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Real-time Dispatching for Energy Aggregators with Energy Storage and Stochastic Renewable Generation in Markets

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***Abstract*— Energy storage systems are flexible resources that can accommodate variability and uncertainty in the load and generation of modern power systems. We consider the management of multiple energy resources, including energy storage, participating in energy markets in order to minimize the cost of energy required to balance expected load. We propose a real-time stochastic optimization approach for solving this problem that involves solving day-ahead and real-time optimization problems in a receding horizon fashion, akin to economic model predictive control, and that explicitly takes into account uncertainties associated with load and renewable generation. When forecasting errors are normally distributed random variables, the probabilistic load balancing constraint can be reformulated as a linear inequality constraint, and the resulting optimization problems can be formulated as linear programs. We present a case study involving management of an energy storage system, a solar photovoltaic system, and a wind turbine participating in ISO New England's day-ahead and real-time energy markets to balance commercial loads.**

I. INTRODUCTION

Flexible resources, such as energy storage (ES), are playing an increasingly large role in the development of future electric power grids due to a changing generation mix, highly distributed loads and generation, and a growing need for resilience against contingencies like severe weather events. ES systems are quickly becoming viable and effective resources for many power and energy applications, and numerous energy management and optimization methods for grid ES have been developed [1]. One application for ES is accommodating the variability and uncertainty associated with loads and renewable generation. Explicitly considering this uncertainty is imperative as mismatch between forecasts and realized power can result in excessive operating costs, unnecessary investment in over-sized ES, or lack of required power in a critical situation.

Thanks to the emerging smart grid paradigm allowing bi-directional communication between loads, generation resources, and market operators, multiple energy resources can be operated as a single entity that can participate in wholesale energy markets. Furthermore, energy management systems can be used to control the resources in such a way that minimizes the cost of purchased energy. These entities can take the form of utilities, virtual power plants, microgrids, or aggregators. We consider the problem of operating multiple energy resources participating in day-ahead and real-time energy markets with the goal of minimizing the cost of energy purchased from the grid (or, equivalently, maximizing revenue from energy sold to the grid) while balancing an expected net load.

Many of the key challenges in energy management problems come from uncertainty associated with parameters including load, generation, and energy market prices. Methods for decision making under uncertainty in electricity markets, and energy systems in general, are discussed in [2] and [3], respectively. Uncertainty can be addressed with accurate forecasts of uncertain parameters, and numerous schemes are available for predicting future variations in load, renewable generation [4], [5], and electricity prices [6], [7]. In contrast, a real-time approach to energy management may be employed to address uncertainty without the need for highly accurate forecasts. For example, although the accuracy of persistent forecasting methods decreases significantly with increasing forecasting horizon, a real-time receding horizon scheme that updates forecasts at every time step could be considered to mitigate this shortcoming.

In this work, we propose a two-stage stochastic optimization approach for real-time energy management that involves solving a day-ahead optimization problem for determining supply/demand bids in the day-ahead energy market and solving real-time optimization problems to determine real-time dispatch commands. The real-time approach is akin to model predictive control (MPC) [8]in that a stochastic optimization problem is solved at each time step, in a receding horizon fashion, with updated real-time forecasts and feedback measurements. MPC is popular due to its ability to explicitly handle constraints and even nonlinear dynamics, uncertainty, noise, and disturbances [9], [10]. MPC has been effectively used in energy management applications, including microgrid operation [11], [12], [13], operating ES as part of an energy hub [14], operating a hybrid wind-battery ES system [15], and adaptive dispatch of ES to better capture nonlinearities in technology-specific battery models [16].

There is a large body of related work regarding sizing, management, analysis, and dispatch of ES. In many studies, both sizing and operation of ES with renewable generation are considered at the same time. For example, operation, sizing, and economic evaluation of several ES technologies for solar and wind power plants are considered in [17]. Sizing storage by minimizing the cost of electricity purchased from

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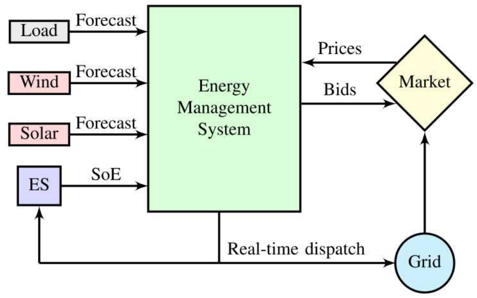


Fig. 1. Problem architecture.

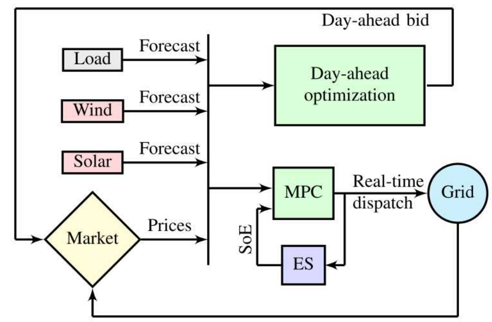


Fig. 2. Two-stage stochastic optimization architecture.

the grid while maintaining load balance with deterministic PV generation is studied in [18]. Other studies explicitly consider uncertainty. Stochastic load and PV generation forecasts are used in an approach to optimally size and schedule behind-the-meter ES to balance critical load in [19]. In [20], the optimal size and usage of storage is determined, considering stochastic wind forecasts. Other work considering both economics (e.g., price volatility, market structures for energy exchange, and operating costs), as well as stochastic operation of ES with renewable generation include [21], [22], [23], [24], [25], [26].

