Using the MATPOWER Optimal Scheduling Tool to Test Power System Operation Methodologies Under Uncertainty

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***Abstract*—Short-term power system operational planning problems that consider multi-stage uncertainties pose significant challenges, not only in the design of tractable optimization frameworks for implementing them, but also in the testing and benchmarking of such frameworks. This paper presents an implementation using the open-source MATPOWER Optimal Scheduling Tool (MOST) to study and compare a stochastic day-ahead, security-constrained unit commitment problem with a more traditional deterministic approach. The comparison is based on a testing methodology for day-ahead plans designed to produce expected performance estimates with minimal biases from modeling assumptions. Emphasis is given in the proposed stochastic approach to explicit modeling of the operational characteristics of the technologies available, their spatial and temporal coupling, and the regulatory constraints that assure reliability and adequacy. The problem formulations and testing methodology are described and simulation results from MOST are presented, with discussion of implications for future market design. All of the code and data to replicate the simulations is provided online.**

***Index Terms*—Stochastic and robust dispatch, unit commitment, optimal power flow, renewable energy sources.**

NOMENCLATURE

Variable and Parameter Indexing

T — Set of time periods considered, n_t elements indexed by t.

J^t — Set of states in the system in period t, indexed by j.

K^{tj} — Set of post-contingency states in the system in state j at time t, indexed by k, where $k = 0$ for the base state.

I^{tjk} — Set of all units available for dispatch in post-contingency state k of state j at time t, indexed by i.

L^{tjk} — Set of all reserve zones defined in post-contingency state k of state j at time t, indexed by l.

Z_l^t — Set of generators providing reserves in zone l at time t.

Optimization Variables comprising full optimization variable x

p^{tijk} — Active injection for unit i in post-contingency state k of state j at time t.

p_c^{ti} — Active power contract quantity for unit i at time t.

r_z^{ti} — Zonal reserve quantity provided by unit i at time t.

r_+^{ti}/r_-^{ti} — Upward/downward active contingency reserve quantity provided by unit i at time t.

$\delta_+^{ti}/\delta_-^{ti}$ — Upward/downward load-following ramping reserves needed from unit i at time t for transition to time $t+1$.

θ^{tjk}, p^{tjk} — Voltage angles and active injections for power flow in post-contingency state k of state j at time t.

u^{ti} — Binary commitment state for unit i in period t, 1 if unit is on-line, 0 otherwise.

v^{ti}/w^{ti} — Binary startup and shutdown states for unit i in period t, 1 if unit has a startup/shutdown event in period t, 0 otherwise.

Cost Functions and Parameters

$C_P^{ti}(\cdot)$ — Cost function for active injections for unit i at time t.

$\widetilde{C}_P^{ti}(\cdot)$ — Modified cost function for active injection i at time t with the no load cost subtracted, $\widetilde{C}_P^{ti}(p) \equiv C_P^{ti}(p) - C_P^{ti}(0)$.

$C_z^{ti}(\cdot)$ — Cost function for zonal reserve purchased from unit i at time t.

$C_{R+}^{ti}(\cdot)/C_{R-}^{ti}(\cdot)$ — Cost function for upward/downward contingency reserve purchased from unit i at time t.

$C_{\delta+}^{ti}(\cdot)/C_{\delta-}^{ti}(\cdot)$ — Cost of upward/downward load-following ramp reserve for unit i at time t for transition to time $t+1$.

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C_v^{ti}/C_w^{ti} Startup/shutdown costs for unit i at time t in \$ per startup/shutdown.

Constraint Functions and Parameters

$g^{tjk}(\cdot)$ Nodal power balance equations in post-contingency state k of state j at time t.

$h^{tjk}(\cdot)$ Transmission, voltage and other limits in post-contingency state k of state j at time t.

$P_{\min}^{tijk}, P_{\max}^{tijk}$ Limits on active injection for unit i in post-contingency state k of state j at time t.

$R_{\max+}^{ti}/R_{\max-}^{ti}$ Upward/downward contingency (or zonal) reserve capacity limits for unit i at time t.

R_l^t MW reserve requirement for zone l at time t.

Δ_+^i/Δ_-^i Upward/downward physical ramping limits for unit i for transitions from base ($k = 0$) to contingency cases.

τ_i^+, τ_i^- Minimum up and down times for unit i in number of periods.

Other Parameters

$\phi^{tj_2j_1}$ Probability of transitioning to state j_2 in period t given that state j_1 was realized in period $t-1$.

ψ^{tjk} Probability of contingency k in state j at time t.

γ^t Probability of making it to period t without branching off the central path in a contingency in periods $1 \ldots t-1$.

I. INTRODUCTION

POWER systems operations are facing an increasing amount of uncertainty when making decisions in the scheduling process. This issue stems from several factors, most notably the inclusion of active demand and renewable sources of energy in the generation pool. Consequently, there is a need for operation methodologies that consider this uncertainty explicitly.

Historically, load forecasts were the main source of uncertainty in the planning process, followed perhaps by the occurrence of discrete events, such as disconnection of a piece of equipment. The error in the load forecast when using modern prediction techniques is relatively small, prompting little concern about the propriety of the scheduling decisions taken, for example, a day ahead. More recently, however, the main source of uncertainty is the availability of renewable resources at the time of delivery [1]. Yet, the lead time that many generation technologies require to make their resources available remains unchanged. Thus, decisions must be made ahead of time with regards to the commitment of units, fuel procurement, network configuration and other issues [2]–[4]. Traditionally, a lead time of one day is a practical one because it fits the lead time requirements of many types of generating units, as well as the administrative processes associated with deregulated market operations. In theory, said decisions could be made several times a day, or even every hour. Thus, the general problem facing an Independent System Operator (ISO) is that of making decisions in the face of forecasts with pervasive time-varying uncertainty. Even though the uncertainty-revealing process is continuous in time, decisions are typically made in well-defined stages due to practical computing and administrative restrictions [5].

