# Hybrid Energy Storage and Generation Planning with Large Renewable Penetration

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***Abstract*—Energy storage is important in a power grid with high penetration of renewable energy, especially for isolated grids or micro-grids. Considering the different characteristics of energy storage devices and the different availability of renewable energy sources, planning a good portfolio of them is important for efficient system operation and investment cost minimization. In this paper we consider the planning problem as a chance-constrained optimization problem and solve the problem using scenario approximation. To reduce the computational time, we formulate the original problem as a consensus problem, and employ the alternating directional method of multipliers to solve the optimization problem in a distributed manner. The results potentially help make decisions on energy storage and renewable generation planning, and guide policy making related to renewable energy sources.**

## I. Introduction

Currently, only about 3% of the electricity generated in the United States is from wind and solar [1]. According to the National Renewable Energy Laboratory (NREL), renewable energy potentially can support about 80% of the total electricity consumption in the U.S. in 2050 [2]. Therefore, high penetration of renewable energy has become the trend for future grids. This is especially true for an isolated grid, or a micro-grid that is self-sustained most of the time.

Most renewable energy sources, including wind and solar, are highly intermittent, and the amount of generation depends on the time of day, season, and weather conditions. A grid with high renewable energy penetration needs to build sufficient energy storage to ensure an uninterrupted supply to end users. There are different types of energy storages, including super-capacitors, flywheels, chemical batteries, water pumps, and hydrogen [3]-[7]. Different types of energy storage have different characteristics; for example, they vary in round-trip energy efficiency, maximum capacity/power rating, and energy loss over time. Although there has been research on planning and/or operating a specific type of energy storage system for isolated electricity grids [8]-[11], few works consider exploiting the different characteristics of multiple types of energy storage, forming a hybrid energy storage system. In addition, different renewable energy sources have different availability. Jointly planning for energy storage along with renewable generation potentially results in a more economical and efficient system.

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In this paper, we consider the scenario of an isolated grid or a micro-grid, whose energy is generated both from renewable energy sources and traditional thermal generators. The thermal generator on its own is insufficient to supply the demand of the grid, as its generation capacity is significantly less than the peak load. We formulate a chance-constrained optimization problem, with the objective of minimizing the investment cost of energy storage and renewable generators. The renewable generation and user demands change with time, and have different characteristics at different time of day and different dates of year. It is often difficult to obtain an accurate probability density function to reflect these complex characteristics. Therefore we propose to solve the original problem using scenario approximation, where the scenarios are based on historical data. To reduce the time complexity due to a large number of scenarios, we formulate the scenario approximation problem as a consensus problem, which can then be solved in a distributed manner based on the alternating direction method of multipliers (ADMM) [12]. The results of this paper provide information on planning energy storage systems for isolated grids or micro-grids, and guide policy making related to renewable energy sources.

The rest of this paper is organized as follows. In Sec. II we describe the system model, including the energy storage and generators. In Sec. III we formulate the optimization problem and solve it in a distributed manner. We provide numerical examples in Sec. IV, and conclude the paper in Sec. V.

## II. System Model

### A. Energy storage model

We consider that there is a set $\mathcal{S}$ of different types of energy storages. We use superscript $\mathrm{s} \in \mathcal{S}$ to denote the type of the storage. Each type of energy storage is characterized by the following parameters:

- $\eta^{\mathrm{s}}$: one-way energy efficiency
- $\delta^{\mathrm{s}}$: rated power/energy ratio
- $\xi^{\mathrm{s}}$: energy loss ratio per unit time
- $c^{\mathrm{s}}$: installation cost per unit storage.

Let $S_t^{\mathrm{s}}$ denote the energy in storage s at the beginning of time period $t$, satisfying the following equation:

$$S_{t+1}^{\mathrm{s}} = \begin{cases} S_t^{\mathrm{s}} - \dfrac{1}{\eta^{\mathrm{s}}} P_t^{\mathrm{s}} - \xi^{\mathrm{s}} S_t^{\mathrm{s}} & \text{if } P_t^{\mathrm{s}} \geq 0, \\ S_t^{\mathrm{s}} - \eta^{\mathrm{s}} P_t^{\mathrm{s}} - \xi^{\mathrm{s}} S_t^{\mathrm{s}} & \text{if } P_t^{\mathrm{s}} < 0, \end{cases} \tag{1}$$

where positive $P_t^{\mathrm{s}}$ denotes discharge from storage s during time period $t$, and negative $P_t^{\mathrm{s}}$ denotes charge to the storage. Make the following substitution:

$$P_t^{\mathrm{s}} = P_t^{\mathrm{s},+} - P_t^{\mathrm{s},-}, \quad P_t^{\mathrm{s},+} \geq 0, \quad P_t^{\mathrm{s},-} \geq 0, \tag{2}$$

and we can then rewrite (1) as

$$S_{t+1}^{\mathrm{s}} = S_t^{\mathrm{s}} - \frac{1}{\eta^{\mathrm{s}}} P_t^{\mathrm{s},+} + \eta^{\mathrm{s}} P_t^{\mathrm{s},-} - \xi^{\mathrm{s}} S_t^{\mathrm{s}}. \tag{3}$$

An interpretation of (3) is that the energy stored in a specific energy storage type equals the stored energy at the beginning of the previous time point, minus (plus) the discharge (charge) during the previous time period, minus the energy loss due to the nature of the storage. For convenience of formulating the optimization problem, we impose an additional assumption that the state of charge remain the same at the beginning and the end of the optimization horizon, as used in [9], i.e.,

$$S_T^{\mathrm{s}} = S_0^{\mathrm{s}}, \quad \forall \mathrm{s} \in \mathcal{S}. \tag{4}$$

Thus the storages achieves "net zero" energy increase during each optimization horizon. The amount of stored energy and the charge/discharge power is constrained as follows

$$0 \leq S_t^{\mathrm{s}} \leq S_{\max}^{\mathrm{s}} \tag{5}$$

$$0 \leq P_t^{\mathrm{s},+} \leq P_{\max}^{\mathrm{s},+}, \quad 0 \leq P_t^{\mathrm{s},-} \leq P_{\max}^{\mathrm{s},-}. \tag{6}$$

In this work we use $\delta^{\mathrm{s}}$ to denote the ratio between the rated power and the rated energy of the storage. Therefore $P_{\max}^{\mathrm{s},+} = \eta^{\mathrm{s}} \delta^{\mathrm{s}} S_{\max}^{\mathrm{s}}$ and $P_{\max}^{\mathrm{s},-} = \delta^{\mathrm{s}} S_{\max}^{\mathrm{s}}$.

### B. Generator model

The generators are classified into thermal generators and renewable generators. For thermal generators, the constraints include the generation capacity and generator ramp constraints. Denote the thermal generation as $H_t$, and we then have

$$0 \leq H_t \leq H_{\max} \tag{7}$$

$$H_{\mathrm{ramp}}^{-} \leq H_{t+1} - H_t \leq H_{\mathrm{ramp}}^{+}. \tag{8}$$

We employ multiple types of renewable generators, including wind and solar, which are considered as non-dispatchable generations. Let $R_t^{\mathrm{r}}$ denote the renewable generation from type $\mathrm{r} \in \mathcal{R}$ generator during time period $t$, and $R_{\max}^{\mathrm{r}}$ denote the installed capacity. Then the generation can be written as

$$R_t^{\mathrm{r}} = r_t^{\mathrm{r}} R_{\max}^{\mathrm{r}} \tag{9}$$

where $r^{\mathrm{r}}$ is a random variable denoting the renewable generation per unit generation capacity.

### C. Load balance constraint

The total generation should equal the total demand in a power grid. Let $G_t$ denote the energy shortage for an isolated grid, or energy drawn from the main grid for a micro-grid. We can then write the load balance constraint as follows:

$$D_t = \sum_{\mathrm{r} \in \mathcal{R}} R_t^{\mathrm{r}} + H_t + \sum_{\mathrm{s} \in \mathcal{S}} \left( P_t^{\mathrm{s},+} - P_t^{\mathrm{s},-} \right) + G_t \tag{10}$$

where $D_t$ denotes the demand from users. Note that $G_t$ can be negative, which denotes energy injection to the main grid from a micro-grid, or dumped energy in an isolated grid.