Many stochastic optimization approaches, like scenario-based approaches or stochastic dynamic programming, are computationally expensive methods whose computation time increases exponentially with the number of investigated scenarios or the horizon time of the optimization. Other approaches employ robust optimization, and examples include bidding strategies for virtual power plants [27], an approach for energy management in microgrids [28], and a real-time demand response model [29]. Our proposed stochastic optimization approach employs a probabilistic constraint to ensure that the expected net load is balanced using power supplied by the ES and purchased from the grid in each time step. If forecast errors have a normal distribution, the probabilistic constraint can be reformulated as a linear inequality constraint, and the resulting optimization problems can be efficiently solved as linear programs.

The contributions of this work are: 1) A two-stage stochastic optimization approach for managing multiple energy resources, bidding into day-ahead energy markets and dispatching in real-time, that explicitly considers load, generation, and price uncertainty; 2) A real-time, receding horizon algorithm that can utilize any available forecasts and is effective even without highly accurate forecasts; 3) A case study using the proposed approach to reduce costs for an energy aggregator in ISO New England that operates ES, wind, and solar PV resources and participates in day-ahead and real-time markets.

II. Problem Formulation

We consider the problem of operating multiple energy resources to minimize the cost of purchasing energy from the grid in day-ahead and real-time energy markets while balancing an expected load. This is often the goal of energy aggregators who have the ability to participate in wholesale energy markets. The architecture of this problem is shown in Figure 1, where it is assumed that the aggregator operates wind, solar PV, and ES resources. Smart grid technology enables bi-directional communication between the aggregator and the resources and energy markets. Because of their variability and uncertainty, the aggregator generates or receives forecasts for the load, the power generated from wind and solar resources, and the day-ahead and real-time locational marginal prices (LMPs). Forecast errors are considered to be random variables. In addition, the aggregator has the ability to measure the state of energy (SoE) of the ES device.

Within this architecture, we employ a two-stage stochastic optimization approach to find optimal market bids and real-time dispatch signals. A diagram of this approach is shown in Figure 2. The first stage uses day-ahead forecasts of load, renewable generation, and energy prices and solves a day-ahead optimization problem, resulting in hourly day-ahead market bids and a schedule for the ES. The second stage uses real-time forecasts of load, renewable generation, and energy prices, as well as feedback measurements of the ES device's SoE, and solves a real-time optimization problem at every time step, resulting in dispatch signals for the aggregator's ES device on a sub-hourly basis (e.g., every 5-minutes).

In general, bids for each market interval have both power quantity and price components. We assume a "price-taker" agreement, so bids only include power quantity, and the price paid is the cleared market price. This is often allowable if power quantity bids are relatively small so as to not affect market prices. The power quantity bid acts as a demand bid if the quantity is positive (i.e., purchasing from the market) and as a supply bid if negative (i.e., selling to the market). Common market time intervals are one hour for day-ahead markets and five to fifteen minutes for real-time markets.

The two financial settlements from the day-ahead and real-time markets can be calculated as follows. The day-ahead cost can be calculated for a single day as

$$\Lambda_{\text{DA}} = \sum_{h=1}^{24} \lambda_h^{\text{DA}} p_h^{g,\text{DA}}, \tag{1}$$

where Λ_{DA} is the total cost [$], λ_h^{DA} is the cleared day-ahead energy price [$/kWh] during hour h, and $p_h^{g,\text{DA}}$ is the day-ahead power quantity bid [kW] in the day-ahead energy market for hour h. The real-time cost for each day is

$$\Lambda_{\text{RT}} = \sum_{t=1}^{T_{\text{day}}} \lambda_t^{\text{RT}} (p_t^g - p_t^{g,\text{DA}})\tau, \tag{2}$$

where T_{day} denotes the number of real-time market time intervals in a day, λ_t^{RT} is the cleared real-time energy price [$/kWh] at time t, p_t^g is the actual power [kW] purchased from the grid in the real-time energy market at time t, $p_t^{g,\text{DA}}$ is the power that was bid into the day-ahead market at time t, i.e., $p_t^{g,\text{DA}} = p_h^{g,\text{DA}}$ for all t satisfying

$$\frac{h-1}{\tau} + 1 \leq t \leq \frac{h}{\tau}, \tag{3}$$

and τ denotes the sub-hourly real-time market time interval between times t and $t+1$.

Then, the final combined cost can be calculated as the sum of the day-ahead cost and the real-time cost as

$$\Lambda = \sum_{t=1}^{T_{\text{day}}} \Big(\lambda_t^{\text{DA}} p_t^{g,\text{DA}} + \lambda_t^{\text{RT}} (p_t^g - p_t^{g,\text{DA}}) \Big)\tau, \tag{4}$$

where $\lambda_t^{\text{DA}} = \lambda_h^{\text{DA}}$ for all t satisfying (3). Therefore, the objective of the aggregator is to operate its energy resources to minimize the total cost in (4) while balancing customer demand, as described above.

III. Models and Forecasts

In this section we provide a model for the ES system and discuss forecasting of the stochastic net load and prices.

A. Energy storage model

The SoE of the ES is the amount of energy capacity [kWh] remaining in the system, and it can be modeled using the following linear energy flow model [1]

$$s_{t+1} = \eta_s s_t + \eta_c p_t^c \tau - p_t^d \tau, \tag{5}$$

where s_t is the SoE of the ES at time t, η_s is the self-discharge efficiency, η_c is the round-trip efficiency, and p_t^c and p_t^d are nonnegative scalars denoting the power charge and discharge commands at time t, respectively. Separate charging and discharging efficiencies may be equivalently used, as discussed in [1].