The most common structure put in place by ISOs involves a day-ahead decision process that includes a day-ahead market (DAM) and a so-called (day-ahead) reliability unit commitment (RUC), followed by subsequent finer-grained decisions as real-time operation approaches. With this two-layered structure, a large part of the planning problem is solved day-ahead, followed by adjustments intended to steer the system toward appropriate real-time operation as the time of execution approaches. It is thus not surprising that most literature on the subject focuses on the day-ahead planning problem, particularly the security-constrained unit commitment (SCUC) problem (see e.g., multiple surveys including [6], [7]). A viable day-ahead planning formulation involves modeling decisions that allow the resulting problem to be tractable and computationally solvable [8]. It should take into account the day-ahead market settlement aspect; it should internalize uncertainty into the decision process; and it should weigh the economic benefits of reliable operation in light of the possible outcomes presented by the chosen uncertainty model [9]–[13]. Typically, many simplifying assumptions go into these modeling decisions, introducing differences between the problem that is being solved and what we might call the "true" problem with its more accurate time-varying uncertainty model and the different lead-times of each unit being considered in the decision process.

Because these day-ahead planning models are approximations of reality, it follows that their performance cannot be easily compared based solely on the value of the objective function at their corresponding solutions, especially because the resulting plan was based on a simplified uncertainty model with some potentially *ad hoc* assumptions (cf., [14]).

Indeed, benchmarking the quality of a day-ahead plan requires a new set of modeling decisions based on a more realistic set of assumptions. The more simplifying the initial modeling assumptions are, the more relevant the subsequent quality assessment becomes. This assessment could include more detailed modeling decisions about (1) how to meet power imbalances due to differences in realized load and renewable generation, (2) how to settle the deviations from the day-ahead schedule,[1] and (3) how to benchmark the day-ahead plan in light of all the possible outcomes of the "true" or more realistic uncertainty model.

It must be decided, for example, whether to use a simple secure optimal power flow to settle imbalances when closer to real-time, or whether to use a more complicated procedure with receding-horizon look-ahead instead (see e.g., [15], [16]). Either alternative could be deterministic, using (point) forecasts, or stochastic, using a (potentially simplified) model of the unrealized uncertainties.

These are all practical considerations which must be decided upon in each market and which are implemented in one way or another by each ISO. Therefore, when testing the quality of

[1]These first two issues may or may not be linked to a real-time balance market.

day-ahead solutions, one must separate (1) the "true" or more realistic uncertainty model; (2) the uncertainty model employed in the day-ahead planning process; (3) the process by which the day-ahead plan is adapted to the time-varying revelation of uncertainty up to the real-time operation moment, and perhaps also a third model of the uncertainty if the said adaptation process involves stochastic look-ahead; and finally (4) a procedure to statistically characterize the performance properties of the day-ahead plan. One direct procedure for this testing is using statistical simulation, in which many day-ahead plans are presented with many possible realizations of the uncertainty, and then each outcome is evaluated. The uncertainty model from which these realizations are drawn requires yet another modeling decision; ideally, the model employed should be as close as possible to the "true" model, i.e., not carry on the simplifying assumptions employed in the day-ahead planning process or the adaptation process. Additionally, the process by which the realization is presented to the day-ahead plan must also be stochastic if the real-time adaptation process employed utilizes look-ahead of any kind, so as to preserve causality.

In this work, we further build upon the open-source MATPOWER Optimal Scheduling Tool (MOST) [17], [18], available in the MATPOWER package [19], and the open-source simulation framework MP-Sim [20], to benchmark a particular choice of stochastic day-ahead planning against a more traditional approach. In doing so, all of the previous considerations are addressed and the choices taken are clearly specified. The stochastic day-ahead reliable unit commitment method being tested is one of the many possible planning schemes that can be implemented within MOST. The traditional approach is a form of secure deterministic unit commitment with set rules for determining operating reserves. The primary contributions of this work are the thorough comparison of the two operation methodologies explicitly including the four considerations above, and the presentation of a testing methodology for day-ahead plans intended to produce expected performance estimates with minimal biases from modeling assumptions, both based on the open software platform MOST. Along the text we highlight further advantages of our approach.

The remainder of this article is organized as follows. The next section provides a succinct background for our work and describes its place in the literature. Section II delineates the framework to model day-ahead planning and real-time operation/assessment methodologies in MOST, explains the connection to the stochastic approach developed in [17], and describes certain operation practices used by ISOs that serve as a standard benchmark. The testing framework for our model and the numerical results are presented in Sections III and IV, respectively, with concluding remarks and future research directions in Section V.

Background and Related Work

To verify whether the solution obtained for the day-ahead planning problem can properly dispatch the system in real-time, most previous works select scenarios consistent with the realm of possibilities considered in the initial planning, i.e., scenarios that are consistent with the uncertainty sets used in day-ahead decisions. Although these approaches can be used to approximate the original multistage problem, their performance is seldom estimated [21].

