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Towards a sustainable power grid: Stochastic hierarchical planning for high renewable integration

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ABSTRACT

Driven by ambitious renewable portfolio standards, large-scale inclusion of variable energy resources (such as wind and solar) are expected to introduce unprecedented levels of uncertainty into power systems operations. The current practice of operations planning with deterministic optimization models may be ill-suited for a future with abundant uncertainty. To overcome the potential reliability and economic challenges, we present a stochastic hierarchical planning (SHP) framework for power systems coordinated by a centralized planner. 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 stochastic optimization of individual problems (e.g., unit commitment, economic dispatch) have been studied, this paper studies an integrated framework of *planning under uncertainty*, where stochastic optimization models are stitched together in a hierarchical setting, which parallels the deterministic hierarchical planning approach that is widely adopted in the power industry. Our experiments, based on the NREL-118 dataset, reveal that under high renewable integration, significant operational improvements can be expected by transitioning to the SHP paradigm. In particular, the computational results show that significant improvements can be achieved in several metrics, including system reliability, environmental sustainability, and system economics, solely by making a strategic choice to adopt the new SHP paradigm.

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1. Introduction

Lawmakers throughout the U.S. have mandated that renewable resources meet a significant percentage of the electricity supply. Each state has set its own goals, with California being the most aggressive, requiring 50% renewables by 2026, 60% by 2030, and 100% by 2045 (see Proctor, 2018). European countries have also set ambitious targets both at the national level, as well as the European Union as a whole (International Renewable Energy Agency, 2018). State and local authorities such as Independent System Operators (ISOs) in the U.S. and Transmission System Operators (TSOs) in Europe have commissioned studies to assess operational considerations such as system reliability, market design, incorporation of storage technologies, and other avenues. A recent simulation study (Olson et al., 2015), 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 the daytime, and perhaps, load-shedding around sundown. Higher levels of renewable integration exacerbate these issues.

Power systems operations planning processes are mainly based on a hierarchical strategy coordinated by a centralized planner. This strategy leverages layers of optimization models, solved in sequence using a rolling horizon approach, to improve the reliability and economics of power systems operations. Typically, at the top layers of this hierarchy, long-horizon and low-resolution models are executed to determine commitment plans for generators with slower-ramping capabilities (e.g., nuclear). These plans are then passed to downstream layers of the hierarchy, where the decision space is gradually refined with higher-resolution models. The higher-resolution models use more accurate forecasts for demand and renewable generation to determine the commitment plans of most generators. Finally, a few minutes before dispatch, the economic dispatch model is solved to refine the generation plan for the committed generators. Electricity supply in this setup can be thought of as an aggregation of several products supplied to the consumer via a "middle-man", the ISO/TSO. These entities use a portfolio of power contracts that obligates a producer to provide electricity at a cleared price during the corresponding time

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  [1] This work was completed prior to Semih Atakan's employment at Amazon.com.
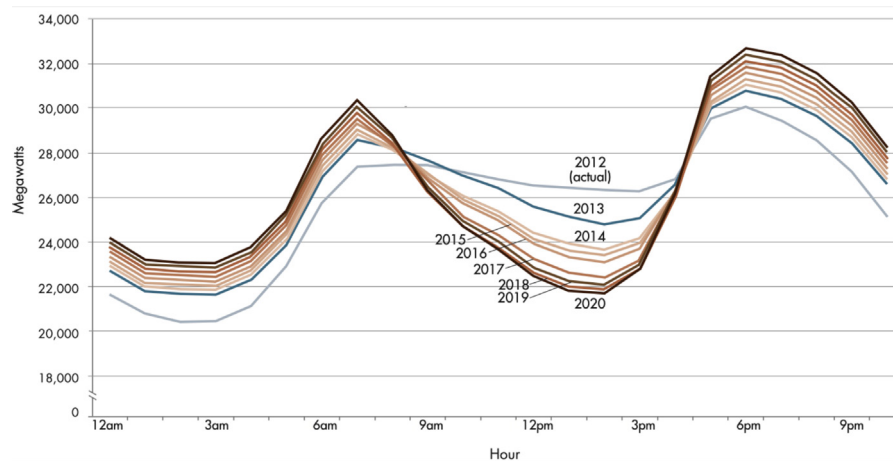
Fig. 1. CAISO's duck chart, predicting four emerging ramping patterns with increased renewable integration California ISO (2016).

window. The market time windows are aligned with the operations in a similar manner. For instance, a low-resolution market in the day-ahead is followed by a higher resolution real-time market closer to the time of actual dispatch. In systems with centralized planners, the operational elements (generator commitments, generation amounts, etc.) and the market elements (electricity prices) are outputs of the rolling-horizon optimization models.

Today's power system planning processes mostly use *deterministic* optimization models in all layers of the hierarchy, with the notable exception being hydropower scheduling in certain parts of the world. Such a process can be termed as deterministic hierarchical planning (DHP). The adoption of DHP predates the introduction of vast amounts of renewable energy into the grid. The significant levels of volatility of renewable resources pose one of the major challenges to maintaining reliable supply under DHP. Indeed, a recent study points to a significant increase in costs to maintain a fully renewable power system while meeting today's level of system adequacy (Zappa, Junginger, & van den Broek, 2019).

A popular illustration of issues related to renewable integration is captured by the so-called *duck chart* of CAISO (see Fig. 1). This figure depicts the daily net load (total 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 the 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 during 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 the daytime could lead to negative prices in the market, resulting in, for instance, large exports of energy to neighboring states (e.g., from California to Arizona) while paying these states to accept the surplus (see Penn, 2017). Additionally, it is important to recognize that Fig. 1 is based on point forecasts and overlooks the uncertainty in demand and renewable generation. During actual operations, the trajectory of the net load is unknown to the operators and can significantly deviate from the point forecast. Therefore, plans based on deterministic models that use point forecasts as input will result in immense reliability challenges.

To overcome the challenges of renewable integration and "tame the duck", so to speak, a recent U.S. Department of Energy (DOE) report (Bergman, Denholm, Steinberg, & Rosner, 2016) has distilled a myriad of operational guidelines (for maintaining reliability) into

four specific rules: (1) Power generation and transmission capacity must be sufficient to meet the peak demand for electricity; (2) Power systems must have adequate flexibility to address variability in demand and generation resources; (3) Power systems must be able to maintain a steady frequency; (4) Power systems must be able to maintain a steady voltage at various points on the grid. The focus of these rules is on expected changes over the next several years due to the inclusion of a new generation resources, especially variable energy resources (VER). The first two rules address operations *planning*, whereas the last two rules pertain to operations *control*. It is fair to suggest that technological solutions for operations control, which permit high renewable integration, are well underway.