B. Forecasts

Similar to [19], [22], [25], [26], we express load, PV generation, and wind generation as

$$p_t^{\text{load}} = \hat{p}_t^{\text{load}} + \Delta p_t^{\text{load}}, \tag{6}$$
$$p_t^{\text{PV}} = \hat{p}_t^{\text{PV}} + \Delta p_t^{\text{PV}}, \tag{7}$$
$$p_t^{\text{wind}} = \hat{p}_t^{\text{wind}} + \Delta p_t^{\text{wind}}, \tag{8}$$

respectively, where $\hat{p}_t^{\text{load}}$, $\hat{p}_t^{\text{PV}}$, and $\hat{p}_t^{\text{wind}}$ are the load, PV generation, and wind generation forecasts at time t, respectively, and Δp_t^{load}, Δp_t^{PV}, and Δp_t^{wind} are the corresponding forecast errors. These errors depend on the forecasting method and horizon and are considered to be random variables.

Considering PV and wind generation as a negative load, we can write the net load at time t as

$$p_t^{\text{net}} = p_t^{\text{load}} - p_t^{\text{PV}} - p_t^{\text{wind}}, \tag{9}$$

which can also be expressed as

$$p_t^{\text{net}} = \hat{p}_t^{\text{net}} + \Delta p_t^{\text{net}}, \tag{10}$$

where $\hat{p}_t^{\text{net}}$ denotes the net load forecast, and Δp_t^{net} is the corresponding forecast error.

In the same way, we can express the day-ahead and real-time energy prices, respectively, as

$$\lambda_h^{\text{DA}} = \hat{\lambda}_h^{\text{DA}} + \Delta \lambda_h^{\text{DA}}, \tag{11}$$
$$\lambda_t^{\text{RT}} = \hat{\lambda}_t^{\text{RT}} + \Delta \lambda_t^{\text{RT}}, \tag{12}$$

where $\hat{\lambda}_h^{\text{DA}}$ and $\hat{\lambda}_t^{\text{RT}}$ denote the day-ahead and real-time price forecasts, respectively, and $\Delta\lambda_h^{\text{DA}}$ and $\Delta\lambda_t^{\text{RT}}$ are the corresponding forecast errors.

C. Load balancing

With the net load formulated, we can write the balanced power at time t as

$$p_t^{\text{balance}} = p_t^{\text{net}} + p_t^c - p_t^d - p_t^g, \tag{13}$$

where p_t^g is the power purchased from the grid at time t. Given forecasts for the net load, the objective is to operate the ES to balance expected load while minimizing the cost of energy purchased from the grid. Therefore, we would like to find values for p_t^c, p_t^d, and p_t^g to make $p_t^{\text{balance}} \leq 0$ for all times t, while also minimizing the cost of purchasing p_t^g.

IV. Operation with Perfect Knowledge

If load, generation, and day-ahead and real-time prices are all known perfectly before bidding into the day-ahead market, ideal operation of the ES device to minimize the cost of purchasing energy from the grid for each day (as given in (4)) can be determined by solving a single optimization problem. This optimization is subject to the following ES and load balancing constraints for all times $t \in \{1, 2, \dots, T_{\text{day}}\}$:

$$0 \leq \bar{p}_t^c \leq p_{\text{ES}} \tag{14a}$$
$$0 \leq \bar{p}_t^d \leq p_{\text{ES}} \tag{14b}$$
$$\underline{\delta} s_{\text{ES}} \leq \eta_s \bar{s}_t + \eta_c \bar{p}_t^c \tau - \bar{p}_t^d \tau \leq (1 - \bar{\delta}) s_{\text{ES}} \tag{14c}$$
$$\eta_s \bar{s}_{T_{\text{day}}} + \eta_c \bar{p}_{T_{\text{day}}}^c \tau - \bar{p}_{T_{\text{day}}}^d \tau = s_1 \tag{14d}$$
$$p_t^{\text{net}} + \bar{p}_t^c - \bar{p}_t^d - \bar{p}_t^g = 0 \tag{14e}$$

Constraints (14a) and (14b) ensure that the power charged/discharged from the ES is nonnegative and does not exceed the ES power rating p_{ES}. Constraint (14c) ensures that the predicted SoE of the ES, $\bar{s}_t$, (computed using model (5) with $\bar{p}_t^c$ and $\bar{p}_t^d$) is nonnegative and is less than or equal to a desired fraction of its energy capacity s_{ES} for all times t. Scalars $\underline{\delta}$, $\bar{\delta} \in [0, 0.5)$ are desired fractions of unused SoE at the lower and upper limits of the ES energy capacity, respectively, and can be chosen to limit depth of charge/discharge to, e.g., improve cycle life of the ES or ensure the linear SoE dynamics are valid. Constraint (14d) enforces that predicted SoE at the end of the day is equal to s_0, a desired initial daily SoE. Finally, constraint (14e) ensures that the (net) load is balanced at each time t by the power charged/discharged from the ES and purchased from the grid.

In this section, and in the remainder of the paper, we introduce the following shorthand notation: given a signal z_t and two times t_1 and t_2, with $t_1 < t_2$, we write $z_{t_1:t_2}$ to denote the sequence $\{z_{t_1}, z_{t_1+1}, \dots, z_{t_2}\}$.

