# Operations Planning Experiments for Power Systems with High Renewable Resources

Semih Atakan*[1], Harsha Gangammanavar†[2], and Suvrajeet Sen‡[1]

[1]Department of Industrial and Systems Engineering, University of Southern California, Los Angeles, CA

[2]Department of Engineering Management, Information, and Systems, Southern Methodist University, Dallas TX

April 15, 2020

**Abstract**

Driven by ambitious renewable portfolio standards, large scale inclusion of variable energy resources (such as wind and solar) is expected to introduce unprecedented levels of uncertainty to power system operations. The current practice of operations planning with deterministic optimization models may be ill-suited for a future where uncertainty is abundant. To overcome the potential reliability challenges, we present a stochastic hierarchical planning (SHP) framework. This framework captures operations at day-ahead, short-term and hour-ahead timescales, along with the interactions between the stochastic processes and decisions. In contrast to earlier studies where the stochastic optimization of individual problems (e.g., unit commitment, economic dispatch) have been studied, this paper provides a comprehensive treatment of *planning under uncertainty*, where stochastic optimization models are stitched together in a hierarchical setting, in a way that parallels the widely adopted deterministic hierarchical planning (DHP) of the power industry. Our experiments, based on NREL118 dataset, allude to significant improvements in sustainable and reliable operations under high renewable penetration, solely by moving from the current paradigm of DHP towards SHP. Such advances in operations planning, along with improved equipment technology and market designs, are essential to the transition into the next generation of power systems.

## 1 Introduction

Lawmakers throughout the U.S. have mandated that a significant percentage of electricity supply should be derived from renewable resources. Each state has set its own goal, with California being the most aggressive, requiring 50% renewables by 2026, 60% by 2030, and 100% by 2045 (see [1]). State and local authorities (e.g., independent system operators (ISOs)) have commissioned studies to assess operational considerations such as system reliability, market design, incorporation of storage technologies, and other avenues. A recent simulation study [2], commissioned by California ISO (CAISO), suggests that for renewable-integration levels beyond 33%, one can expect a fair amount of over-generation and renewable curtailment during daytime, and perhaps, load-shedding around sundown. These issues are exacerbated at higher levels of renewable penetration, and maintaining system reliability becomes a challenge.

*atakan@usc.edu

†harsha@smu.edu

‡s.sen@usc.edu

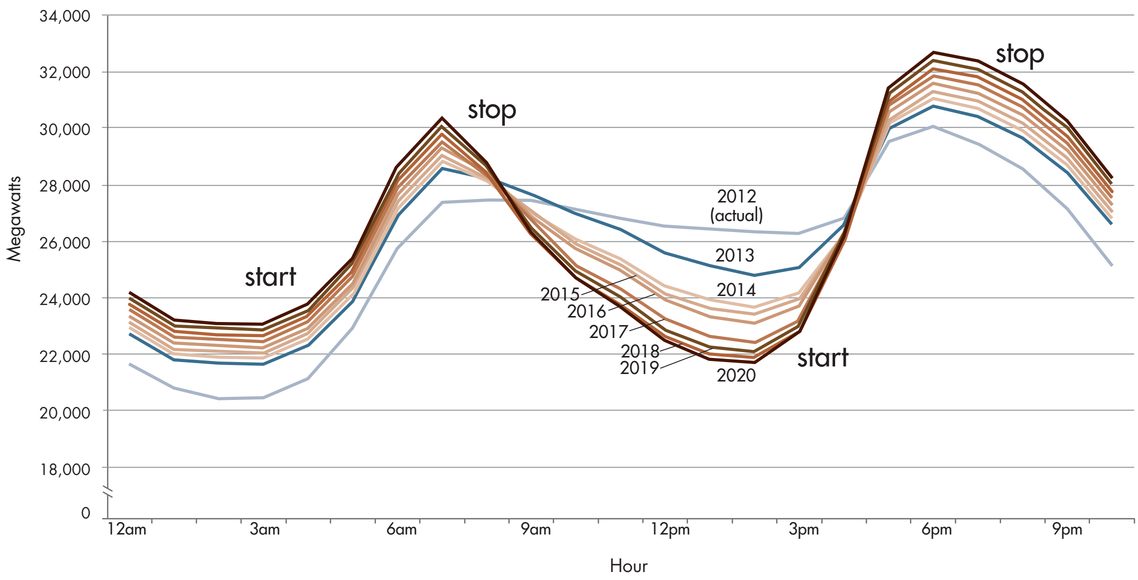



Figure 1: CAISO's duck chart, predicting four emerging ramping patterns with increased renewable integration [4].

A popular illustration of the above issues are captured by the so-called "duck-chart" of CAISO (see Fig. 1). This figure depicts the daily net-load (total electric load minus generation from "must-run" units) across successive years with increasing levels of solar added to the generation mix. A surplus of solar energy during daytime leads to a dip in the net-load, followed by a significant upward ramp around sundown. In a grid with limited storage capabilities, excess supply during daytime poses significant challenges as utilities will be required to procure sufficient ramp-up capabilities to meet the electric load of evening hours. The absence of substantial ramping capabilities can push the loss-of-load probability to unacceptable levels, and may even cause load-shedding in certain areas, jeopardizing system reliability and performance. On the other hand, over-generation during daytime could lead to negative prices in the market, resulting in, for instance, large shipments of energy to neighboring states (e.g., from California to Arizona), while paying these states to accept the surplus at home (see [3]).

In order to meet the challenges discussed above and "tame the duck", so to speak, a recent U.S. Department of Energy (DOE) report [5] has distilled a myriad of operational guidelines (for maintaining reliability) into four specific rules:

- Power generation and transmission capacity must be sufficient to meet peak demand for electricity;
- Power systems must have adequate flexibility to address variability and uncertainty in demand and generation resources;
- Power systems must be able to maintain steady frequency;
- Power systems must be able to maintain steady voltage at various points on the grid.

These rules are particularly focused on changes that are expected over the next several years due to the inclusion of new production resources, especially variable energy resources (VER). The first two rules can be seen as addressing operations *planning*, whereas the last two rules pertain to operations *control*. The latter are typically addressed via controlling devices such as inverters. To quote a recent study associated with a photovoltaic (PV) demonstration project, the authors observe that modern inverters "mitigate the impact of [PV] variability on the grid, and contribute to important system requirements more like traditional generators" [6, p. 5]. Another innovation which is credited to improving power system control is flexible AC transmission systems. These devices used to be relatively expensive several years ago, but are relatively inexpensive now, and should be looked upon as part of the modern grid.

In contrast to the operations control studies, the focus of this paper is on the first two rules which are crucial for operations planning. While there are some proposals for completely decentralized electricity production and markets, it is commonly accepted that the presence of an ISO enhances the reliability of the power system. Accordingly, in order to accommodate extensive use of VERs as expected for the next generation of the power grid, we propose an important paradigm shift: from the contemporary deterministic hierarchical planning (DHP), to a future which allows pre-positioning of resources based on new agile technology via smart grid solutions. Given the above focus, our paper will demonstrate the reliability, economic and environmental impacts of a *stochastic hierarchical planning* (SHP) framework, and contrast it with the DHP paradigm.

Both the SHP and DHP paradigms require coordination via a central planning authority (e.g. ISO). Most ISOs in the U.S. currently implement some form of a DHP framework, which divide the daily planning activities into three principal layers: a) *day-ahead unit commitment* based on a daily forecast of load and generation limits, producing a production and transmission plan, b) *short-term unit commitment* over a shorter planning window (typically three to four hours), producing some commitment decisions and updated transmission plans, and c) *hour-ahead economic dispatch* where the production and transmission plans are finalized and, if necessary, reserve capacities are committed. There are some variations of this multi-layer hierarchy, such as updating the dispatching plan in 15-minute intervals to accommodate high levels of VER. All layers in this hierarchical setup use some form of deterministic optimization, and as such, all forecasts used in the optimization models are *point forecasts*.

With growing VER share in the grid, the reliability challenges will only get bigger, which the above planning process can inefficiently address by more conservative reserve restrictions. To this end, we recommend SHP, whose main difference is that at each layer of the hierarchy, the model uses a stochastic programming setup, so that the decisions are cognizant of various potential uncertainties (load, generation, failures etc.). These models are solved using stochastic programming (SP) algorithms, some of which have been studied rigorously over the past twenty-five years [7, 8] with more recent versions in [9, 10]. In this paper we coalesce our research from SP, including discrete SP [11], with the work in power systems research for economic dispatch (ED) [12, 13] and unit commitment (UC) [14]. We caution that not all algorithms which solve a particular class of models are equally effective in solving equivalent models. This is particularly true for stochastic programming (SP) models for which certain types of structures (e.g., fixed and complete recourse models with linear structures) are much more amenable to specialized solution algorithms, than general purpose SP algorithms [15]. While such algorithmic and modeling issues have significant importance, this paper takes a system-wide perspective and focuses on *operational outcomes* of using such models and algorithms. Readers who are interested in these aspects should refer to papers where models and algorithms for individual problems are discussed in detail.

We will compare the performance of DHP and (two) SHP strategies using the NREL118 dataset. Our analysis will examine questions that pertain to the metrics of the operations planning guidelines of the DOE report [5]. More specifically, our comparisons will focus on the following questions at different levels of penetration of VER:

- Are there significant differences between results for unmet demand for DHP v SHP? Does one dominate the other?
- Are there significant differences between conventional over-generation and renewable curtailment for DHP v SHP?
- To what degree does each approach rely on reserve generation?

- What percentage of daily power generation was due to short-term unit commitment?

In addition to the above system reliability questions, we will also compare costs and greenhouse gas (GHG) emissions. Our conclusions regarding the viability of these approaches will be based on these comparisons.

While there are many studies of stochastic optimization within any one layer of the hierarchical system (see [16, 17] for comprehensive reviews), no other study pits the standard hierarchy of deterministic models against a hierarchy of stochastic models. It is such a comparison which provides a preview of potential advantages and disadvantages of these alternative hierarchies. Thus, this study examines whether a system-wide overhaul which introduces stochastic optimization and coordination among all layers of the hierarchy can mitigate difficulties associated with high penetration of renewable energy into the grid. Our experiments point to the potential of a transition from the DHP to the SHP framework.

