A Multi-Time Scale Co-Optimization Method for Sizing of Energy Storage and Fast-Ramping Generation

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***Abstract*—Power systems need to have sufficient generation capacity to support the demand at all times. In addition, dispatchable generation resources should be capable of adjusting their power output on a short term basis not only to alleviate uncertainties of nondispatchable generation and load fluctuations but also to correct for forecast errors. This paper presents a long-term planning approach to co-optimize capacities of energy storages and fast-ramping generation. We model and integrate the capability of the storage to provide multiple services for the system. Our formulation takes into account wind generation and demand forecast errors as well as short-term fluctuations. A stochastic optimization problem is formulated consisting of hourly and intrahour time scales. The approach determines the optimal size of newly deployed generation and storage resources to provide adequate generation capacity and ramping needed to support hourly demand. Additionally, our method ensures that the system is capable of following the net load in intrahour time intervals, as well as mitigating the impact of short-term wind power and load fluctuations. In this formulation, power balance, network security, and system ramping capability are stochastic constraints being modeled as chance constraints. A 3-bus and the IEEE 24-bus test systems are studied to show the effectiveness of the proposed approach.**

***Index Terms*—Energy storage, fast-ramping unit, load following, ramping capability, short-term fluctuations, regulation.**

NOMENCLATURE

Sets and Parameters:

b	Index for bus.
f	Index for fast-ramping unit.
g	Index for thermal unit.
h	Index for hour.
l	Index for line.
s	Index for energy storage system.
t	Index for intra-hour time interval.
w	Index for wind power generation.
N_h	Number of hours under study.
N_t	Number of intra-hour time intervals in each hour.
T_{res}	Intra-hour time resolution.
$OC_x(\cdot)$	Operation/maintenance cost of dispatchable resource x, in \$.
$PC_x(\cdot)$	Investment cost of dispatchable resource x, in \$.
$C_x^{\Delta}(\cdot)$	Cost of intra-hour power adjustment of dispatchable resource x, in \$.
$C_{ens}(\cdot)$	Cost of demand response, in \$.
$\overline{E}_{s,\underline{cap}}$	Minimum allowable capacity of storage s, in MWh.
$\overline{E}_{s,\overline{cap}}$	Maximum allowable capacity of storage s, in MWh.
$\overline{P}_g, \underline{P}_g$	Upper and lower bounds on generation output of thermal unit g, in MW.
$\Delta\overline{P}_{g,t}, \Delta\underline{P}_{g,t}$	Upper and lower bounds on adjustment in power provided by thermal unit g in intra-hour time interval t, in MW.
$\overline{PL}_l$	Capacity of line l, in MW.
$RC_{s,t}$	Regulation capacity of storage s.
PR_t^u, PR_t^d	Total ramping up/down required to respond to short-term fluctuations in time interval t, in MW/h.
$LOLP$	Loss of load probability.
$TLOP$	Transmission line overload probability.
SF	Shift factor.
γ_s	One-way efficiency of storage s.
χ_s	Power rating of storage s.
$\Pr\{\cdot\}$	Probability measure.
$\alpha, \beta, \rho, \phi$	Confidence level of chance constraints.
$\mu(\cdot)$	Forecasted (expected) value of the parameter.
$\sigma_{d,t}^2$	Variance of forecast error of disturbance d in time interval t.
$\widetilde{\sigma}_{d,t}^2$	Variance of short-term fluctuations of disturbance d in time interval t.
Z_α	Inverse CDF of standard normal distribution evaluated at α.

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Variables:

$\overline{E}_s$	Capacity of energy storage s, in MWh.
$E_{s,t}$	Energy in storage s in time interval t, in MWh.
$\overline{P}_s^{out}$	Maximum discharge rate of storage s, in MW.
$\overline{P}_s^{in}$	Maximum charge rate of storage s, in MW.
$P_{s,t}^{out}$	Discharge from storage s in time interval t, in MW.
$P_{s,t}^{in}$	Charge to storage s in time interval t, in MW.
$\overline{P}_f$	Capacity of fast-ramping unit f, in MW.
$P_{f,h}$	Generation of fast-ramping unit f in hour h, in MW.
$\Delta P_{f,t}$	Power adjustment of fast-ramping unit f in time interval t in MW.
$P_{g,h}$	Power provided by thermal unit g in hour h, in MW.
$\Delta P_{g,t}$	Adjustment in power provided by thermal unit g in intra-hour time interval t, in MW.
$PD_{b,t}^{sh}$	Load curtailment at bus b in intra-hour time interval t, in MW.
$P_{x,t}^{ru}, P_{x,t}^{rd}$	Ramping up/down capability of dispatchable generating unit x for participating in regulation up/down in intra-hour time interval t, in MW/h.

Random Variables:

$P_{w,t}$	Wind power generation in time interval t, in MW.
$PD_{b,t}$	Load demand at bus b in time interval t, in MW.

I. Introduction

THE main part of the electric power consumption in many countries around the world, including the US, is currently supplied by fossil-fueled power plants. It has been recognized that the emissions from these plants cause major environmental issues. Thus, one of the most important issues in electric power industries is to find solutions which enable the transition to a more sustainable electric energy supply system [1].

Renewable energy deployment to produce electricity has been rapidly increasing to make the electric power grid a green energy infrastructure. As renewable generation resources such as wind and solar generation are non-dispatchable, their expected power outputs over the considered scheduling horizon need to be predicted to enable an efficient and cost-effective dispatch of the other resources [2], [3]. However, it is generally more difficult to predict renewable power outputs than expected demand [4] leading to increased uncertainties in systems with large penetrations of renewable resources. To ensure reliable operation of the power grid, resources need to be available which cannot only balance the variability from renewable generation but also make up for the forecast errors. This requires adequate available capacity as well as ramping capability.

Storage devices and fast-ramping generating units are key enablers for renewable power integration as they enhance the grid flexibility and provide a solution to the aforementioned challenges [5]. Energy storage devices and fast-ramping units provide the flexibility to balance the net load and form a buffer for uncertainties [6]. In order to reduce the cost for the integration of renewable generation, it is critical that the storages and fast-ramping units' capacities to be installed are chosen appropriately.