In [7], the authors suggest that the approaches to deal with uncertainty can be classified into three groups: stochastic optimization e.g., [22], [23], robust optimization e.g., [24], [25], and chance-constrained optimization e.g., [26]. Within the vast literature on the subject, there are a few works that are particularly related to our approach as follows: Bakirtzis et al. [27] present a model for merging the unit-commitment (UC) and economic dispatch (ED) problems, solving complex short run (intraday) commitments and dispatches, and simpler schedules for longer horizons (e.g., 24h), including different time scales according to the proximity to dispatch time. Dvorkin et al. [28] formulate a hybrid stochastic UC (SUC) and interval UC (IUC), with the SUC applied to the periods closer to execution, and then switching to the IUC for the rest of the horizon. They optimize the switching time by balancing the costs and security benefits obtained. In [16], the authors propose a stochastic approach to UC based on affine dispatch policies to deal with uncertainty in a rolling horizon framework that respects causality as both commitment and dispatch decisions are made contingent only on realized uncertainties. This approach can be seen as a methodology to test a predetermined day-ahead plan. In [29], the authors emphasize the relevance of enforcing causality (or non-anticipativity) constraints in UC formulations for a robust framework. This work suggests that including such constraints is particularly relevant when ramping capabilities are scarce and net loads are highly variable.

II. FORMULATION

Our problem consists of a day-ahead planning problem followed by a real-time operation problem used to assess the day-ahead plan. The structure of the uncertainty (e.g., of wind and demand) underlying the day-ahead problem is multi-stage in the sense that the uncertainty faced when planning the UC for the horizon is revealed sequentially in multiple steps. The recourse (dispatch) decisions subsequent to the UC occur consecutively, each one in the presence of diminishing uncertainty, rather than all at once, in a single second stage following the UC decision but prior to a dispatch decision for the full horizon. So, whereas the structure of the underlying planning problem itself includes multi-stage uncertainty, the modeling of the uncertainty in the optimization problem formulated to solve that problem is a separate question. A classical, full multi-stage formulation is clearly out of the question due to the sheer scale of the resulting problem, so an approximation is needed.

One common approach is to approximate the problem as a two-stage problem, neglecting the impact of the progressive revelation of uncertainty during the recourse decisions. Our stochastic formulation takes a different approach that preserves the multi-stage nature of the uncertainty but approximates the full multi-stage decision tree with a Markovian decision process. Our testing framework, that is, the real-time operation and assessment formulation, is also explicitly designed to take into account the inherent multi-stage nature of the uncertainty in the underlying problem.

Our stochastic formulation in this article shows a subset of the capabilities of the MATPOWER Optimal Scheduling Tool [17], [18]. The model is a particular form of a day-ahead, stochastic, $n-1$ security-constrained unit commitment problem with DC power flow constraints. One of the main differences in our approach from past formulations is that we discretize the range of realizations that can occur, conditioning the ranges in period $t+1$ to the information in period t only, and providing a hull for the range of operating points. The real-time operations problem used for assessing the day-ahead plan is a single-period $n-1$ secure problem, similar to current practices. In contrast to most other approaches, our real-time problem is still stochastic regarding the operational reliability of the units.

We benchmark our stochastic approach against a secure deterministic solution, also implemented in MOST. The latter is based on a methodology inspired by current operational practices of ISOs in the US, in which uncertainty is dealt with primarily by relying on heuristic exogenous reserve requirements and on the sequential solution of deterministic optimization programs that incorporate updated point forecasts of the system uncertainties. Such specification of reserve requirements may lead to highly suboptimal solutions under significant uncertainty and provide no guarantee of solution robustness with regards to feasibility.

A. Day-Ahead Planning Formulation

The nomenclature section summarizes the notation for the reduced form of the problem considered in this article. The objective function for the ISO is the expected total welfare of all the participants, consisting of four components: (1) the expected cost of energy delivered, (2) the cost of ancillary services for high probability events (i.e., load following reserve), (3) the unit commitment cost, and (4) the cost of (up and down) reserves for low probability events (i.e., contingency reserve),

$$\min_x f(x) = f_p(p) + f_{\mathrm{lf}}(\delta_+, \delta_-) + f_{\mathrm{uc}}(u, v, w) + f_r(r_z, r_+, r_-), \tag{1}$$

where

$$f_p(p) = \sum_{t\in T} \sum_{j\in J^t} \sum_{k\in K^{tj}} \psi^{tjk} \sum_{i\in I^{tjk}} \widetilde{C}_P^{ti}(p^{tijk}), \tag{2}$$

$$f_{\mathrm{lf}}(\delta_+, \delta_-) = \sum_{t\in T} \gamma^t \sum_{i\in I^t} \left[C_{\delta+}^{ti}(\delta_+^{ti}) + C_{\delta-}^{ti}(\delta_-^{ti}) \right], \tag{3}$$

$$f_{\mathrm{uc}}(u, v, w) = \sum_{t\in T} \gamma^t \sum_{i\in I^t} \left(C_P^{ti}(0) u^{ti} + C_v^{ti} v^{ti} + C_w^{ti} w^{ti} \right), \tag{4}$$

and the specification of the reserve cost $f_r(r_z, r_+, r_-)$, described below, depends on whether the formulation is for the stochastic or deterministic method.[2]

[2]The benefit that consumers receive from having their load serviced is included as a negative term in the expected cost of energy delivered in (2).

