Energy Storage System Dispatching Optimization in Stacked Applications for Utility Grid

Shijie Tong[1], Handa Yangy[2], and William Torre[1]

[1]*Center for Energy Research, University of California San Diego, 9500 Gilman Drive, La Jolla CA, USA*

[2]*Department of Mechanical and Aerospace Engineering, University of California San Diego, 9500 Gilman Drive, La Jolla CA, USA*

Corresponding author: stong at ucsd.edu

***Abstract-* An optimal dispatching algorithm for five different utility grid energy market applications was developed using mixed-integer- linear-programming. This study explores the value propositions of operating an energy storage system (ESS) under each application individually, as well as together, in stacked applications through simulations using market pricing data obtained from the California Independent System Operator. Three different ESSs were simulated at energy-to-power ratios (EtoP) of 2, 4, and 8. In all cases, operation under stacked applications provided the best value proposition, and the effects of EtoP are discussed in light of the current market conditions, as well as potential future market conditions.**

***Keywords-* energy storage systems, dispatching, optimization, mixed-integer linear programming, stacked applications, energy market.**

I. Introduction

Energy storage systems (ESSs) are becoming crucial components in the modern utility grid as electricity sources shift from fossil fuel power plants to more sustainable but intermittent wind and solar resources. An ESS can provide many services to the grid, such as improving power quality, responding to short-term ramping needs, and matching the load with the demand [1], [2]. Techno-economic analysis on energy applications such as frequency regulation (FQ) [3], energy time shifting, and renewable integration [4] has revealed that cost and cycle life are among the most sensitive factors in designing an ESS for the grid. Battke et al. [5] estimated life cycle costs and their uncertainties for different battery technologies and found different technologies take the cost leaderships in specific applications, yet no single technology surpasses over other solutions by a significant margin. In addition to seeking better and more cost effective ESS solutions, it is also important to investigate better value propositions for grid integrated ESSs to achieve higher adoption [6]. Many studies have been conducted on the dispatching of distributed energy resources, solar plus storage systems, and virtual power plants [7]–[10] to improve ESS performances and economic returns. Atzeni et al. [7] developed an optimization scheme for energy storage, implementing non-cooperative game theory to preserve user privacy. Hoke et al. [11] developed a linear programming-(LP) based optimization scheme for economic dispatching of an ESS in a micro-grid. Nottrott et al. [12] investigated LP optimal dispatching of battery and PV system with load forecasting and local time of use (TOU) utility pricing. Soares et al. [13] proposed a particle swarm optimization to solve a distributed energy resource dispatching problem of large dimension. Dispatching optimization under multiple energy storage applications has also been discussed. For example, Pandvzic et al. [8] provided a case study of stacked energy storage applications by combining long-term bilateral contracts and market participation. Other works investigating the stacked-benefits of ESS have been published [14]–[17]. Previous works mostly focused on the co-optimization of two applications, with one emphasizing on power and the other on energy [15], [16]. In addition, previous works often identified one application as the primary service and treated others as secondary applications in the optimization process [14]. Our work took a market-oriented approach and investigated suitable energy applications at a broader spectrum by considering energy storage service products across retail and wholesale market sectors, with three different pricing tariffs (i.e., retail TOU tariff, wholesale day-ahead (DA) price, real-time-pre-dispatch price) and five distinctive application products.

By combining multiple energy storage applications, different aspects of an ESS's capabilities, including power, energy and fast response, capacities can be better exercised. By incorporating the product design and pricing data of each application from California independent system operator (CAISO) and local utility - San Diego Gas & Electric, the developed dispatching algorithm will provide real-world guidance for energy-management controller design and help evaluate the benefits of energy storage assets deployed on the grid.

II. Energy Storage Applications

As illustrated in Fig. 1, an ESS was simulated to perform five different energy storage applications (e.g., Demand Charge Management (DC), Energy Time Shifting in the DA market, Energy Time Shifting in the Real-time market (RT), Flexible Ramping (FR), and FQ. The five applications cover both the behind-meter retail market and the front-of-meter wholesale market. They cover both lower uncertainty, steadier return services like bulk energy management, and higher uncertainty, greater return services like power quality regulation. It should be noted that the behind-meter and front-of-meter applications don't typically apply to the same ESS because the battery sizes are significantly different and the price is settled from different meters. For the benefit of investigating the performance of stacked applications, the constraint is lifted in this work.