Optimal sizing of energy storages and fast-ramping units has been previously studied in the literature [7]–[14]. A sizing approach for a zinc-bromine flow battery-based energy storage system and effects of a control strategy on the proper sizing are studied in [7]. In [8], a stochastic dynamic program is formulated for optimal sizing and management of energy storage systems taking into account the uncertainty from renewable resources and dynamic pricing of the electricity. Reference [9] proposes control and sizing strategies to utilize energy storage devices for managing the energy imbalance resulting from the difference between the hourly actual and scheduled wind power generation. In [10], a probabilistic optimal power flow along with a genetic algorithm is utilized to determine the size of energy storages with the objective to improve the reliability and operability of wind integration. References [11] and [12] present approaches to jointly size energy storage systems and generators in stand-alone microgrids. The latter includes renewable generation and takes into account the uncertainty from these resources. A multi-objective particle swarm optimization approach is presented in [13] for energy storage siting and sizing taking into consideration wind power uncertainty.

While in the above mentioned literature, the hourly renewable generation and demand forecast errors are taken into account, intra-hour ramping capability and short-term fluctuations are usually ignored in the problem formulation. This is important because in addition to the adequate capacity to maintain the hourly load balance, the system also needs to have sufficient intra-hour ramping capability. This improves the grid flexibility and ensures that the system is capable of sub-hourly load following as well as alleviating short-term wind power and load fluctuations [15]. Insufficient intra-hour ramping capability increases the system vulnerability and could cause considerable frequency deviations [16]. Both energy storages and fast-ramping generation are capable of providing the required ramping capability and alleviating the minute-to-minute variations in the net load. This additional requirement of providing short term balancing services impacts the optimal capacities and power rating/ramping capabilities of the newly deployed energy storages and fast-ramping units. Consequently, it is important to co-optimize the storages and fast-ramping units' capacities and ramping capabilities for hourly as well as sub-hourly operation.

The goal of this paper is to determine the optimal size of newly deployed energy storages and fast-ramping generators accounting for multi-time scale operation of a utility. We model and integrate the capability of the storage to provide multiple services for the system. The optimization variables include the capacities and the power ratings of storages, as well as capacities and ramping capabilities of fast-ramping units. The objective is to minimize overall cost including capital investment cost and operation/maintenance cost. The investment cost of the storage devices consists of capacity and power rating costs. The considered planning horizon is divided into hourly and intra-hour time intervals. Our formulation ensures that variations and forecast errors on both time scales can be balanced by the combination of existing and newly deployed generation resources and storages. Our formulation models intermittencies, e.g., wind power and demand uncertainties, power balance, network security, and system ramping capability, as chance constraints. These chance-constraints are then replaced by their equivalent linear inequality constraints and integrated into the problem formulation. The numerical results for a 3-bus and the modified IEEE 24-bus test systems show the impact of accounting for sub-hourly ramping requirements and the effectiveness of the proposed approach. A sensitivity analysis is performed to study the impact of chance constraints confidence levels, variable wind power penetration, and forecast accuracy on the optimal size of the newly deployed storage devices and fast-ramping units.

In this paper, we have assumed that the load and power generation of a wind farm are given by a forecasting tool. The forecasting tool provides the expected values of the load and wind generation, as well as the forecast errors which are modeled by normal probability density functions. The normal PDF has been considered in various papers to account for the load and wind generation forecast errors (i.e., the difference between the actual measured and predicted values) [17]–[24]. It is also assumed that the correlation and rampability of the wind generation between successive time intervals are taken into account by the forecasting tool [12], [25]–[28].

The rest of this paper is organized as follows. The problem is formulated in Section II. The solution methodology is defined in Section III. Numerical results are presented in Section IV. Finally, Section V concludes the paper.

II. Problem Formulation

In a power system, generators daily scheduling and grid operation is preformed in three main steps: an hourly scheduling, an intra-hour rescheduling, and a regulation process [29]. At first, in the hourly scheduling step, the operator determines the hourly power output of dispatchable generation resources taking into account the hourly wind power and load forecasts. To follow the net load in sub-hourly time intervals, an intra-hour rescheduling (e.g., 5 minutes) is performed in the second step to define charge/discharge power of storages and adjust power outputs of fast-ramping and the existing thermal units. As this sub-hourly rescheduling is carried out for load following purposes, we term the intra-hour rescheduling on a 5-minute basis as load following. In the third step, dispatchable resources are adjusted in real-time to alleviate the impact of short-term wind and demand fluctuations. This step is termed regulation process which is equivalent to balancing sub 5-minute fluctuations in net load. The maximum ramping up/down that could be provided by a dispatchable generating unit in one minute is assumed to be the unit's ramping capability for participation in the regulation process [29]. Note, this paper presents a planning problem formulation which takes into account the three discussed operation steps. Also, the transmission network is modeled using the DC approximation.

Although the combination of hourly and intra-hourly time scales increases the complexity of the optimization problem, this combination improves power systems reliability (by considering the ramping requirements for responding to short-term fluctuations) and economics (installation of proper sizes of energy storage and fast-ramping units). Given the fact that this is a planning problem, it is reasonable to accept the increased complexity of the resulting optimization problem. Note though that the proposed planning problem is an off-line convex optimization problem.

A. Objective Function

The objective function of the proposed model consists of costs of investment, operation/maintenance, and load curtailment, and it is given as

$$\begin{aligned}\min \sum_{s}\{&PC_s(\overline{E}_s, \overline{P}_s^{out}, \overline{P}_s^{in}) + \sum_{t} OC_s(P_{s,t}^{out}, P_{s,t}^{in})\}\\ &+ \sum_{f}\{PC_f(\overline{P}_f, \Delta\overline{P}_{f,t}) + \sum_{h} OC_f(P_{f,h})\\ &+ \sum_{t} OC_f^{\Delta}(\Delta P_{f,t})\}\\ &+ \sum_{g}\{\sum_{h} OC_g(P_{g,h}) + \sum_{t} OC_g^{\Delta}(\Delta P_{g,t})\}\\ &+ \sum_{b}\sum_{t} C_{ens}(PD_{b,t}^{sh}) \end{aligned} \tag{1}$$

where the variables over which the objective function is optimized are $\overline{E}_s$, $\overline{P}_s^{out}$, $\overline{P}_s^{in}$, $P_{s,t}^{out}$, $P_{s,t}^{in}$, $\overline{P}_f$, $\Delta\overline{P}_{f,t}$, $P_{f,h}$, $\Delta P_{f,t}$, $P_{g,h}$, $\Delta P_{g,t}$, and $PD_{b,t}^{sh}$. The investment cost of energy storage s ($PC_s(\cdot)$) depends on its capacity and power rating. Similarly, the capacity and ramp rate of fast-ramping unit f determine the required investment cost ($PC_f(\cdot)$). Moreover, the operating cost of a storage ($OC_s(\cdot)$) depends on its charge/discharge power. The operating costs of fast-ramping generators and the existing thermal units consist of an hourly generation cost, $OC_f(\cdot)$ and $OC_g(\cdot)$, and the cost of intra-hour power adjustment, $OC_f^{\Delta}(\cdot)$ and $OC_g^{\Delta}(\cdot)$. The cost of demand response in intra-hour time interval t ($C_{ens}(\cdot)$) is determined according to the value of energy not supplied for the non-critical part of the load located at bus b. Specific functions for these costs are defined for the considered test cases in the simulation section.