As for operations planning, we posit that it is necessary to reassess the structure of the DHP paradigm to accommodate the volatility associated with renewable energy that affects every layer of this hierarchy. Such an assessment involves studying alternative setups that allow combinations of contemporary deterministic planning models and novel stochastic planning models. Given this focus, the main contributions of this paper are as follows:

1. *Overarching Goal: Comparing Stochastic and Deterministic Hierarchical Planning.* We study the implications of transitioning from DHP towards *stochastic hierarchical planning* (SHP) in a system with a centralized planner. We investigate whether it is possible to fully realize the promise of VER integration via reduced greenhouse gas (GHG) emissions, without deteriorating system reliability and significantly increasing production and distribution costs. The novelty of our work lies in an integrated assessment of combinations of models which are integrated within a hierarchy, and are cognizant of system volatility due to VERs.

2. *A Decision Evolution Architecture.* The decision processes used in this paper are driven by the NREL-118 dataset (Pena, Brancucci, & Hodge, 2017), which not only provides the grid data, but also the renewable energy environment for our experiments. In particular, the evolution of decisions and uncertainty embodied by this dataset lets us investigate the goal set forth in Item 1 above. Our architecture allows us to draw conclusions regarding costs, GHG emissions, load shedding, etc., based on the specific decision-modeling choices.

3. *Experimental Study.* We perform a comprehensive computational study of SHP under different models (deterministic v. stochastic) at individual layers of the hierarchy, with varying renewable integration levels and system reliability requirements. Our computational study demonstrates the potential of SHP when

compared to the current DHP strategy and acts as a precursor to an ISO-scale study.

It is important to emphasize that this study focuses on the NREL-118 dataset, and while similar studies can be undertaken using other datasets, the conclusions of this paper pertain only to those power systems which have similar VER levels and weather patterns. Our thesis is that the choice of the decision hierarchy of a system should be made in a manner that reflects the renewable integration levels. To give the reader a brief preview of our results, it turns out that the current DHP framework may not be as effective for decision-making under uncertainty. We present strong evidence that for NREL-118, SHP provides superior metrics for operational costs, lost-load, as well as GHG emissions.

Studies of using stochastic optimization for power system operations can be traced back at least forty years to Murphy, Sen & Soyster (1982). While there are many studies of stochastic optimization within any one layer of the hierarchical system, no other study pits the standard hierarchy of deterministic models against a hierarchy of stochastic ones in a system operated by a centralized planner. It is such a comparison that provides a preview of the potential advantages and disadvantages of alternative hierarchies on electricity production planning. Thus, this study examines whether a system-wide overhaul that introduces stochastic optimization to one or more layers of the hierarchy can mitigate difficulties associated with efficient integration of renewable energy into the grid.

The remainder of this paper is organized as follows. We begin with an overview of today's power system operations in Section 2 and discuss relevant literature in Section 3. In Section 4, we present a detailed description of the SHP framework, including optimization models and solution algorithms used to simulate system performance. In Section 5, we present our experimental results. Finally, in Section 6, we conclude with a brief discussion of how one might proceed to the next phase of tests, which would require ISO-size networks and technologies. The overall structure of each model used in the hierarchy is discussed in Appendix A, and details on solar and wind inputs are given in Appendix B. In the interest of enhancing the reproducibility of our study, the code and data associated with our experiments are available at USC 3D Lab (2021).

2. An overview of power systems operations planning

Electric power systems are very large-scale networks interconnecting many sources of electric power to points of consumption. The entire network is arranged at several voltage levels, converted from one to another by transformers. The overarching goal of the system operators (centralized planners) is to minimize costs while ensuring reliable power delivery to customers. Given the continuous and very large-scale nature of operations, 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.

Our hierarchical planning paradigm assumes coordination via a central planning authority (e.g., ISO or TSO). Most ISOs/TSOs currently implement some form of a DHP framework, which divide the daily planning activities into three principal layers: (a) *day-ahead unit commitment* (DA-UC) based on a daily forecast of load and generation limits leading to a production and transmission plan, (b) *short-term unit commitment* (ST-UC) over a shorter planning window (typically three to four hours), producing some commitment decisions and updated transmission plans, and (c) *hour-ahead economic dispatch* (HA-ED) where the production and transmission plans are finalized and necessary reserve capacities

are committed. There are some variations of this multi-layer hierarchy, such as updating the dispatch plan at 15-minute intervals to accommodate high levels of VER. However, all layers in this hierarchical setup adopt some form of deterministic optimization models, and as such, all forecasts used in these models are *point forecasts*. In what follows, we give further details on the three principal layers mentioned above and provide notes on how our setup (described in greater depth later) accommodates these layers.

2.1. Day-ahead (DA) operations

This phase begins by estimating demand and renewable supply, as well as collecting generation and demand bids via electricity markets. This information is used in simultaneous co-optimization for the next operating day, using security-constrained unit commitment (UC) and security-constrained economic dispatch (ED) models. In most settings (including ours), these models are formulated over a 24-hour planning horizon, with decisions and constraints specified 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, as well as ISO-specific practices. DA planning also involves committing resources for reliability assessment and emergency operations. For simplicity, 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. This model determines generation, regulating, and spinning reserve amounts for all committed resources, as well as 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.

2.2. Short-term (ST) operations

Some advanced ISOs use additional instruments that commit fast-start resources to ensure that the schedules meet all reliability requirements. The associated models are solved independently against DA transactions and generation bids. At certain ISOs (e.g., NYISO), these operations are considered a part of the real-time (RT) markets and are referred to as the RT-UC. Following the terminology at CAISO, we will refer to these operations as Short-Term UC (ST-UC). These models are formulated at a finer resolution (e.g., 15 minutes), allow adaptive (de)commitment decisions, and are solved over a horizon of a few hours (e.g., 4.5 hours at CAISO and 2.5 hours in NYISO). In our setup, we define these models at a resolution of 15 minutes and a horizon of 4 hours, solved every 3 hours.