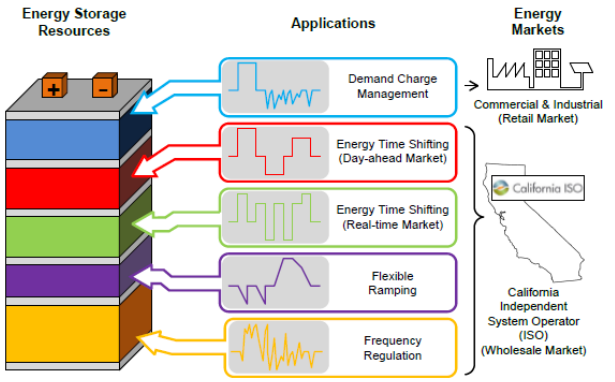

Fig. 1. Five energy storage applications under both retail and whole sale markets; from top to bottom: Demand Charge Management (Blue), Day-ahead Energy Time Shifting (Red), Real-time Energy Time Shifting(Green), Flexible Ramping (Purple), and Frequency Regulation (Orange).

The ***DC*** is an energy service designed for commercial and industrial businesses. The cost of power demand in a billing cycle could be significant because short but large peak load drives up the "demand charge." After implementing an ESS, the demand charge can be reduced by charging an ESS during off-peak usage and discharging during peak usage. If a business is under the TOU tariff, meaning the energy price is different between peak and off-peak hours, the same ESS can also perform energy peak shaving. In this study, a simulated school campus load profile was utilized for the DC application. The average load is 344 kW with a 944 kW peak. During the summer months, from July to September, when school is out of session, the campus will have lower average load demand.

The ***Energy Time Shifting*** application captures the price fluctuation in the market throughout a day, and charges an ESS during off-peak price and discharges during peak price. The DA and RT applications are energy time shifting applications, but implemented in two different market segments. In the DA market, an ESS will submit their bid in the previous day before 10 a.m. The DA market prices are usually more predictable, but the returns are relatively low. In the RT market, an ESS will submit their bid 75 minutes ahead of the clearing interval. The RT price is more difficult to predict, but offers higher potential returns. It fluctuates more, but the returns can be higher.

The ***FR*** products for real-time pre-dispatch and real time dispatch markets were developed in a stakeholder process at CAISO [18]. With the proliferation of renewable resources, the electricity grid has begun to observe a lack of sufficient ramping capability and flexibility. Insufficient ramping capacity on the grid will have to be resolved out of the feasible system-wide schedule or rely on ancillary services and regulation, which will increase the probability of power balance violation. As a result, many utility grids have started considering FR products.

The ***FQ*** is procured by CAISO to obtain regulation capacity each hour, based on the total system-wide demand for power. It is assumed that the system-wide FQ capacity demand is orders of magnitude higher than any single ESS. For that reason, if it is desirable to enter the FQ application, the simulated ESS can procure as much capacity as the ESS allows. The mileage component of the FQ product was created because of a Federal Energy Regulatory Commission order to introduce pay-for-performance measures for regulation products on the grid [19]. The mileage is a way to reward devices that can fluctuate and match load profiles more accurately. It is defined as the sum of the absolute values of the regulation control signal movements.

III. Optimization Algorithm

A mixed-integer linear programming algorithm was implemented to develop the optimization solver. The algorithm dispatches the energy storage resources among the applications by maximizing the revenue (minimizing the cost) from stacked applications:

$$\underset{P,W}{\text{minimize}} \quad J(P,W) \tag{1a}$$

$$\text{subject to } A(P,W) \leq B \tag{1b}$$

$$Aeq(P,W) = Beq \tag{1c}$$

where J is the cost function. A, B, Aeq, Beq are composed matrices to form the inequality and equality constraints. By committing the resources to different applications, the ESS can earn a collective of revenues described in the following equation:

$$J(P,W)=\sum_{i=1}^{N}\sum_{k=1}^{K}J_{ene,k,i}(p_{k,i},w_{k,i}) + \sum_{i=1}^{N}\sum_{k=1}^{K}J_{app,k,i}(p_{k,i},w_{k,i}) \tag{2}$$