B. Load Following Constraints

Load following constraints guarantee that the system is capable of following net load for a 5-minute resolution.

1) Energy Storage Constraints: The capacity of the storage and its power rating are decision variables in the optimization problem. These variables need to be within pre-defined bounds as given by [12]:

$$\overline{E}_{s,\underline{cap}} \leq \overline{E}_s \leq \overline{E}_{s,\overline{cap}} \tag{2}$$

$$\overline{P}_{s,\underline{cap}} \leq \{\overline{P}_s^{out}, \overline{P}_s^{in}\} \leq \overline{P}_{s,\overline{cap}} \tag{3}$$

Additionally, there are operational constraints: the energy stored in storage s and its charging/discharging power at each intra-hour time interval need to stay within their limits, i.e.,

$$0 \leq E_{s,t} \leq \overline{E}_s \tag{4}$$

$$0 \leq P_{s,t}^{out} \leq \overline{P}_s^{out} \tag{5}$$

$$0 \leq P_{s,t}^{in} \leq \overline{P}_s^{in} \tag{6}$$

Furthermore, the storage's energy level at time $t+1$ is equal to its energy level at time t plus the energy injected to the storage minus the withdrawn energy during time period t to $t+1$. This leads to the following constraint:

$$E_{s,t+1} = E_{s,t} + \gamma_s P_{s,t}^{in} \Delta t - \frac{1}{\gamma_s} P_{s,t}^{out} \Delta t \tag{7}$$

Note that as the storage might be deployed for various purposes, the operator could set a maximum state of charge change ($\Delta\overline{SOC}$) to guarantee that the energy assigned to load following stays limited, i.e.,

$$|E_{s,t+1} - E_{s,t}| \leq \Delta\overline{SOC}_{s,t+1} \tag{8}$$

The following equations give the relation between capacity and maximum charge/discharge power of storage s with its power rating and efficiency parameter:

$$\overline{P}_s^{out} = \gamma_s \chi_s \overline{E}_s \tag{9}$$

$$\overline{P}_s^{in} = \frac{1}{\gamma_s} \chi_s \overline{E}_s \tag{10}$$

Note that as the operational cost of storage s is an increasing function of both P_s^{out} and P_s^{in}, considering the storage operating cost in the objective function prevents $P_{s,t}^{out}$ and $P_{s,t}^{in}$ from being simultaneously non-zero [12].

2) Fast-Ramping and the Existing Thermal Units' Constraints: A fast-ramping unit is a type of thermal unit with low inertia and high ramping capability. Fast-ramping units are typically gas turbines which can be used by the operator in response to unexpected phenomena and renewable generation/load fluctuations. Fast-ramping units and the existing thermal units are scheduled to supply the predicted net load on an hourly time interval. The system operator then reschedules these generation resources in sub-hourly time intervals to account for sub-hourly fluctuations and prediction errors. Figure 1 visualizes the sub-hourly time intervals with the operation horizon h to $h+1$ and the dependency of the power output of fast-ramping unit f at each of these sub-hourly intervals on the hourly schedule of this unit. According to this figure, the power output of the dispatchable generation unit in intra-hour time step t is equal to its power output in hour h plus the sum of generation adjustments in all intra-hour intervals before t. Consequently, the hourly and intra-hour generation and load following constraints of fast-ramping unit f are:

$$\Delta\underline{P}_f \leq \Delta P_{f,t} \leq \Delta\overline{P}_f \quad \forall t \tag{11}$$

$$\underline{P}_f \leq P_{f,h} + \sum_{i=1}^{t} \Delta P_{f,i} \leq \overline{P}_f$$
$$\forall t \in \{1, \ldots, N_t\}, h \in \{0, \ldots, N_h - 1\} \tag{12}$$

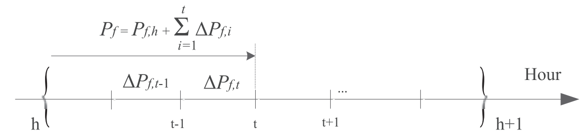


Fig. 1. Fast-ramping unit generation in intra-hour horizon.

$$P_{f,h+1} = P_{f,h} + \sum_{i=1}^{N_t} \Delta P_{f,i} \quad \forall h \in \{0, \ldots, N_h - 1\} \tag{13}$$

N_t is the number of intra-hour time intervals in each hour. It means that in (12) and (13), the term Σ only includes time intervals between hours h and $h+1$. Inequality (11) imposes upper and lower limits on the power adjustment of fast-ramping unit f in intra-hour time interval t. Constraint (12) is included to guarantee that the power output of fast-ramping unit f is always within its limit. Equality (13) establishes the dependency between the power output of fast-ramping unit f at hours h and $h+1$. The same set of constraints are also formulated for all other thermal generating units and included in the optimization problem. However, note that the capacity ($\overline{P}_f$), intra-hour power adjustment limits ($\Delta\underline{P}_f$ and $\Delta\overline{P}_f$), hourly power generation ($P_{f,h}$), and intra-hour power adjustment ($\Delta P_{f,i}$) of fast-ramping units (to be installed additionally in the system) are among the decision variables, whereas the capacity ($\overline{P}_g$) and intra-hour power adjustment limits ($\Delta\underline{P}_g$ and $\Delta\overline{P}_g$) of the existing thermal units are constant parameters. Similar to energy storage, the following constraints on minimum/maximum capacity and ramping capabilities need to be taken into account for fast-ramping unit f:

$$\overline{P}_{f,\underline{cap}} \leq \overline{P}_f \leq \overline{P}_{f,\overline{cap}} \tag{14}$$

$$\Delta\overline{P}_{f,\underline{cap}} \leq \Delta\overline{P}_f \leq \Delta\overline{P}_{f,\overline{cap}} \tag{15}$$

3) Load Balance Constraint: Wind power generation and demand are uncertain parameters. They are modeled by Gaussian probability density functions (PDFs) at each time interval (see Section III for details). Thus, the power balance constraint for time step t is a stochastic constraint. We account for that by formulating the power balance constraint as the following chance constraint:

$$\Pr\Bigg\{\sum_g \left(P_{g,h} + \sum_{i=1}^{t} \Delta P_{g,i}\right) + \sum_f \left(P_{f,h} + \sum_{i=1}^{t} \Delta P_{f,i}\right)$$
$$+ \sum_w P_{w,t} + \sum_s \left(P_{s,t}^{out} - P_{s,t}^{in}\right) \geq \sum_b \left(PD_{b,t} - PD_{b,t}^{sh}\right)\Bigg\}$$
$$\geq (1 - LOLP_t) \quad \forall t \in \{1, \ldots, N_t\}, h \in \{0, \ldots, N_h - 1\} \tag{16}$$

where $\Pr\{\cdot\}$ indicates the probability of the argument to hold. This chance constraint indicates that the total power generation comprised of the power outputs of thermal and fast-ramping units, wind farms, and energy storage needs to meet the demand requirements and power input to storage in intra-hour time interval t with a pre-specified confidence level of (1-$LOLP_t$).

