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Opportunities and Trends for Energy Storage Plus Solar in CAISO: 2014-2018

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***Abstract*—The state of California is leading the nation with respect to solar energy and storage. The California Energy Commission has mandated that starting in 2020 all new homes must be solar powered. In 2010 the California state legislature adopted an energy storage mandate AB 2514. This required California's three largest utilities to contract for an additional 1.3 GW of energy storage by 2020, coming online by 2024. Therefore, there is keen interest in the potential advantages of deploying solar combined with energy storage. This paper formulates the optimization problem to identify the maximum potential revenue from pairing storage with solar and participating in the California Independent System Operator (CAISO) day ahead market for energy. Using the optimization formulation, five years of historical market data (2014-2018) for 2,172 price nodes were analyzed to identify trends and opportunities for the deployment of solar plus storage.**

I. Introduction

Energy storage is a unique grid asset in that it is able to both source and sink electric power to the grid. This bidirectional capability makes energy storage an extremely flexible asset that can provide a number of grid benefits [1]–[3]. These benefits can be categorized based on the time scale. On a longer time scale are energy supply interactions, where large amounts of energy are supplied or pulled from the grid. These are often referred to as "energy" applications. Examples include renewable energy time shift and energy arbitrage in market areas. On the other hand, "power" applications normally transpire on a much shorter time scale and are employed to support real-time control of the electric power grid. Examples include voltage support and small signal stability. A summary of grid benefits, divided into energy and power applications, appears in Table I. Since the operation of an energy storage system often involves deciding which service to provide at each time interval to maximize revenue or grid benefit, it is naturally formulated as an optimization problem.

This paper focuses on energy arbitrage and renewable energy time shift. In a market area, the value of a grid asset comes from participating in the market. Therefore, an asset is only compensated for grid services for which there is a corresponding market product. The state of California is leading the nation with respect to solar energy and storage. The California Energy Commission has mandated that starting in 2020 all new homes must be solar powered [4]. In 2010 the California state legislature adopted an energy storage mandate AB 2514 [5]. This required California's three largest utilities to contract for an additional 1.3 GW of energy storage by 2020, coming online by 2024. Therefore, there is keen interest in the potential advantages of deploying solar combined with energy storage.

TABLE I
Summary of energy storage applications [3].

Energy Applications	**Power Applications**
Arbitrage	Frequency regulation
Renewable energy time shift	Voltage support
Demand charge reduction	Small signal stability
Time-of-use charge reduction	Frequency droop
T&D upgrade deferral	Synthetic inertia
Grid resiliency	Renewable capacity firming

This paper formulates the optimization problem to identify the maximum potential revenue from pairing storage with solar and participating in the California Independent System Operator (CAISO) day ahead energy market. Five years of historical market price data and solar irradiance data were analyzed for 2,172 pricing nodes to identify opportunities and trends for energy storage plus solar deployments. It should be noted that this analysis assumes that the size of the energy storage plus solar system is small with respect to the size of the market and is therefore a price taker. For large systems a production cost modeling approach must be employed to quantify the impact on energy prices.

The paper is organized as follows. A review of the related literature is summarized in Section II. The energy storage and solar model are discussed in Section III. Results from analyzing five years of CAISO price data for 2,172 nodes are presented in Section IV. Concluding remarks are found in Section V.

II. Related Work

There has been a significant amount of work looking at quantifying the maximum potential revenue from energy storage participating in energy and ancillary service markets. Modeling storage for arbitrage and frequency regulation in the CAISO market is described in [6], arbitrage and frequency regulation with pay-for-performance is modeled in [7], and

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arbitrage between the day ahead and real time market is addressed in [8]. Modeling storage for arbitrage and frequency regulation in the New York Independent System Operator (NYISO) market is described in [9]. The revenue optimization problem for energy storage participating in the PJM energy and frequency regulation markets is outlined in [10]. A dynamic programming solution to the revenue optimization problem with a nonlinear efficiency model, typical of flow batteries, is proposed in [11]. This includes a case study of the the potential revenue from a Vanadium Redox Flow Battery (VRFB) system in PJM's energy and frequency regulation market. A description of the market opportunities for energy storage in PJM is summarized in [12]. The arbitrage, frequency regulation, regional network services (RNS), forward capacity market (FCM) and resilience value of energy storage for a municipal light department in ISO New England appears in [13]. Revenue opportunities for energy storage in the Southwest Power Pool (SPP) integrated marketplace are considered in [14].