For each application, there are two types of revenues: the energy revenue, with subscript ene, is from the price differences between buying and selling energy; the application revenue, with subscript app, is based on the specific service that an ESS performs. k is the application index: $k=1,2,...,5$ refers to DC, DA, RT, FR, FQ applications, respectively. *i* is the time index. For this optimization task, each time step has an interval of 15 minutes and an optimization horizon of 24 hours, which gives *N* = 96. *P* are continuous variables representing the ESS charging and discharging. In each time interval, there could be either charging (with superscript +) or discharging (with superscript −) actions, their differences are the actual ESS power (with superscript 'o'). The ESS power output is confined by the power constraints:

$$p_{k,i}=\{p^o_{k,i},p^+_{k,i},p^-_{k,i}\} \tag{3}$$

$$p^o_{k,i}=p^+_{k,i}-p^-_{k,i} \tag{4}$$

$$0\le p^+_{k,i}\le \overline{p_k} \tag{5}$$

$$0\le p^-_{k,i}\le \underline{p_k} \tag{6}$$

$$0<\sum_{k=1}^{K}p^+_{k,i}<\overline{p_k} \tag{7}$$

$$0<\sum_{k=1}^{K}p^-_{k,i}<\underline{p_k} \tag{8}$$

where $\overline{p_k}$ and $\underline{p_k}$ are power limits for ESS charging and discharging, respectively. And collectively, the ESS's state-of-charge must be limited within the energy constraints:

$$SoC_i=SoC_0+\sum_{i=1}^{n}\sum_{k=1}^{4}\left(\frac{\eta p^+_{k,i}-p^-_{k,i}}{Q}\right)\Delta t + \sum_{i=1}^{n}\frac{\eta\frac{900}{M_i^+}p^+_{5,i}-\frac{900}{M_i^-}p^-_{5,i}}{Q}\Delta t \tag{9}$$

$$\underline{SoC_{bat}}<SoC_{bat,i}<\overline{SoC_{bat}} \tag{10}$$

The time interval Δt is 15 minutes in this study. η is battery round trip efficiency. *Q* is battery capacity. The $SoC_{bat,0}$ is the initial state-of-charge. The $\underline{SoC_{bat}}$ and $\overline{SoC_{bat}}$ are the upper and lower SoC limits, respectively. For FQ application, the reserved power capacity $\frac{900}{M_i^+}p^+_{5,i}$ and $\frac{900}{M_i^-}p^-_{5,i}$ were used instead of the actual clearing power. Five applications were considered for stacking. Based on the product design of each application, additional constraints and revenue models were implemented.

The DC application is the only behind-meter application among the five. Because an ESS needs to be scaled to match the simulated commercial and industrial load data, the power limits for DC application were set to be 100kW Also, because the metering is $(\overline{p_1}=\underline{p_1}=0.1MW)$. separate from the other applications, the DC application can only purchase energy at the local TOU price. One way to apply this restriction is to enforce the daily net *SoC* change to be zero:

$$\sum_{i=t_0}^{t_{end}}\left(\frac{\eta * p^+_{1,i}-p^-_{1,i}}{Q}\right)\Delta t=0 \tag{11}$$

where $t_0=00:00$ and $t_{end}=23:45$ in hh : mm are the start time and stop time. The DC energy revenue (cost) is based on grid consumption reduction:

$$J_{1,ene}=\sum_{i=1}^{N}E_{tou}(p^o_{1,i})\Delta t \tag{12}$$

where E_{tou} is the TOU pricing. The application revenue is based on the cost reduction from demand charge:

$$J_{1,app}=E_{dc}(max(p^o_{1,i}+L_i)-max(L_i)),\, i=1,2,..,N \tag{13}$$

where E_{dc} is the demand charge cost per in $\$/MW$. L is the load consumption. Because the demand charge cost settles monthly, which is a longer optimization horizon compared to the rest of the applications. A simplified approach was implemented to estimate a peak load Lpk for each month, and penalizes the cost function whenever the grid load exceeds the Lpk . The cost function in (11) is now simplified for optimization with shorter interval:

$$J_{1,app}=E_{dc}max\{p^o_{1,i}+L_i-Lpk_i,0\},\, i=1,2,..,N \tag{14}$$

The ***Energy Time Shifting*** applications in the DA market and the RT obtain the energy revenue through buying and selling in the respected markets:

$$J_{2,ene}=\sum_{i=1}^{N}E_{da}(p^o_{2,i})\Delta t \tag{15}$$

$$J_{3,ene}=\sum_{i=1}^{N}E_{rt}(p^o_{3,i})\Delta t \tag{16}$$

where the DA market has a E_{da} bidding interval of 1 hour and the bidding must be submitted 1 day ahead before 10 a.m. to enter the market. The RT utilizes E_{rt} the real-time pre-dispatching price that has a bidding interval of 15 minutes, and the bidding must be submitted 75 minutes ahead to enter the market. Both markets are location specific. In this study, the local marginal pricing data from the La Jolla node (*LAJOLLA_6_N*007) from CAISO were utilized. The dispatcher is also applicable to other locations if the local marginal price of that node is given.

The ***FR*** application energy revenue utilizes the same pricing data as the RT:

$$J_{4,ene} = \sum_{i=1}^{N} E_{rt}(p_{4,i}^{o})\Delta t \tag{17}$$

The application revenue of FR comes from ramping up/down service. Based on the product design, resources will submit FR bidding according to the ramping requirement for the next bidding interval and get paid by the clearing price of the accepted bidding. For simulation purposes, the algorithm utilized the ramping up/down shadow prices from CAISO as the ramping clearing prices and assumed that the ESS always won the bid:

$$J_{4,app} = -\sum_{i=1}^{N}(E_{fr,down}\Delta p_{4,i}^{+} + E_{fr,up}\Delta p_{4,i}^{-})\Delta t \tag{18}$$

$$\Delta p_{4,i}^{+} = max\{(p_{4,i}^{o}) - (p_{4,i-1}^{o}), 0\} \tag{19}$$

$$\Delta p_{4,i}^{-} = max\{-(p_{4,i}^{o}) + (p_{4,i-1}^{o}), 0\} \tag{20}$$

where $E_{fr,down}$ and $E_{fr,up}$ are the FR down and ramping up shadow prices. Δp_4^{+} and Δp_4^{-} are the ramping down and ramping up movements performed in each bidding interval.

The ***FQ***'s application revenue is generated from two types of payments: capacity and mileage. The capacity payment comes from the amount of power capacity reserved for FQ application to dispatch, represented by The mileage payment PC_{fq}. comes from the actual mileage dispatched by the system coordinator. The typical FR control signal has a time interval of 4 s. Given 1 h as an application time interval for FQ, the mileage of a FQ resource output is calculated within the interval, indicated in the following equation as AGC time step *j*, which should not be confused with the higher-level optimization time step *i*:

$$\begin{aligned} M_i^{\pm} &= \sum_{j=1}^{900} \frac{|p_{5,j}^{\pm}|}{PC_{fq,i}^{\pm}} \\ &= \frac{900|p_{5,i}^{\pm}|}{PC_{fq,i}^{\pm}} \end{aligned} \tag{21}$$

Given that the mileage data *M* is available from CAISO market, we can back calculate PC_{fq} based on average power p_5. As a result, the revenue function of FQ application can be represented as:

$$\begin{aligned} J_{5,app} = \\ &(C_{fq}^{+}\sum_{i=1}^{N}\frac{900}{M_i^{+}}p_{5,i}^{+} + C_{fq}^{-}\sum_{i=1}^{N}\frac{900}{M_i^{-}}p_{5,i}^{-})\Delta t \\ &+ (E_{fq}^{+}\sum_{i=1}^{N}900p_{5,i}^{+} + E_{fq}^{-}\sum_{i=1}^{N}900p_{5,i}^{-})\Delta t \end{aligned} \tag{22}$$

where $\frac{900}{M_{i.}^{\pm}}p_{5,i}^{\pm}$ calculates the reserved regulation up/down capacity. $C_{fq}^{\pm}$ and $E_{fq}^{\pm}$ are capacity payment price and mileage payment price respectively. The FQ application's energy revenue utilizes the same pricing data as the DA market.

$$J_{5,ene} = -\sum_{i=1}^{N} E_{da}(p_{5,i}^{0})\Delta t \tag{23}$$

The market data from Jan. 1st to Dec. 31st of 2016 were scraped from the CAISO web API for DA, RT, FR, FQ applications and TOU tariff and demand charge pricing information from San Diego Gas & Electric was utilized for DC application. Since the FR application is under development, the shadow prices for ramping up/ramping down revenue was used instead. A set of forecasted pricing data was generated, by applying time delay and moving average to the true data. For the day ahead market, the signal was estimated using data from 2 days ahead.