By choosing a proper value for $LOLP$ (loss of load probability), a reasonable trade-off between reliable and economic operation of the system can be achieved. The power outputs for the dispatchable generators thereby correspond to the outputs of the hourly schedule plus the intra-hourly adjustments for load following.

4) Demand Response Constraint: Demand response is considered as an alternative to adjusting the output of dispatchable generators. It is assumed that consumers are willing to participate in demand response programs which allow the utility to directly control the load by shedding non-critical load. This could influence the optimal size of fast-ramping units and energy storages. Thus, the availability of demand response is taken into account in the proposed optimization problem by the following constraint:

$$\Pr\{\sum_{b} PD_{b,t}^{sh} \leq \sum_{b} \overline{PD}_{b,t}^{sh}\} \geq \alpha_t \quad \forall t \tag{17}$$

We assume that each load can offer a percentage of its power consumption, i.e. non-critical part, for direct demand response. As power consumption is modeled using a probability density function, (17) is again formulated as a chance constraint. This chance constraint ensures that the total load curtailment in the system ($\sum_b PD_{b,t}^{sh}$) in intra-hour time interval t does not exceed its maximum value with a pre-specified confidence level α_t.

5) Network Constraints: Transmission system constraints are taken into account using shift factors. Given that the load and wind generation are modeled using PDFs, the transmission constraint is formulated as the following chance constraint:

$$\begin{aligned}\Pr\Bigg\{\Bigg|&\sum_{g} SF_{l,g}\cdot(P_{g,h}+\sum_{i=1}^{t}\Delta P_{g,i})+\sum_{w} SF_{l,w}P_{w,t}\\ &+\sum_{f} SF_{l,f}\cdot(P_{f,h}+\sum_{i=1}^{t}\Delta P_{f,t})+\sum_{s} SF_{l,s}\cdot(P_{s,t}^{out}-P_{s,t}^{in})\\ &-\sum_{b} SF_{l,b}\cdot(PD_{b,t}-PD_{b,t}^{sh})\Bigg|\leq \overline{PL}_l\Bigg\}\geq(1-TLOP_{l,t})\\ &\forall t\in\{1,\ldots,N_t\}, h\in\{0,\ldots,N_h-1\}\end{aligned} \tag{18}$$

where $SF_{l,x}$ represents the linear sensitivity of the power flow on line l with respect to generation/load changes at bus x. This chance constraint ensures that the power flow on line l stays within its bounds in intra-hour time interval t with a pre-specified confidence level of (1-$TLOP_{l,t}$). The first term in (18) reflects the effect of the existing thermal units on line flows. Line flows resulting from wind power injections are taken into account by the second term. The third term represents the effect of future fast-ramping units on the power flows in the lines. The impact of power consumption on line flows as modeled by the fourth term. Similar to $LOLP$, $TLOP$ (transmission line overload probability) needs to be properly selected by the operator to compromise between economics and reliability of the system operation. In order to reduce the computation complexity of this planning problem, an operator could perform an off-line analysis based on historical data to identify and consider critical line flow constraints, i.e., lines that are historically utilized close to their capacity limits and only integrate these constraints into the optimization problem.

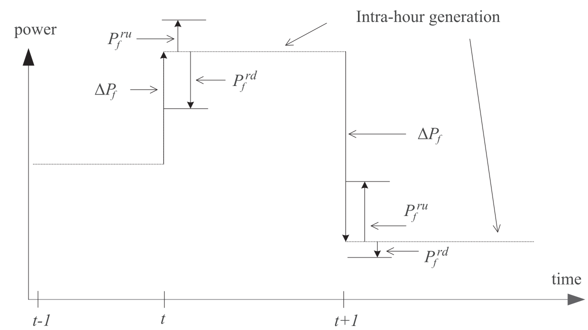


Fig. 2. One-minute up and down ramping capabilities of fast-ramping unit f.

C. Regulation Constraints

Taking into consideration the forecast errors in the load following constraints, the operator optimally determines the hourly power generations as well as the sub-hourly power adjustments of each dispatchable generator. Additionally, the system has to be capable of responding to the short-term fluctuations to keep the minute-to-minute generation-consumption balance. Thus, sufficient regulation resources (ramping capability) need to be available in the intra-hour time intervals to equilibrate the net load within around one minute [29]. Consequently, the following constraints focus on providing one minute ramping capability.

Regulation resources need to be available to provide adjustments in both directions, i.e., the system needs to be able to ramp up as well as down. The operator utilizes the regulation-down resources to balance the system when power generation is greater than consumption. Regulation-up resources are employed to equilibrate the net load when there is a shortage of power generation. All dispatchable generation resources, e.g., fast-ramping units, existing thermal units, and energy storage devices, could potentially participate in the regulation process if they have the necessary ramping capabilities.

It is important to consider that some of the ramping capability of the resources is reserved for load following. Consequently, the combined requested ramping for load following and for regulation should not exceed the total ramping capability of the resources. For illustration purposes, consider Fig. 2 which depicts three intra-hour time intervals $t-1$, t, and $t+1$. The power demand in interval t is greater than that in interval $t-1$. Assume that fast-ramping unit f utilizes a portion of its ramping capability and increases its power output to follow this increase in load. As a consequence, the participation of this unit in the regulation process (to alleviate the short-term fluctuations) is limited to its available extra ramping up/down capability.