The trade-offs between ac and dc connected storage plus solar are discussed in [15]. A discussion of the value of energy storage plus solar for community distrubuted generation (CDG) projects in NYISO is presented in [16]. The New York analysis did not consider charging from the grid. An assessment of the energy storage required to meet renewable ramp rate limitations is discussed in [17]–[19]. The contributions of this paper include formulating the revenue optimization problem for storage plus solar participating in an energy market as well as an in-depth analysis of CAISO historical market data to identify trends and opportunities in California. In this paper, the storage model is formulated to allow charging from the grid or from solar.

III. Modeling

To evaluate the potential opportunities for energy storage plus solar in the CAISO day ahead market, a notional 1 MW solar plant and a 1 MW, 4 MWh energy storage system were modeled at 2,172 CAISO price nodes. Five years (2014-2018) of LMP price data was analyzed. The following subsections describe in more detail the energy storage and solar modeling.

A. Energy Storage Model

The analysis in this paper employs a discrete time energy flow model to represent the energy storage system [6]. Because the CAISO day ahead energy market operates on an hourly interval, the time step size, τ, for the model is 1 hour. The state of charge at time step i is given by:

$$s_i = s_{i-1}\eta_s + q_i^{\mathrm{r}}\eta_c - q_i^{\mathrm{d}} \tag{1}$$

where η_s is the storage efficiency over a time period, η_c is the conversion efficiency associated with conversion losses, q_i^{r} is the amount of energy charged at time step i, and q_i^{d} is the amount of energy discharged at time step i. For a typical lithium ion battery storage system, the losses over each time step are often negligible, so a common value for η_s is 1.0. A round trip conversion efficiency of 85-90 percent is representative of most lithium ion energy storage systems. In order to accommodate the storage plus solar consideration, an additional term is added to account for the solar energy that is used to recharge the storage system at time step i, denoted by q_i^{s}

$$s_i = s_{i-1}\eta_s + (q_i^{\mathrm{r}} + q_i^{\mathrm{s}})\eta_c - q_i^{\mathrm{d}} \tag{2}$$

This model assumes an ac coupling between the storage system and solar system as the conversion losses are the same for charging from the grid or from solar. The model can be easily modified to account for a dc coupling between the solar and storage by using a separate conversion efficiency, η_{s2s}, to model the lower conversion losses associated with a dc coupling. This is expressed as

$$s_i = s_{i-1}\eta_s + q_i^{\mathrm{r}}\eta_c + q_i^{\mathrm{s}}\eta_{s2s} - q_i^{\mathrm{d}} \tag{3}$$

An alternative modeling formulation is to account for the conversion losses associated with charging and discharging independently. While this is more representative of the underlying physics of an energy storage system, associating the losses with charging has the benefit of yielding a state of charge quantity which represents the available state of charge. Both models are mathematically equivalent [3]. The energy storage model parameters and values used for the analysis in this paper are summarized in Table II.

TABLE II
Energy storage model parameters.

s_i		State of charge at time step i (MWh)
η_s	1.0	Storage efficiency (percent)
η_c	0.85	Storage grid conversion efficiency (percent)
η_{s2s}	0.85	Storage solar conversion efficiency (percent)
q_i^{r}		Quantity of energy purchased from the market at time step i for charging (MWh)
q_i^{s}		Quantity of energy charged from solar at time step i (MWh)
q_i^{d}		Quantity of energy sold to the market (discharged) at time step i (MWh)
$\bar{Q}$	1.0	Maximum energy that may be charged/discharged in one time step (MWh)
$\bar{S}$	4.0	Maximum state of charge (MWh)
τ	1.0	Model time step (hours)

B. Solar Model

The solar plant modeling was based on the publicly available PVLIB model [20]. A representative solar panel, the Canadian Solar CS5P-220M, was selected from the Sandia module database [20]. A representative 1 MW ABB inverter, ABB: ULTRA-1100-TL-OUTD-2-US-690-x-y-z 690V [CEC 2013], was selected from the California Energy Commission (CEC) inverter database. The panels were over sized for the inverter by a factor of 1.4, which is typical for new installations [21]. The solar array paremeters are: array azimuth = 180 degrees; array tilt = local latitude; 22 modules in series; and 350 parallel strings. The irradiance and weather parameters for each location, dry bulb temperature, wind speed, barometric pressure, direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), and global horizontal irradiance (GHI), were downloaded from the National Solar Radiation Data Base [22]. The altitude for each pricing node location was downloaded from Google Earth based on the latitude and longitude [23].