With the constraints formulated, we can write the optimization problem with perfect knowledge as

$$\begin{aligned} \underset{\bar{p}^c, \bar{p}^d, \bar{p}^g}{\text{minimize}} \quad & \sum_{t=1}^{T_{\text{day}}} (\lambda_t^{\text{DA}} - \lambda_t^{\text{RT}}) \bar{p}_t^g \tau \\ \text{subject to} \quad & \text{(14a)–(14e)}, \end{aligned} \tag{15}$$

where the decision variables are the ES charge and discharge sequences $\bar{p}^c := \bar{p}^c_{1:T_{\text{day}}}$ and $\bar{p}^d := \bar{p}^d_{1:T_{\text{day}}}$, respectively, and the sequence of power purchased from the grid $\bar{p}^g := \bar{p}^g_{1:T_{\text{day}}}$. We denote the sequences that solve the optimization problem (15) as $\bar{p}^{c*} := \bar{p}^{c*}_{1:T_{\text{day}}}$, $\bar{p}^{d*} := \bar{p}^{d*}_{1:T_{\text{day}}}$, and $\bar{p}^{g*} := \bar{p}^{g*}_{1:T_{\text{day}}}$.

In practice, we do not have perfect knowledge of the load, generation, and day-ahead and real-time prices before scheduling or dispatching resources. Thus, we next propose a two-stage optimization approach that explicitly accounts for uncertainty in the net load and energy prices. Moreover, the real-time dispatch involves a receding horizon approach that uses feedback to improve performance as variables change in real-time and, therefore, is less sensitive to forecast errors.

V. Two-Stage Stochastic Optimization

The objective is to operate resources to minimize the cost of energy purchased from the grid required to balance the load over a given time horizon, i.e., minimize (4). Given forecasts of the stochastic load, renewable generation, and energy prices, this can be done by optimally bidding into the day-ahead market and dispatching the ES to charge and discharge in real-time. Therefore, a two-stage optimization is performed; first, the day-ahead supply/demand bid is computed, and then the real-time dispatch is solved.

A. Stage 1: Day-ahead scheduling

The day-ahead scheduling optimization results in optimal values of the charge, discharge, and hourly day-ahead bid for each hour in the day. In this stochastic setting, given forecasts of the net load, constraint (14e) becomes a probabilistic constraint and requires the amount of power provided by the ES and the power purchased from the grid to be greater than or equal to the forecast of the net load with some probability. Specifically, we desire the value of $\hat{p}_h^{\text{net}} + \tilde{p}_h^c - \tilde{p}_h^d - \tilde{p}_h^g$ to be nonpositive with at least probability α. This can be written as follows for all $h \in \{1, 2, \dots, 24\}$:

$$\mathbb{P}\{\hat{p}_h^{\text{net}} + \tilde{p}_h^c - \tilde{p}_h^d - \tilde{p}_h^g \le 0\} \ge \alpha \tag{16}$$

This constraint is similar to the probabilistic constraints (or chance constraints) considered in [22], [20], [19]. In some special cases (e.g., forecasting errors have normal probability distributions), we can reformulate the constraint in (16) to be $f(\tilde{p}_h^c, \tilde{p}_h^d, \tilde{p}_h^g) \ge \alpha$, where the function $f(\cdot) : \mathbb{R}^3 \to \mathbb{R}$ depends on the statistics of the net load forecast's probability distribution. We discuss this further in Section V-C.

Then, we can write the day-ahead scheduling optimization problem as

$$\begin{aligned} \underset{\tilde{p}^c, \tilde{p}^d, \tilde{p}^g}{\text{minimize}} \quad & \sum_{h=1}^{24} \lambda_h^{\text{DA}} - \hat{\lambda}_h^{\overline{\text{RT}}} \tilde{p}_h^g \\ \text{subject to} \quad & \text{(14a)–(14d), (16)}, \end{aligned} \tag{17}$$

with variables with subscript t in (14a)–(14c) replaced by the appropriate variables with subscript h, for all $h \in \{1, 2, \dots, 24\}$, and the variables with subscript T_{day} in (14d) replaced by the appropriate variables with subscript 24. The day-ahead, hourly-averaged forecast of the real-time energy price for hour h is denoted by $\hat{\lambda}_h^{\overline{\text{RT}}}$. The decision variables are the charge and discharge sequences $\tilde{p}^c := \tilde{p}^c_{1:24}$, $\tilde{p}^d := \tilde{p}^d_{1:24}$, respectively, and the hourly day-ahead bids $\tilde{p}^g := \tilde{p}^g_{1:24}$. We denote the sequences that solve the optimization problem (17) as $\tilde{p}^{c*} := \tilde{p}^{c*}_{1:24}$, $\tilde{p}^{d*} := \tilde{p}^{d*}_{1:24}$, and $\tilde{p}^{g*} := \tilde{p}^{g*}_{1:24}$.

B. Stage 2: Real-Time Dispatch

The real-time dispatch optimization problem is solved at each time step and results in optimal values for charge, discharge, and power purchased from the grid, p_k^c, p_k^d, and p_k^g, respectively, for all times $k \in \{t, t+1, \dots, t+T-1\}$, where T is the optimization time horizon. For example, with $\tau = 5$ minutes, $T = 48$ corresponds to a horizon of 4 hours.