$$\tilde{E}_{da,i} = \frac{\sum_{j=1}^{n} E_{da,i-j-191}}{n} \tag{24}$$

For the RT, the signal was estimated using data from one day ahead.

$$\tilde{E}_{rt,i} = \frac{\sum_{j=1}^{n} E_{rt,i-j-95}}{n} \tag{25}$$

IV. Results and Discussion

An ESS model of 1 MW/2 MWh was used $(Q = 2MWh,\, p_k = \underline{p_k} = 1MW)$. The round trip efficiency η is assumed to be 90%. Fig. 2 shows the 7 days of ESS dispatching power profiles among all five applications. The color coded bars (blue: DC, Red: DA, Green: RT Purple: FR

Orange: FQ) indicate whether applications are charging (positive) or discharging (negative) in each time interval.

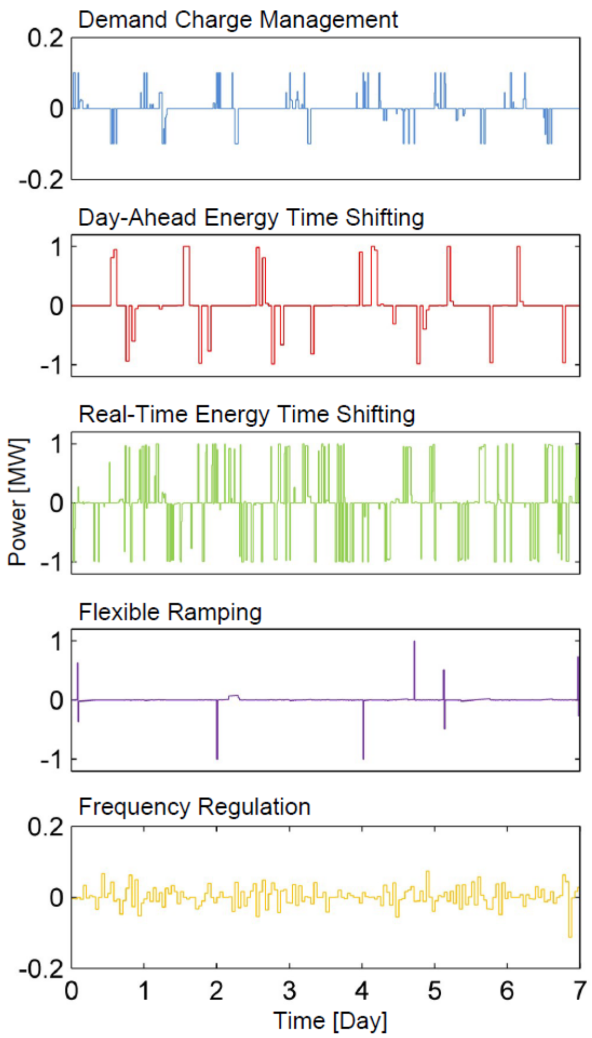

Fig. 2. Dispatching duty cycles of each energy service under stacked applications; from top to bottom: Demand Charge Management (blue), Day-ahead Energy Time Shifting (red), Real-time Energy Time Shifting (green), Flexible Ramping (purple), and Frequency Regulation (orange).

The dispatcher was able to operate the ESS system based on economic incentives of different applications. The DC application mainly reduces the peak load demand. When peak load is not present, it will also dispatch the ESS to perform peak shaving based on the TOU price. The DC application only activates for a short period of time each day. The DA and RT application need to move bulk energy in and out of the ESS, and as a result, they are mutually exclusive and occupy most of the ESS time. For the FR application, when the ramping demand occurs, the ESS will capture it by reserving ramping up or ramping down capacity for the next interval and performing the ramping to earn extra revenue. The FQ application mainly dispatches the ESS's power capacity. It is compatible with the rest of the energy-focused applications and stays active throughout the course of the simulation. As shown in Fig. 3, for stacked and single use applications, their power profile and energy throughput are largely similar. Under stacked applications, a 1 MW/2 MWh ESS will dispatch about 2 cycles per day and earn average revenue of $398 each day, over 100% more compared to only participating in the RT application, at the similar cost of ESS usage. Further simulation was conducted of three ESSs of the same peak power (1 MW) and round trip efficiency (90%) but at different EtoP of 2, 4, and 8 respectively.