The power output of a representative solar plant is found in Figure 1. The dc power represents the output power of the solar panels that is the input to the inverter. The ac power is the output power of the inverter. The clipping of the ac power occurs because the panels are over-sized relative to the inverter.

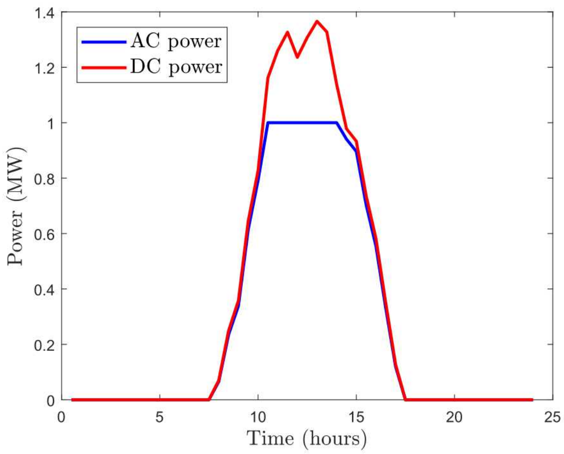

Fig. 1. ENCINA_1_N001 node solar plant dc and ac power, January 10, 2018.

The amount of solar energy generated over each time period is defined as q_i^{pv}. This energy must flow to the storage system or be sold in the market. The amount of solar energy used to charge the storage system at each time step was previously defined as q_i^{s}. Therefore, the amount of solar energy sold in the market at each time step is defined as

$$q_i^{\mathrm{sm}} = q_i^{\mathrm{pv}} - q_i^{\mathrm{s}} \tag{4}$$

C. Optimization Formulation

Estimating the maximum potential revenue from energy storage plus solar can be formulated as a linear program (LP) optimization. The cost function is defined as

$$J = \sum_{i=1}^{T} \left[(\lambda_i - C_d) q_i^{\mathrm{d}} - (\lambda_i + C_r) q_i^{\mathrm{r}} + \lambda_i q_i^{\mathrm{sm}} \right] \tag{5}$$

with the following financial quantities

λ_i	Price of electricity (LMP) at time step i
C_d	Cost of discharging at time step i
C_r	Cost of recharging at time step i

The first term of the cost function is the revenue associated with selling discharged energy from the energy storage system into the market. The second term is the cost associated with recharging by purchasing energy from the market. The last term is the revenue associated with selling some fraction of the solar energy into the market. The decision variables for the revenue maximization problem, which are non-negative quantities, are summarized in Table III.

The cost terms associated with operating the energy storage system, C_r and C_d, can be used to model system degradation. The most straightforward approach is to define the discharge cost as the capital cost divided by the expected throughput of the system. This is a simplistic approximation that allows an LP optimization formulation. Better degradation models involve counting cycles [24], which is often not amenable to an LP formulation. These cost terms were not employed in the analysis.

TABLE III
SUMMARY OF DECISION VARIABLES.

q_i^{r}	Quantity of energy purchased from the market at time step i for charging (MWh)
q_i^{s}	Quantity of energy charged from solar at time step i (MWh)
q_i^{d}	Quantity of energy sold to the market (discharged) at time step i (MWh)

The constraints associated with the optimization formulation include limits on the energy storage state of charge,

$$0 \leq s_i \leq \bar{S} \tag{6}$$

limits on the energy storage dispatch at each time interval, including the solar energy that is used for charging,

$$0 \leq q_i^{\mathrm{r}} + q_i^{\mathrm{d}} + q_i^{\mathrm{s}} \leq \bar{Q} \tag{7}$$

and the solar energy used for charging must always be less than or equal to the solar generation.

$$q_i^{\mathrm{s}} \leq q_i^{\mathrm{pv}} \tag{8}$$

It should be noted that this formulation assumes that the solar inverter power rating is the same as the energy storage inverter power rating. This assumption is easily relaxed if necessary.