2.3. Real-time (RT) 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 RT balancing of loads and generation. This balance is maintained through a combination of spinning and ancillary services along with the units providing regulation reserves, which are managed by 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. The planning of dispatch amounts for RT operations is done using ED models with 5 to 15-minute intervals. Our setup will consider ED models at

a 15-minute resolution with a 75-minute horizon but set aside tasks associated with downstream models (managing actual dispatch and transmission control) as being outside the scope of this paper.

3. Literature review

Even with the decomposition of operations planning into DA, ST, and RT phases, generation scheduling and dispatching problems are truly stochastic optimization problems, therefore they are computationally very challenging. Under a DHP setting, system operators approximate the random variables with their point forecasts, converting these stochastic problems into large-scale deterministic (mixed-integer) problems, which can be handed off to commercial solvers. Note that electricity production and distribution are governed by nonlinear equations which can lead to non-convex problems. For the sake of scalability, we focus on linear approximations of all non-linear model elements (similar to the literature cited in this section).

Both deterministic UC and ED problems are fundamental to power system operations planning, and both have been studied extensively in the literature. Comprehensive treatments of state-of-the-art UC formulations can be found in Knueven, Ostrowski, & Watson (2019). The surveys (Chowdhury & Rahman, 1990; Frank, Steponavice, & Rebennack, 2012) provide an overview of deterministic ED models.

Typical UC formulations studied in the literature (such as Atakan, Lulli, & Sen, 2018; Knueven et al., 2019; Ostrowski, Anjos, & Vannelli, 2012) do not include a transmission network, and model dispatch at an aggregate level. In the interest of greater accuracy with transmission constraints, we adopt the dispatch model studied in Gangammanavar, Sen, & Zavala (2015). This formulation involves a linear objective function that captures production costs and over-generation/load-shedding penalties, as well as constraints corresponding to generation capacities, ramping, flow balance, linearized power flow (DC approximation), operating reserve utilization, bounds on bus angles, and line capacities.

The traditional approach for addressing uncertainty has been, in essence, over-producing, which creates a reserve of electricity that is used as a buffer against unexpected volatility. Some ISOs (e.g., New England ISO) have already recognized the shortcomings of deterministic planning within the context of renewable integration, and recommend certain deterministic policies (Zhao, Zheng, & Litvinov, 2015). Over the last decade or so, developments in stochastic modeling and optimization have allowed uncertainty to be explicitly handled within the decision process. In particular, 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 (Wallace & Ziemba, 2005). Two-stage stochastic programs (2-SPs), including models with discrete first-stage variables, have gained acceptance among both the power systems research community as well as practitioners.

Stochastic UC models have been studied to better accommodate wind uncertainty (Papavasiliou, Oren, & Neill, 2011; Ruiz, Philbrick, Zak, Cheung, & Sauer, 2009) or other sources of stochasticity such as generator/transmission failures and demand uncertainty (Cheung et al., 2015; Zheng, Wang, Pardalos, & Guan, 2013). For a review of stochastic UC, we refer the reader to Zheng, Wang, & Liu (2015). To account for uncertainty closer to the time of dispatch, stochastic ED models have been investigated using stochastic programming (e.g., Gangammanavar et al., 2015; Gu & Xie, 2016) or robust optimization (e.g., Lorca & Sun, 2014).

In addition to deterministic v. stochastic comparisons of individual models, the longer-term impact of stochastic models is assessed in Sturt & Strbac (2012); Tuohy, Meibom, Denny, & O'Malley (2009). In contrast to earlier citations, these studies capture the temporal dynamics of operations by solving sequences of stochastic planning models over a rolling time horizon (i.e., model predictive control as in Lopez, Ydstie, & Grossman, 2003). Our setup is similar in this respect, as it also involves (multiple types of) models solved over a rolling time horizon. Under (supply) uncertainty, studies were conducted to bridge the gap between DA planning and RT execution (e.g., Choi, 2018; Reddy & Bijwe, 2016). Both of these studies leverage deterministic linear optimization models and their focus is on coordinating DA and RT operations as opposed to assessing the impact of VER integration.

In contrast, Ilic (2007) calls for considering a hierarchical framework involving *stochastic* dynamic problems evolving at different timescales. While their paper provides a high-level assessment, it does not provide a quantitative evaluation. On the other hand, Schulze & McKinnon (2016) investigates the advantages that might accrue from using stochastic optimization in stochastic DA and intra-day (ST) UC problems over a multi-year time horizon. It is important to highlight some of the differences between their setup and ours. First, their study does not consider ED as part of the planning process, and their models and data may be described as a somewhat lower resolution representation, which includes a much smaller set of scenarios in their stochastic programs. The dataset used in our study (Pena et al., 2017) was specifically introduced by NREL to investigate systems with high VERs. Due to the level of detail provided in this dataset, as well as our focus on methods which allow a very large collection of scenarios, our conclusions happen to be different from that reported by Schulze & McKinnon (2016), whose experiments observed only modest improvements resulting from stochastic models with a very coarse-grain description of scenarios and time resolutions.

It is worthwhile to recall that prices in power systems are settled through hierarchically arranged markets that involve power generation companies, consumers (i.e., loads) as well as transmission owners as participants. Each participant (e.g., a generator company) bids their price and capacity, and the ISO/TSO is given the responsibility of clearing the market. We emphasize that our study focuses on operational models which are instantiated by such centralized planners (e.g., ISO/TSO) using bids submitted via the market. Moreover, we assume competitive markets, risk-neutral market players, and cost-optimal bid prices for all market participants. We refer the reader to Conejo, Carrión, Morales et al. (2010) for a detailed treatment of electricity markets under uncertainty; Ralph & Smeers (2015) for treatment of risk-aware market participants.

In the context of markets, there have been some attempts to capture multiple layers at different timescales. For instance, Dorostkar-Ghamsari, Fotuhi-Firuzabad, Lehtonen, Safdarian, & Hoshyarzade (2019) considers the IEEE-33 instance and adopt a two-layer hierarchy with DA and RT layers. Aasgard, Fleten, Kaut, Midthun, & Perez-Valdes (2019) provides a conceptual study where it is argued that the benefits of a multi-market (hierarchical) bidding process (mainly for hydro-generators). Ottesen, Tomasgard, & Fleten (2018) consider an optimal bidding problem over a three-layer energy market, where stochastic programs under price uncertainty are adopted at each layer. Finally, Morales, Zugno, Pineda, & Pinson (2014) consider a two-layer energy market, analyze shortcomings of conventional and stochastic market-clearing models and provide a bi-level programming solution.