The remainder of the paper is arranged as follows. In §2 we present a detailed description of the SHP framework including the optimization models and solution algorithms employed. In §3 we present the experimental results conducted using the NREL118 dataset on the DHP and SHP frameworks. Finally, we will conclude with a brief discussion in §4. The overall structure of each of the models used in the hierarchy are summarized in Appendix A, the online supplement.

# 2 Stochastic Hierarchical Planning

Electric power systems are very large-scale networks interconnecting many sources of electric power (generators) to points of consumption (loads). The entire network is arranged at several voltage levels, converted from one to the other by step-up or step-down transformers. This network is operated with the overall goal of minimizing total cost while ensuring reliable power delivery. The implementation of this objective is complex when viewed as a single decision making problem. Therefore, system operators use a reformulation involving a hierarchy of optimization models defined over overlapping horizons with different time resolutions for decisions and constraints.

The particular rules, design, and operational elements differ markedly across different system operators. In addition to the ISOs which oversee the operations over larger geographic areas, balancing area authorities (BAA) for smaller regions also operate under notably different practices. For instance, Bonneville Power Administration, which primarily oversees hydroelectricity production, performs bulk-hourly generation-scheduling, and has sufficient range of reserves and ramping capabilities for handling imbalances [18]. However, in the case of ISOs as well as BAAs, the operations can be classified into two phases: day-ahead (DA) and real-time (RT) [19, 20, 21]. In line with the current practices, we also adopt a hierarchical decision process comprising of DA and RT phases.

### Day-ahead Operations

This phase begins by estimating demand and renewable-supplies as well as collecting generation and demand bids. This information is used in simultaneous co-optimization of the next operating day using security constrained UC and security constrained ED models. In our setting, these optimization models are formulated over a 24-hours horizon with decisions and constraints defined at an hourly resolution. The UC model commits and schedules resources for regulation. The amount of resources (mainly spinning operating reserves) scheduled in DA are based on estimates generated using historical data and ISO-specific practices. The DA planning also involves committing resources for reliability assessment and emergency operations, however, we do not consider these in our setup. The UC optimization model involves continuous as well as binary decision variables, resulting in a mixed integer program (MIP).

The UC decisions are used to instantiate the DA security constrained ED model. The ED model is used to determine the generation, regulating and spinning reserve amounts for all committed resources, as well as the ex ante DA prices. While the ED model in the DA phase is often solved separately for each hour of the day, we formulate the ED model as a single optimization model defined over an entire day at an hourly resolution. In our models we do not allow for generator self-scheduling and do not consider system operations under contingency/emergency.

**Real-time Operations**

There is always some RT deviation of actual generation and load from what was scheduled during DA planning. One of the key functions of the ISO is to perform real-time balancing of loads and generation. RT balance is maintained through the combined use of spinning and ancillary services along with the units providing regulation reserves, which are managed by the automatic generation control (AGC). The non-AGC units are dispatched every few minutes (usually 5 to 15 minutes), while the regulation units are used only to respond instantaneously to system imbalances.

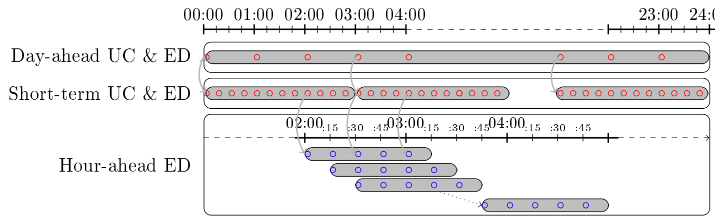
In our setting we will use an Hour-ahead ED (HA-ED) model for balancing the supply and demand at least cost while recognizing the operating conditions of the system a few minutes ahead of the actual dispatch. The model will determine the generation quantities and reserve levels for non-AGC units. These models are defined at a resolution of 15 minutes and a horizon of 75 minutes. Furthermore, HA-ED model is solved every 15 minutes in a rolling horizon manner. This allows us to revise the generation amounts of committed units closer to the time of dispatch when updated forecasts are available.

**Short-term Operations**

Some of the advanced ISOs use additional instruments that commit fast-start resources in order to ensure that schedules meet all the reliability requirements. The associated models are solved independently against DA transactions and generation bids. At certain ISOs, these operations are considered to be part of the RT markets and are referred to as the RT-UC (e.g., NYISO). Following its usage at CAISO, we will refer to these operations as Short-Term UC (ST-UC). These models are formulated at finer resolution (15 minutes) that allows adaptive (de)commitment decisions, and are solved over a horizon of few hours (e.g., 4.5 hours at CAISO and 2.5 hours in NYISO). In our setting we define these models at a resolution of 15 minutes and a horizon of 4 hours.

In summary, the framework considered in this work comprises of three phases – day-ahead, short-term and real-time. These phases are arranged in a hierarchical manner with progressively (from DA to RT) shorter horizon, higher resolution, and using updated forecasts of demand and renewable generation. The interactions and timeline of our modeling framework are illustrated in Fig. 2. Notice that our framework does not involve an energy market, or ancillary services such as ramping reserves. We assume that the latter can serve any unmet demand that might be revealed during our planning process, albeit at a higher cost. Finally, since the framework is focused on planning phases, we do not consider real-time AGC.

Even with this temporal decomposition, both generation scheduling and dispatch problems are truly stochastic optimization problems, and as such are computationally very challenging. Therefore, the power systems operators employ deterministic optimization methods which approximate these stochastic optimization models with point forecasts to be used in deterministic optimization models. Some ISOs (e.g., New England ISO) have recognized the shortcomings of such deterministic planning within the context of renewable integration, and recommend certain deterministic policies (e.g., "do-not-exceed" limits on wind and hydro power [22]). However, in the absence of significant storage capacity in the system, such vast swings may result in over-




| | Horizon | Resolution | Frequency |
|---|---|---|---|
| DA | 24 hrs | 60 minutes | 24 hrs |
| ST | 4 hrs | 15 minutes | 4 hrs |
| RT | 75 minutes | 15 minutes | 15 minutes |

Figure 2: Hierarchical Structure and Timescale of the Operating Framework used for Experiments.

generation, which, in turn, require bi-lateral agreements and exchanges between neighboring ISOs to ensure supply matches demand. Nevertheless, the current approaches to power systems operations remain beholden to deterministic models and policies. Our goal is to explore whether there are benefits to using stochastic optimization models within power systems planning, especially, in the context of high penetration levels of VER.

Accordingly, we will consider deterministic planning models as our benchmark. Then, we will investigate the potential of using stochastic optimization models, by replacing the deterministic approaches with their stochastic counterparts. We will next discuss the optimization models used in our framework.

## 2.1 Optimization Models

Both the UC and ED problems are fundamental to power systems planning and operations. These problems are posed as deterministic optimization models, often with linearized objective functions and constraints. Due to the presence of commitment decisions, which are formulated as binary variables, the UC models are mixed-integer programs. [23] provides a comprehensive treatment of the state-of-the-art UC formulations, including a comparative computational study.

For assessing the impact of large-scale integration of VERs into power systems, we propose transitioning from traditional deterministic approaches to stochastic optimization for both UC and ED. Stochastic programming (SP) has played a prominent role to enable decision making under uncertainty in real-scale problems across many application domains including power systems [24]. In particular, the two-stage stochastic programs (2-SPs), including models with discrete first-stage variables, have gained acceptance of both the power systems research community as well as practitioners (see surveys by [25] for UC and [16] for ED). We will use such 2-SPs to model DA, ST and RT operations.

Typical UC formulations studied in the literature (such as [14, 23, 26]) are deterministic MIPs and do not include transmission constraints. In our study, we extend a variant of the UC model in [14] into a 2-SP with the commitment decisions in the first-stage along with minimum up/downtime requirements. The ED model in the second-stage is based on [12]. This formulation includes a linear objective function that captures production cost along with over-generation/load-shedding penalties, and constraints corresponding to generation capacities, ramping, flow balance, linearized power flow (DC approximation), operating reserve utilization, bounds on bus angles, and line capacities.

For HA-ED, we use a 2-SP model where the first-stage is used to determine the generation levels of committed slow-ramp generators while the second-stage determines the utilization of committed operating reserves in response to realizations of uncertain renewable generation and demand. We refer the reader to [14] and [12] for detailed descriptions and additional considerations in UC and ED models, respectively. Here we provide only high-level models with a particular focus on the interactions between various model instances inside our hierarchical framework.

Let $x$ and $y$ be the vector variables that model the generators' on/off statuses and production levels, respectively, for the entire planning period (say, a week), and define $z = (x, y)$. We will use superscripts $d$, $s$ and $r$ on objective functions, constraint sets and parameters associated DA, ST and HA, respectively. A subscript $[\bullet]$ (as in, $x_{[\bullet]}$) is used to refer to the set of time indices starting at 0, and ending at the time specified in the argument. We use three such subscripts, $[i]$, $[j]$, and $[k]$, corresponding to the DA-UC, ST-UC, and HA-ED models, respectively. The randomness associated with the renewable supplies and the demand is embodied in random vectors that evolve over time. We denote these random vectors as $\tilde{\xi}_{[i]}$, $\tilde{\xi}_{[j]}$, and $\tilde{\xi}_{[k]}$, for the $i^{th}$, $j^{th}$, and $k^{th}$ instances of the DA-UC, ST-UC, and HA-ED models, respectively. To make our notation clear (refer to the timescales in Fig. 2), the DA operations of the first day will be captured by DA-UC instance indexed by $i = 1$; the ST operations between 9:00 am - 12:00 pm will be captured by the ST-UC instance indexed by $j = 4$; and the RT operations for 10:00 am will be captured by the HA-ED indexed by $k = 11$.

We begin by presenting the deterministic models used in the DHP framework. Given the above notation, for a given day $i$, we define the DA-UC model as follows:

$$\begin{aligned} \text{DA-UC}\,(z^\star_{[0]} \dots z^\star_{[i-1]},\, \tilde{\xi}^d_{[i]}) = \min\ & f^d_{[i]}(x_{[i]},\, y_{[i]}) \\ \text{subject to: } & (x_{[i]},\, y_{[i]}) \in \mathcal{X}^d_{[i]}\left(z^\star_{[0]} \dots z^\star_{[i-1]},\, \bar{\xi}^d_{[i]}\right). \end{aligned} \tag{1}$$

Above, the function DA-UC$\,(\cdot)$ uses the history of the generators (i.e., $z^\star_{[0]} \, \dots \, z^\star_{[i-1]}$) and a single forecast of the renewable supplies and the demand (denoted as $\bar{\xi}_i$) to determine feasible commitment schedules for the DA generators. The feasible region of the model is denoted as $\mathcal{X}^d_{[i]}\,(\cdot)$, and the function $f^d_{[i]}(\cdot)$ captures the combined commitment and dispatch costs. We refer to the optimal solution of this model as $z^\star_{d,[i]} = (x^\star_{d,[i]},\, y^\star_{d,[i]})$.