We write the real-time dispatch optimization problem as

$$\begin{aligned} \underset{\bar{p}^c_{\text{RT}}, \bar{p}^d_{\text{RT}}, \bar{p}^g_{\text{RT}}}{\text{minimize}} \quad & \sum_{k=t}^{t+T-1} \hat{\lambda}_k^{\text{RT}} \bar{p}_k^g \tau \\ \text{subject to} \quad & \text{(14a)–(14c), (16)}, \end{aligned} \tag{18}$$

with variables with subscript h in (16) and subscript t in (14a)–(14c) replaced by the appropriate variables with subscript k, for all $k \in \{t, t+1, \dots, t+T-1\}$. The decision variables are the charge and discharge sequences $\bar{p}^c_{\text{RT}} := \bar{p}^c_{t:t+T-1}$ and $\bar{p}^d_{\text{RT}} := \bar{p}^d_{t:t+T-1}$, respectively, and the sequence of power to be purchased from the grid $\bar{p}^g_{\text{RT}} := \bar{p}^g_{t:t+T-1}$. We denote the sequences that solve the optimization problem as $\bar{p}^{c*}_{\text{RT}} := \bar{p}^{c*}_{t:t+T-1}$, $\bar{p}^{d*}_{\text{RT}} := \bar{p}^{d*}_{t:t+T-1}$, and $\bar{p}^{g*}_{\text{RT}} := \bar{p}^{g*}_{t:t+T-1}$.

The real-time optimization problem (18) can be solved at each time t in a receding horizon fashion using an MPC approach, as described in Algorithm 2 in Section VI.

C. Normally distributed forecast errors

If the probability distributions of the forecasting errors can be approximated with normal distributions, as is common in the literature (see e.g., [26], [30], [22]), we are able to calculate the probabilistic constraint (16) as a function of the decision variables $\tilde{p}_h^c$, $\tilde{p}_h^d$, and $\tilde{p}_h^g$, the statistics of the net load forecasting error, and the desired fraction α. Then (16) becomes the following linear inequality constraint

$$\tilde{p}_h^d + \tilde{p}_h^g - \tilde{p}_h^c \ge \sqrt{2}\sigma_h^{\text{net}} \times \text{erf}^{-1}(2\alpha - 1) + \hat{p}_h^{\text{net}} + \mu_h^{\text{net}}, \tag{19}$$

where $\text{erf}(\cdot)$ denotes the error function, $\hat{p}_h^{\text{net}}$ denotes the net load forecast at hour h, and μ_h^{net} and σ_h^{net} denote the mean and standard deviation, respectively, of the net load forecast error at hour h. By replacing constraint (16) with (19) in both the day-ahead scheduling and real-time dispatch optimization problems (17) and (18), respectively, both optimization problems can be formulated and solved as linear programs.

VI. Operational algorithms

We present two operational algorithms for bidding into the day-ahead market and dispatching resources in real-time. Algorithm 1 is only used for comparison and involves solving the day-ahead optimization problem (17), bidding into the day-ahead energy market, and then implementing the resulting day-ahead schedule in real-time. This approach is commonly considered by energy market participants but does not take advantage of real-time feedback information.

Algorithm 1: Solve & Implement Day-Ahead Schedule

procedure FOR A GIVEN DAY
  Receive/compute hourly day-ahead net load forecasts $\hat{p}_{1:24}^{\text{net}}$.
  Receive/compute hourly day-ahead price forecasts $\hat{\lambda}_{1:24}^{\text{DA}}$, $\hat{\lambda}_{1:24}^{\text{RT}}$.
  Solve (17).
  Bid resulting supply/demand $\tilde{p}^{g*}$ into the day-ahead market.
  for each hour $h \in \{1, 2, \ldots, 24\}$ **do**
    Implement $p_t^c = \tilde{p}_h^{c*}$ and $p_t^d = \tilde{p}_h^{d*}$ for all t satisfying (3).
  end for
end procedure
Repeat procedure each day.

Algorithm 2 is a novel real-time operational algorithm that solves the two-stage optimization problem in order to bid into the day-ahead market and also adjust the dispatch in real-time to take advantage of real-time fluctuations in net load and energy prices. Specifically, in the day-ahead, Algorithm 2 involves solving the day-ahead optimization problem (17) and bidding into the day-ahead energy market, as is done in Algorithm 1. Then in real-time, information of the net load, energy prices, and SoE of the ES are used in solving the real-time optimization problem (18) at each sub-hourly time t. The ES is then dispatched by implementing

$$p_t^c = \bar{p}_t^{c*}, \tag{20a}$$
$$p_t^d = \bar{p}_t^{d*} \tag{20b}$$

at each time t, and energy is bought/sold in the real-time energy market. This procedure is repeated at every time t in a receding horizon fashion.

Algorithm 2: Solve Day-Ahead Schedule, Solve & Implement Real-Time Dispatch

procedure FOR A GIVEN DAY
  Receive/compute hourly day-ahead net load forecasts $\hat{p}_{1:24}^{\text{net}}$.
  Receive/compute hourly day-ahead price forecasts $\hat{\lambda}_{1:24}^{\text{DA}}$, $\hat{\lambda}_{1:24}^{\text{RT}}$.
  Solve (17).
  Bid resulting supply/demand $\tilde{p}^{g*}$ into the day-ahead market.
  for each time t **do**
    Measure/receive s_t, p_{t-1}^{net}, and $\lambda_{t-1}^{\text{RT}}$.
    Receive/compute real-time forecasts $\hat{p}_{t:t+T-1}^{\text{net}}$, $\hat{\lambda}_{t:t+T-1}^{\text{RT}}$
    Solve (18).
    Implement (20).
  end for
end procedure
Repeat procedure each day.