Studies that focus on electricity markets with multiple layers (as mentioned above) are only a few exceptions. Overall, it is fair to suggest that most models are limited to a single layer in the hierarchy. Even when 2-SPs are studied or used with power system studies, the evaluation (using Monte Carlo simulations or against historical data in a rolling horizon setting) is restricted to first-stage (or some primary) decisions. In contrast, our investi-
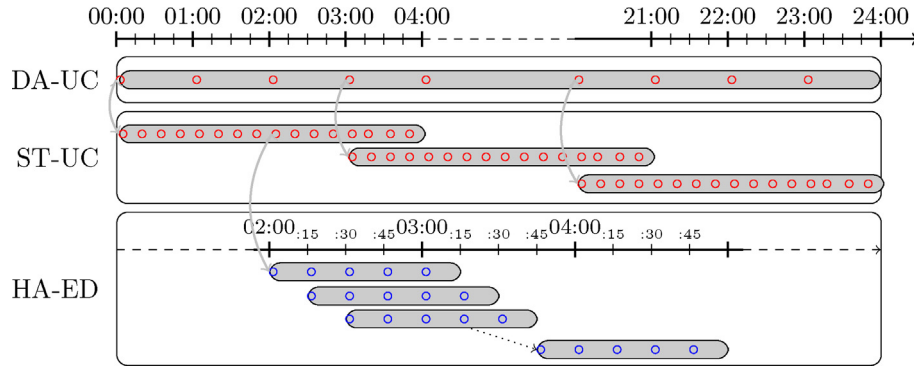
Fig. 2. Hierarchical structure with timescales of the operating framework.

Table 1
Model timescale used for experiments.

	Horizon	Resolution	Solution frequency
DA	24 hours	60 minutes	24 hours
ST	4 hours	15 minutes	3 hours
RT	75 minutes	15 minutes	15 minutes

gation is designed to evaluate the impact of decisions across *all layers* and tracks several operational metrics such as unmet demand, over-generation, GHG emissions, and others, as summarized in Section 5.

4. Stochastic hierarchical planning

In this section, we introduce the details of the SHP framework illustrated in Fig. 2. We provide an abstract description of SP models used in each individual layer and defer the detailed descriptions to Appendix A.

4.1. The multilayer framework

Our setup captures power systems operations across multiple days. We use three subscripts, $[i]$, $[j]$, and $[k]$, corresponding to the DA-UC, ST-UC, and HA-ED model instances, respectively. Following the timescales presented in Table 1, the subscript $[i]$ is used to index the 24 (hourly) decision epochs of the DA-UC instance corresponding to the ith day. Since a ST-UC instance is solved every 3 hours, 8 ST-UC instances are solved on a given day, each with a 4-hour horizon. The subscript $[j]$ is used to index the 16 (15-minute) decision epochs corresponding to the jth ST-UC instance. Finally, given an HA-ED instance is solved every 15 minutes, 96 HA-ED instances are solved on a given day. For the kth instance, the 5 decision epochs are captured by $[k]$. To make our notation clear, assume that the operations begin at 12:00 am. The DA operations of the first day are captured by the DA-UC instance indexed by $i = 1$; the ST operations between 9:00 am and 12:00 pm are captured by the ST-UC instance indexed by $j = 4$; and the RT operations for 10:00 am are captured by the HA-ED instance indexed by $k = 11$.

Let $\mathbf{x}$ and $\mathbf{y}$ be the decision vectors that model commitment and dispatch decisions, respectively. We use superscripts d, s, and r on decision variables, objective functions, constraint sets, and parameters associated with DA, ST, and HA, respectively. A subscript $[\bullet]$ (as in, $\mathbf{x}_{[\bullet]}$) is used to refer to the decision vector corresponding to the specific instances. For example, $\mathbf{x}_{[6]}^d$ denotes the commitment decisions in the DA-UC instance for the 6th day. Similarly, $\mathbf{y}_{[11]}^s$ denotes the dispatch decisions in the 11th ST-UC instance (based on Table 1, this corresponds to 6:00 am–10:00 am of the second day). Finally, the randomness associated with renewable supplies

and electricity demand is captured by random vectors that evolve over time. We denote these random vectors by $\tilde{\xi}_{[i]}^d$, $\tilde{\xi}_{[j]}^s$, and $\tilde{\xi}_{[k]}^r$, for the ith, jth, and kth instances of the DA-UC, ST-UC, and HA-ED models, respectively.

A model instance is built using optimal solutions obtained by solving the previous instances at all three levels of the hierarchy. We summarize these optimal solutions as a state vector, $\mathcal{H}_{[\bullet]}$. For instance, the jth ST-UC instance is built using (a) the optimal solution of the DA-UC instance corresponding to time periods $[j]$, (b) the solutions of the previous ST-UC instances, viz. $[j-1], [j-2]$, etc., and (c) the solutions of the HA-ED instances for time periods immediately preceding $[j]$. The components corresponding to (a) and (b) affect the minimum up/downtime constraints, while (c) affects the ramping constraints of the next instance. These will be collectively referred to as $\mathcal{H}_{[j]}$. The flow of decisions between different layers is illustrated in Fig. 3. Furthermore, we use $f_{[\bullet]}$ and $\mathcal{X}_{[\bullet]}$, with appropriate indices, to denote the objective function and feasible region of the optimization problems. We refer the reader to Appendix A for explicit descriptions of these model elements.

It should be noted that the underlying operations can be modeled as a multiscale, multistage, stochastic mixed-integer program (MMSMIP). Clearly, the state-of-the-art in theory or algorithms do not support such models. Therefore, with the goal of providing evidence on the value of SHP, we adopt a sequence of 2-SPs at each layer. In our setup, the higher layer passes decisions to the lower layer, and the lower layer provides both sampled objective values and subgradients at finer granularity to the upper layers. This exchange between the layers provides sufficient coordination to improve performance compared to deterministic models. Future research should be directed towards more integrated studies of MMSMIPs.

