DR contract (Day 1)
2) Decision about dispatch plan and retail rates, announced to generation facilities and consumers (Day 1)
3) Execution of dispatch with real-time recourse adjustment to account for fluctuations in demand and renewable generation (Day 2)

As for the prediction task, an array of data-driven or model-based approaches can be employed. Based on our evaluation, the most accurate and reliable method is "forecast combination", which combines a pool of forecasters to form a "committee", whose suggestions are weighted according to past accuracy. It has been shown to be superior among other candidates for prediction tasks in power scheduling [4].

III. Case Studies

A. Influence of retail rates on system efficiency

For a retailer with DERs such as PV, battery, and CHP (see case A in Table II), considering the following *rate structures*:

- **Daily rate:** flat rate across the day
- **TOU:** three levels in off-, mid-, and on-peak hours
- **RTP:** hourly differentiated rates

The goal is to study how optimized rates under specific structures influence system efficiency, as measured by:

- *Economic factor:* daily profit due to energy retail

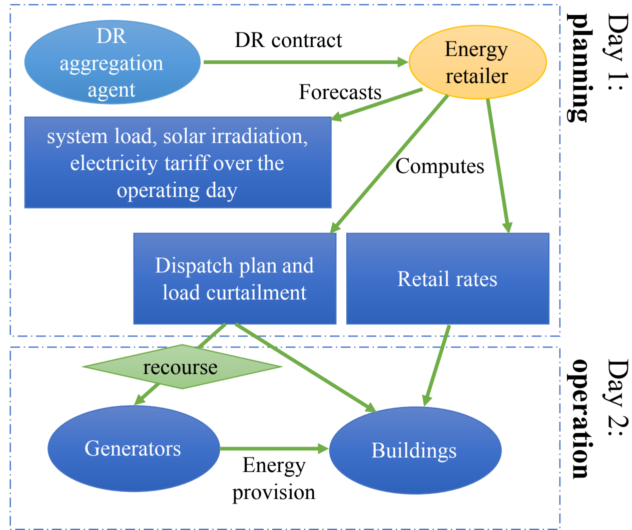

Fig. 9. Implementation strategy of dispatch and retail plans.

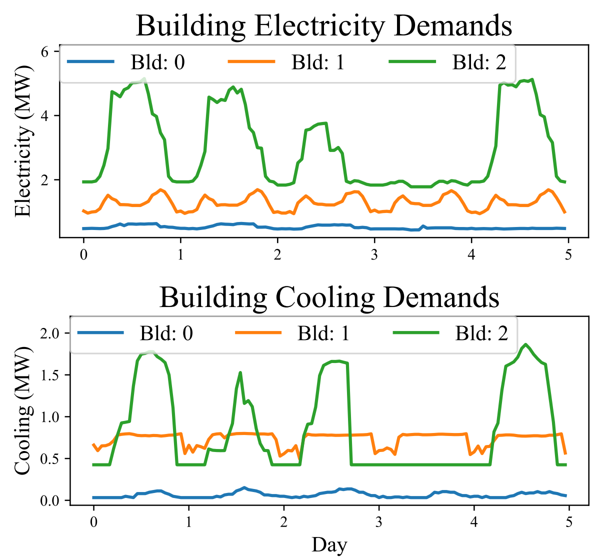

Fig. 10. Electricity (top) and cooling (bottom) load profiles for three buildings.

- *Environmental factors:* community total energy usage and CO_2 emission in energy production
- *System indicators:* peak electricity usage, peak-valley distance (difference between peak and valley usage), and load factors (ratio between average and peak loads)

The optimized retail rates for electricity and thermal energy over a month of evaluation are shown in Fig. 11 (shaded region indicates 90% confidence interval). Based on the results (Fig. 12), main findings are as follows:

- RTP and TOU can capture dynamic energy generation cost, with RTP exhibiting more flexibility in accommodating hourly fluctuations
- RTP and TOU lead to increased retailer profit and reduced total energy and CO_2 emission

TABLE II
CASE SPECIFICATION OF DER TECHNOLOGIES. THE STORAGE CAPACITIES CORRESPOND TO HEATING/COOLING/ELECTRIC STORAGE. THE PARAMETER SPECIFICATIONS CAN BE FOUND IN [4].