Ramping Capability for Regulation: The available ramping for regulation provided by unit f is therefore restricted by not only the one-minute ramping capability but also the ramping that has been set aside for load following. Consequently, the constraints for up and down ramping are given as follows:

$$0 \le P_{f,t}^{ru} \le \frac{\Delta\overline{P}_f - \Delta P_{f,t}}{T_{res}} \tag{19}$$

$$0 \le P_{f,t}^{rd} \le -\Delta\underline{P}_f^m \tag{20}$$

$$0 \le P_{f,t}^{ru} \le \Delta\overline{P}_f^m \tag{21}$$

$$0 \le P_{f,t}^{rd} \le \frac{-\Delta\underline{P}_f + \Delta P_{f,t}}{T_{res}} \tag{22}$$

where T_{res} is the length of the intra-hour time step in minutes, i.e., intra-hour time resolution, which in this paper is 5 minutes. $\Delta\overline{P}_f^m$ and $\Delta\underline{P}_f^m$ are the up and down ramping capabilities provided by fast-ramping unit f in one minute. It should be noted that in (21) and (22), $\Delta\underline{P}_f$ and $\Delta\underline{P}_f^m$ are negative. Combining these constraints results in the following conditional constraints:

$$0 \le P_{f,t}^{ru} \le min\left\{\frac{\Delta\overline{P}_f - \Delta P_{f,t}}{T_{res}}, \Delta\overline{P}_f^m\right\} \tag{23}$$

$$0 \le P_{f,t}^{rd} \le min\left\{\frac{-\Delta\underline{P}_f + \Delta P_{f,t}}{T_{res}}, -\Delta\underline{P}_f^m\right\} \tag{24}$$

Constraints (23) and (24) restrict the ramp up and ramp down for fast-ramping unit f, respectively. The same set of constraints are also formulated for the regular thermal units. Note that for the one-minute ramp up/down constraints associated with the fast-ramping unit f, $\Delta P_{f,t}$, $\Delta\underline{P}_f$, $\Delta\overline{P}_f$, $\Delta\underline{P}_f^m$, and $\Delta\overline{P}_f^m$ are decision variables. However, $\Delta\underline{P}_g$, $\Delta\overline{P}_g$, $\Delta\underline{P}_g^m$, and $\Delta\overline{P}_g^m$ are fixed values.

Energy storage devices can quickly adjust their output/input power and are therefore very well equipped to provide regulation services. Their maximum ramping for participation in the regulation process is limited by the power rating and charge/discharge power. Furthermore, as the operator might utilize storage devices for various purposes, a regulation capacity index is introduced to restrict deployment and contribution of storages in the regulation process. The value of $RC_{s,t}$ is defined by the operator as a percentage of the system ramping requirements in time interval t. This leads to the following constraints:

$$\begin{aligned}\Pr\{P_{s,t}^{ru} \le min\{&\overline{P}_s^{out} - (P_{s,t}^{out} - P_{s,t}^{in}),\\ &RC_{s,t} \cdot PR_t^u\}\} \ge \beta_t^{ru}\end{aligned} \tag{25}$$

$$\begin{aligned}\Pr\{P_{s,t}^{rd} \le min\{&\overline{P}_s^{in} - (-P_{s,t}^{out} + P_{s,t}^{in}),\\ &RC_{s,t} \cdot PR_t^d\}\} \ge \beta_t^{rd}\end{aligned} \tag{26}$$

PR_t^u and PR_t^d, the total system ramping up and down requirements for the regulation process, are PDFs which equal to the short-term wind power and demand fluctuations. Thus, inequalities (25) and (26) are modeled as chance constraints with confidence levels β_t^{ru} and β_t^{rd}.

The system needs to have certain amounts of total up and down regulation reserves available during any interval t. Fast-ramping units, other generators as well as storage devices contribute to this amount. Consequently, to guarantee the availability of these resources with confidence ϕ_t^{ru} and ϕ_t^{rd}, the following constraints are introduced:

$$\Pr\left\{\sum_g P_{g,t}^{ru} + \sum_f P_{f,t}^{ru} + \sum_s P_{s,t}^{ru} \ge PR_t^u\right\} \ge \phi_t^{ru} \forall t \tag{27}$$

$$\Pr\left\{\sum_g P_{g,t}^{rd} + \sum_f P_{f,t}^{rd} + \sum_s P_{s,t}^{rd} \ge PR_t^d\right\} \ge \phi_t^{rd} \forall t \tag{28}$$

In summary, these two constraints set lower bounds for the system flexibility.

D. Note on Chance-Constrained Programming

Chance-constrained programming is a relatively robust approach to solve optimization problems and incorporate uncertainty. This approach provides the option for the operator to set a desired confidence level for stochastic constraints and to take into account trade-off between two or more objectives. When the problem is linear and convex, and the probability density functions of the uncertain variables are known, we can decouple variables with and without uncertainty. In such a case, we can easily transform the stochastic chance constraints into deterministic functions and efficiently solve the problem [30], [31].

In this paper, our optimization algorithm is linear and convex, and we know the probability density functions of uncertain variables, hence, we can decouple variables with and without uncertainty. Thus, all the desired conditions for a chance-constrained approach are met, and we can simply convert our stochastic planning problem into a deterministic one and efficiently solve the problem.

III. Solution Methodology

A. Forecast Errors and Short-Term Fluctuations Modeling

From historical data for actual predictions and true realizations of wind power output and demand, probability density functions (PDFs) of wind generation and demand forecast errors can be derived for every time interval. Hence, forecast errors have the same time resolution (5 minutes) as the predictions. Various distribution functions have been used in the literature to account for the wind generation and load forecast errors and short-term fluctuations [17]–[24], [32], [33]. Here, the wind generation and demand forecast errors are modeled using normal probability density functions where the mean values are zero and σ_t^2 is the variance at time interval t as assumed in [17]–[24]. Using $\mu(\cdot)$ to indicate forecasted (expected) value of the parameter, the distributions for wind generation output and demand are given by:

$$P_{w,t} \sim \mu(P_{w,t}) + N(0, \sigma_{w,t}^2) \tag{29}$$

$$PD_{b,t} \sim \mu(PD_{b,t}) + N(0, \sigma_{b,t}^2) \tag{30}$$

Similar to the forecast errors, the short-term wind generation and demand fluctuations can also be modeled by normal PDFs obtained from historical data of sub 5-minute wind and load data. The variances of PDFs of short-term fluctuations in intra-hour time interval t are denoted by $\widetilde{\sigma}_t^2$ to differentiate between the variances for short-term fluctuations and the variance of the PDFs of forecast errors. Note that the values of $\widetilde{\sigma}_{w,t}^2$ and $\widetilde{\sigma}_{b,t}^2$ determine the amounts of required up-ramping PR_t^u and down-ramping PR_t^d in the regulation constraints (25)–(28).