Given the notation introduced above, for day i, we define the DA-UC model as a 2-SP, where the first stage involves commitment decisions and the second stage has a security-constrained ED defined over the entire model horizon. This program can be abstracted as follows:

$$\text{DA-UC} \quad \left(\mathcal{H}_{[i]}, \tilde{\xi}_{[i]}^d\right) = \min f_{[i]}^d\left(\mathbf{x}_{[i]}^d, \mathbf{y}_{[i]}^d\right)$$
$$\text{subject to:} \quad \left(\mathbf{x}_{[i]}^d, \mathbf{y}_{[i]}^d\right) \in \mathcal{X}_{[i]}^d\left(\mathcal{H}_{[i]}, \tilde{\xi}_{[i]}^d\right). \tag{1}$$

Above, the function DA-UC $(\cdot)$ uses the history of the generators (i.e., $\mathcal{H}_{[i]}$) and a representation of renewable supplies and demand stochastic processes $\tilde{\xi}_{[i]}^d$ to determine commitment schedules for DA generators. The feasible set of this model is denoted as $\mathcal{X}_{[i]}^d(\cdot)$, and the expectation-valued function $f_{[i]}^d(\cdot)$ captures the combined commitment and dispatch costs. We denote the optimal solution of this model as $(\mathbf{x}_{[i]}^{\star,d}, \mathbf{y}_{[i]}^{\star,d})$. This recommendation acts as an input to the lower level optimization problems, viz. ST-UC and HA-ED. Since the resolution of the lower level optimization problems is higher
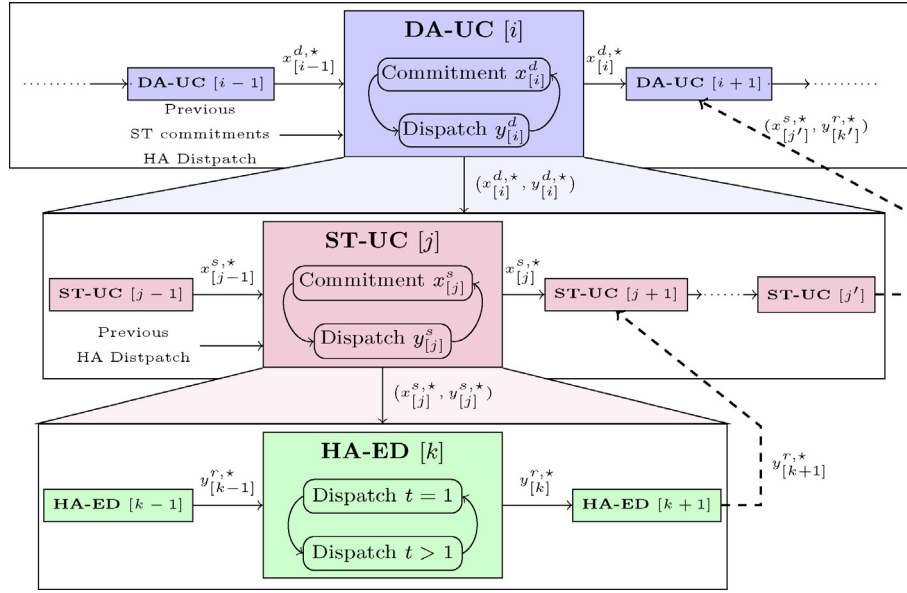
Fig. 3. Flow of decisions between layers of the hierarchical structure.

(15 minutes) when compared to the DA-UC (60 minutes), the same DA-UC decisions are undertaken for each 15-minute interval of an hour.

Using the optimal decisions obtained from previously solved instances (i.e., $\mathcal{H}_{[j]}$), the jth ST-UC instance, formulated as a 2-SP, is given as follows:

$$
\begin{aligned}
\text{ST-UC} \quad & \left(\mathcal{H}_{[j]}, \tilde{\xi}^s_{[j]}\right) = \min f^s_{[j]}\left(\mathbf{x}^s_{[j]}, \mathbf{y}^s_{[j]}\right) \\
\text{subject to:} \quad & \left(\mathbf{x}^s_{[j]}, \mathbf{y}^s_{[j]}\right) \in \mathcal{X}^s_{[j]}\left(\mathcal{H}_{[j]}, \tilde{\xi}^s_{[j]}\right),
\end{aligned}
\tag{2}
$$

The ST-UC $(\cdot)$ and DA-UC $(\cdot)$ are similar in nature, except for two additional sets of constraints. The first set of constraints imposes that the DA commitment decisions $(\mathbf{x}^{\star,d}_{[j]})$ are respected in the ST-UC model for generators that are included in the DA-UC model. We allow the generation levels for these generators to be updated in the ST-UC model. However, we ensure that these deviations are within bounds defined by an input parameter. The second set of constraints are intended for this purpose and are placed to avoid myopic solutions of ST-UC models as they have shorter horizons than the DA-UC model.

Using all the commitment decisions and generation levels (captured by $\mathcal{H}_{[k]}$) prescribed by higher-level UC models, the kth HA-ED instance, again formulated as a 2-SP, is instantiated as shown below:

$$
\begin{aligned}
\text{HA-ED} \quad & \left(\mathcal{H}_{[k]}, \tilde{\xi}^r_{[k]}\right) = \min f^r_{[k]}\left(\mathbf{x}^r_{[k]}, \mathbf{y}^r_{[k]}\right) \\
\text{subject to:} \quad & \left(\mathbf{x}^r_{[k]}, \mathbf{y}^r_{[k]}\right) \in \mathcal{X}^r_{[k]}\left(\mathcal{H}_{[k]}, \tilde{\xi}^r_{[k]}\right).
\end{aligned}
$$

The first stage of HA-ED $(\cdot)$ captures generation levels for the first decision epoch, whereas the second stage involves the remaining decision epochs of the planning horizon. Note that only the first-stage (i.e., the here-and-now) decisions are implemented. Since the commitment decisions are fixed, the resulting model only has continuous decision variables. As in the case of ST-UC, $\mathcal{X}^r_{[k]}$ involves constraints that prevent HA generation levels from deviating significantly from the generation decisions of the upper layer problem (i.e., ST-UC). This is done to overcome the myopic nature of the HA-ED problem, as its planning horizon is shorter compared to the UC models.

The deterministic variants of the model instances defined above use only point forecasts $\bar{\xi}_{[\cdot]}$ and the objective functions are defined as the costs associated with both unit commitment decisions and dispatch under such forecasts. In these models, we replace the expectation-valued objective functions with their deterministic counterparts. The second stage is defined only for a single scenario (the point forecast), as opposed to a set of scenarios in stochastic models.