	NG boiler	Electric chiller	Storage	PV	Solar thermal	Absorp. chiller	CHP
A	5MW	10MW	1/1/4MW	1.5MW	.75MW	10MW	1.5/2/3/4MW
B	5MW	10MW	1/1/4MW	15MW	.75MW	10MW	1.5/2/3/4MW

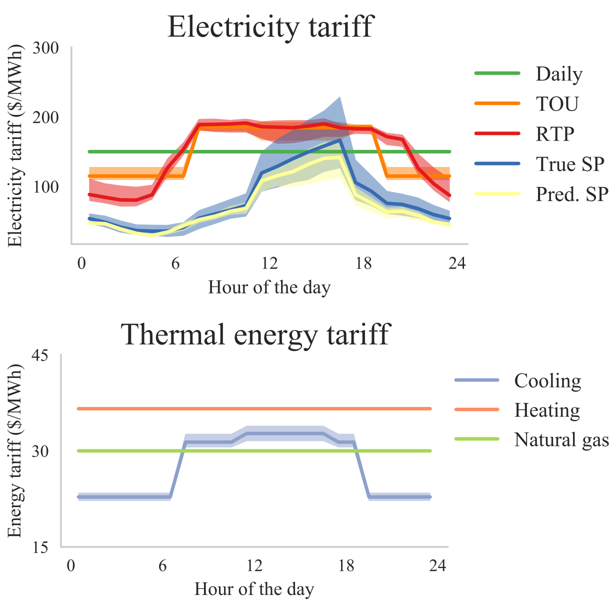

Fig. 11. Optimized electricity (top) and thermal (bottom) retail rates under different pricing structures in case A.

- According to system indicators like peak-valley distance, load factors, and peak usage, time-differentiated pricing improves resource management and system reliability

In summary, time-differentiated rates exploit demand flexibility as an energy resource, a capability that can be enhanced in the future with the adoption of internet-of-things (IoT) devices to enable automated price response mechanism.

B. System-wide solution to mitigate oversupply risk

Oversupply arises as more renewable energy is added to the grid but demand for electricity does not increase. As indicated by the "duck curve" (Fig. 13) identified by California Independent System Operator (CAISO) [1], the risk is heightened as net load drops (the difference between forecasted load and expected electricity production from variable generation resources).

The scenario is illustrated in Fig. 14 for a local energy system with substantial renewable generation capacity (see case B in Table II), when total energy demand is lower than electricity generated from PVs.

To mitigate oversupply risk, a system-wide solution from both DER and consumer sides is proposed to optimize dispatch and retail (Fig. 14). Key findings are as follows:

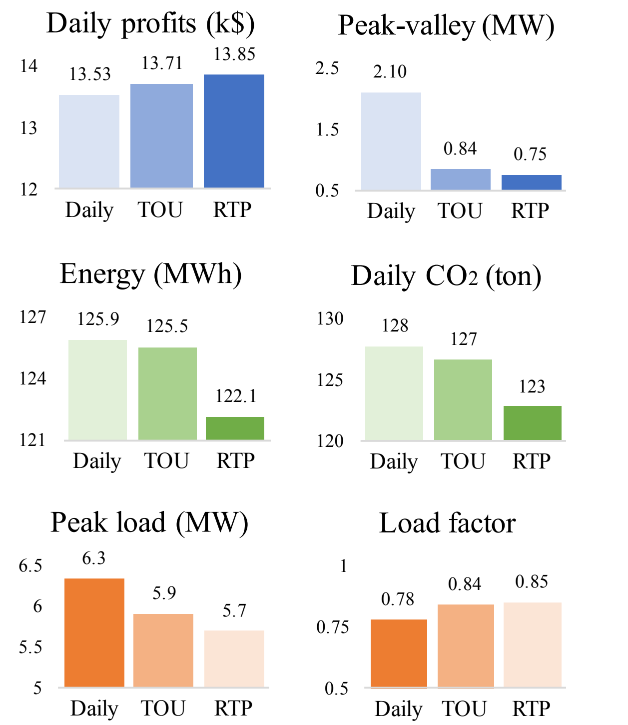

Fig. 12. Evaluation results of daily, TOU, and RTP rate structures on system efficiency and reliability metrics.