This minimization is subject to four categories of constraints, for all $t \in T$, all $j \in J^t$, all $k \in K^{tj}$, all $i \in I^{tjk}$, and, for the deterministic case, all $l \in L^{tjk}$. The four categories of constraints are:

- *Standard OPF Constraints*, including the full set of equality (e.g., power balance equations) and inequality (e.g., branch flow and generator limits) constraints,

$$g^{tjk}(\theta^{tjk}, p^{tjk}) = 0 \tag{5}$$

$$h^{tjk}(\theta^{tjk}, p^{tjk}) \le 0 \tag{6}$$

- *Load-following Ramping Limits and Reserves*

$$0 \le \delta_+^{ti} \le \delta_{\max+}^{ti} \tag{7}$$

$$0 \le \delta_-^{ti} \le \delta_{\max-}^{ti} \tag{8}$$

$$p^{tij_2 0} - p^{(t-1)ij_1 0} \le \delta_+^{(t-1)i}, \quad j_1 \in J^{t-1}, j_2 \in J^t \tag{9}$$

$$p^{(t-1)ij_1 0} - p^{tij_2 0} \le \delta_-^{(t-1)i}, \quad j_1 \in J^{t-1}, j_2 \in J^t \tag{10}$$

- *Unit Commitment*, including injection limits, startup and shutdown events, minimum up and down times and integrality constraints

$$u^{ti} P_{\min}^{tijk} \le p^{tijk} \le u^{ti} P_{\max}^{tijk} \tag{11}$$

$$u^{ti} - u^{(t-1)i} = v^{ti} - w^{ti} \tag{12}$$

$$\sum_{y=t-\tau_i^+ +1}^{t} v^{yi} \le u^{ti}, \qquad \sum_{y=t-\tau_i^- +1}^{t} w^{yi} \le 1 - u^{ti} \tag{13}$$

$$0 \le v^{ti} \le 1, \quad 0 \le w^{ti} \le 1, \quad u^{ti} \in \{0, 1\} \tag{14}$$

- *Security Constraints*, depending on whether the formulation is for the stochastic or deterministic method.

The primary differences in formulation between the stochastic and deterministic cases are in the last set of constraints, (the security constraints), and in the states modeled in each period, which also affects the load-following reserves.

1) Stochastic Method: For the stochastic method, the problem is structured as a set of co-optimized DC optimal power flow (OPF) problems, one for each period t, for each system base state j and each of the corresponding contingency states k, whose costs are probability weighted and whose operating points are tied together by additional constraints and costs related to reserves, ramping, storage and unit commitment. The stochastic resources (e.g., wind, solar, demand) are modeled as a Markov Decision Process (MDP) with a discretized probability distribution over a finite number of states, equivalent to recombining scenarios in a traditional stochastic program but with improved tractability. Security is handled by guarding against an explicit set of credible contingencies. The fourth category of constraints, the security constraints, define reserves by the maximum deviation in any contingency from a contracted reference dispatch, restricting the ramping from base to contingency states.

$$0 \le r_+^{ti} \le R_{\max+}^{ti}, \quad 0 \le r_-^{ti} \le R_{\max-}^{ti} \tag{15}$$

$$p^{tijk} - p_c^{ti} \leq r_+^{ti}, \quad p_c^{ti} - p^{tijk} \leq r_-^{ti} \tag{16}$$

$$-\Delta_-^i \leq p^{tijk} - p^{tij0} \leq \Delta_+^i, \quad k \neq 0 \tag{17}$$

The reserve costs from the last term in (1) are then based on these contingency reserves.

$$f_r(r_z, r_+, r_-) = \sum_{t \in T} \gamma^t \sum_{i \in I^t} \left[C_{R+}^{ti}(r_+^{ti}) + C_{R-}^{ti}(r_-^{ti}) \right], \tag{18}$$

The load-following ramp constraints (7)–(10) are the maximum deviations between base state dispatches in consecutive periods.

2) Deterministic Method: The implementation of the deterministic method is essentially a simplified version of the stochastic problem, where all contingency states have been removed and there is a single base state with expected availability of RES and expected load for each period. That is, $J^t = \{1\}$, $K^{tj} = \{0\}$, and $\psi^{t10} = \gamma^t = 1$, turning (2) into a summation over t and i. In place of the multiple RES and contingency states per period, we rely on a set of fixed zonal reserve requirements for the security constraints.

$$0 \leq r_z^{ti} \leq \min(R_{\max+}^{ti}, \Delta_+^i) \tag{19}$$

$$p^{tijk} + r_z^{ti} \leq u^{ti} P_{\max}^{tijk} \tag{20}$$

$$\sum_{i \in Z_l^t} r_z^{ti} \geq R_l^t \tag{21}$$

The non-negative value r_z^{ti}, for generator i in period t, has a user-provided upper bound $R_{\max+}^{ti}$ (e.g., a reserve offer quantity) as well as the physical ramp rate Δ_+^i. The two additional sets of constraints ensure that, for each generator, the total amount of energy plus reserve provided does not exceed the capacity of the unit and that the sum of the reserve allocated within each zone l in period t meets the stated requirements. The load-following ramp requirements (7)–(10) are still present. However, because a single state is considered per period, they only apply to the expected amount of ramping between periods. The reserve cost term of (1), in this case, is also based on the reserves allocated toward these zonal requirements.

$$f_r(r_z, r_+, r_-) = \sum_{t \in T} \sum_{i \in I^t} C_z^{ti}(r_z^{ti}). \tag{22}$$

B. Real-Time Operation and Assessment Formulation

1) Stochastic Method: The real-time problem for the stochastic approach is described in Section IV of [30] and in Section III-A of [31]. It is essentially a single-period version of the day-ahead problem, including all of the network constraints. We assume the uncertainty of RES and demand has been largely resolved and that we have point forecasts for each one that are accurate enough to ignore the remaining forecast error. So we no longer use multiple base cases to represent a distribution of realizations, but rather a single base case with the expected realization of both demand and RES. On the other hand, the dispatch must still be secure, so a credible set of contingencies are still included, with probability weighted costs on their dispatches. Additionally, the ISO can procure energy and additional reserves at real-time prices to cover trajectories outside of the realm considered in the day-ahead problem.