Using the DA decisions (i.e., $z^\star_{d,[i]}$), the $j^{th}$ ST-UC model is formulated as follows:

$$\begin{aligned} \text{ST-UC}\,(z^\star_{[0]} \dots z^\star_{[j-1]},\, z^\star_{d,[j]},\, \tilde{\xi}^s_{[j]}) = \min\ & f^s_{[j]}(x_{[j]},\, y_{[j]}) \\ \text{subject to: } & (x_{[j]}, y_{[j]}) \in \mathcal{X}^s_{[j]}\left(z^\star_{[0]} \dots z^\star_{[j-1]},\, \bar{\xi}^s_{[j]}\right), \\ & x_{d,[j]} = x^\star_{d,[j]}, & \text{(2a)} \\ & |y_{d,[j]} - y^\star_{d,[j]}| \leq \epsilon_j. & \text{(2b)} \end{aligned}$$

The ST-UC$\,(\cdot)$ and DA-UC$\,(\cdot)$ are similar in nature, except for (2a) and (2b). The former ensures that the DA commitment decisions are respected in the ST-UC model for generators that participate only in the DA market, and the later allows for their generation levels to be updated only within a bound defined by the parameter $\epsilon_j$. Such bounds are placed to avoid myopic solutions of ST models as they have a shorter horizon than the DA model. Generators that participate only in ST markets can be (de)committed and all generators' output levels can be adjusted in compliance with the constraints defining the feasible set $\mathcal{X}^s(\cdot)$.

Using all the commitment decisions $x^\star_{[k]}$ and generation levels $y^\star_{[k]}$ prescribed by higher levels UC models, the HA-ED model is instantiated as shown below:

$$\begin{aligned} \text{ED}\,(z^\star_{[0]} \dots z^\star_{[k-1]},\, z^\star_{[k]}, \tilde{\xi}^r_{[k]}) = \min\ & f^r_{[k]}(x_{[k]},\, y_{[k]}) \\ \text{subject to: } & (x_{[k]}, y_{[k]}) \in \mathcal{X}^r_{[k]}\left(z^\star_{[0]} \dots z^\star_{[k-1]},\, \bar{\xi}^r_{[k]}\right), \\ & x_{[k]} = x^\star_{[k]}, & \text{(3a)} \\ & |y_{[k]} - y^\star_{[k]}| \leq \epsilon_k. & \text{(3b)} \end{aligned}$$

Since the dispatch decisions are fixed in (3a), the resulting model only has continuous decision variables. As in the case of ST-UC, the constraint (3b) ensures that the HA generation does not deviate beyond $\epsilon_k$ to overcome the myopic nature of HA-ED model resulting from shorter horizon when compared to UC models at higher levels of hierarchy.

The deterministic variants of models defined in (1), (2) and (3) use only a point forecast $\bar{\xi}_{[\cdot]}$ and the objective function is defined as the cost associated with both unit commitment decisions as well as dispatch under such a point forecast. The main distinction between the models used in the DHP hierarchy and SHP hierarchy is that the objective functions of the latter are defined with a deterministic first-stage cost and expected recourse (second-stage) cost as follows:

$$f_{[t]}(x,y) = g_{[t]}(x,y) + \mathbb{E}[h_{[t]}(x,y,\tilde{\xi})] \quad t = i,j,k. \tag{4}$$

Notice that the recourse value $h_{[t]}$ is the optimal value of a second-stage optimization model that is instantiated by the first-stage decisions $(x, y)$ and a realization of the random variable $\tilde{\xi}$. Additional details can be found in previous work of the authors cited in the References.

### 2.2 Solution Methods

The deterministic UC and ED models are solved using MIP and LP algorithms available in off-the-shelf solvers. In the 2-SP model for UC, we use a finite set of scenarios to represent the uncertainty. Even with modest numbers of scenarios, the resulting deterministic equivalent models could be very large and cannot be handled by off-the-shelf solvers. Given that the second-stage programs can be decoupled by scenarios and are LPs, we use the L-shaped (also known as Benders decomposition) algorithm to solve the stochastic UC models [27]. The basic idea of the L-shaped method is to approximate the expectation in the first-stage objective function in (4) using affine functions that are obtained via exact (dual) solutions of all second-stage LPs. The first-stage master program is solved as a linear MIP that comprises of the original constraints $\mathcal{X}_{(\cdot)}$ and the affine lower bounding functions.

The 2-SP formulation of HA-ED has linear first- and second-stage programs. We solve these models using a sequential sampling method called regularized stochastic decomposition (SD) algorithm [8]. Like the L-shaped method, SD is also a cutting-plane method that builds outer-approximations of the first-stage objective function. However, unlike the L-shaped method (which uses a fixed finite set of scenarios), SD operates with a scenario set that grows over the course of the algorithm (and hence the classification as a sequential sampling method). This allows the algorithm to determine a sufficient number of scenarios to ensure statistical optimality while optimization is being carried out concurrently (see [28] for details). While such a feature is desirable for SPs, there is a lack of such algorithms for models with discrete decision variables. Hence, we do not use successive sampling methods for UC models.

The scenarios that constitute stochastic UC instances and those used within the SD algorithm are generated using two time-series simulators, one for solar and another one for wind generators. The simulators are based on a vector auto-regression (VAR) model that captures temporal and spatial correlation of the stochastic processes governing generator outputs. A separate VAR model is estimated for each level of the hierarchy using the forecast time series in the NREL118 dataset. Subsequently, scenarios for optimization are simulated at their respective timescales using these prediction models (see [13] for a similar application).

## 3 Experimental Study

We conduct our experiments with the NREL118 dataset [29] that was introduced by the National Renewable Energy Laboratory for large-scale VER integration studies, such as the one undertaken in this paper. The topology of this system is based on the IEEE118 dataset which is widely recognized as a reasonable experimental prototype. The NREL118 instance contains 327 generators (75 solar and 17 wind), 118 buses, and 186 transmission lines, along with forecasts and real-time outputs of renewable generators and demand. This dataset has a power system that is rich in solar, wind, and hydro resources, and may be consider futuristic/progressive.

We assess three factors that have significant impact on power system operations. These are solar and wind penetration, reserve requirements, and the planning strategy adopted for handling the UC and ED problems. By varying these factors, we analyze their impact on certain reliability metrics, as well as economic, and environmental ones, such as unmet demand, operating costs, and GHG emissions. In Table 1, we summarize the values considered for these factors in our experiments. We use a three letter identifier to recognize the type of optimization model (**D**eterministic or **S**tochastic) employed at the three planning levels in the hierarchy. Following this notation, the DDD setting is the benchmark planning framework (i.e., DHP), whereas both DDS and SDS can be considered as examples of SHP framework.

Table 1: Investigated factors and their levels.

| **Category** | **Label** | **Description** |
| --- | --- | --- |
| **Solar & Wind Integration** | Low SW: | Original solar & wind outputs in the NREL118 dataset. |
| | Med. SW: | Twice the original values. |
| | High SW: | Thrice the original values. |
| **Reserve Requirements** | Very Low: | 5% for UCs, 1.25% for ED. |
| | Low: | 10% for UCs, 2.5% for ED. |
| | Med. | 15% for UCs, 5% for ED. |
| | High: | 20% for UCs, 10% for ED. |
| **Planning Setting** | DDD: | Deterministic DA-UC, ST-UC, ED. |
| | DDS: | Deterministic DA-UC, ST-UC; stochastic ED. |
| | SDS: | Deterministic ST-UC; stochastic DA-UC, ED. |

Evaluations of the hierarchical frameworks are carried out in a rolling horizon manner. While the simulated scenarios from VAR models are used for optimization, the evaluations are carried using the actual observations (also available in the NREL118 dataset) made at every 15 minutes over a time-span of 7 days. In particular, the actual observations are used to setup instances of the first-stage programs. Note that both the deterministic as well as stochastic frameworks are evaluated on the same actual observation time series. In what follows, we present the results obtained from these evaluations.

### 3.1 Reliability Impact

Significant amounts of unmet demand revealed in the planning process may potentially result into actual blackouts with damaging economic consequences for customers. Due to its importance to ISOs and customers, we start our discussion with an illustration of average and maximum unmet demand values in Table 2.

In general, we notice higher unmet demand values when more solar and wind resources introduced into the system. More conservative reserve requirements substantially reduce these values, but, possibly, comes with additional economic cost. On the other hand, *adopting stochastic planning approaches into the modeling framework can zero out unmet demand, even at less conservative reserve requirements.* For instance, to completely eliminate unmet demand from the planning process, DDD, DDS, and SDS necessitate high, medium, and low reserve requirements, respectively, under Medium SW and High SW settings. This observation supports the use of stochastic planning approaches to accommodate the variability of VERs, and reduce reliance on (manually-imposed) reserve restrictions. More importantly, it suggests the possibility of a more economical way of operating the system.

Table 2: Average and maximum unmet demand amounts (MW)

| | | Avg. Unmet Demand | | | Max. Unmet Demand | | |
|---|---|---|---|---|---|---|---|
| Planning | Reserve | Solar & Wind Integ. | | | Solar & Wind Integ. | | |
| Setting | Req. | Low | Med. | High | Low | Med. | High |
| DDD | V Low | 1.9 | 4.4 | 17.0 | 320.0 | 595.1 | 956.1 |
| | Low | 0.5 | 3.0 | 1.5 | 246.9 | 336.5 | 274.3 |
| | Med. | 0.0 | 0.4 | 1.2 | 0.0 | 252.6 | 552.5 |
| | High | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| DDS | V Low | 1.2 | 0.7 | 3.9 | 172.0 | 162.8 | 494.3 |
| | Low | 0.0 | 0.0 | 0.5 | 0.0 | 0.8 | 217.8 |
| | Med. | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | High | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SDS | V Low | 0.0 | 1.9 | 0.6 | 19.2 | 182.0 | 356.6 |
| | Low | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | Med. | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | High | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

During our planning process, certain fast-ramping generators can be committed by the ST-UC problems to recover from unexpected supply shortages during the day. We evaluate the reliance on ST-UC problems by looking at the percentage of time that these generators were active (see Table 3). We observe a consistent trend where the DDD setting heavily relies on ST-UC problems to maintain reliability. In contrast, DDS and SDS substantially reduces these requirements even under higher renewable-integration settings.