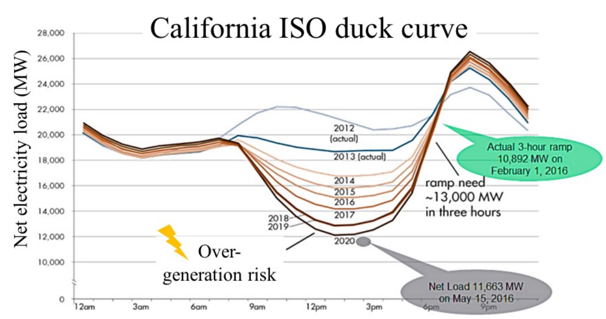

Fig. 13. Illustration of California "duck curve", adapted from [1].

- Retail rates are lowered during noon time to encourage consumption, e.g., electric vehicle charging
- Electricity generation is switched predominantly to PV panels, as CHP is turned off
- Electric battery is charged during noon to "shift" the excessive generation to night time

In summary, an effective mitigation strategy can be developed by utilizing flexibility enabled by elastic demand, energy storage, and fuel switching.

IV. CONCLUSION

This study investigates integration of DERs to meet local community energy consumption while optimizing dispatch and energy retail. DER modeling provides abstractions of physical constraints to be incorporated into an optimization,

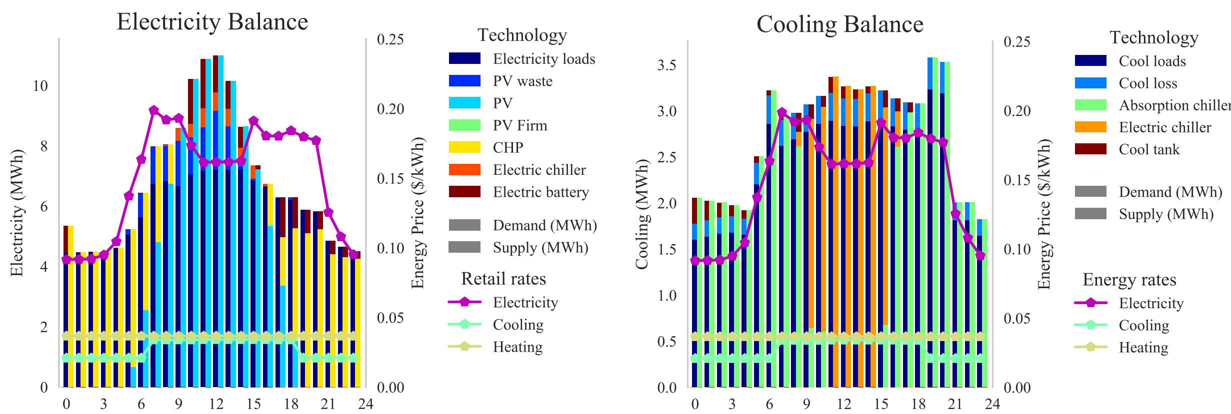

Fig. 14. Electricity and cooling dispatch to mitigate PV overgeneration during the noon. The graph also shows the energy retail rates, which exhibits a "dip" during noon to encourage consumption. Since the experiment is conducted during the summer, the heat balance is not shown due to insignificant loads.

where the objective is to increase retailer profit and reduce environmental impact. The method is evaluated in two case studies: the first study shows that time-differentiated pricing can effectively improve system efficiency and reliability, and the second study illustrates a solution that coordinates both supply and demand sides to mitigate renewable overgeneration risk. The study facilitates DER integration and enables end-user demand response to support a more efficient and reliable power grid. In the future work, we are investigating the privacy and security aspects of the deregulated market scheme, such as against potential cyber attacks [26].

References

[1] California Independent System Operator Corporation, "What the duck curve tells us about managing a green grid," https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf, accessed: 2017-6-20.

[2] P. D. Ferreira, P. M. Carvalho, L. A. Ferreira, and M. D. Ilic, "Distributed energy resources integration challenges in low-voltage networks: Voltage control limitations and risk of cascading," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 82–88, 2013.

[3] T. Niknam, R. Azizipanah-Abarghooee, and M. R. Narimani, "An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation," *Applied Energy*, vol. 99, pp. 455–470, 2012.

[4] M. Jin, W. Feng, P. Liu, C. Marnay, and C. Spanos, "Mod-dr: Microgrid optimal dispatch with demand response," *Applied Energy*, vol. 187, pp. 758–776, 2017.

[5] M. Jin, N. Bekiaris-Liberis, K. Weekly, C. J. Spanos, and A. M. Bayen, "Occupancy detection via environmental sensing," *IEEE Transactions on Automation Science and Engineering*, vol. 99, pp. 1–13, 2016.