B. Deterministic Model of the Chance Constraints

A common approach to handle chance constraints in an optimization problem is to transform them into deterministic constraints. To solve the proposed planning problem, we convert the chance constraints associated with the load following and regulation processes into equivalent deterministic constraints. To do so, we need to decouple variables with and without uncertainty, and we also need to specify probability density functions of the uncertain variables, i.e., wind power generation and load. Knowing the confidence level of a chance constraint (which is pre-specified by the operator) and the distribution functions of the uncertain variables in that constraint, the value of z corresponding to that confidence level can be calculated. Then with respect to the mean value and variance of the uncertain variables, the chance constraint can be replaced by a deterministic constraint (the stochastic term of the chance constraint is indeed replaced by an equivalent deterministic term). Hence, we replace the load following constraints (16), (17), and (18) by their equivalent linear inequality constraints as follows [30], [31], [34]:

$$\sum_g (P_{g,h} + \sum_{i=1}^{t} \Delta P_{g,i}) + \sum_f (P_{f,h} + \sum_{i=1}^{t} \Delta P_{f,i}) + \sum_w \mu(P_{w,t}) + \sum_s (P_{s,t}^{out} - P_{s,t}^{in}) \geq \sum_b \mu(PD_{b,t} - PD_{b,t}^{sh}) + Z_{LOLP_t}\{\sum_w \sigma_{w,t}^2 + \sum_b \sigma_{b,t}^2\}^{1/2} \quad \forall t \in \{1,\ldots,N_t\}, h \in \{0,\ldots,N_h-1\} \tag{31}$$

$$PD_{b,t}^{sh} + Z_{\alpha_t} \cdot \sigma_{b,t} \leq \overline{PD}_{b,t}^{sh} \quad \forall b, \forall t \tag{32}$$

$$\Big| \sum_g SF_{l,g}(P_{g,h} + \sum_{i=1}^{t} \Delta P_{g,i}) + \sum_w SF_{l,w} \cdot \mu(P_{w,t}) + \sum_f SF_{l,f}(P_{f,h} + \sum_{i=1}^{t} \Delta P_{f,t}) + \sum_s SF_{l,s}(P_{s,t}^{out} - P_{s,t}^{in}) - \sum_b SF_{l,b} \cdot \mu(PD_{b,t} - PD_{b,t}^{sh}) \Big| + Z_{TLOP_{l,t}}\{\sum_w (SF_{l,w} \cdot \sigma_{w,t})^2 + \sum_b (SF_{l,b} \cdot \sigma_{b,t})^2\}^{1/2} \leq \overline{PL}_l \quad \forall t \in \{1,\ldots,N_t\}, h \in \{0,\ldots,N_h-1\} \tag{33}$$

where Z_x is the $100 \times (1-x)$th percentile of the standard normal distribution which can be determined by taking the inverse CDF of the standard normal distribution evaluated at x. Similarly, $\mu(\cdot)$ indicates forecasted (expected) value of the parameter, with respect to the PDFs of short-term wind generation and demand fluctuations. The regulation constraints (25), (26), (27), and (28) are modeled by the following linear inequality constraints:

$$P_{s,t}^{ru} \leq min\{\overline{P}_s^{out} - (P_{s,t}^{out} - P_{s,t}^{in}), Z_{\beta_t^{ru}} RC_{s,t}\{\sum_w \widetilde{\sigma}_{w,t}^2 + \sum_b \widetilde{\sigma}_{b,t}^2\}^{1/2}\} \quad \forall t \tag{34}$$

$$P_{s,t}^{rd} \leq min\{\overline{P}_s^{in} - (-P_{s,t}^{out} + P_{s,t}^{in}), Z_{\beta_t^{rd}} RC_{s,t}\{\sum_w \widetilde{\sigma}_{w,t}^2 + \sum_b \widetilde{\sigma}_{b,t}^2\}^{1/2}\} \quad \forall t \tag{35}$$

$$\sum_g P_{g,t}^{ru} + \sum_f P_{f,t}^{ru} + \sum_s P_{s,t}^{ru} \geq Z_{\phi_t^{ru}}\{\sum_w \widetilde{\sigma}_{w,t}^2 + \sum_b \widetilde{\sigma}_{b,t}^2\}^{1/2} \quad \forall t \tag{36}$$

$$\sum_g P_{g,t}^{rd} + \sum_f P_{f,t}^{rd} + \sum_s P_{s,t}^{rd} \geq Z_{\phi_t^{rd}}\{\sum_w \widetilde{\sigma}_{w,t}^2 + \sum_b \widetilde{\sigma}_{b,t}^2\}^{1/2} \quad \forall t \tag{37}$$

Note that the proposed approach is general and other distribution functions, such as the Weibull distribution, can be used instead of the normal PDF to model the wind power and load forecast errors. In that case, only the equivalent models of the chance constraints need to be modified [35]. We set the confidence level of the chance constraint before solving the optimization problem. Thus, a constant value is determined with respect to the characteristics of the PDF, which is used for forecast error modeling, and it is include in the equivalent model of the chance constraints [35]. On the other hand, as the inequalities inside the probability measure $Pr\cdot$ in chance constraints (16)–(18) and (25)–(28) are originally linear, the equivalent deterministic models of the chance constraints are linear if we use either a normal PDF or a Weibull distribution to account for the forecast errors. We refer to [35] for more details.

IV. Numerical Results

The proposed planning approach is tested on a 3-bus test system for illustration purposes. Also this section presents the simulation results for a modified IEEE 24-bus test system. The simulation results are preformed utilizing ILOG CPLEX 12.4's QP solver on a 3.4GHZ computer.

A. 3-Bus Test System

This system has one thermal unit (coal power plant), three branches and two loads participating in demand response. A wind farm is located at bus 3, and it is assumed that 5% of the load is curtailable. A fast-ramping unit (gas turbine) and a battery energy storage are planned to be installed at buses 2 and 3, respectively. The heat rate curves for coal and gas power plants are assumed to be quadratic as provided by the values in Tables I and II. The operating costs of the generators are calculated assuming coal price and gas price as 2.5 \$/MBtu and of 5 \$/MBtu. The load shedding cost varies over time. The minimum and maximum load shedding costs are 42.13 \$/kWh and 104.74 \$/kWh, respectively. The average load shedding cost is

TABLE I
EXISTING THERMAL UNIT DATA

$\underline{P}$ (MW)	$\overline{P}$ (MW)	RU/RD (MW/h)	c (MBtu/h)	b (MBtu/MWh)	a (MBtu/MW^{2}h)
40	220	20	250	10	0.01

TABLE II
FAST-RAMPING UNIT DATA

$\overline{Pf_{cap}}$ (MW)	Inv. cost (k$/MW)	Inv. cost (k$/(MW/h))	c (MBtu/h)	b (MBtu/MWh)	a (MBtu/MW^{2}h)
150	1000	200	200	13	0.08

TABLE III
ENERGY STORAGE SYSTEM DATA

$\underline{E_{cap}}$ (MWh)	$\overline{E_{cap}}$ (MWh)	Inv. cost (k$/MWh)	Inv. cost (k$/MW)	γ
0	100	1500	300	0.9

71.66 $/kWh over the planning horizon. The characteristics of the considered battery energy storage are shown in Table III. The operation/maintenace cost of the storage is set to 1% of its capital costs. The life time of the fast-ramping and energy storage is 20 years. We have used four years of the ERCOT load data, from the beginning of 2011 to the end of 2014, while assuming that there are 48 representative days which model the load behavior over the four years [36]. We assume that the representative days are consecutive and have uniform distribution functions of occurrence. However, the proposed planning algorithm is general and one can model non-consecutive representative days in the optimal sizing problem. We have the average hourly load data for every day, and 5-minute load data for each hour. The load growth is taken into account in the forecast data. Note that the average yearly investment costs of the battery storage and fast-ramping unit are calculated, and then, these average costs are used in the optimization to calculate the total investment cost over the four years planning horizon.