Table 3: Average percentage of time ST-UC generators were active.

| Planning Setting | Low SW | Med. SW | High SW |
|---|---|---|---|
| DDD | 11.0 | 11.7 | 11.8 |
| DDS | 9.7 | 8.3 | 7.8 |
| SDS | 8.7 | 6.5 | 5.3 |

Fig. 3 shows the average amounts of over-generation (by conventional generators) estimated under all settings. We observe the smallest amounts under the DDD setting. This is not surprising as it would never be optimal to over-produce in a deterministic optimization model provided that ramping capabilities are sufficient to cover ramping needs within the model's horizon. In contrast, stochastic optimization (i.e., DDS and SDS) compensates for the variability in future time periods by over-generating in significantly larger amounts, thereby preventing situations where upwards-ramping capabilities may not be sufficient under certain settings.

In terms of solar and wind curtailment, Fig. 4 shows a significant trend where higher renewable integration leads to substantial amounts of curtailment, providing support to the need for energy storage. In addition, we still observe that both DDS and SDS leads to slightly more curtailment than that in DDD.

Fig. 5 illustrates intra-day generation profiles under DDD and SDS settings. Notice that the duck-chart is clearly visible. Another phenomenon to notice is that unmet demand, over-generation, and renewable curtailment may all occur simultaneously (at different buses), and the former two typically occur at day-time, when solar generators are active, and transmission capacity constitutes the bottleneck. This underscores the importance of accounting for the transmission networks in power system experiments. As seen from the figure under discussion, SDS leads to more over-generation but reduces unmet demand from 16.9 MW to 0.7 MW. Furthermore, we observe higher variability in hydro-based generation under SDS (coefficient of variation of hydro-based generation is 0.13 in SDS vs. 0.05 in DDD). Hydro generators have

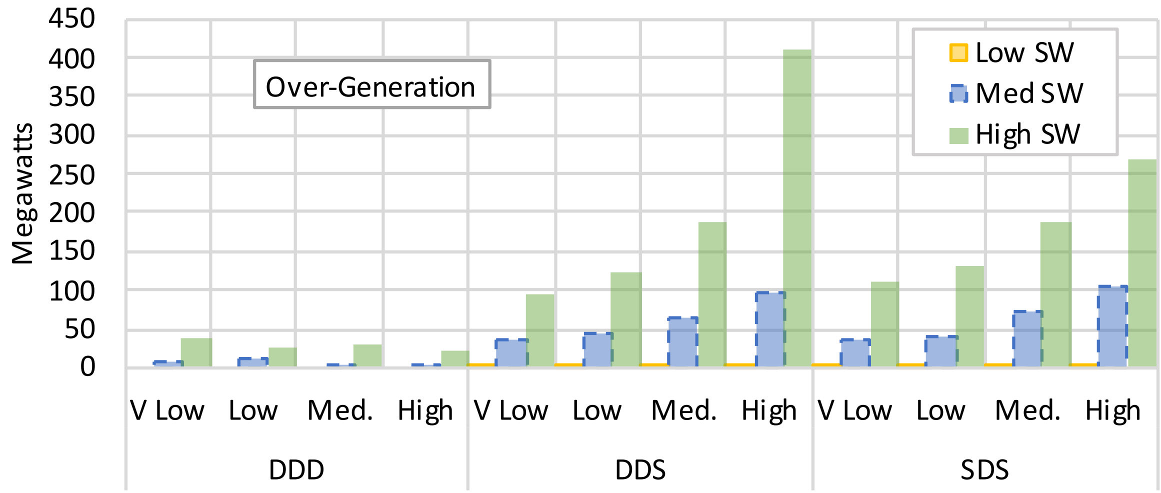



Figure 3: Average over-generation amounts by conventional generators.

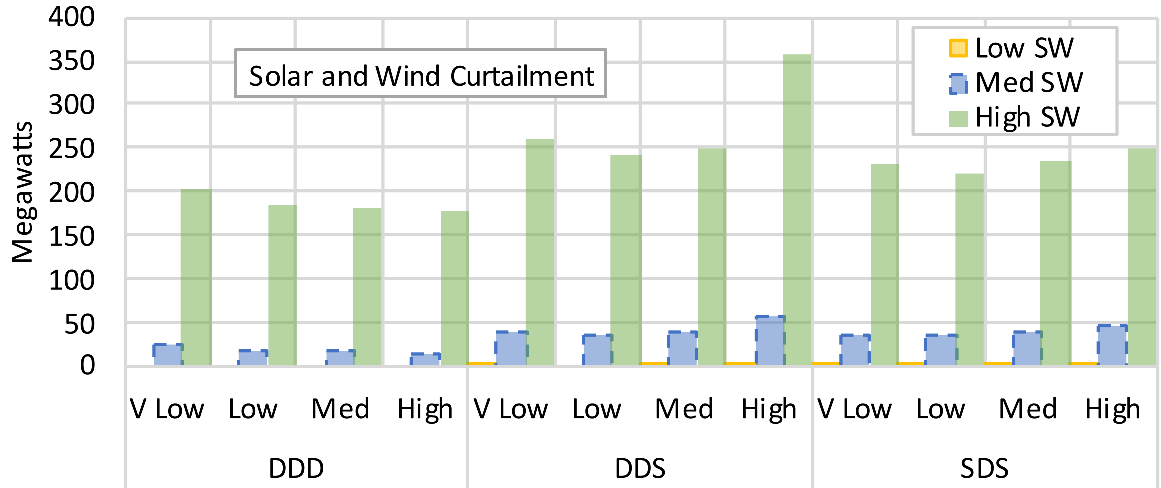



Figure 4: Average curtailed solar and wind energy.

better ramping capabilities, which makes them suitable for accommodating uncertainty. SDS naturally leverages this fact seamlessly.

### 3.2 Economic Impact

Fig. 6 demonstrates the average daily generation costs recorded in our experiments[1]. In line with expectations, increased renewable integration leads to lower costs whereas increased reserve requirements have the opposite effect.

We next turn our focus to the minimum reserve requirements levels at which the network demand is seamlessly fulfilled (in other words, no unmet demand is observed). Table 4 illustrates the daily operating costs corresponding to the minimum reserve requirements that must be set at each level of the hierarchy in order to ensure zero unmet demand. The figure indicates that, with stochastic optimization, reserve requirements can be relaxed as the models are able to dynamically adjust production levels by accounting for uncertainty in the future. As a result, operating cost of the network can be reduced by up to 10.4% (e.g., compare \$11.23M with DDD

[1] The total operating costs will additionally include the penalty for load curtailment which is not presented in this figure.

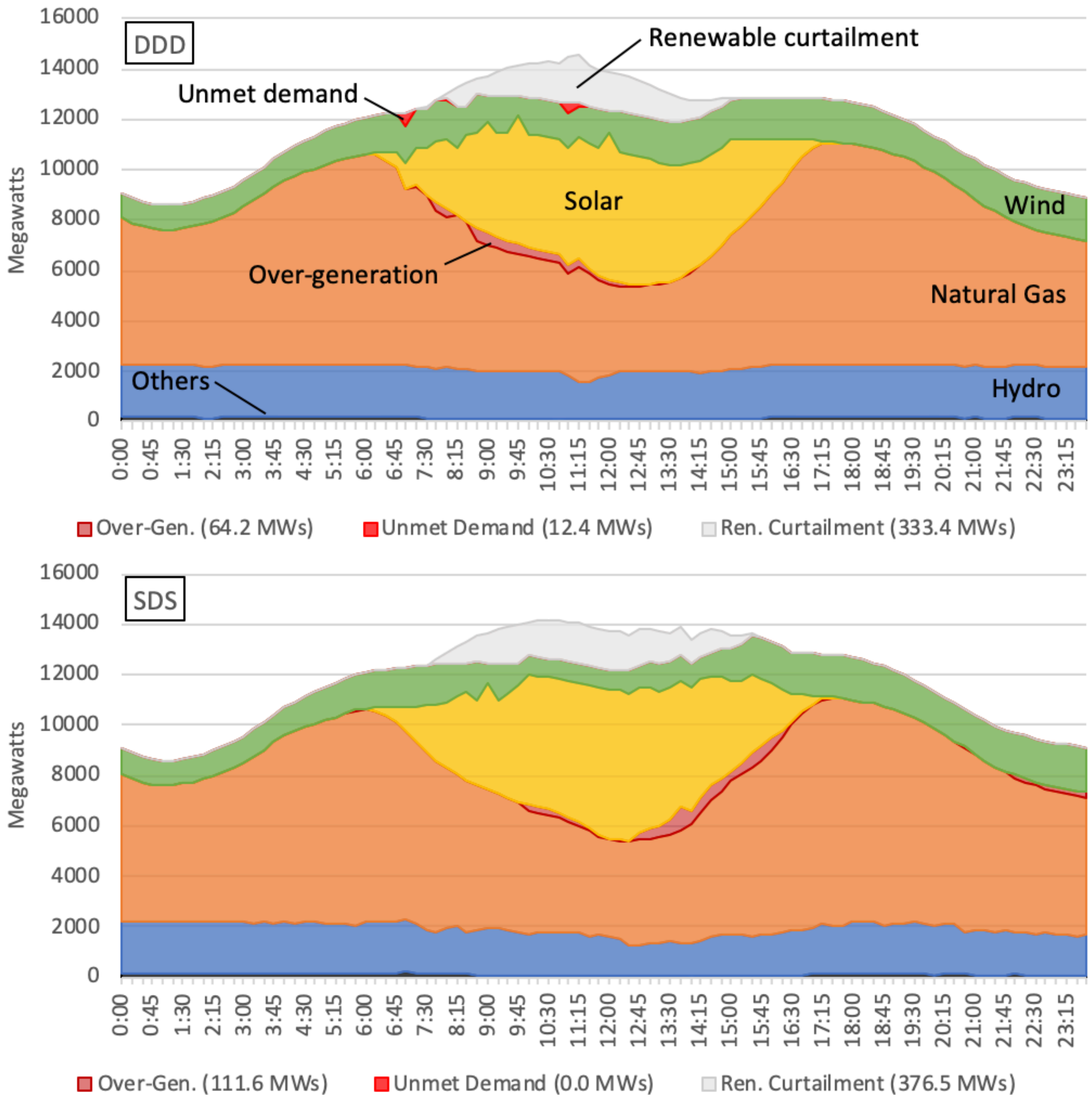



Figure 5: Generation mix, unmet-demand, and over-generation in DDD and SDS settings (very low reserves, High SW, and a sample day).
to \$10.06M with SDS, under high renewable integration).