2) Deterministic Method: The real-time problem for the deterministic approach is a DC OPF, based on updated system conditions, with an updated set of zonal reserve requirements. The requirements are updated to reflect the fact that some of the contracted reserves may be deployed to cover errors in the load and/or RES forecasts. Specifically, for each zone in which the demand net of RES generation has increased from the values assumed for the day-ahead problem, the reserve requirements are decreased by a corresponding amount. This amount is further reduced by a factor β_{zr} to reflect the fact that fewer reserves are needed since the vast majority of the uncertainty has been resolved. In our real-time results, we optimize over a set Γ of random trajectories of the realized uncertainties consistent with the day-ahead optimization.

III. Testing Framework

A. Causal, Single-Period Real-Time Operations Problem for Assessment

Testing power system scheduling problems with multi-stage uncertainties is often done in a non-causal way, using Monte Carlo (MC) simulations over a set of many trajectories, where each represents the realization of all uncertainties across the entire optimization horizon. Operating cost is then computed for each trajectory as a deterministic problem, ignoring the fact that, in each period, the system must still be operated subject to subsequent uncertainties, which in reality are not yet resolved. Our framework, on the other hand, respects these causal constraints by guarding against subsequent uncertainty in each single-period real-time optimization.

B. Stochastic Inputs

We use an autoregressive moving average model with exogenous variables (ARMAX) to generate multiple random trajectories of the stochastic system conditions, namely wind power availability and load, for all time periods and locations, to represent possible individual realizations of those conditions for the planning horizon. The methodology is explained in [32], [45], and is summarized in Algorithm 1.

We partition the total set of created trajectories into two. One subset of these trajectories is utilized to represent a forecasting model whose distributions are used to create the inputs for the day-ahead problem (training), varying over time and space. Another subset of these trajectories, the set Γ, are used for MC testing of the real-time operations subject to the unit commitment chosen day-ahead (validation). In contrast to other works, these two sets are independently generated in our proposal.

C. Contingency Analysis

We perform an extensive off-line contingency filtering procedure as input data for our comparisons (cf., [33], [34]). Broadly, this consists in selecting a limited set of critical transmission and generator contingencies to act as a surrogate for the $n-1$

Algorithm 1: Simulating Random System Conditions.

1: Estimate ARMAX temperature model based on deterministic cycles daily, weekly, seasonal).
2: Use temperature/deterministic cycles, estimating ARMAX models for log of wind speed, log of load for each location.
3: Use variance-covariance residuals from these models to generate N_1 trajectories drawing from a multivariate normal distribution for wind speed and load, as a forecasting model for the day-ahead problem.
4: Convert wind speed to potential wind power generation using a multi-turbine power curve.
5: *Stochastic:* At each time period in the planning horizon, Discretize the joint load and wind distribution into n_j states for each t, determine transition probability matrices based on these n_j states. *Deterministic:* At each time period in the planning horizon, compute the expected load and wind power availability or each t.
6: Randomly generate the set Γ of N_2 additional trajectories, via steps 3 and 4 above, to use as realizations for MC testing in the real-time problem.

security criterion. Though the $n - 1$ criterion is generally more conservative, it can make the resulting optimization problem prohibitively large unless tailored decomposition techniques are used [35].[3]

D. Reserve Criteria

To build a standard benchmark that allows comparing the performance of the proposed model to a fixed reserves criterion, we focus on designing reasonable zones and reasonable criteria for those zonal reserve requirements. The determination of fixed zones (with possible overlaps) within a transmission network is an *ad hoc* methodology that seeks to internalize the need to guarantee the availability of deliverable reserves in the presence of stochastic suppliers and possible contingencies. In our proposed benchmark, we use congestion patterns observed in the solutions to deterministic formulations of the problem under different states (including contingent states). Moreover, besides the usual requirements for fixed reserves, several zonal reserve requirement criteria have been developed with two additional considerations. First, each criterion allows the designer to scale reserve requirements with a scalar parameter in order to vary its conservativeness; and second, the inter-zonal flows have been accounted for in computing the zonal requirements when necessary. For the deterministic method used to benchmark our proposed model, we simulate reserve criteria following practices in real-world operations. First, reserve zones are established based on congestion patterns observed in deterministic OPF runs under a variety of system states, including contingent states. For example, in the adjusted 118-bus system we use for demonstration there is a “backbone” connecting sources in the western part of the system to sinks in the eastern demand centers. We establish overlapping zones under high loading conditions to avoid internal congestion. However, when the system is highly loaded, some inter-zonal ties may be used at their maximum capacity. Once the zones are established, we implement a convex combination of two policies: (1) the so-called “3 + 5” policy rule [1], budgeting reserves according to 3% of the hourly load forecast and 5% of the hourly wind forecast. (2) the largest outage policy schedules a reserve quantity equal to the amount necessary to cover the single largest contingency. This condition for $n - 1$ reliability includes an offline analysis of the credible contingencies, covering both generation and line outages. The reserve requirement for a given zone can be set by an import from another zone if the outage of a tie line is the largest contingency.[4]

E. Load Shedding

All demand in both the stochastic and deterministic treatments is modeled as curtailable at the value of lost load (VOLL), which is nominally set to \$10,000/MWh. In some of our studies we vary this value across a range in order to see the effect on the cost statistics for the stochastic and deterministic methods being compared.