## III. Storage and Renewable Generation Planning

### A. Problem formulation

The goal of hybrid energy storage planning is to minimize the initial investment cost for different types of energy storage and generators, so that most of the needs of the grid can be satisfied. The objective function is the total cost for the investment in the storage and generators, i.e.,

$$f(\boldsymbol{S}_{\max}, \boldsymbol{R}_{\max}) = \sum_{\mathrm{s} \in \mathcal{S}} c^{\mathrm{s}} S_{\max}^{\mathrm{s}} + \sum_{\mathrm{r} \in \mathcal{R}} c^{\mathrm{r}} R_{\max}^{\mathrm{r}}. \tag{11}$$

The grid reliance constraint (for micro-grids) or the energy shortage constraint (for isolated grids) can be written as

$$\Pr(G_t \leq G_{\mathrm{th}}) \geq 1 - \alpha \tag{12}$$

where $G_{\mathrm{th}}$ is a threshold which can be a function of time and load, and $\alpha \in [0, 1]$ is a pre-specified probability. Constraint (12) means that local generators and storages have a probability of greater than or equal to $1 - \alpha$ to be short of energy less than $G_{\mathrm{th}}$. The optimization problem is formulated as

$$\begin{array}{ll} \displaystyle\min_{\boldsymbol{S}_{\max}, \boldsymbol{R}_{\max}} & f(\boldsymbol{S}_{\max}, \boldsymbol{R}_{\max}) \\ \text{subject to} & \text{Storage const. } (3)-(6), \quad \forall \mathrm{s}, t \\ & \text{Generator const. } (7)-(9), \quad \forall \mathrm{r}, t \\ & \text{Load balance const. } (10), \quad \forall t \\ & \text{Energy shortage const. } (12), \quad \forall t. \end{array} \tag{13}$$

### B. Scenario approximation

The renewable generation and user loads in (13) are all random, and therefore the constraint (12) makes the problem challenging to solve. Previous works have shown that the probability constraint (12) can be approximated by a set of deterministic constraints,

$$G_t^j \leq G_{\mathrm{th}}, \quad \forall t, j \in \mathcal{J} \tag{14}$$

with the number of required scenarios $J = \mathrm{card}(\mathcal{J})$ determined by the number of design parameters and the probability measure. For details please refer to [13], [14].

Let $\boldsymbol{x}^j = [(\boldsymbol{S}_{\max}^j)^\top, (\boldsymbol{R}_{\max}^j)^\top]^\top$, $\boldsymbol{z} = [\boldsymbol{S}_{\max}^\top, \boldsymbol{R}_{max}^\top]^\top$, $\mathcal{C}^j$ denote the feasible set for the $j$th scenario, and $p^j$ denote the probability of the $j$th scenario. We can then formulate the original optimization problem as a consensus problem.

$$\begin{array}{ll} \displaystyle\min_{\boldsymbol{z}, \boldsymbol{x}^j \in \mathcal{C}^j, j \in \mathcal{J}} & \displaystyle\sum_{j \in \mathcal{J}} p^j f^j(\boldsymbol{x}^j) \\ \text{subject to} & \boldsymbol{x}^j = \boldsymbol{z}, \quad j \in \mathcal{J}. \end{array} \tag{15}$$

### C. Distributed Optimization

The challenge in solving (15) is that as the number of scenarios increases, the problem becomes increasingly difficult due to high time complexity. We propose to solve the problem in a distributed manner based on the alternating direction method of multipliers (ADMM) [12], which mitigates the time complexity issue.

For notational simplicity, we include the probability term $p^j$ into $f^j(\boldsymbol{x}^j)$. The augmented Lagrangian of (15) is then

$$L_\rho\left(\{\boldsymbol{x}^j\}, \boldsymbol{z}, \{\boldsymbol{v}^j\}\right) = \sum_{j\in\mathcal{J}} \left( f(\boldsymbol{x}^j) + \boldsymbol{v}^{j\top}(\boldsymbol{x}^j - \boldsymbol{z}) + \frac{\rho}{2}\|\boldsymbol{x}^j - \boldsymbol{z}\|_2^2 \right), \quad (16)$$

where $\{\boldsymbol{v}^j\}$ denote the dual variables, and $\rho$ is a pre-defined parameter which is the dual variable update step size. The additional quadratic term penalizes the difference between the local variables $\{\boldsymbol{x}^j\}$ and the global variable $\boldsymbol{z}$. The ADMM algorithm iterates among the following steps, with subscript $k$ denoting the iteration number.