IV. CAISO Results

In order to assess the opportunity for energy storage plus solar in the CAISO day ahead market, five years (2014-2018) of CAISO market data for 2,172 nodes combined with irradiance data for those locations were analyzed for a notional storage plus solar system. The model assumes perfect foresight which yields an upper bound to the maximum potential revenue. The optimization problem was formulated using the Pyomo optimization framework [25]. The distribution of average annual additional revenue provided from pairing energy storage with solar is presented in Figure 2. This is defined as the revenue from solar plus storage minus the revenue from solar alone. The geographic distribution of average annual solar plus storage revenue is illustrated in Figure 3. The geographic distribution of additional revenue provided from pairing energy storage with solar is found in Figure 4.

In order to quantify the trend in benefit of combining energy storage with solar in CAISO, a linear regression model was fitted to the additional revenue enabled by energy storage.

$$AR(t) = AR_0 + Kt \tag{9}$$

The additional revenue, $AR(t)$ is a function of a constant, AR_0, plus a term multiplying the time in years. The K term from the regression provides an estimate of the trend. The coefficient of determination, or R^2, is sometimes used as a crude measure of the strength of a relationship fit by least squares [26]. R^2 is the proportion of the variance in the dependent variable, $AR(t)$, that is predictable from the independent variable t [26]. The coefficient of determination is defined as:

$$R^2 = 1 - \frac{S_{\hat{e}}^2}{S_y^2} \tag{10}$$

where $S_{\hat{e}}^2$ is the variance of the residuals from the fit and S_y^2 is the variance of the dependent variable. An R^2 of 0.5 implies that 50% of the variability of the dependent variable has been accounted for by the model. Regression results for representative nodes are illustrated in Figure 5. It should be noted that because of the definition of R^2, a horizontal slope will have an $R^2 = 0$. Summary results for the trend appear in Figure 6. Results are only shown for nodes with an $R^2 > 0.5$. Of the nodes with an $R^2 > 0.5$, the median R^2 value is 0.72. 2079 of 2172 nodes meet this criterion.

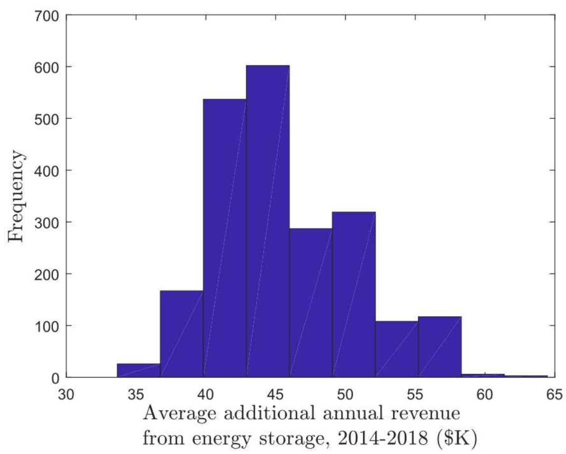

Fig. 2. Distribution of average annual revenue from solar, 2014-2018.

V. Conclusion

This paper presents the optimization formulation to estimate the maximum potential revenue from pairing solar generation with energy storage and participating in an energy market. Using a notional 1MW solar plant model and a 1 MW, 4MWh energy storage model, five years of CAISO historical day ahead market data and irradiance data were employed to estimate opportunities for energy storage plus solar in California. Based on the results, the additional revenue provided from energy storage is probably not enough to justify an investment given current storage capital costs. However, this analysis only considered one value stream - participation in the day ahead energy market. Additional value streams such as frequency regulation and participating in the real time energy market might provide additional revenue. In addition, the analysis identified a clear trend in the value created by pairing energy

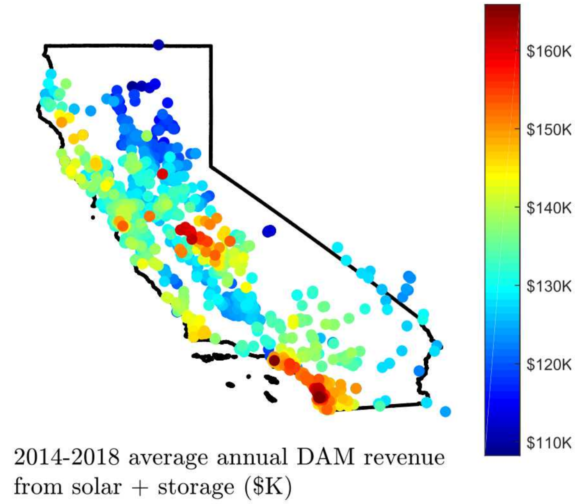

Fig. 3. Average annual solar plus storage revenue, 2014-2018.