Three cases are studied to show the importance and the impact of the intra-hour time scales on the optimal size of energy storage and fast-ramping unit. In the first case, only hourly scheduling is considered in the planning problem ignoring the intra-hourly load following and regulation requirements. In the second case, the proposed planning approach considering the hourly scheduling, intra-hour load following and short-term regulation is implemented. In the third case, a sensitivity analysis is performed to study the impact of wind power penetration, confidence levels of the chance constraints, and forecast accuracy on the optimal size of energy storage and fast-ramping unit. The maximum SOC deviation ($\Delta\overline{SOC}$) is set to 50% in all cases.

Case 1: Given that sub-hourly scheduling is neglected in this case, ΔP_g and ΔP_f are zero, and constraints (34)–(37) are disregarded. Note that, disregarding these variables/constraints render our planing method almost similar to the existing methods discussed before.

The annual amount of wind energy produced divided by gross annual electricity demand (wind power penetration level) is 20%. The hourly wind power and load forecast errors have a standard deviation of 30% and 3% of the forecasted values, respectively. Note that The value of the standard deviation is only a constant in the equivalent models of the chance constraints, and it does not affect the generality of the proposed formulation. An operator/planner can use any values of the standard deviation for the forecast errors given by a forecasting tool. The confidence level α is 95%, and $LOLP = TLOP = 5\%$. The execution time for Case 1 is approximately 1 second. The results are shown in Table IV. The optimal capacity of the fast-ramping unit is determined to be 109.59 MW, and its ramping capability is 15.85 MW/h. This fast-ramping unit along with the wind power generation and the thermal generator are capable of supporting the electricity demand with the pre-specified confidence level for the chance constraints. The battery storage size is determined to be zero as the existing thermal units and the newly deployed fast-ramping generator are capable of supplying the hourly demand. The resulting total investment cost including cost associated with both capacity and ramping is $109.59M.

TABLE IV
OPTIMAL RESULTS OF CASES 1 AND 2

Case No.	Sizing variables	$\overline{E}_s$ (MWh)	Storage power rating (MW)	$\overline{P}_f$ (MW)	$\Delta\overline{P}_f$ (MW/h)
1	Opt. value	0	0	106.42	15.85
	Cost(M$)	0	0	106.42	3.17
2	Opt. value	4.42	22.91	88.35	88.35
	Cost(M$)	6.63	6.87	88.35	17.67

Case 2: In this case, the intra-hour load following and regulation are taken into account by the intra-hour power adjustments and ramping capability of dispatchable generation resources. We divide each hour into twelve time intervals. Hence, the intra-hour time resolution is 5 minutes, and there are $1152 \times 12 = 13824$ intra-hour time intervals. We assume that the wind generation and load forecast data are available for every 5 minutes. The intra-hourly wind power and load forecast errors are 20% and 2% of the forecasted values, whereas short-term wind power and demand fluctuations are 10% and 1% of the forecasted intra-hour values (these values indicate standard deviations). Note, the values of α, β, and ϕ are set to 95%, while $LOLP$ and $TLOP$ are set to 5%.

Table IV shows the results for this case. The simulation runtime is approximately 26 seconds. Unlike Case 1 where the battery storage size is zero, in this case, the optimal capacity of the storage is determined to be 4.42 MWh and its power rating is 22.91 MW. The ramping capability of the fast-ramping unit has considerably increased compared with Case 1. The total ramping provided by the additional fast-ramping unit and the battery energy storage, combined with the existing thermal unit ensures that the system is capable of intra-hour load following and regulation. The total system ramping capability is almost 25 MW/min. Figure 3 shows a histogram of the short-term fluctuations over the considered planing horizon. This histogram is obtained from PDFs of the power demand and wind power generation over the planning time horizon. The short-term fluctuation are less than 25 MW most of the time.

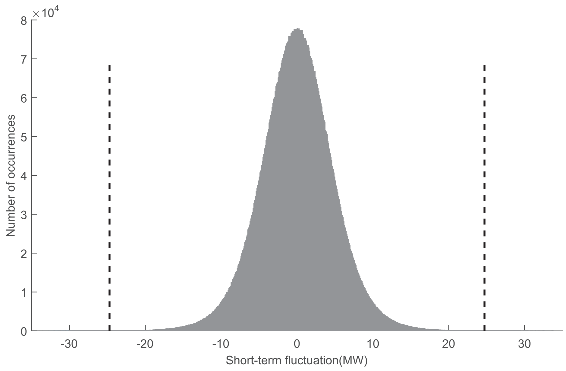
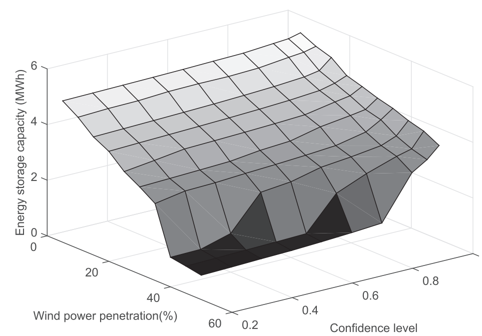
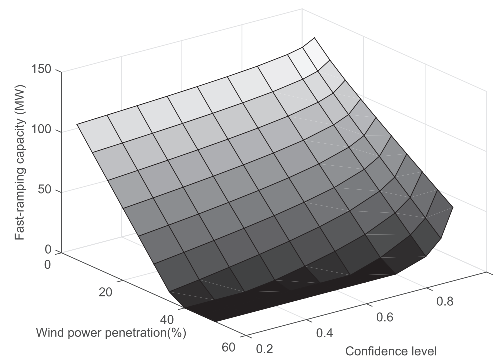


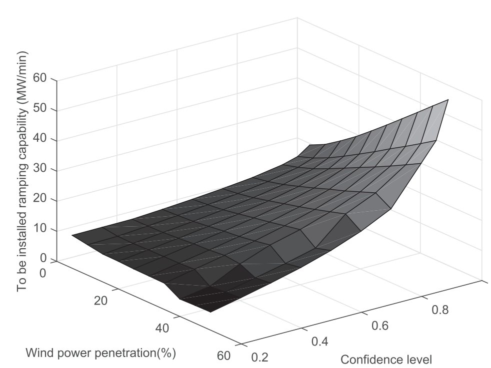
Fig. 3. Histogram of possible short-term fluctuation.