4.2. Modeling and solving individual optimization problems

The deterministic UC and ED models are solved using MIP and LP algorithms available in off-the-shelf solvers (e.g., CPLEX, Gurobi). In 2-SPs for UC, we use a finite set of scenarios to represent the uncertainty (100 scenarios, to be specific). 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 the recourse problems are LPs and can be decoupled by scenarios, we use the well-known L-shaped method (also known as Benders decomposition) to solve the stochastic UC problems (Benders, 1962; Van Slyke & Wets, 1969). The 2-SP for the HA-ED problem does not have integer variables in either stage. We solve these models using a sequential sampling method called regularized stochastic decomposition (SD) algorithm (Higle & Suvrajeet, 1994). Table 2 provides a summary of model characteristics and algorithmic choices adopted in our study. It is worth noting that the recourse problems of both UC and ED involve multiple periods that can be modeled as multi-stage stochastic programs. As mentioned in Section 4.1, such details are not supported by the current theory and algorithms and are left as future research.

The solution quality of an SP is directly influenced by the number of scenarios considered. We label a solution to an SP model to be *statistically-optimal* (for a given confidence level α) if the optimal value reported by the algorithm falls within an acceptable confidence interval computed using an independent validation process. We refer the reader to Sen & Liu (2016) for details regarding statistical optimality and the validation process. In our setup, the SD algorithm can achieve statistical optimality by increasing its sample size on the fly, whereas a fixed sample size used in stochastic mixed-integer UC models makes statistical optimality a demanding requirement to impose for the current state-of-the-art.

In our framework, our knowledge of the underlying stochastic process improves as we get closer to the time of dispatch. This leads to more accurate point forecasts (from DA to ST, and eventually HA forecasts) of wind and solar generation amounts. Deter-

Table 2
Problem class and solution algorithms used for individual instances.

Operational layer	Deterministic		Stochastic	
	Problem type	Solver	Problem type	Algorithms
DA-UC	MIP	CPLEX default	Stochastic MIP	Benders/L-Shaped
ST-UC	MIP	CPLEX default	Stochastic MIP	Benders/L-Shaped
HA-ED	LP	CPLEX default	Stochastic LP	Regularized SD

ministic models are set up using point-forecast time series available just before their execution. On the other hand, the scenarios used to instantiate and solve stochastic UC and ED problems are generated using separate time series simulators for solar and wind. These simulators are based on vector autoregressive (VAR) models that capture the spatio-temporal correlation of the stochastic processes governing generator outputs. The VAR models are trained using the point-forecast time series available immediately before the execution of the respective stochastic models. We refer the reader to Appendix B for an extensive discussion on the prediction and scenario generation aspects of our study.

4.3. Evaluating the performance of hierarchical planning frameworks

We evaluate the performance of both DHP and SHP frameworks by solving the individual model instances in a rolling horizon fashion over multiple days against the actual observations of demand and renewable generation (see Fig. 2). The actual observation data is available in the NREL-118 dataset Pena et al. (2017). The historical commitment decisions, summarized in $\mathcal{H}_{[i]}$ with $i = 1$, serve as input to our simulation setup. The DA-UC and ST-UC instances use a representation of the stochastic process that is built based on the forecast data, which is also available in the NREL-118 dataset. On the other hand, the first stage of HA-ED uses the actual observations, while the scenarios in the second stage are based on the forecast available at the time when the model is instantiated. Once the HA-ED problem is solved, the current period's generation amounts are recorded and all metrics (such as load shedding, cost) are computed based on these decisions. The simulation clock is then moved forward and the next problem (possibly from the upper layers of the hierarchy) is solved. Notice that only the HA-ED problem's first-stage generation solutions (and the associated commitment decisions) constitute our final outputs, while the solutions of the UC problems can only *influence* these outcomes.

5. Experimental study

The NREL-118 instance includes 327 generators (75 solar and 17 wind), 118 buses, and 186 transmission lines, along with DA forecasts and RT outputs of renewable generators and demand. This dataset has a power system that is rich in solar, wind, and hydro resources, and may be considered as forward-looking. We assess three factors that have a significant impact on power system operations. These are solar and wind integration, 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 3, we summarize the considered values of these factors in our experiments. We use a three-letter code to identify specific types of models (i.e., **D**eterministic or **S**tochastic) used within the three-layer planning hierarchy (DA, ST, RT). Following this notation, the DDD setting is the benchmark deterministic planning framework (i.e., DHP), whereas both DDS and SDS can be considered as examples of the SHP framework.

Note that in actual operations, both the ST-UC and HA-ED problems are solved during the dispatch day and optimal solutions

from both must be computed in very short time intervals. This is especially important for ST-UC, as these problems commit fast-ramp resources to respond to reliability concerns that may emerge in real-time. For the HA-ED solutions obtained from stochastic linear programs, the state-of-the-art algorithms are capable of delivering *statistically-optimal solutions rapidly*, using very detailed representations of the stochastic processes. For instance, in our experiments, the SD algorithm that solves the HA-ED instances used a minimum of 256 simulated multivariate time series of wind and solar stochastic processes (75 solar and 17 wind locations resulting in a 92 dimensional time series). However, the solver technology for stochastic MIPs is nowhere near the same level of maturity to deliver high-quality solutions within tight computational-time bounds. On these grounds, academic studies on these models are typically conducted with only a handful of scenarios, and their solutions are seldom validated to ensure that the coarse representation of uncertainty indeed provides a prediction of the optimal objective function (which lies within an upper bound confidence interval of the true SP problem). In contrast, our study adopts the prudent step of following the standard industry practice today, namely, solving ST-UC problems as deterministic MIPs. In subsequent sections, our experiments will reveal promising results even with a deterministic ST-UC, providing *lower bounds on achievable gains* through the SHP framework with fully-stochastic layers.[2] This also reinforces the need for further research on two aspects of renewable integration: (a) reasonably accurate probabilistic forecasts of wind energy over short intervals of time (less than six hours; Carroll, Cradden et al., 2018) and (b) specialized (fast) algorithms for large-scale ST-UC problems which can deliver near-optimal solutions for real-scale models with binary (start-up/shut-down) variables. For this reason, our study does not include the following combinations: (●, S, ●).