IV. Numerical Results

We compare the results from the real-time problem for both fixed and stochastic reserves, by applying them to a set of 500 trajectories over the optimization horizon, with each trajectory representing a realization of the initial forecasts. These trajectories are consistent with the information used in the day-ahead problem, derived from a MC-type simulation of wind data obtained from the National Renewable Energy Laboratory (NREL) Eastern Wind Integration and Transmission Study [36]. The simulations are based on MP-Sim [20], an open-source, object-oriented, Matlab-language simulation framework developed by two of the authors. They were run using MATPOWER [19] and MOST with the Gurobi optimizer [37]. Currently, the problem is passed in a standard form to the solver without employing decomposition techniques to solve it, see e.g., [38]–[41]. Improving performance through such techniques is a subject of future work. We modified extensively a version of the IEEE 118 bus network for illustrative purposes. The adjustments include modifying the generators according to guidelines from the FERC RTO Unit Commitment Test System, including the ramping capabilities per fuel type [42], adding wind turbines to the system (20% of generating capacity at 11 buses) according to NREL data [43], and converting all of the 345 kV lines to double circuits. All of the code and data for the simulations

[3] Note that this procedure is conducted completely off-line with no iterative process used to update the set of contingencies per period, rather using an ample range of operating points (e.g., loading conditions) instead of a single operating point. This data serves to calculate endogenous contingency reserves in our setup. This methodology is based on a combination of prioritized contingency-severity criteria, thus resembling traditional practices based on expert knowledge of the network.

[4] The final reserve requirement used for each zone is the larger of the requirements from these two policies, resulting in a relatively conservative operating mode. We multiply these base requirements by a single scaling factor to vary the enforced level of security for part of our results.

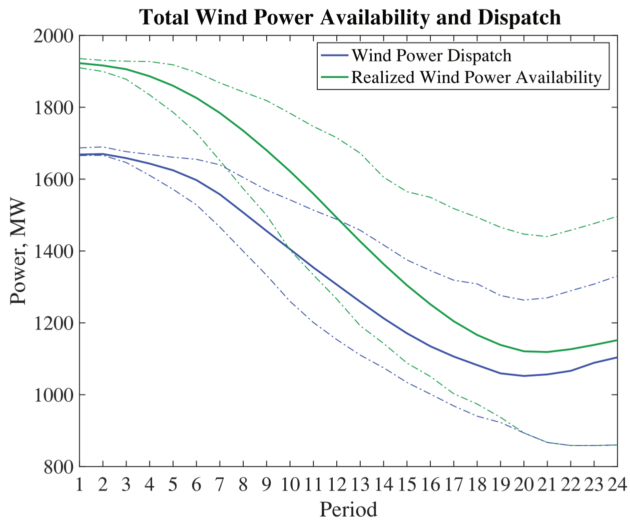

Fig. 1. Total wind availability and dispatch expected + min/max range.

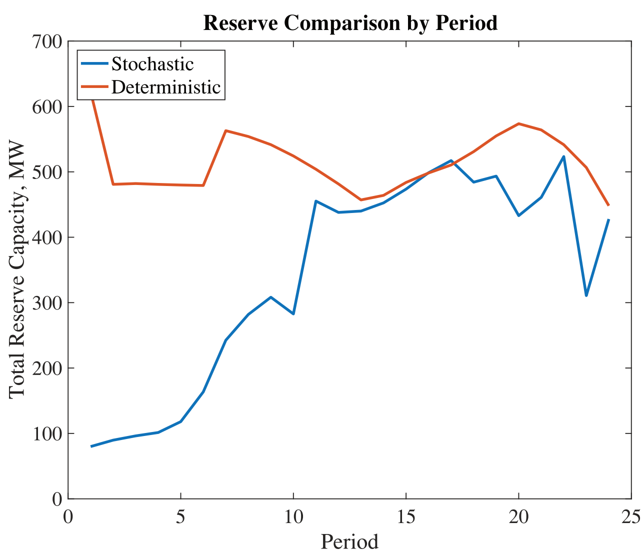

Fig. 2. Reserve comparison by period.

is publicly available on the "MOST Paper Simulation" GitHub site [44].

The system-wide wind power availability and dispatch is shown in Fig. 1 for the stochastic case, displaying the amount of supply uncertainty considered in our simulations apart from the uncertainty from low probability contingencies.[5] Notably, both approaches spill more wind in early hours when wind availability is higher due to transmission congestion restricting deliverability. Fig. 2 shows the aggregate amount of reserves scheduled by the two approaches for each hour. The deterministic approach, which schedules more reserves than the stochastic approach for nearly all hours of the horizon, shows temporal variations caused primarily by the changing dispatch of the largest unit for different hours. On the other hand, the reserves scheduled in the stochastic approach increase throughout the planning horizon as uncertainty from wind and load increases. These results indicate that the zonal reserve requirements needed to ensure security under contingencies are systematically higher than the endogenously determined nodal reserves determined by the stochastic approach, even with the uncertainty added.

[5]Naturally, the uncertainty of wind availability increases as we predict further into the future, as illustrated by the widening min/max ranges observed. A similar plot for the deterministic case (not shown) reveals a negligible difference in the expected wind dispatch for the two approaches.

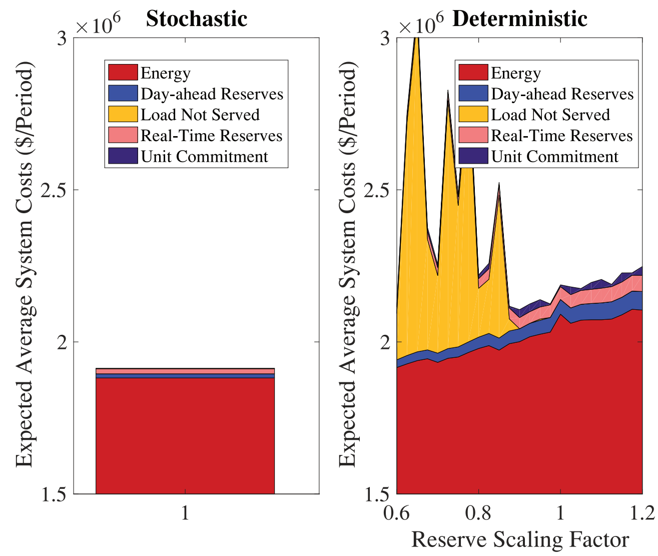

Fig. 3. Expected average system costs, day-ahead planning, and operation.