TABLE I
Nominal Parameter Values

Parameter	Description	Value	Units
ρ	Air density	1.2	kg/m^3
$\underline{v}$	Wind turbine cut-in speed	4	m/s
$\overline{v}$	Wind turbine cut-out speed	25	m/s
v^*	Wind turbine rated speed	10	m/s
η_{PV}	PV panel efficiency	0.15	-
η_{conv}	PV conversion efficiency	0.90	-
η_s	ES self-discharge efficiency	1.00	-
η_c	ES round-trip efficiency	0.85	-
A_{PV}	Total area of solar panels	1000	m^2
A_{wind}	Total swept area of turbine blades	1357	m^2
p_{ES}	ES power rating	1000	kW
s_{ES}	ES energy capacity	1000	kWh
s_0	Daily initial SoE	$s_{\text{ES}}/2$	kWh
$\bar{\delta}$	Desired fraction of unused SoE	0.1	-
$\underline{\delta}$	Desired fraction of unused SoE	0.1	-
τ	Real-time optimization time step	1/12	hours
T	Real-time optimization horizon	48	-
α	Load balancing probability	0.99	-

VII. Case Study

In this section we present a case study of an energy aggregator in ISO New England operating an ES system, a wind turbine, and a solar PV system with the goal of minimizing the cost of energy to be purchased from the grid to balance commercial loads. We assume that the systems are small enough that the market supply/demand bids do not affect the market prices, and the aggregator has a "price-taker" agreement. The following data were used:

- Fifteen-minute load from commercial customers in Massachusetts from January 2017 to February 2018.
- Thirty-minute solar Global Horizontal Irradiance (GHI) data for a location near Boston, MA from the National Solar Radiation Database (NSRDB) [31] from January 2015 to January 2017.
- Thirty-minute wind speed data for a location near Boston, MA from the Modern-Era Retrospective Analysis for Research and Applications (MERRA) database [32] from January 2015 to January 2017.
- Hourly day-ahead and five-minute real-time LMP data for Brighton pricing node near Boston, MA from ISO New England [33], February 2017 to March 2018.

The sub-hourly load, GHI, and wind speed data were interpolated to produce 5-minute data, and solar and wind generation were computed using standard models, as can be found in, e.g., [34], with parameter values given in Table I.

A. Forecasts

We use the following persistent forecasts.

1) Day-ahead forecasts: The load forecast $\hat{p}_h^{\text{load}}$ is equal to the true load for the same hour in the previous week. The solar and wind generation forecasts $\hat{p}_h^{\text{PV}}$ and $\hat{p}_h^{\text{wind}}$, respectively, are equal to the average true generation in hour h of the previous day. The day-ahead price forecast $\hat{\lambda}_h^{\text{DA}}$ is equal to the cleared price for hour h in the previous day. The day-ahead forecast of the hourly-averaged real-time price $\hat{\lambda}_h^{\overline{\text{RT}}}$ is equal to the average cleared real-time price during hour h in the previous day.

2) Real-time forecasts: The load, solar generation, and wind generation forecasts over the entire real-time optimization horizon T are constant and equal to the measured real-time load, solar generation, and wind generation from the previous five minutes, i.e.,

$$\hat{p}_{t:t+T-1}^{\text{load}} := \{p_{t-1}^{\text{load}}, p_{t-1}^{\text{load}}, \ldots, p_{t-1}^{\text{load}}\}, \tag{21}$$

$$\hat{p}_{t:t+T-1}^{\text{PV}} := \{p_{t-1}^{\text{PV}}, p_{t-1}^{\text{PV}}, \ldots, p_{t-1}^{\text{PV}}\}, \tag{22}$$

$$\hat{p}_{t:t+T-1}^{\text{wind}} := \{p_{t-1}^{\text{wind}}, p_{t-1}^{\text{wind}}, \ldots, p_{t-1}^{\text{wind}}\}, \tag{23}$$

Net load forecasts over the real-time optimization horizon T are constant and equal to the measured load minus solar and wind generation from the previous five minutes, i.e.,

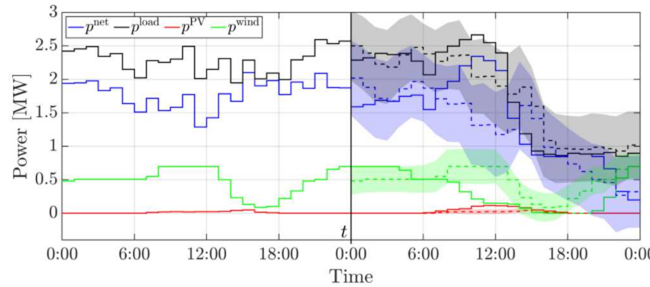
$$\hat{p}_{t:t+T-1}^{\text{net}} := \{p_{t-1}^{\text{net}}, p_{t-1}^{\text{net}}, \ldots, p_{t-1}^{\text{net}}\}. \tag{24}$$

Price forecasts for the next five-minute interval are equal to the cleared real-time price from the previous five minutes, and the rest of the price forecasts are equal to the cleared day-ahead price for those time intervals, i.e.,

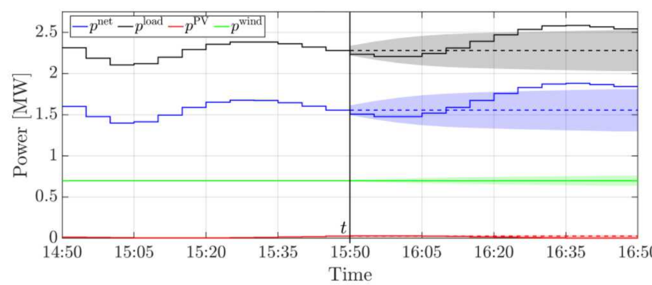
$$\hat{\lambda}_{t:t+T-1}^{\text{RT}} := \{\lambda_{t-1}^{\text{RT}}, \lambda_{t+1}^{\text{DA}}, \lambda_{t+2}^{\text{DA}}, \ldots, \lambda_{t+T-1}^{\text{DA}}\}. \tag{25}$$

Forecast error statistics were computed from the available data described above and were fit to normal distributions to determine the statistics used in the probabilistic load balancing constraint (19). We assume that the expected values of the energy prices are equal to the forecasted values.