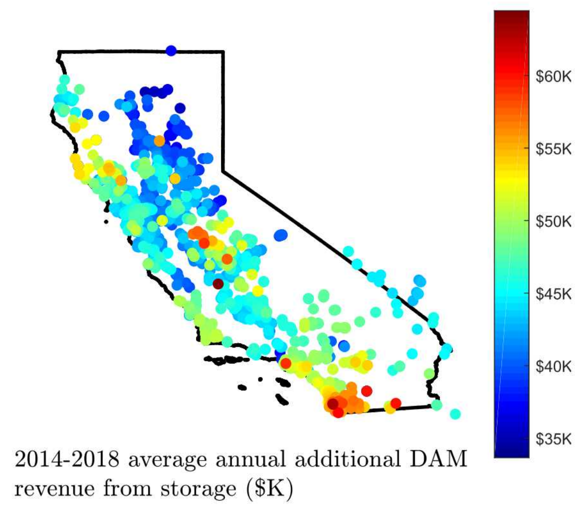

Fig. 4. Average annual additional DAM revenue from storage, 2014-2018.

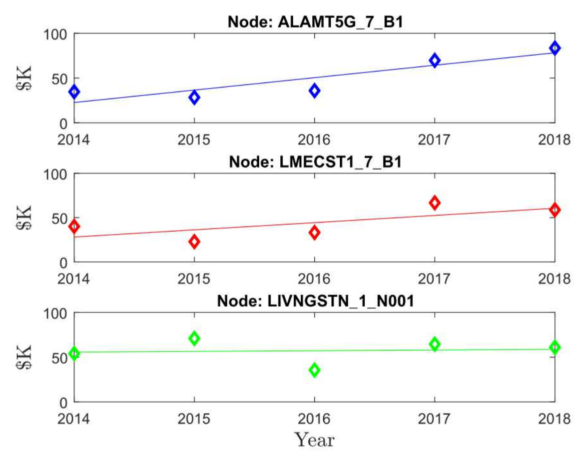

Fig. 5. Representative regression results for additional revenue from energy storage in the day-ahead market, 2014-2018. Node: ALAMT5G_7_B1, R^2 = 0.80, slope = $13,893/year; Node: LMECST1_7_B1, R^2 = 0.50, slope = $8,119/year; Node: LIVNGSTN_1_N001, R^2 = 0.01, slope = $763/year.

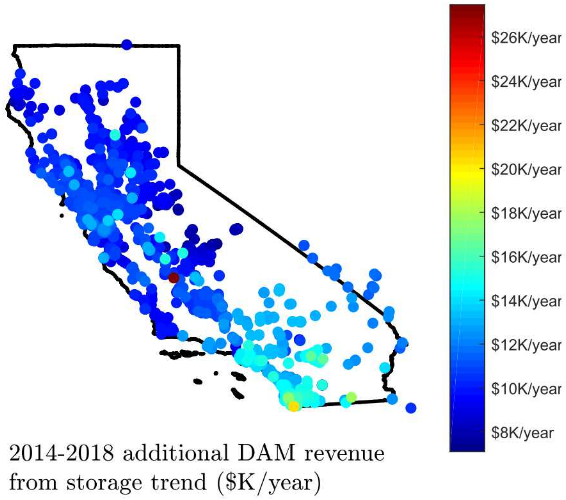

Fig. 6. Annual additional DAM revenue from storage trend, 2014-2018 (2079 of 2172 nodes with $R^2 > 0.5$).

storage with solar. This is likely caused by the increasing penetration of solar and the associated downward pressure on energy prices. If this trend continues, the value of energy storage to solar will only continue to increase.

Future research areas include estimating maximum potential revenue from participating in additional markets: the real time energy market, the frequency regulation market, and the ramping product market. In addition, further research is required to develop accurate market price forecasts to harvest a large fraction of the maximum potential revenue when providing multiple grid services.

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