In Fig. 3 we report the total operation costs incurred throughout a single day averaged across the 500 MC simulations under both the stochastic (left) and several deterministic approaches (right). Each of the deterministic cases corresponds to a different multiplicative scaling parameter applied to the zonal reserve requirements as a heuristic to adjust the level of security of the methodology. By and large, the stochastic approach dominates the deterministic approach, yielding uniformly lower average costs of energy, reserves, and commitment. Not surprisingly, the reserve scaling parameter controls a trade-off between high costs of load not served (LNS) and high costs of energy, primarily, and reserves to a lesser extent. This is because larger reserve requirements force less expensive generators to provide more reserves and less energy, shifting that energy to more expensive generators. These results suggest that there is an "optimal" scaling parameter for the given reserve requirements that (1) minimizes the expected operation costs induced by the deterministic approach, (2) may differ from the one chosen by the ISO (i.e., 1), (3) would be difficult to compute efficiently for a large-scale system, (4) may be too risky due to the potential underestimation of low probability LNS events, and (5) that is consistently outperformed by the endogenous allocation of reserves throughout the network by the stochastic formulation. Figs. 4 and 5 show the maximum capacity committed excluding wind (for adequacy) and the expected energy delivered by fuel type. The stochastic approach commits and uses more coal and less gas Combustion Turbines (CT) resources than the deterministic approach across the varying levels of reserve requirements. As the reserve requirement levels increase, more coal is replaced

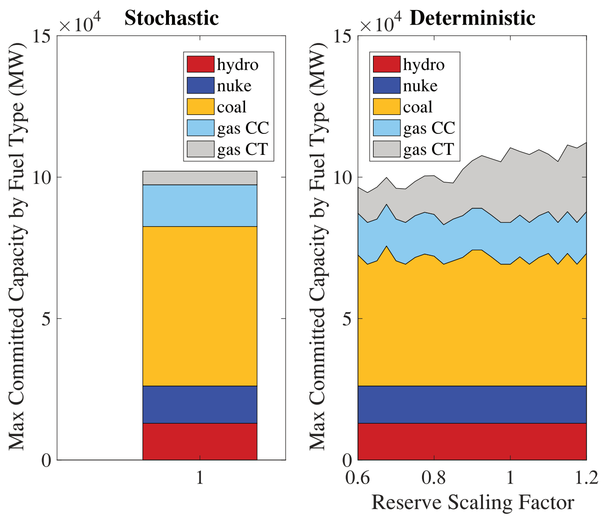

Fig. 4. Max. committed capacity by fuel type.

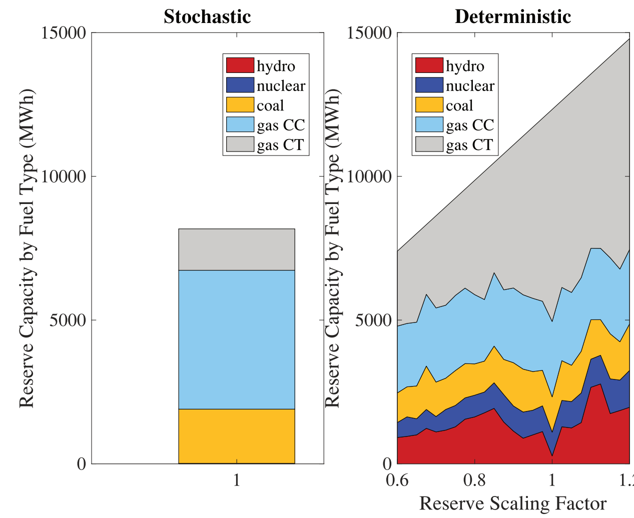

Fig. 6. Reserve comparison by fuel type.

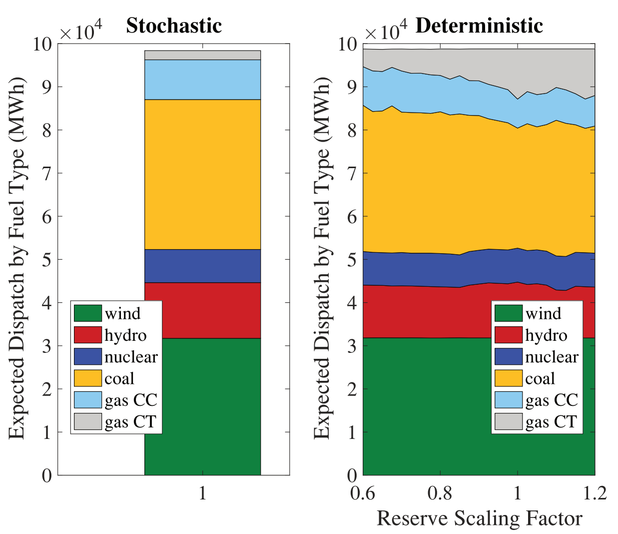

Fig. 5. Expected real-time dispatch by fuel type.