Figure 3 shows snapshots of example data used within Algorithms 1 and 2, and Figure 4 shows an example solution of the real-time optimization (18), at a given time t.



(a) Day-ahead data snapshot.



(b) Real-time data snapshot.

Fig. 3. Data snapshots. True values are shown as solid lines, forecasts are dashed lines, and standard deviations of the forecast errors are shaded regions. The current time t is marked by the vertical black line.

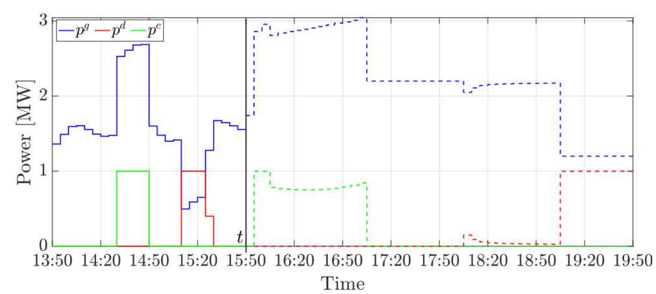


Fig. 4. Snapshot of the real-time optimization solution. The current time t is 15:50. The implemented signals before time t are shown as solid lines, and the future signals computed at time t are shown as dashed lines.

B. Results

We present results for three different scenarios:

Stochastic: Day-ahead forecasts described in Section VII-A.1, and real-time forecasts given in (21)–(25) are used. Uncertainty is considered, so constraint (19) is used.

Deterministic: Day-ahead forecasts described in Section VII-A.1, and real-time forecasts given in (21)–(25) are used. Uncertainty is not considered (constraint (14e) is used).

Perfect Forecasts: Day-ahead and real-time forecasts are equal to the true values of the net load and prices, i.e.,

$$\hat{p}_h^{\text{net}} := p_h^{\text{net}}, \tag{26a}$$

$$\hat{p}_{t:t+T-1}^{\text{net}} := p_{t:t+T-1}^{\text{net}}, \tag{26b}$$

$$\hat{\lambda}_h^{\text{DA}} := \lambda_h^{\text{DA}}, \tag{26c}$$

$$\hat{\lambda}_h^{\overline{\text{RT}}} := \lambda_h^{\overline{\text{RT}}}. \tag{26d}$$

Uncertainty is not considered (constraint (14e) is used).

Table II gives the total cumulative costs from March 1, 2017 to January 24, 2018[1] for the three scenarios described above with parameter values given in Table I resulting from Algorithm 1, Algorithm 2, and the case where there is no ES (i.e., the only decision variables are the hourly day-ahead supply/demand bids $\tilde{p}_h^g$). Optimization problems (17) and (18) were formulated as linear programs and solved numerically using CVX in MATLAB [35].

The main results are: 1) Real-time decision-making reduces costs; Algorithm 2 results in the lowest total costs for all three scenarios. In the stochastic scenario, Algorithm 2 produces a 9.5% lower total cost than the 'No ES' case and a 12% lower total cost than Algorithm 1. Therefore, the use of real-time feedback information is advantageous, and the ES device is effectively operated to take advantage of

[1]The load and price data were from this period, but the weather data corresponded to March 1, 2015 to January 24, 2016

TABLE II
TOTAL CUMULATIVE COST FROM 3/1/2017 TO 1/24/2018.

	Algorithm 1	Algorithm 2	No ES
Stochastic	$422,059	$371,411	$410,566
Deterministic	$444,674	$394,023	$433,181
Perfect Forecasts	$441,017	$366,449	$432,716

fluctuations in real-time prices. 2) The real-time approach of Algorithm 2 is effective even without sophisticated forecasts. For the deterministic scenario, which uses simple persistent forecasts, Algorithm 2 produces a 9% lower total cost than the 'No ES' case. While the total cost from the perfect forecasts scenario using Algorithm 2 results in a 7% lower total cost than the deterministic scenario, the difference is significantly narrowed by considering uncertainty, as in the stochastic scenario. 3) Considering uncertainty can be advantageous; the stochastic approach results in a lower cost than the deterministic approach for both algorithms and the 'No ES' case. 4) Implementing a day-ahead schedule for ES in real-time (Algorithm 1) can result in a higher total cost than if no ES system is used, as it does for all three scenarios.