In all experiments, we consider a total planning horizon of 7 days, and a maximum resolution of 15 minutes. Recall that evaluations of the hierarchical frameworks are carried out in a rolling horizon manner. We assume that the DA-UC and ST-UC problems commit distinct sets of generators, and ST-UC problems cannot decommit DA resources (see Appendix A for details). The reported metrics are based on generator heat rates, fuel consumption rates, and emission rates given in the NREL-118 dataset, as well as first-period generation decisions of HA-ED problems that are based on actual observations. Note that both the deterministic and the stochastic models are evaluated based on the same actual observations time series. In what follows, we present the results from these evaluations.

5.1. Reliability impact

Significant amounts of unmet demand revealed in the planning process may result in blackouts with damaging economic consequences for system constituents. Due to its importance to ISOs as

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[2] For a given input state, the stochastic ST-UC will outperform the deterministic one, due to the well-known non-negativity of the value of stochastic solution (Birge & Louveaux, 1997).

Table 3
Investigated factors and their levels.

Category	Label	Description
Solar & Wind Integration	Low SW:	Original solar & wind outputs in the NREL-118 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.

Table 4
Average and maximum unmet demand amounts (Megawatt).

Planning setting	Reserve req.	Avg. unmet demand Solar & wind integ.			Max. unmet demand Solar & wind integ.		
		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

Table 5
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. 4. Average over-generation amounts by conventional generators.

well as customers, we start our discussion by presenting the average and maximum unmet demand values in Table 4.

In general, we notice higher unmet demand when more solar and wind resources are introduced to the system with fully deterministic planning (DDD). More conservative reserve requirements substantially reduce these values but possibly come with an additional monetary cost. On the other hand, *adopting stochastic planning models 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 models to accommodate the uncertainty associated with VERs and reduce reliance on (manually-imposed) reserve restrictions. More importantly, it suggests the possibility of a more economic manner of system operations.

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 5). We observe a consistent trend where the DDD setting heavily relies on ST-UC problems to maintain reliability. In contrast, DDS and SDS settings substantially reduce these requirements even under higher renewable-integration settings.
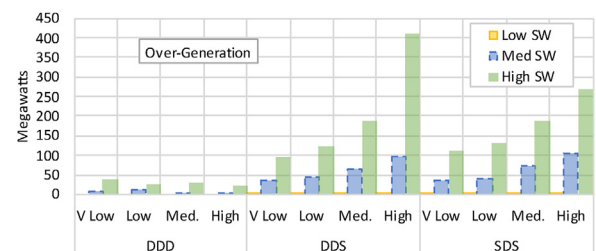
Fig. 4 shows the average amounts of over-generation (by conventional generators) estimated under all settings. Recall that in the absence of significant storage capacity in the system (such as today), vast swings in renewable supply may result in over-generation by conventional generators (Olson et al., 2015). This, in turn, leads to negative electricity prices or costly exchanges between neighboring ISOs to ensure supply and demand matches without damaging physical infrastructure or posing financial concerns for market participants (Penn, 2017).

We observe the smallest over-generation 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. This may mitigate the duck chart phenomenon discussed in the introduction.

In terms of solar and wind curtailment, Fig. 5 shows a significant trend where higher renewable integration leads to substantial amounts of curtailment, providing support for the need to intro-
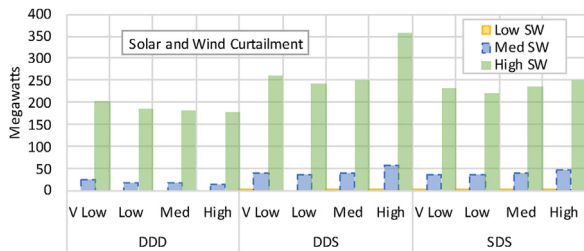
Fig. 5. Average curtailed solar and wind energy.

Table 6

Average number of committed generators in each framework across different reserve requirement levels.

Reserve req:	V Low	Low	Med.	High
DDD	162.9	170.7	180.3	186.4
DDS	157.6	162.8	168.0	174.2
SDS	154.5	159.8	166.3	174.6

Table 7

Avg. daily operating cost of the system corresponding to the minimum reserve requirements leading to zero unmet demand (in million $; Reserve requirements in parenthesis).

	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)

duce greater energy storage. In addition, we still observe that both DDS and SDS lead to slightly more curtailment than that in DDD.

Overall, the outcomes suggest that a transition to SHP leads to reduced loss-of-load, through conventional over-generation and renewable curtailment, which is dynamically adjusted across the buses based on the uncertainty that lies ahead. This indicates that reliability can be improved by better planning models, as opposed to increasing the reserve requirements. In subsequent sections, we will see promising results on the economic and environmental impacts of operating the network with lower reserve requirements, which will reveal further contributions of stochastic power systems planning models.

Fig. 6 illustrates intra-day generation profiles under DDD and SDS settings. Observe 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), with the first occurring typically at day-time, when solar generators are active, and transmission capacity is 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 Megawatt to 0.7 Megawatt. 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 better ramping capabilities, making them better suited to accommodate uncertainty. SDS naturally leverages this fact seamlessly.

5.2. Economic impact

Fig. 7 demonstrates the average daily operating costs recorded in our experiments. The reported amounts exclude the potential costs associated with the consequences of operating a grid with low reliability (e.g., penalties associated with load-shedding). In line with expectations, increased renewable integration leads to lower costs as these resources have negligible generation costs. On the other hand, increased reserve requirements have the opposite effect, since more (and possibly expensive) resources need to be committed to maintain these requirements. Table 6 illustrates this, where there is a consistent trend of growing number of committed generators as the reserve requirements are increased.

Table 6 reveals another trend. The number of committed generators under DDS and SDS settings are consistently lower than that in DDD. A particular reason for this is the number of ST generators that are committed near dispatch time, which has already been il-

lustrated in Table 5. Overall, however, we posit that the stochastic models can mitigate concerns over reliability without committing an abundance of resources.

We now turn our attention to cases where reliability is achieved with the smallest reserves. Specifically, we look at reserve requirement levels at which the network demand is seamlessly fulfilled. Table 7 presents the daily operating costs corresponding to the minimum reserve requirements that must be set at each level of the hierarchy to ensure zero unmet demand. The cost figures indicate that, with stochastic optimization, reserve requirements can be relaxed as the models can dynamically adjust production levels by accounting for uncertainty in the future. As a result, the operating cost of the network can be reduced by up to 10.4% (e.g., compare $11.23M with DDD to $10.06M with SDS, under high renewable integration). This is a promising finding as it points towards approaches which might mitigate financial concerns regarding the use of higher shares of VER in the European grid (e.g., Zappa et al., 2019).