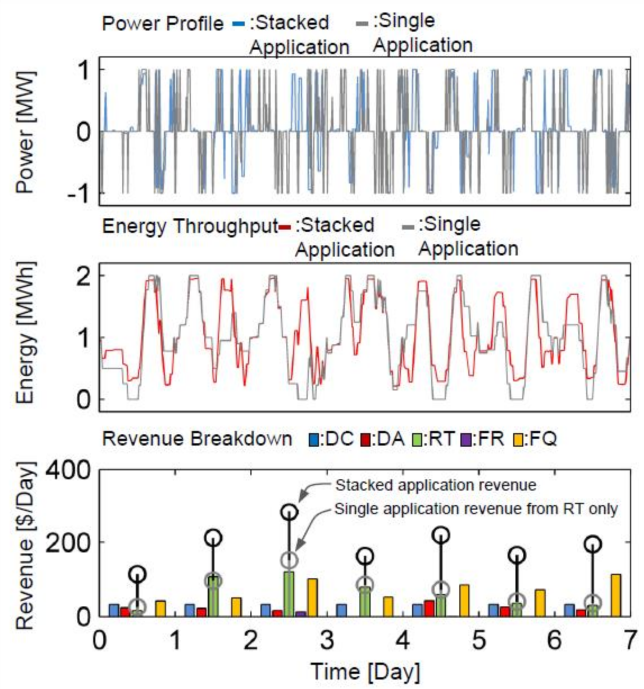

Fig. 3. Comparison between the stacked application and single real-time energy shifting application; from top to bottom: Dispatching power profile, Energy throughout, and Revenue breakdown.

As shown in Fig. 4, the black marks indicate the stacked daily revenues and the gray marks indicate the stacked daily revenues, excluding FQ. For long duration ESSs, they earn a higher portion of bulk energy management applications revenue from the total revenue mix. For short duration ESSs, they earn a higher portion of power applications revenue from the total revenue mix. However, under the current market, the revenue from FQ application are more profitable than the rest of the applications. As a result, extending the ESS duration from 2 hours to 8 hours only improves revenue by 30%. However, as the market progresses, the regulation market capacity will soon be filled; if excluding revenue from the FQ application, extending the ESS duration from 2 hours to 8 hours will improve its revenue by over 72%. It should be noted that because the FR application is still under development, the economic benefit of performing FR service is still possibly underestimated.

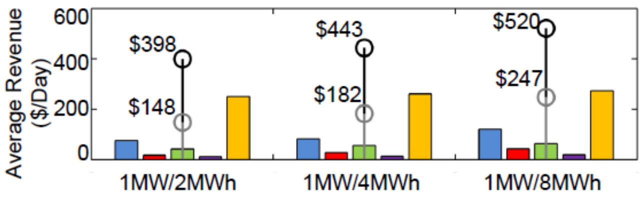

Fig. 4 Comparison among the revenues of three Energy Storage Systems with different durations of 1-hour, 2-hour and 3-hour. Colored bars: revenue breakdown of the applications. Black mark: stacked revenue. Gray mark: stacked revenue, excluding the frequency regulation application.

V. Conclusions

This work developed an optimal dispatching algorithm using mixed-integer-linear-programming to operate an ESS under five different utility grid energy market applications. The study shows that operation under stacked applications provides better value proposition compared to single use application. Further simulation unveils system performances under various energy to power ratios representing different types of ESS solutions.

To improve the dispatching algorithm, further work can be performed on acquiring more application data to develop a better market forecasting model using machine learning techniques. In addition, for applications like RT energy shifting, FQ, and flexible ramping, stochastic models can be constructed to account for uncertainties in the market participation process and help design a dispatcher weighing expected earnings and earning covariances.

Acknowledgements

The research team gratefully acknowledges the funding from Advanced Research Projects Agency-Energy (ARPA-E) under Grant No. DE-AR0000520. A.O. The authors would like to express their gratitude to Peter Klauer from CAISO and Spence Gerber from Olivine, Inc. for providing guidance on the CAISO market simulation. The authors would also like to acknowledge Prof. Y. Shirley Meng, Prof. Graham Elliott, and Daniel Davies at the University of California San Diego whose work was influential in deciding on, and producing the application duty cycles used in this study.