### 3.3 Environmental Impact

To assess the environmental impact of increasing renewable energy in the power system, we estimate the daily GHG emissions using the recorded generation amounts and mixes. Analogous to Table 4, Fig. 7 demonstrates daily $CO_2$ emission estimates under the minimum reserve requirements that lead to zero unmet demand. These estimates are based on generators' heat and emission rates, which are given in the NREL118 dataset, as well as their generation levels, which is determined by the optimization. Similar observations were made for the $NO_x$ and $SO_2$ emissions.

With respect to $CO_2$ emissions, we have two observations. First, in the experimented power system, higher renewable integration leads to lower levels of $CO_2$ emissions. While this sounds intuitive, opponents of this intuition typically suggest that the duck-chart phenomenon could actually lead to more emissions. This increase is attributed to over-generation and reliance on significant amount of gas-fired fast generators to overcome insufficient ramping capabilities and

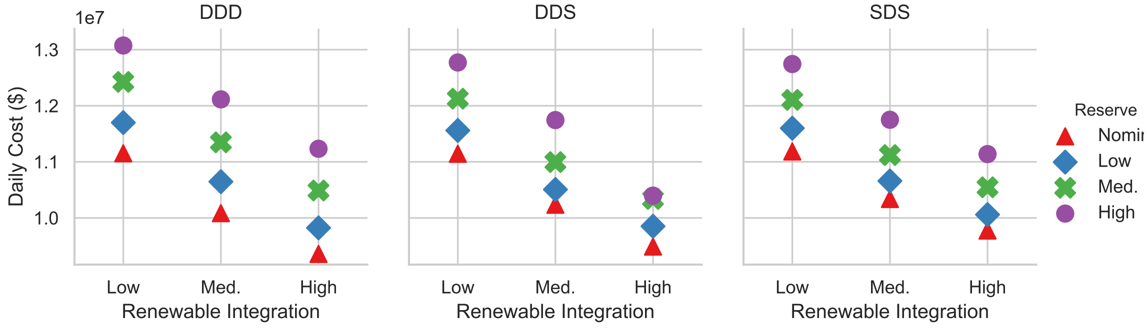



Figure 6: Average daily generation cost of the power system under different reserve requirements and operations planning strategies.

Table 4: Average daily operating cost of the power system corresponding to the minimum reserve requirements leading to zero unmet demand (in million $; Reserve requirements in paranthesis).

| | DDD | DDS | SDS |
|---|---|---|---|
| Low SW | 12.42 (Med.) | 11.56 (Low) | 11.60 (Low) |
| Med. SW | 12.11 (High) | 11.00 (Med.) | 10.66 (Low) |
| High SW | 11.23 (High) | 10.34 (Med.) | 10.06 (Low) |

volatility of VERs. Our experiments suggest that this is not the case for power systems with similar characteristics. Second, while stochastic modeling (i.e., DDS, SDS) also leads to over-generation and renewable curtailment (see Fig. 3-4), their impact can largely be reversed by the lower reserve requirements necessary to achieve the same level of reliability. In this regard, a concurrent optimization-simulation approach to obtain statistically appropriate measure of reserve requirement is presented in [30].

# 4 Discussion and Conclusions

We presented an SHP framework for power systems with large-scale VER penetration. While the call for a framework comprising of stochastic dynamic problems evolving at different timescales have been made before (e.g., [31]), this is the first study to conduct comprehensive computational experiments on such a framework. Our framework captures the operations and their interactions across day-ahead, short-term and hour-ahead timescales.

Our experiments indicate that the SHP framework overcomes many of the shortcomings of the DHP approach that is currently in practice. We observed that the SHP framework typically outperforms DHP in terms of reliability: Even at lower levels of reserve requirements, SHP is more effective in eliminating the unmet demand from the planning process. Moreover, with SHP, reliance on ST-UC problems (to avoid unmet demand) reduces. On the other hand, the SHP framework is more conservative and leads to more conventional over-generation and renewable curtailment, which can be mitigated by introducing storage resources to the grid. Finally, we observed that being able to operate *reliably* at lower levels of reserve requirements can mitigate excessive over-generation and renewable curtailment, as well as reduce the operating costs and GHG emissions.

The challenges associated with meeting ambitious renewable portfolio standards set in light of climate change concerns can be addressed principally through (i) efficient generator designs and power electronics, (ii) market designs, and (iii) optimization software used in planning and operations. In order to "tame the duck", advances along all these three fronts will be critical. Efforts in this paper lay the groundwork for addressing (iii) through the SHP framework and the use of stochastic optimization tools. The results essentially show that systems with high

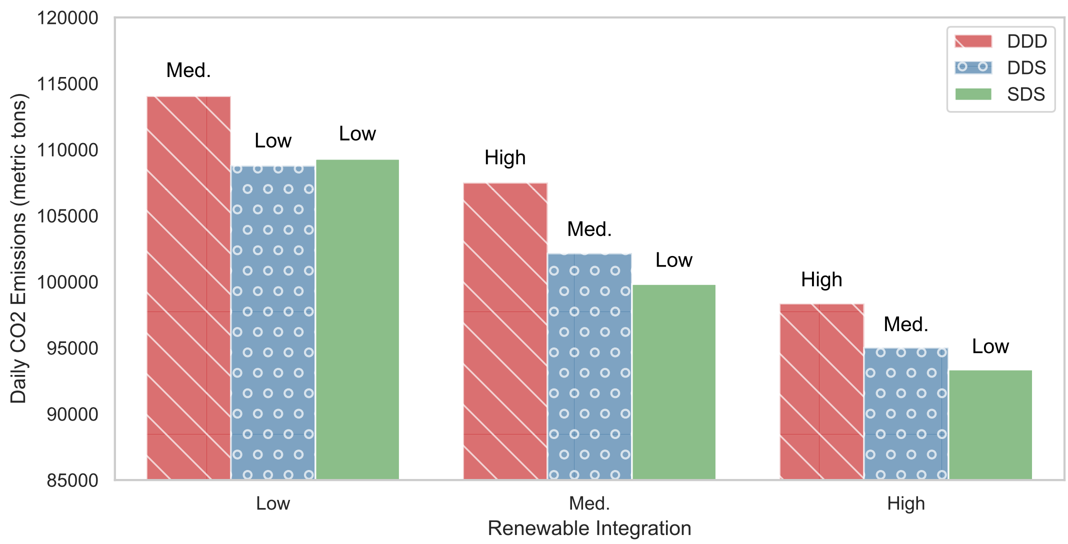



Figure 7: Average daily $CO_2$ emissions of the power system corresponding to the minimum reserve requirements leading to zero unmet demand (reserve requirements are noted on top of the bars).

penetration of renewable resources can lead to more sustainable and reliable operations solely by transitioning from a deterministic to a stochastic planning hierarchy. Our results are encouraging and point to the next steps that must involve experiments with actual ISO data. This will be undertaken as part of our future research endeavours.

## References

[1] D. Proctor, "California mandates 100% renewable energy," *POWER Magazine*, Jul. 2018, retrieved from https://www.powermag.com/california-mandates-100-renewable-energy/.

[2] A. Olson, A. Mahone, E. Hart, J. Hargreaves, R. Jones, N. Schlag, G. Kwok, N. Ryan, R. Orans, and R. Frowd, "Halfway There: Can California Achieve a 50% Renewable Grid?" *IEEE Power and Energy Magazine*, vol. 13, no. 4, pp. 41–52, 2015.

[3] I. Penn, "California invested heavily in solar power. now there's so much that other states are sometimes paid to take it," *Los Angeles Times*, Jun. 2017, retrieved from http://www.latimes.com/projects/la-fi-electricity-solar/.

[4] California ISO, "Fast facts: What the duck curve tells us about managing a green grid," Tech. Rep., 2016, retrieved from https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf. [Online]. Available: https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

[5] A. Bergman, P. Denholm, D. C. Steinberg, and D. Rosner, "Maintaining reliability in the modern power system," Tech. Rep., 2016. [Online]. Available: https://www.energy.gov/sites/prod/files/2017/01/f34/Maintaining%20Reliability%20in%20the%20Modern%20Power%20System.pdf

[6] C. Loutan, V. Gevorgian, and M. Morjaria, "Using renewables to operate a low-carbon grid," National Renewable Energy Laboratory (NREL), Tech. Rep., 2016. [Online]. Available: https://www.caiso.com/Documents/UsingRenewablesToOperateLow-CarbonGrid.pdf

[7] J. L. Higle and S. Sen, "Stochastic Decomposition: An Algorithm for Two-Stage Linear Programs with Recourse," *Mathematics of Operations Research*, vol. 16, no. 3, pp. 650–669, 1991.

[8] ——, "Finite master programs in regularized stochastic decomposition," *Mathematical Programming*, vol. 67, no. 1, pp. 143–168, Oct 1994. [Online]. Available: https://doi.org/10.1007/BF01582219

[9] S. Sen and Y. Liu, "Mitigating uncertainty via compromise decisions in two-stage stochastic linear programming: Variance reduction," *Operations Research*, vol. 64, no. 6, pp. 1422–1437, 2016.