C. Sensitivity analysis

In this section, we vary parameter values to show how sensitive the results are to those values. Each case used the nominal parameter values given in Table I except for the modified parameter values listed below. Table III shows the resulting total cumulative costs for each case using Algorithm 1 and Algorithm 2 with the three scenarios discussed above and for the following modified parameter values:

Case 1: Nominal parameter values as given in Table I.
Case 2: $p_{\text{ES}} = 500$ kW, $s_{\text{ES}} = 500$ kWh
Case 3: $p_{\text{ES}} = 2000$ kW, $s_{\text{ES}} = 2000$ kWh
Case 4: $T = 24$
Case 5: $T = 96$
Case 6: $\alpha = 0.75$
Case 7: $\alpha = 0.50$
Case 8: No energy storage system
Case 9: No solar power generation
Case 10: No wind power generation

In Cases 2 and 3, the power rating p_{ES} and the energy capacity s_{ES} of the ES are decreased and increased, resulting in higher and lower total costs, respectively. In Case 4, the real-time optimization horizon T is reduced to 24 intervals of 5 minutes (2-hour horizon), and the results of Algorithm 2 are slightly worse than those from Case 1; this is because a shorter optimization horizon provides less information about, and opportunity to plan for, future changes in price and net load. On the other hand, T is increased in Case 5 to 96 intervals of 5 minutes (8-hour horizon), and results of Algorithm 2 are slightly better than those from Case 1. However, this slight improvement comes at the expense of additional computation time. In Cases 6 and 7, the desired fraction α in the probabilistic constraint (19) is decreased. The effect of this is discussed below. Finally, Cases 8, 9, and 10 show how much the total costs increase if there were no ES to modulate the net load, no solar power generation, and no wind power generation, respectively.

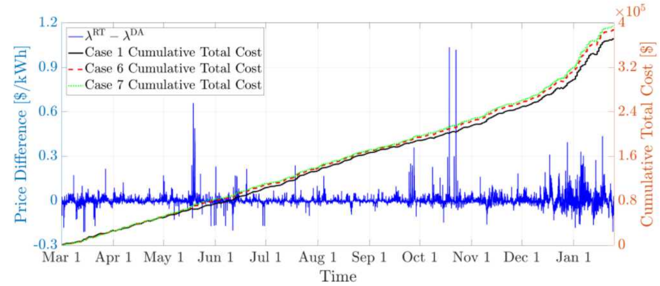


Fig. 5. Cumulative total cost for Cases 1, 6, and 7 (right axis) and the difference between the real-time and day-ahead prices (left axis).

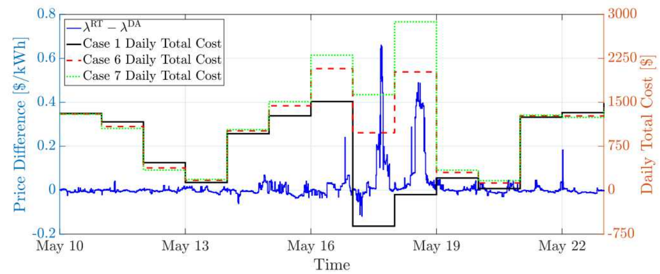


Fig. 6. Daily total costs for Cases 1, 6, and 7 (right axis) and the difference between real-time and day-ahead prices (left axis) from May 10 to May 23.

In this study, real-time prices are often higher than day-ahead prices, so it is advantageous to choose a larger value for α so that day-ahead market bids are large and less energy is purchased in the real-time market. This is shown in Figure 5 in which the cumulative total costs for Cases 1, 6, and 7 are shown with the difference between real-time and day-ahead prices. The more conservative (larger α) Cases 1 and 6 result in lower cumulative total costs due to the large positive difference between prices. Figure 6 shows the difference in daily total costs (computed using (4)) for different values of α when there is a significant difference between real-time and day-ahead prices. If, instead, day-ahead prices are larger than real-time prices, it would be advantageous to submit smaller demand bids in the day-ahead market and buy more energy in real-time. In general, choosing α to be time-varying, larger when real-time prices are forecasted to be higher than day-ahead prices and smaller when real-time prices are forecasted to be lower than day-ahead prices, could be advantageous. However, this type of strategic bidding may be constrained by the rules of the energy market.

VIII. CONCLUSIONS AND FUTURE WORK

We proposed a two-stage stochastic optimization approach for managing multiple energy resources and participating in wholesale energy markets to minimize the cost of energy required to balance a net load. The two stages include a day-ahead optimization, which results in a day-ahead schedule and bids for the day-ahead energy market, and a real-time optimization, which results in real-time dispatch commands. These optimization problems include a probabilistic constraint requiring that the uncertain net load be balanced with a desired probability. We presented a case study involving an

TABLE III

TOTAL COST FROM 3/1/2017 TO 1/24/2018 FOR MULTIPLE CASES.

	Case	1	2	3	4	5	6	7	8	9	10
Alg. 1	Stochastic	$422,059	$416,292	$433,562	$422,059	$422,059	$438,117	$444,674	$410,566	$428,866	$493,538
	Deterministic	$444,674	$438,907	$456,176	$444,674	$444,674	$444,674	$444,674	$433,181	$451,470	$514,933
	Perfect Forecasts	$441,017	$436,870	$449,381	$441,017	$441,017	$441,017	$441,017	$432,716	$447,948	$512,027
Alg. 2	Stochastic	$371,411	$390,987	$332,315	$372,608	$371,083	$387,469	$394,026	$410,566	$378,217	$442,889
	Deterministic	$394,023	$413,601	$354,930	$395,223	$393,697	$394,026	$394,026	$433,181	$400,821	$464,284
	Perfect Forecasts	$366,449	$399,582	$300,182	$367,129	$366,353	$366,449	$366,449	$432,716	$373,380	$437,458

energy aggregator operating an energy storage system, wind turbine, and solar PV system and participating in day-ahead and real-time energy markets in ISO New England. Real-time dispatch of the energy storage system reduces costs, even without sophisticated forecasts, and the stochastic approach reduces costs compared to a deterministic approach.

In future work, additional production-cost models may be incorporated to determine how energy bids affect market prices, and additional revenue streams, such as frequency regulation, will be considered to further reduce costs.

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