[6] J. McCalley, "Lecture notes EE 553: Steady-state analysis - Power system operation and control," http://home.engineering.iastate.edu/~jdm/ee553/SE1.pdf, accessed: 2017-8-1.

[7] R. Velik and P. Nicolay, "Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer," *Applied Energy*, vol. 130, pp. 384–395, 2014.

[8] A. L. Dimeas and N. D. Hatziargyriou, "Operation of a multiagent system for microgrid control," *IEEE Transactions on Power Systems*, vol. 20, no. 3, pp. 1447–1455, 2005.

[9] Y.-H. Chen, S.-Y. Lu, Y.-R. Chang, T.-T. Lee, and M.-C. Hu, "Economic analysis and optimal energy management models for microgrid systems: A case study in taiwan," *Applied Energy*, vol. 103, pp. 145–154, 2013.

[10] T. Ommen, W. B. Markussen, and B. Elmegaard, "Comparison of linear, mixed integer and non-linear programming methods in energy system dispatch modelling," *Energy*, vol. 74, pp. 109–118, 2014.

[11] A. Hawkes and M. Leach, "Modelling high level system design and unit commitment for a microgrid," *Applied energy*, vol. 86, no. 7, pp. 1253–1265, 2009.

[12] L. Guo, N. Wang, H. Lu, X. Li, and C. Wang, "Multi-objective optimal planning of the stand-alone microgrid system based on different benefit subjects," *Energy*, vol. 116, pp. 353–363, 2016.

[13] A. Baziar and A. Kavousi-Fard, "Considering uncertainty in the optimal energy management of renewable micro-grids including storage devices," *Renewable Energy*, vol. 59, pp. 158–166, 2013.

[14] D. T. Nguyen and L. B. Le, "Risk-constrained profit maximization for microgrid aggregators with demand response," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 135–146, 2015.

[15] G. Ghatikar, S. Mashayekh, M. Stadler, R. Yin, and Z. Liu, "Distributed energy systems integration and demand optimization for autonomous operations and electric grid transactions," *Applied Energy*, vol. 167, pp. 432–448, 2016.

[16] S.-J. Kim and G. Giannakis, "Scalable and robust demand response with mixed-integer constraints," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2089–2099, 2013.

[17] M. Jin, R. Jia, and C. Spanos, "Virtual occupancy sensing: Using smart meters to indicate your presence," *IEEE Transactions on Mobile Computing*, vol. PP, no. 99, pp. 1–1, 2017.

[18] M. Jin, N. Bekiaris-Liberis, K. Weekly, C. Spanos, and A. M. Bayen, "Sensing by proxy: Occupancy detection based on indoor co2 concentration," in *The 9th International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, 2015, pp. 1–14.

[19] M. Badami, M. G. Ferrero, and A. Portoraro, "Dynamic parsimonious model and experimental validation of a gas microturbine at part-load conditions," *Applied Thermal Engineering*, vol. 75, pp. 14–23, 2015.

[20] G. Díaz and B. Moreno, "Valuation under uncertain energy prices and load demands of micro-chp plants supplemented by optimally switched thermal energy storage," *Applied Energy*, vol. 177, pp. 553–569, 2016.

[21] M. B. Blarke, "Towards an intermittency-friendly energy system: Comparing electric boilers and heat pumps in distributed cogeneration," *Applied Energy*, vol. 91, no. 1, pp. 349–365, 2012.

[22] Q. QDR, "Benefits of demand response in electricity markets and recommendations for achieving them," *US Dept. Energy, Washington, DC, USA, Tech. Rep*, 2006.

[23] M. Filippini, "Short-and long-run time-of-use price elasticities in swiss residential electricity demand," *Energy policy*, vol. 39, no. 10, pp. 5811–5817, 2011.

[24] S. Borenstein, "The long-run efficiency of real-time electricity pricing," *The Energy Journal*, pp. 93–116, 2005.

[25] A. Alberini and M. Filippini, "Response of residential electricity demand to price: The effect of measurement error," *Energy Economics*, vol. 33, no. 5, pp. 889–895, 2011.

[26] M. Jin, J. Lavaei, and K. Johansson, "A semidefinite programming relaxation under false data injection attacks against power grid ac state estimation," in *IEEE Annual Allerton Conference on Communication, Control, and Computing*, 2017.