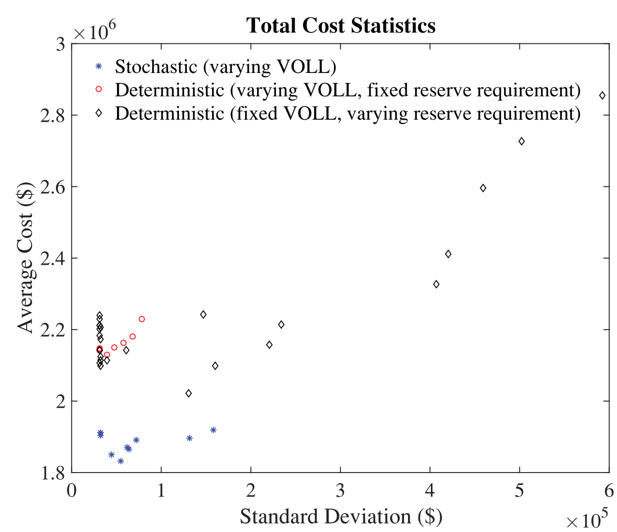

Fig. 7. Total cost statistics, sensitivity to VOLL and reserve levels.

by gas CT in terms of usage, even though comparable amounts of coal resources are committed.

Generally, the stochastic approach was able to find a commitment that avoids the use of the marginally more expensive gas CT resources by committing additional, marginally less expensive, coal capacity at strategic locations. To better understand the way both approaches schedule resources to manage the supply and demand uncertainty, Fig. 6 illustrates the amount of reserves scheduled by fuel type. The deterministic approach schedules less reserves than the stochastic only at the lowest scaling factors, where significant load shedding is still an issue (Fig. 3).

These plots confirm that the deterministic approach consistently requires more reserves, even when the requirements are 40% below the original criteria. Although both approaches schedule reserves predominantly from peaking generators (gas CT and Combined Cycle, CC), the stochastic approach schedules no reserves from hydro or nuclear resources, though some from coal. The increases in reserve requirements of the deterministic approach are almost entirely covered by the marginally most expensive resource, gas CT. This apparent paradox is explained by the fact that the deterministic formulation does not account for the reserve deployment cost, therefore scheduling relatively more reserves from resources with low startup and reserve costs. ISOs are often considered to be overly conservative in their operation practices. This may be interpreted as a preference for scheduling practices that induce more certain ex-post operating costs. Such consideration motivates analyzing not only the average operation costs but also their standard deviation. Fig. 7 depicts both statistics for various deterministic and stochastic approaches, computed from the MC simulations. For the deterministic case we varied the reserve scaling factor from 0.6 to 1.2 while holding the VOLL fixed, and vice versa. For the stochastic approach, only the VOLL was varied since reserve quantities and locations are scheduled endogenously. In this figure, the (black) data points with highest standard deviation costs correspond to deterministic cases with low reserve requirements and varying amounts of load shedding. In general, LNS is the predominant cause for variability in operation costs due to the relatively large magnitude of the VOLL. This explains why increasing reserve requirements in the deterministic approach provides no reductions in variability after a certain threshold. On the other hand, the stochastic approach produces a consistently desirable outcome. At a VOLL of $10,000/MWh, it yields a significantly lower average cost and yet the lowest level of variability.[6] These results show that the stochastic approach consistently produces commitment decisions that are robust to the modeled uncertainties. This may not be the case for the deterministic approach as it is sensitive to the choice of zonal reserve requirements.[7] One can thus conclude that the stochastic approach consistently improves on the levels of average costs and variability that are achievable by a deterministic approach.

V. Conclusion

In this paper we present the open-source MATPOWER Optimal Scheduling Tool to compare the behavior of two alternative approaches to a day-ahead planning problem considering multi-stage uncertainties. The case study uses a testing methodology designed to minimize the impact of modeling assumptions on the performance assessments. A stochastic security-constrained unit commitment (SCUC) with DC power flow constraints is compared against a more traditional, secure, deterministic unit commitment approach, using a causal, single-period real-time operations problem to assess both physical and economic performance under high levels of variability and uncertainty. All of the code and data for the case study is publicly available on the "MOST Paper Simulation" GitHub site [44].

We illustrate how our stochastic model outperforms the deterministic approximations, providing a more secure operation of the system (measured by load shedding) and savings after including all economically incurred benefits and costs. Through a sensitivity analysis on the parameters of the deterministic model we show that we can find a deterministic solution with statistics that are close, but still inferior, to those of the stochastic solution. We demonstrate and differentiate from past work the advantages of our stochastic model using an out-of-sample validation over 500 possible trajectories of the system, with uncertainty characteristics that can fall out of the purview used in the day-ahead problem.

There are several avenues for further development. The amount of reserves required for the stochastic treatment increases further down the planning horizon, driven by the intrinsic difficulty associated with accurately predicting the availability of renewable resources. Therefore, a receding horizon approach would enable the use of updated, more accurate forecasts of the potential generation from renewables, resulting in (1) a reduction in the amount of reserve generating capacity committed and (2) a more efficient management of potential energy storage resources participating in the system. Furthermore, the endogenous assignment of contingency reserves depends on the selected set of credible contingencies, determined in the current work by an extensive offline process and static for all hours of the horizon. Adapting the set of most credible contingencies to reflect changes over time can help improve the reserves scheduled in each period. Even though these issues may not manifest in current system operations, with increased penetration of renewables and storage resources, they have the potential to impact the reliable operation of the electric grid.

[6]For other values of VOLL, significantly lower average costs and comparable levels of cost variability are induced by the stochastic approach.

[7]Indeed, the deterministic approach yields robust commitment decisions when reserve requirements exceed a sharp threshold beyond which unacceptable levels of LNS, average costs and variability are observed.

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