References

[1] *DOE/EPRI 2013 Electricity Storage Handbook in Collaboration with NRECA*, A. A. Akhil, G. Huff, A. B. Currier, B. C. Kaun, D. M. Rastler, S. B. Chen, *et al*., Sandia National Labs., Albuquerque, NM, July 2013, pp. 1-26.

[2] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," Sandia National Labs., Albuquerque, NM, Rep. no. SAND2010-0815, Feb. 2010.

[3] R. L. Fares and J. P. Meyers, "Economic operational planning of grid-connected battery energy storage," *ECS Trans.*, vol. 45, no. 26, pp. 1–16, Jun. 2013.

[4] E. Hittinger, J. Whitacre, and J. Apt, "What properties of grid energy storage are most valuable?" *J. Power Sources*, vol. 206, pp. 436–449, May 2012.

[5] B. Battke, T. S. Schmidt, D. Grosspietsch, and V. H. Hoffmann, "A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications," *Renewable and Sustainable Energy Reviews*, vol. 25, pp. 240–250, Sept. 2013.

[6] A. S. Tsagkou, E. D. K. D. I. Doukas, D. P. Labridis, A. G. Marinopoulos, and T. Tengnér, "Stacking grid services with energy storage techno-economic analysis," in *PowerTech, 2017 IEEE Manchester*, Jun. 2017, pp. 1–6.

[7] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-side management via distributed energy generation and storage optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 866–876, Jun. 2013.

[8] H. Pandžić, I. Kuzle, and T. Capuder, "Virtual power plant midterm dispatch optimization," *Applied Energy*, vol. 101, pp. 134–141, Jan. 2013.

[9] L. Xiaoping, D. Ming, H. Jianghong, H. Pingping, and P. Yali, "Dynamic economic dispatch for microgrids including battery energy storage," in *Power Electron. for Distributed Generation Systems* (PEDG), *2010 2nd IEEE Int. Symp. on. IEEE*, pp. 914–917.

[10] H. Hao, D. Wu, J. Lian, and T. Yang, "Optimal coordination of building loads and energy storage for power grid and end user services," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4335-4345, Jan. 2017.

[11] A. Hoke, A. Brissette, S. Chandler, A. Pratt, and D. Maksimović, "Look-ahead economic dispatch of microgrids with energy storage, using linear programming," in *2013 1st IEEE Conf. Technol. for Sustainability (SusTech)*, pp. 154–161.

[12] A. Nottrott, J. Kleissl, and B. Washom, "Storage dispatch optimization for grid-connected combined photovoltaic-battery storage systems," in *Power and Energy Society General Meeting, 2012 IEEE*, pp. 1–7.

[13] J. Soares, M. Silva, T. Sousa, Z. Vale, and H. Morais, "Distributed energy resource short-term scheduling using signaled particle swarm optimization," *Energy*, vol. 42, no. 1, pp. 466–476, Jun. 2012.

[14] A. Dubey, P. Chirapongsananurak, and S. Santoso, "A framework for stacked-benefit analysis of distribution-level energy storage deployment," *Inventions*, vol. 2, no. 2, p. 6, Mar. 2017.

[15] B. Cheng and W. Powell, "Co-optimizing battery storage for the frequency regulation and energy arbitrage using multi-scale dynamic programming," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1997-2005, Sept. 2016.

[16] K. Anderson and A. E. Gamal, "Co-optimizing the value of storage in energy and regulation service markets," *Energy Systems*, vol. 8, no. 2, pp. 369–387, Sept. 2017.

[17] D. Wu, C. Jin, P. Balducci, and M. Kintner-Meyer, "An energy storage assessment: Using optimal control strategies to capture multiple services," in *Power & Energy Society General Meeting, 2015 IEEE*, pp. 1–5.

[18] L. Xu and D. Tretheway, "Flexible ramping products," 2012. [Online]. Available: http://www.caiso.com/documents/draftfinalproposal-flexiblerampingproduct.pdf

[19] S. Tao, "Business requirements specification," 2012. [Online]. Available: https://www.caiso.com/Documents/BusinessRequirementsSpecification-pay-PerformanceYearOneDesignChanges.pdf