$$\boldsymbol{x}_{k+1}^j = \underset{\boldsymbol{x}^j\in\mathcal{C}^j}{\operatorname{argmin}}\, f(\boldsymbol{x}^j) + \boldsymbol{v}^{j\top}(\boldsymbol{x}^j - \boldsymbol{z}_k) + \frac{\rho}{2}\|\boldsymbol{x}^j - \boldsymbol{z}_k\|_2^2, \forall j \in \mathcal{J}, \quad (17)$$

$$\begin{aligned} \boldsymbol{z}_{k+1} &= \underset{\boldsymbol{z}}{\operatorname{argmin}} \sum_{j\in\mathcal{J}} \left( \boldsymbol{v}^{j\top}(\boldsymbol{x}_{k+1}^j - \boldsymbol{z}) + \frac{\rho}{2}\|\boldsymbol{x}_{k+1}^j - \boldsymbol{z}\|_2^2 \right) \\ &= \frac{1}{J}\sum_{j\in\mathcal{J}} \left( \boldsymbol{x}_{k+1}^j + \frac{1}{\rho}\boldsymbol{v}_k^j \right), \end{aligned} \quad (18)$$

$$\boldsymbol{v}_{k+1}^j = \boldsymbol{v}_k^j + \rho\left(\boldsymbol{x}_{k+1}^j - \boldsymbol{z}_{k+1}\right), \forall j \in \mathcal{J}. \quad (19)$$

Steps (17) and (19) can be parallelized, making the problem scalable as the number of scenarios increases.

*Remark:* The convergence of this approach is guaranteed [12]. For faster convergence, an heuristic approach is to replace the step (18) with

$$\boldsymbol{z}_{k+1} = \mathrm{max\_el}_{j\in\mathcal{J}} \left( \boldsymbol{x}_{k+1}^j + \frac{1}{\rho}\boldsymbol{v}_k^j \right). \quad (20)$$

where $\mathrm{max\_el}$ is an operator that selects the element-wise maximum value. Our numerical experiments show that (20) results in faster convergence than (18).

## IV. Numerical Examples

### *A. Data and parameters*

We take user load data from the MISO daily reports by the U.S. Federal Energy Regulatory Commission (FERC) [15], wind generation data from the Ontario Power Authority [16], and solar generation data from Elia [17], all for the duration of one year[1]. All the data used in this section are normalized. The user load data is normalized by the average hourly demand, and the wind and solar generation data is normalized by the installed capacity. The reason for using real data instead of randomly generating data from certain distributions is for better reflection of the temporal characteristics of consumer demands and renewable energy availability. Fig. 1 shows a set of box plots of the data we use. Note that the data also exhibit seasonal variations, which we do not show here due to limitation of space. In practice, multiple years of historic data for the region of study should be used for more accurate results. In fact, the number of scenarios should be set following the results from [13], if sufficient data is available.

[1]The solar generation data is not complete for one year, and therefore partial missing data is generated by replicating data from months with similar weather conditions

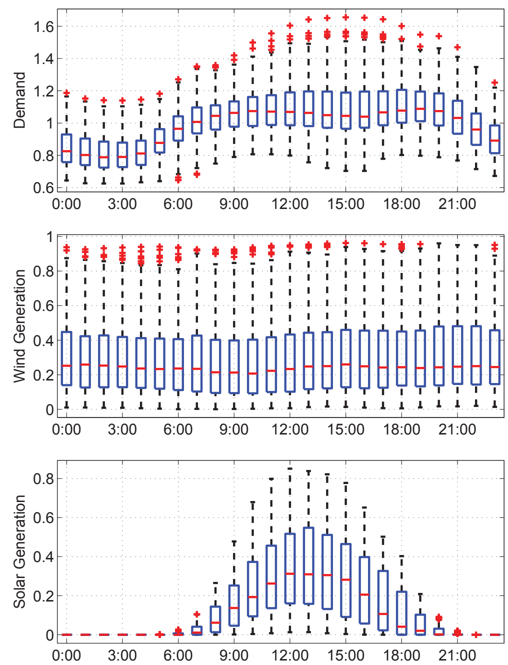


Fig. 1: Box plots for demand, wind, and solar data used in the numerical examples.

TABLE I: Parameters for different types of energy storage and renewable generators

| Type | $S^1$ | $S^2$ | $S^3$ | $R^1$ | $R^2$ |
|---|---|---|---|---|---|
| Roundtrip efficiency | 0.95 | 0.85 | 0.60 | – | – |
| Power/energy ratio | 1.00 | 0.20 | 0.10 | – | – |
| Energy loss ratio | 0.05 | 0.01 | 0.00 | – | – |
| Unit investment cost | 1.00 | 1.25 | 1.20 | 2.00 | 1.80 |
| Min install capacity | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Max install capacity | 5.00 | 5.00 | 5.00 | 5.00 | 5.00 |

We consider three types of energy storage, and two types of renewable generators, with the parameters listed in Table I. For convenience and simplicity, the cost and capacity are also normalized, with per unit (p.u.) as the units.