[10] S. Sen and Z. Zhou, "Multistage stochastic decomposition: a bridge between stochastic programming and approximate dynamic programming," *SIAM Journal on Optimization*, vol. 24, no. 1, pp. 127–153, 2014. [Online]. Available: http://epubs.siam.org/doi/abs/10.1137/120864854

[11] S. Atakan and S. Sen, "A progressive hedging based branch-and-bound algorithm for mixed-integer stochastic programs," *Computational Management Science*, vol. 15, no. 3, pp. 501–540, Oct 2018. [Online]. Available: https://doi.org/10.1007/s10287-018-0311-3

[12] H. Gangammanavar, S. Sen, and V. M. Zavala, "Stochastic Optimization of Sub-Hourly Economic Dispatch With Wind Energy," *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–11, 2015. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7065337

[13] H. Gangammanavar and S. Sen, "Two-scale stochastic optimization for controlling distributed storage devices," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 2691–2702, July 2018.

[14] S. Atakan, G. Lulli, and S. Sen, "A state transition MIP formulation for the unit commitment problem," *IEEE Transactions on Power Systems*, vol. 33, no. 1, 2018.

[15] S. Sen, *Stochastic Programming.* Boston, MA: Springer US, 2013, pp. 1486–1497. [Online]. Available: https://doi.org/10.1007/978-1-4419-1153-7_1005

[16] S. Frank, I. Steponavice, and S. Rebennack, "Optimal power flow: a bibliographic survey i," *Energy Systems*, vol. 3, no. 3, pp. 221–258, Sep 2012. [Online]. Available: https://doi.org/10.1007/s12667-012-0056-y

[17] Q. P. Zheng, J. Wang, and A. L. Liu, "Stochastic optimization for unit commitment—a review," *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 1913–1924, July 2015.

[18] J. D. Lyon, K. W. Hedman, and M. Zhang, "Reserve requirements to efficiently manage intra-zonal congestion," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 251–258, Jan 2014.

[19] California ISO, "Fast facts: Impacts of renewable energy on grid operations," Tech. Rep., 2017, retrieved from https://www.caiso.com/Documents/CurtailmentFastFacts.pdf. [Online]. Available: https://www.caiso.com/Documents/CurtailmentFastFacts.pdf

[20] New England ISO, "Business practices manual: Energy and operating reserve markets," Tech. Rep., September 2017, retrieved from https://www.misoenergy.org/legal/business-practice-manuals/. [Online]. Available: https://www.misoenergy.org/legal/business-practice-manuals/

[21] ——, "Market operations: Manual m-11," Tech. Rep., October 2018, retrieved from https://www.iso-ne.com/static-assets/documents/2018/10/manual_11_market_operations_rev55_20181004.pdf. [Online]. Available: https://www.iso-ne.com/static-assets/documents/2018/10/manual_11_market_operations_rev55_20181004.pdf

[22] J. Zhao, T. Zheng, and E. Litvinov, "Variable resource dispatch through do-not-exceed limit," *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 820–828, March 2015.

[23] B. Knueven, J. Ostrowski, and J. P. Watson, "On mixed integer programming formulations for the unit commitment problem," Department of Industrial and Systems Engineering University of Tennessee, Knoxville, TN 37996, Tech. Rep., 2019.

[24] S. Wallace and W. Ziemba, *Applications of Stochastic Programming*, S. W. Wallace and W. T. Ziemba, Eds. Society for Industrial and Applied Mathematics, 2005. [Online]. Available: https://epubs.siam.org/doi/abs/10.1137/1.9780898718799

[25] Q. P. Zheng, J. Wang, P. M. Pardalos, and Y. Guan, "A decomposition approach to the two-stage stochastic unit commitment problem," *Annals of Operations Research*, vol. 210, no. 1, pp. 387–410, 2013.

[26] J. Ostrowski, M. F. Anjos, and A. Vannelli, "Tight mixed integer linear programming formulations for the unit commitment problem," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 39–46, 2012.

[27] R. M. Van Slyke and R. Wets, "L-shaped linear programs with applications to optimal control and stochastic programming," *SIAM Journal on Applied Mathematics*, vol. 17, no. 4, pp. 638–663, 1969.

[28] J. L. Higle and S. Sen, "Statistical approximations for stochastic linear programming problems," *Annals of Operations Research*, vol. 85, no. 0, pp. 173–193, 1999.

[29] I. Pena, C. Brancucci, and B. M. Hodge, "An Extended IEEE 118-bus Test System with High Renewable Penetration," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 281–289, 2017.

[30] S. Wang, H. Gangammanavar, S. Ekşioğlu, and S. J. Mason, "Statistical estimation of operating reserve requirements using rolling horizon stochastic optimization," *Annals of Operations Research*, Nov 2019. [Online]. Available: https://doi.org/10.1007/s10479-019-03482-x

[31] M. D. Ilic, "From hierarchical to open access electric power systems," *Proceedings of the IEEE*, vol. 95, no. 5, pp. 1060–1084, May 2007.

[32] L. L. Garver, "Power generation scheduling by integer programming - development of theory," *Power Apparatus and Systems, Part III, Transactions of the American Institute of Electrical Engineers*, vol. 81, no. 3, pp. 730–734, 1962.

[33] D. Rajan and S. Takriti, "Minimum up / down polytopes of the unit commitment problem with start-up costs," IBM, Tech. Rep., 2005.

[34] P. Damcı-Kurt, S. Küçükyavuz, D. Rajan, and A. Atamtürk, "A polyhedral study of production ramping," *Mathematical Programming*, vol. 158, no. 1, pp. 175–205, 2015.

# A Mathematical Models for Power System Planning Problems

This section outlines the mathematical models of DA-UC, ST-UC, and HA-ED problems. For brevity, we first describe the used constraints, then, refer to these while constructing each model. All models are presented in static form; the reader is referred to §2.1 which describes their role within the hierarchical planning processes, solved in a rolling horizon fashion. A nomenclature is provided in Table 5.

Table 5: Nomenclature for mathematical formulations.

| **Sets** | | |
|---|---|---|
| $\mathcal{B}$: buses.<br>$\mathcal{L}$: transmission lines.<br>$\mathcal{G}$: generators. | $\mathcal{G}_r$: solar and wind generators.<br>$\mathcal{G}_c$: conventional generators ($\mathcal{G}_c = \mathcal{G} \setminus \mathcal{G}_r$). | $\mathcal{G}_j$: generators that are located in bus $j \in \mathcal{B}$.<br>$\mathcal{T}$: time periods. |

| **Parameters** | |
|---|---|
| $G_g^{\max}$: generation capacity of $g \in \mathcal{G}_c$.<br>$G_g^{\min}$: minimum generation requirement for $g \in \mathcal{G}_c$.<br>$G_{gt}^{\mathbf{avail}}$: wind/solar availability for $g \in \mathcal{G}_r$, in $t \in \mathcal{T}$.<br>$\Delta G_g^{\max}$: ramp up limit for $g \in \mathcal{G}_c$.<br>$\Delta G_g^{\min}$: ramp down limit for $g \in \mathcal{G}_c$.<br>$UT_g$: minimum uptime requirement of $g \in \mathcal{G}_c$.<br>$DT_g$: minimum downtime requirement of $g \in \mathcal{G}_c$.<br>$B_{ij}$: susceptance of arc $(i,j) \in \mathcal{L}$.<br>$D_{jt}$: load in bus $j \in \mathcal{B}$, in period $t \in \mathcal{T}$.<br>$R_{jt}$: reserve requirement in bus $j \in \mathcal{B}$ and period $t \in \mathcal{T}$.<br>$F_{ij}^{\max}$: maximum permitted flow through arc $(i,j) \in \mathcal{L}$. | $c_g^s$: start up cost of $g \in \mathcal{G}$.<br>$c_g^f$: no-load cost of $g \in \mathcal{G}$ (i.e., the intercept of the cost curve).<br>$c_g^p$: variable generation cost of $g \in \mathcal{G}$ (i.e., the slope of the cost curve).<br>$\theta_j^{\max}$: upper bound on the voltage-angle at bus $j \in \mathcal{B}$.<br>$\theta_j^{\min}$: lower bound on the voltage-angle at bus $j \in \mathcal{B}$.<br>$\phi_g^o$: penalty for over-generation by $g \in \mathcal{G}_c$.<br>$\phi_g^c$: penalty for renewable curtailment in $g \in \mathcal{G}_r$.<br>$\phi_j^u$: penalty for unmet demand in bus $j \in \mathcal{B}$. |

| **Decision Variables** | |
|---|---|
| $s_{gt}$: 1 if $g \in \mathcal{G}$ is turned on in $t \in \mathcal{T}$, 0 otherwise.<br>$x_{gt}$: 1 if $g \in \mathcal{G}$ is operational in $t \in \mathcal{T}$, 0 otherwise.<br>$z_{gt}$: 1 if $g \in \mathcal{G}$ is turned off in $t \in \mathcal{T}$, 0 otherwise.<br>$G_{gt}^+$: generation amount of $g \in \mathcal{G}$, in $t \in \mathcal{T}$, which is consumed by the grid. | $G_{gt}^-$: over-generation amount by $g \in \mathcal{G}_c$, in $t \in \mathcal{T}$.<br>$G_{gt}^-$: renewable curtailment in $g \in \mathcal{G}_r$, in $t \in \mathcal{T}$.<br>$F_{ij,t}$: electricity flow through $(i,j) \in \mathcal{L}$, in $t \in \mathcal{T}$.<br>$\theta_{jt}$: voltage angle at $j \in \mathcal{B}$, in $t \in \mathcal{T}$.<br>$D_{jt}^{\mathbf{shed}}$: amount of unmet load at $j \in \mathcal{B}$, in $t \in \mathcal{T}$. |

Generator commitment decisions are often modeled using three sets of binary variables ($x_{gt}$, $s_{gt}$, $z_{gt}$) that indicate whether $g$ is operational, turned on, and turned off in period $t$, respectively [32]. These variables are linked with the following constraints:

$$x_{gt} - x_{gt-1} = s_{gt} - z_{gt}, \qquad \forall g \in \mathcal{G},\, t \in \mathcal{T}. \tag{5}$$

To model the minumum uptime and downtime requirements of generators, we use the turn on and off inequalities of [33]:

$$\sum_{j=t-UT_g+1}^{t-1} s_{gt} \leq x_{gt}, \qquad \forall g \in \mathcal{G},\, t \in \mathcal{T}, \tag{6}$$

$$\sum_{j=t-DT_g}^{t} s_{gt} \leq 1 - x_{gt}, \qquad \forall g \in \mathcal{G},\, t \in \mathcal{T}. \tag{7}$$

We use two sets of variables to model generation levels. The $G_{gt}^+$ variable denotes the amount of electricity produced by generator $g$ in period $t$ *and consumed by the grid.* The second variable $G_{gt}^-$ can assume two different meanings, depending on the type of the generator. For solar and wind generators (i.e., $\forall g \in \mathcal{G}_r$), these variables capture the amount of renewable supply that is curtailed, whereas for all other generators (i.e., $\forall g \in \mathcal{G}_c$), they represent the amount of electricity that is over-generated in period $t$. Here, we assume the existence of a mechanism that can consume over-generation at the buses where conventional generators are located in. In more realistic settings, the over-generated electricity should be accounted for at certain locations where a consumer (e.g., a neighboring grid or energy-storage facilities) exists. Such information is not available in the NREL118 dataset.