For reserve requirements higher than those cited in Table 7, conflicting outcomes can be observed. For instance, the operating costs of DDS is better than that of SDS under medium and high reserve requirements, and high renewable integration. Clearly, this would not be a suggested manner of operations, as it costs more compared to what Table 7 reports. However, it shows that just the stochastic HA-ED can accommodate fluctuations in VERs well with high-enough reserve requirements. Specifically, the deterministic DA-UC provides a (short-sighted) cost-optimal generator mix for a given forecast, and stochastic HA-ED ensures that not many additional ST generators are necessary during dispatch time (see Table 5). In comparison, the stochastic DA-UC provides a generator mix that is more conservative, and therefore, ready for scenarios that can jeopardize reliability, ensuring the sufficiency of lower reserve requirements.

5.3. 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 7, Fig. 8 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 NREL-118 dataset, as well as their generation levels, which is determined by our hierarchical setups. Similar observations were made for the NO_x and SO_2 emissions, therefore omitted in this paper.

Concerning 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 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 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-
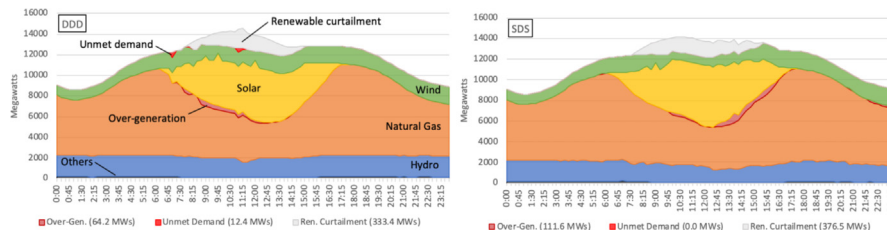
Fig. 6. Generation mix, unmet-demand, and over-generation in DDD and SDS settings (very low reserves, High SW, and a sample day).
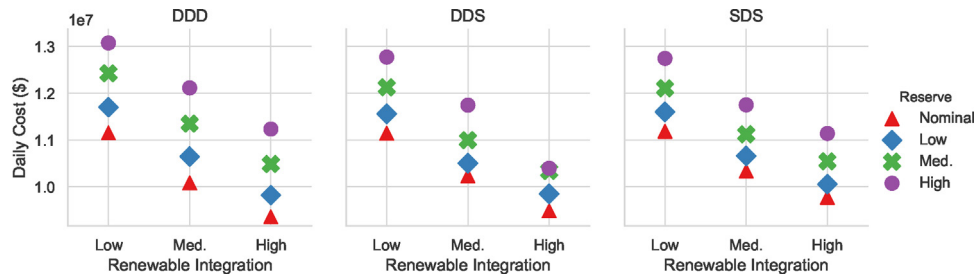

Fig. 7. Average daily generation cost of the power system under different reserve requirements and operations planning strategies.
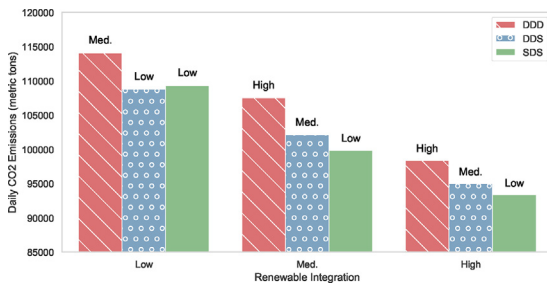

Fig. 8. Average daily CO_2 emissions of the power system corresponding to the minimum reserve requirements leading to zero unmet demand (reserve requirements are noted on top of the bars).

generation and renewable curtailment (see Figs. 4 and 5), 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 Wang, Gangammanavar, Ekşioğlu, & Mason (2020).

6. Conclusions and discussion

We presented the SHP framework for power systems with large-scale VER integration. While the call for a framework comprising of stochastic dynamic problems evolving at different timescales has been made before (e.g., Ilic, 2007), this is the first study to conduct comprehensive computational experiments with such a framework under a centralized planner. Our framework captures the operations and their interactions across day-ahead, short-term, and hour-ahead timescales.

The optimization models in the SHP framework are solved using stochastic programming (SP) algorithms, some of which have been studied rigorously for over thirty years (Higle & Sen, 1991; 1994), with more recent versions in Sen & Liu (2016); Sen & Zhou (2014). In this paper, we coalesce our research from SP, including stochastic mixed-integer programming (Atakan & Sen, 2018), with the work in power systems research for economic dispatch (ED) (Gangammanavar & Sen, 2018; Gangammanavar et al., 2015) and unit commitment (UC) (Atakan et al., 2018).

Our experiments indicate that the SHP framework overcomes many of the shortcomings of the DHP approach currently in prac-

tice. We observed that the SHP framework typically outperforms DHP in terms of reliability. Even at lower reserve requirements levels, SHP is more effective in eliminating unmet demand. Moreover, reliance on ST-UC problems (to avoid unmet demand) reduces by using SHP. On the other hand, the SHP framework leads to more conventional over-generation and renewable curtailment. The introduction of utility-scale storage devices can mitigate both of these drawbacks. The considered NREL-118 dataset is a reasonable approximation of networks with high renewable integration. Remarkably, our study provides hope that the grid of the future may be able to operate *reliably* at lower levels of reserve requirements, while simultaneously reducing both operating costs, as well as GHG emissions. While our paper has made a strong case for a transition to SHP, we have only begun the discussion, and there is much to be gained by refining our methods to incorporate sophisticated stochastic mixed-integer programming algorithms (e.g., Gade, Küçükyavuz, & Sen, 2014; Yuan & Sen, 2009). These algorithms are better suited to include start-up/shut-down variables in the second-stage of stochastic UC models, such as those necessary for advanced ST-UC modeling. We suspect that specialized versions of these algorithms may bear fruit in future studies of the SHP framework.

Given the current climate-change concerns, *(i)* efficient generator designs and power electronics, *(ii)* market design, and *(iii)* optimization software used in planning and operations can help address the challenges associated with meeting ambitious renewable portfolio standards. To "tame the duck", advances along all 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. These results point to the next steps that should involve experiments with actual ISO data, which we hope to undertake as part of our future endeavors.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2021.12.042.

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