To quantify $G_{\mathrm{th}}$ and $H_{\max}$, we define two quantities: the shortfall to demand ratio (SDR), $r_{\mathrm{SD}}$, and the thermal generation ratio (TGR), $r_{\mathrm{TG}}$. We define the threshold $G_{\mathrm{th}}$ at time $t$ as

$$G_{\mathrm{th}} = r_{\mathrm{SD}} D_t, \quad (21)$$

and therefore the SDR is the ratio between the threshold $G_{\mathrm{th}}$ and the current demand. The thermal generator capacity $H_{\max}$ is determined by

$$H_{\max} = r_{\mathrm{TG}} \max(D_t), \quad (22)$$

and therefore the TGR is the ratio between the thermal generator capacity and the peak demand.

The CVX toolbox [18] is used to solve for the x updates.

### *B. Storage and generation planning*

In this subsection we use the parameters described in Sec. IV-A, and set $r_{\mathrm{TG}} = 0.50$, and $r_{\mathrm{SD}} = 0.10$. In this case, the

TABLE II: Optimization results for $r_{\mathrm{TG}} = 0.5$, $r_{\mathrm{SD}} = 0.10$.

| z update | $S^1_{\max}$ | $S^2_{\max}$ | $S^3_{\max}$ | $R^1_{\max}$ | $R^2_{\max}$ | Cost |
|---|---|---|---|---|---|---|
| use (18) | 0.7578 | 0.9261 | 2.7240 | 2.1751 | 0.9697 | 11.281 |
| use (20) | 0.7344 | 1.1495 | 2.5184 | 2.1637 | 0.9782 | 11.280 |

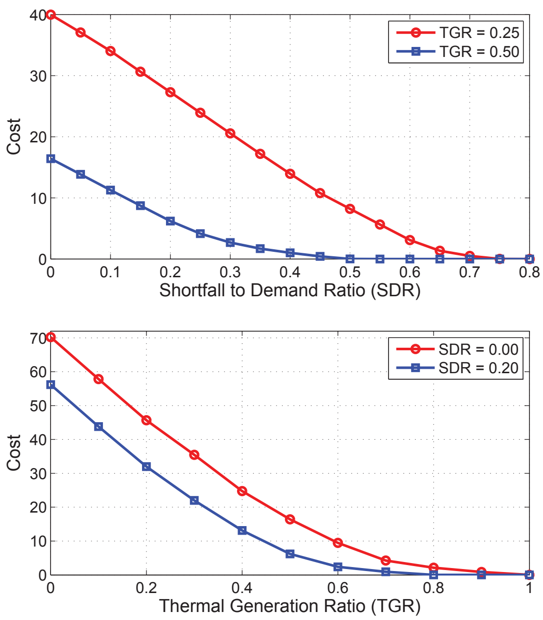


Fig. 2: Investment cost as a function of TGR and SDR.

thermal generator can provide at most half the peak load of the grid, and the grid has to supply at least 90% of its energy from its own generators and storage. We tested both (18) and (20) for the z-update step. The optimization results are shown in Table II. Note that although the resulting portfolios are slightly different, the objective functions (costs) are close. Using (20) results in fewer iterations with the same stopping criteria.

### C. Effects of SDR and TGR

In this subsection we illustrate the effects of SDR and TGR for storage and renewable generation planning. Intuitively, higher TGR and SDR will result in lower investment costs. In Fig. 2 we show how the investment cost changes with SDR and TGR, when one of them is fixed. Note that in the simulations we remove the constraint on the maximum capacity for each type of storage or generator, because otherwise the optimization might become infeasible when both SDR and TGR are low. This analysis potentially helps decision makers decide on the system parameters, e.g., the tolerance of energy shortage and installation capacity for thermal generators, for cost efficiency and environmental considerations.

## V. Conclusions

In this paper we formulated the problem of storage and generation planning for isolated grids or micro-grids with large penetration of renewable energy sources. We proposed to optimize the portfolio of different types of energy storages and renewable generators, to build a hybrid storage and generation system. In order to make the problem scalable with large numbers of scenarios, we formulated the original optimization problem as a consensus problem, which could be solved in a distributed manner. The results provide information for decision makers when planning energy storage and generation systems, and guide policies regarding renewable energy sources.

In our next work we will consider the problem of optimal operation of a given hybrid energy storage system, taking into account the stochastic nature of demand and renewable generation.

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