All conventional generators (including hydro) must obey certain physical requirements for attaining feasible production schedules. The generator capacities and minimum generation requirements are given by

$$G_g^{\min} x_{gt} \leq G_{gt} \leq G_g^{\max} x_{gt}, \qquad \forall g \in \mathcal{G}_c,\, t \in \mathcal{T}, \tag{8}$$

whereas ramping requirements are modeled as follows:

$$-\Delta G_g^{\min} \leq G_{gt} - G_{gt-1} \leq \Delta G_g^{\max}, \qquad \forall g \in \mathcal{G}_c,\, t \in \mathcal{T}. \tag{9}$$

Above (and in the ensuing discussion) $G_{gt}$ is used to simplify exposition and defined as $G_{gt} = G_{gt}^{+} + G_{gt}^{-}$.

Ramping constraints (9) can be strengthened with binary variables to enhance the computational performance of MIP solvers. Our study incorporated some of the developments made in [34] and [14]. For the purpose of conciseness, we do not present them in here.

For solar and wind generators, the forecast and actual supply time-series are assumed to be capturing the physical requirements that these generators are subject to. Accordingly, we only need to impose a solar/wind availability constraints, which are given as follows:

$$G_{gt} = G_{gt}^{\text{avail}} x_{gt}, \qquad \forall g \in \mathcal{G}_r,\, t \in \mathcal{T}. \tag{10}$$

This constraint implies that the amount of available renewable capacity that is not consumed is considered to be curtailed.

Electricity transmission is modeled using three sets of variables which represent the electricity flow ($F_{ij,t}$), bus voltage angles ($\theta_{jt}$), and the amount of unmet demand ($D_{jt}^{\text{shed}}$). We begin with the flow-balance equations:

$$\sum_{i \in \mathcal{B}:(i,j)\in\mathcal{L}} F_{ij,t} - \sum_{i \in \mathcal{B}:(j,i)\in\mathcal{L}} F_{ji,t} + \sum_{g \in \mathcal{G}_j} G_{gt}^{\text{used}} + D_{jt}^{\text{shed}} = D_{jt} + R_{jt},\ j \in \mathcal{B},\, t \in \mathcal{T}. \tag{11}$$

Note that the above constraint also involves reserve considerations ($R_{jt}$), which are modeled as the sum of contingency and regulation requirements.

We consider linear (direct-current) approximations of power-flows in our models. These are given, in terms of the bus voltage-angles, as follows:

$$F_{ij,t} = B_{ij}(\theta_{it} - \theta_{jt}), \qquad \forall (i,j) \in \mathcal{L}, t \in \mathcal{T}, \tag{12}$$

$$\theta_j^{\min} \leq \theta_{jt} \leq \theta_j^{\max}, \qquad \forall j \in \mathcal{B},\, t \in \mathcal{T}. \tag{13}$$

Finally, transmission capacities are given by

$$F_{ij}^{\min} \leq F_{ij,t} \leq F_{ij}^{\max}, \qquad \forall (i,j) \in \mathcal{L},\, t \in \mathcal{T}. \tag{14}$$

Further modeling details that pertain to improving computational performance (such as symmetry breaking constraints, valid inequalities, or basic linear transformations) are omitted in this presentation.

### A.1 Models for Deterministic Optimization

The following is an outline of the UC formulations:

$$\min \sum_{t\in\mathcal{T}}\left(\sum_{g\in\mathcal{G}}\left(c_g^s s_{gt}+c_g^f x_{gt}+c_g^v G_{gt}^+\right)+\sum_{j\in\mathcal{B}}\left(\sum_{g\in\mathcal{G}_j\cap\mathcal{G}_c}\phi_g^o G_{gt}^- + \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_r}\phi_g^c G_{gt}^- + \phi_j^u D_{jt}^{\text{shed}}\right)\right) \tag{$UC$}$$

$$\begin{aligned}
\text{subject to: }\; & (5)-(14),\\
& (x_{gt}, s_{gt}, z_{gt}) \in \{0,1\}^3,\ (G_{gt}^+, G_{gt}^-) \in \mathbb{R}_+^2, \qquad \forall g\in\mathcal{G},\, t\in\mathcal{T},\\
& F_{ij,t}\in\mathbb{R}, \qquad \forall (i,j)\in\mathcal{L},\, t\in\mathcal{T},\\
& \theta_{jt}\in\mathbb{R},\ D_{jt}^{\text{shed}}\in\mathbb{R}_+, \qquad \forall j\in\mathcal{B},\, t\in\mathcal{T}.
\end{aligned}$$

This formulation serves as the foundation of both DA-UC and ST-UC problems, but modifications have been made to accommodate their differences. For instance, the DA-UC problem does not commit certain fast-response generators, which can be ensured by setting $x_{gt}=0$ for such generators. Likewise, the ST-UC problem does not alter the commitment decisions made by the DA-UC problem, in which case, the $x_{gt}$ variables can be fixed according to the solution of the DA-UC problem.

Next, we present the HA-ED formulation:

$$\min \sum_{t\in\mathcal{T}}\left(\sum_{g\in\mathcal{G}} c_g^v G_{gt}^+ + \sum_{j\in\mathcal{B}}\left(\sum_{g\in\mathcal{G}_j\cap\mathcal{G}_c}\phi_g^o G_{gt}^- + \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_r}\phi_g^c G_{gt}^- + \phi_j^u D_{jt}^{\text{shed}}\right)\right) \tag{$ED(x)$}$$

$$\begin{aligned}
\text{subject to: }\; & (8)-(14),\\
& (G_{gt}^+, G_{gt}^-) \in \mathbb{R}_+^2, \qquad \forall g\in\mathcal{G},\, t\in\mathcal{T},\\
& F_{ij,t}\in\mathbb{R}, \qquad \forall (i,j)\in\mathcal{L},\, t\in\mathcal{T},\\
& \theta_{jt}\in\mathbb{R},\ D_{jt}^{\text{shed}}\in\mathbb{R}_+, \qquad \forall j\in\mathcal{B},\, t\in\mathcal{T}.
\end{aligned}$$

Observe that the above (linear programming) problem is defined as a function of $x$ (i.e., $x_{gt}$, $\forall g\in\mathcal{G}$, $t\in\mathcal{T}$, in vector form). Accordingly, the values of these variables must be fixed in (8) and (10), prior to solving an HA-ED the problem. Furthermore, the constraints for idle generators ($x_{gt}=0$) clearly need not be included into the HA-ED formulation.

### A.2 Models for Stochastic Optimization

The stochastic optimization models will retain the fundamental structure of their deterministic counterparts, but will include solar/wind availability as random input. Consider the random vector $\xi$ which represents the solar and wind output. The realization of $\xi$ under scenario $s$ is given by $\xi^s$. The vector $\xi^s$ has $\xi_{gt}^s$, $\forall g\in\mathcal{G}_r$, $t\in\mathcal{T}$, as its components, where $\xi_{gt}^s$ denotes the realization of solar/wind availability under scenario $s$, for generator $g$, in period $t$.

We begin with describing the stochastic UC model. We partition the model into two stages, where the first stage involves commitment decisions, whereas the second involves production decisions. The resulting formulation is given as follows:

$$\min \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}}\left(c_g^s s_{gt}+c_g^f x_{gt}\right)+\mathbb{E}\big[ED(x,\xi)\big] \tag{$SUC$}$$

$$\begin{aligned}
\text{subject to: }\; & (5)-(7),\\
& (x_{gt}, s_{gt}, z_{gt}) \in \{0,1\}^3, \quad \forall g\in\mathcal{G},\, t\in\mathcal{T},
\end{aligned}$$

where,

$$
\begin{aligned}
ED(x,\xi^s) = \min \ & \sum_{t\in\mathcal{T}} \left( \sum_{g\in\mathcal{G}} c_g^v G_{gt}^+ + \sum_{j\in\mathcal{B}} \left( \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_c} \phi_g^o G_{gt}^- + \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_r} \phi_g^c G_{gt}^- + \phi_j^u D_{jt}^{\text{shed}} \right) \right) \\
\text{subject to:} \quad & (8), (9), (11) - (14), \\
& G_{gt} = \xi_{gt}^s x_{gt}, \qquad \forall g \in \mathcal{G}_r,\, t\in\mathcal{T}, \qquad (15) \\
& (G_{gt}^+, G_{gt}^-) \in \mathbb{R}_+^2, \qquad \forall g\in\mathcal{G},\, t\in\mathcal{T}, \\
& F_{ij,t} \in \mathbb{R}, \qquad \forall (i,j)\in\mathcal{L},\, t\in\mathcal{T}, \\
& \theta_{jt} \in \mathbb{R},\, D_{jt}^{\text{shed}} \in \mathbb{R}_+, \qquad \forall j\in\mathcal{B},\, t\in\mathcal{T}.
\end{aligned}
$$

The second-stage problem ($ED(x,\xi^s)$) has the same form as the $ED(x)$ problem, except for the additional input $\xi^s$ and the corresponding solar/wind availability constraint (15). The input $x$ in $ED(x,\xi^s)$ only affects constraints (8) and (15) in above.

Next, we describe the stochastic ED model. The first stage consists of all the decisions associated with the initial time period, whereas the remaining decisions (corresponding to later periods) are made in the second stage. The resulting formulation is given below.

$$
\min \sum_{g\in\mathcal{G}} c_g^v G_{g1}^+ + \sum_{j\in\mathcal{B}} \left( \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_c} \phi_g^o G_{g1}^- + \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_r} \phi_g^c G_{g1}^- + \phi_j^u D_{j1}^{\text{shed}} \right) + \mathbb{E}\big[ED'(x,\xi)\big] \qquad (SED(x))
$$

$$
\begin{aligned}
\text{subject to:} \quad & (8) - (14), \ \text{(excluding } t = 1), \\
& (G_{g1}^+, G_{g1}^-) \in \mathbb{R}_+^2, \qquad \forall g\in\mathcal{G}, \\
& F_{ij,1} \in \mathbb{R}, \qquad \forall (i,j)\in\mathcal{L}, \\
& \theta_{j1} \in \mathbb{R},\, D_{j1}^{\text{shed}} \in \mathbb{R}_+, \qquad \forall j\in\mathcal{B},
\end{aligned}
$$

where,

$$
\begin{aligned}
ED'(x,\xi^s) = \min \ & \sum_{t\in\mathcal{T}\setminus\{1\}} \left( \sum_{g\in\mathcal{G}} c_g^v G_{gt}^+ + \sum_{j\in\mathcal{B}} \left( \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_c} \phi_g^o G_{gt}^- + \sum_{g\in\mathcal{G}_j\cap\mathcal{G}_r} \phi_g^c G_{gt}^- + \phi_j^u D_{jt}^{\text{shed}} \right) \right) \\
\text{subject to:} \quad & (8), (9), (11) - (14), \ \text{(excluding } t = 1), \\
& G_{gt} = \xi_{gt}^s x_{gt}, \qquad \forall g \in \mathcal{G}_r,\, t\in\mathcal{T}\setminus\{1\}, \qquad (16) \\
& (G_{gt}^+, G_{gt}^-) \in \mathbb{R}_+^2, \quad \forall g\in\mathcal{G},\, t\in\mathcal{T}\setminus\{1\}, \\
& F_{ij,t} \in \mathbb{R}, \qquad \forall (i,j)\in\mathcal{L},\, t\in\mathcal{T}\setminus\{1\}, \\
& \theta_{jt} \in \mathbb{R},\, D_{jt}^{\text{shed}} \in \mathbb{R}_+, \qquad \forall j\in\mathcal{B},\, t\in\mathcal{T}\setminus\{1\}.
\end{aligned}
$$

Similar to $ED(x,\xi^s)$, the input $x$ in $ED'(x,\xi^s)$ alters (8) and (16). Note that the components of $x$ corresponding to $t = 1$ are not used in the $ED'(x,\xi^s)$, but preserved for ease of exposition.

# References

[1] D. Proctor, "California mandates 100% renewable energy," *POWER Magazine*, Jul. 2018, retrieved from https://www.powermag.com/california-mandates-100-renewable-energy/.

[2] A. Olson, A. Mahone, E. Hart, J. Hargreaves, R. Jones, N. Schlag, G. Kwok, N. Ryan, R. Orans, and R. Frowd, "Halfway There: Can California Achieve a 50% Renewable Grid?" *IEEE Power and Energy Magazine*, vol. 13, no. 4, pp. 41–52, 2015.

[3] I. Penn, "California invested heavily in solar power. now there's so much that other states are sometimes paid to take it," *Los Angeles Times*, Jun. 2017, retrieved from http://www.latimes.com/projects/la-fi-electricity-solar/.

[4] California ISO, "Fast facts: What the duck curve tells us about managing a green grid," Tech. Rep., 2016, retrieved from https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf. [Online]. Available: https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

[5] A. Bergman, P. Denholm, D. C. Steinberg, and D. Rosner, "Maintaining reliability in the modern power system," Tech. Rep., 2016. [Online]. Available: https://www.energy.gov/sites/prod/files/2017/01/f34/Maintaining%20Reliability%20in%20the%20Modern%20Power%20System.pdf

[6] C. Loutan, V. Gevorgian, and M. Morjaria, "Using renewables to operate a low-carbon grid," National Renewable Energy Laboratory (NREL), Tech. Rep., 2016. [Online]. Available: https://www.caiso.com/Documents/UsingRenewablesToOperateLow-CarbonGrid.pdf

[7] J. L. Higle and S. Sen, "Stochastic Decomposition: An Algorithm for Two-Stage Linear Programs with Recourse," *Mathematics of Operations Research*, vol. 16, no. 3, pp. 650–669, 1991.

[8] ——, "Finite master programs in regularized stochastic decomposition," *Mathematical Programming*, vol. 67, no. 1, pp. 143–168, Oct 1994. [Online]. Available: https://doi.org/10.1007/BF01582219

[9] S. Sen and Y. Liu, "Mitigating uncertainty via compromise decisions in two-stage stochastic linear programming: Variance reduction," *Operations Research*, vol. 64, no. 6, pp. 1422–1437, 2016.

[10] S. Sen and Z. Zhou, "Multistage stochastic decomposition: a bridge between stochastic programming and approximate dynamic programming," *SIAM Journal on Optimization*, vol. 24, no. 1, pp. 127–153, 2014. [Online]. Available: http://epubs.siam.org/doi/abs/10.1137/120864854

[11] S. Atakan and S. Sen, "A progressive hedging based branch-and-bound algorithm for mixed-integer stochastic programs," *Computational Management Science*, vol. 15, no. 3, pp. 501–540, Oct 2018. [Online]. Available: https://doi.org/10.1007/s10287-018-0311-3

[12] H. Gangammanavar, S. Sen, and V. M. Zavala, "Stochastic Optimization of Sub-Hourly Economic Dispatch With Wind Energy," *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–11, 2015. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7065337

[13] H. Gangammanavar and S. Sen, "Two-scale stochastic optimization for controlling distributed storage devices," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 2691–2702, July 2018.

[14] S. Atakan, G. Lulli, and S. Sen, "A state transition MIP formulation for the unit commitment problem," *IEEE Transactions on Power Systems*, vol. 33, no. 1, 2018.

[15] S. Sen, *Stochastic Programming*. Boston, MA: Springer US, 2013, pp. 1486–1497. [Online]. Available: https://doi.org/10.1007/978-1-4419-1153-7_1005

[16] S. Frank, I. Steponavice, and S. Rebennack, "Optimal power flow: a bibliographic survey i," *Energy Systems*, vol. 3, no. 3, pp. 221–258, Sep 2012. [Online]. Available: https://doi.org/10.1007/s12667-012-0056-y

[17] Q. P. Zheng, J. Wang, and A. L. Liu, “Stochastic optimization for unit commitment—a review,” *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 1913–1924, July 2015.

[18] J. D. Lyon, K. W. Hedman, and M. Zhang, “Reserve requirements to efficiently manage intra-zonal congestion,” *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 251–258, Jan 2014.

[19] California ISO, “Fast facts: Impacts of renewable energy on grid operations,” Tech. Rep., 2017, retrieved from https://www.caiso.com/Documents/CurtailmentFastFacts.pdf. [Online]. Available: https://www.caiso.com/Documents/CurtailmentFastFacts.pdf

[20] New England ISO, “Business practices manual: Energy and operating reserve markets,” Tech. Rep., September 2017, retrieved from https://www.misoenergy.org/legal/business-practice-manuals/. [Online]. Available: https://www.misoenergy.org/legal/business-practice-manuals/

[21] ——, “Market operations: Manual m-11,” Tech. Rep., October 2018, retrieved from https://www.iso-ne.com/static-assets/documents/2018/10/manual_11_market_operations_rev55_20181004.pdf. [Online]. Available: https://www.iso-ne.com/static-assets/documents/2018/10/manual_11_market_operations_rev55_20181004.pdf

[22] J. Zhao, T. Zheng, and E. Litvinov, “Variable resource dispatch through do-not-exceed limit,” *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 820–828, March 2015.

[23] B. Knueven, J. Ostrowski, and J. P. Watson, “On mixed integer programming formulations for the unit commitment problem,” Department of Industrial and Systems Engineering University of Tennessee, Knoxville, TN 37996, Tech. Rep., 2019.

[24] S. Wallace and W. Ziemba, *Applications of Stochastic Programming*, S. W. Wallace and W. T. Ziemba, Eds. Society for Industrial and Applied Mathematics, 2005. [Online]. Available: https://epubs.siam.org/doi/abs/10.1137/1.9780898718799

[25] Q. P. Zheng, J. Wang, P. M. Pardalos, and Y. Guan, “A decomposition approach to the two-stage stochastic unit commitment problem,” *Annals of Operations Research*, vol. 210, no. 1, pp. 387–410, 2013.

[26] J. Ostrowski, M. F. Anjos, and A. Vannelli, “Tight mixed integer linear programming formulations for the unit commitment problem,” *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 39–46, 2012.

[27] R. M. Van Slyke and R. Wets, “L-shaped linear programs with applications to optimal control and stochastic programming,” *SIAM Journal on Applied Mathematics*, vol. 17, no. 4, pp. 638–663, 1969.

[28] J. L. Higle and S. Sen, “Statistical approximations for stochastic linear programming problems,” *Annals of Operations Research*, vol. 85, no. 0, pp. 173–193, 1999.

[29] I. Pena, C. Brancucci, and B. M. Hodge, “An Extended IEEE 118-bus Test System with High Renewable Penetration,” *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 281–289, 2017.

[30] S. Wang, H. Gangammanavar, S. Ekşioğlu, and S. J. Mason, “Statistical estimation of operating reserve requirements using rolling horizon stochastic optimization,” *Annals of Operations Research*, Nov 2019. [Online]. Available: https://doi.org/10.1007/s10479-019-03482-x

[31] M. D. Ilic, "From hierarchical to open access electric power systems," *Proceedings of the IEEE*, vol. 95, no. 5, pp. 1060–1084, May 2007.

[32] L. L. Garver, "Power generation scheduling by integer programming - development of theory," *Power Apparatus and Systems, Part III, Transactions of the American Institute of Electrical Engineers*, vol. 81, no. 3, pp. 730–734, 1962.

[33] D. Rajan and S. Takriti, "Minimum up / down polytopes of the unit commitment problem with start-up costs," IBM, Tech. Rep., 2005.

[34] P. Damcı-Kurt, S. Küçükyavuz, D. Rajan, and A. Atamtürk, "A polyhedral study of production ramping," *Mathematical Programming*, vol. 158, no. 1, pp. 175–205, 2015.