(a)



(b)



(c)

Fig. 4. a) Energy storage, b) and fast-ramping capacity, and c) total newly installed ramping capability versus confidence level of chance constraints and wind power penetration level.

Providing 25 MW/min ramping capability guarantees that the chance constraints are satisfied with 95% confidence level.

The total investment cost is \$119.52M which is \$9.93M larger than that obtained in Case 1. This cost increment is because of the energy storage deployment as well as the increase in ramping capability of the fast-ramping unit. However, deployment of a fast-ramping unit and a battery storage with characteristics determined in Case 2 guarantees that the system is capable of load following and alleviating the short-term fluctuations to maintain the minute-to-minute generation and consumption balance.

We have used a Monte Carlo simulation to generate 1000 possible scenarios for short-term fluctuations over the entire planning horizon. Thus, we have 1000 scenarios of short-term fluctuations in each time intervals. The histogram of the short-term fluctuations is shown in Fig. 3. In Case 1, in which the planning problem is solved regardless of the intra-hour load following and regulation constraints, the ramping capability that the existing and newly deployed generation resources can provide for the system is approximately 1 MW/min. However, as it is clear from the histogram of the possible short-term fluctuations, 1 MW/min ramping capability is not sufficient to respond to the wind and load short-term fluctuations. In Case 2, which is based on the proposed algorithm, the planning scheme provides the system with almost 25 MW/min ramping capability. As depicted in Fig. 3, the possible short-term fluctuations lie almost exactly between the limits of the system ramping capability. This ramping capability limit enables the system to alleviate the impact of the possible short-term wind and load fluctuations most of the time (with confidence level of 95%).

Case 3: A sensitivity analysis is performed in this case to study the impact of chance constraints confidence levels and wind power penetration level on the optimal size of the newly deployed energy storage and fast-ramping unit. While the standard deviation of forecast errors and short-term fluctuations are the same as in Case 2, different values are selected for the confidence levels and wind power penetration. The system becomes more secure and reliable against forecast errors and short-term fluctuations by setting the confidence levels to larger values. Figure 4 gives an overview over the results. When the confidence levels are small, increasing the wind power penetration considerably reduces the needs for deploying new generation resources as wind generation can supply the demand. However, there is fairly high uncertainty associated with this supply, i.e. in many cases, the requirement for supply and ramping may not be met. In order to have a more secure and reliable operation, the confidence levels need to be increased which leads to a considerable increase in $\overline{E}_s$ and $\overline{P}_f$. The one-minute ramping capability provided by the energy storage and fast-ramping unit is shown in Fig. 4 (c). When the wind power penetration and chance constraints confidence levels are low, also the required ramping capability provided by the storage and fast-ramping is low. However, as both the confidence level and the level of wind generation jointly increase, the ramping capability needs to be increased significantly as well. Increasing just one of these

TABLE V
OPTIMAL RESULTS OF THE MODIFIED IEEE 24-BUS SYSTEM

Resource	Optimal capacity	Optimal ramping
Storage 1	5.4 (MWh)	32.5 (MW)
Storage 2	8.1 (MWh)	46.8 (MW)
Fast-ramping 1	41.2 (MW)	41.2 (MW/h)
Fast-ramping 2	39.0 (MW)	39.0 (MW/h)

parameters has only limited impact as with low wind penetration but high confidence level only the fluctuations in the load need to be balanced and with high wind penetration and low confidence level, it is accepted that the reliability of the system is low.

In this sensitivity analysis, we also would like to determine the impact of a more accurate forecasting tool. The wind power penetration level is set to 20%, and all the confidence levels are set to 95%. It is assumed that the standard deviation of the forecasting errors of the intra-hourly wind generation is now 10%, and the standard deviation of short-term wind generation fluctuations is 7.5%. This forecast improvement reduces the total investment cost by $8.63M compared to the case with 20% and 10% standard deviations for wind forecast errors and short-term fluctuations.

B. A Modified IEEE 24-Bus Test System

The proposed chance-constrained co-optimization problem is also tested on a modified IEEE-RTS 24-bus system. The system has 10 thermal units and 2 wind generation resources. Two new fast-ramping units and two new energy storages are planned to be installed in the system at buses 2, 16, 1, and 15, respectively. The maximum allowable capacity of the fast ramping units is 100 MW, and it is 100 MWh for the energy storage devices. Wind power penetration is 10%, and the confidence levels of the chance constraints are set to 95%.

At first, a conventional planning algorithm with only hourly time scale is solved. The optimal sizes of the newly deployed fast-ramping units one and two are 51.48 and 55.34 MW, respectively, and their ramping capabilities are determined to be 2.89 and 4.39 MW/h. Optimal sizes of the battery storages are zero, which means there is no need to install a storage device in this system. The combination of the existing thermal units and the newly deployed fast-ramping generators provides adequate hourly capacity and hourly ramping to support the hourly load. Although the system has adequate hourly ramping to follow the hourly load curve, the residual of ramping capability during many operation hours is zero. This means that the system has no additional ramping capability (intra-hour) which might be required to respond to any possible short-term fluctuations.

To account for the intra-hour time horizon, the proposed multi-time scale planning problem is implemented. The results are shown in Table V. The computation time is less than 2 minutes. The capacities of fast-ramping units one and two are 41.2 and 39 MW, and their ramping capabilities are 41.2 and 39 MW/h, respectively. The ramp rate of the fast-ramping units have significantly increased compared with the case in which only hourly time horizon is taken into consideration. In addition, the sizes of the newly deployed storages one and two are determined to be 5.4 and 8.1 MWh, and their maximum power ratings are 32.5 and 46.8 MW, respectively. The results show a significant increase in the newly installed ramping capability compared with the results determined by the conventional planning algorithm. Installation of these new devices, i.e., two fast-ramping units and two storage devices, ensures that the system has adequate capacity to supply the power consumption, and there is sufficient (with 95% confidence level for the chance constraints) ramping capability for load following and regulation processes. The total resulting investment cost is $ 121.5M.

V. CONCLUSION

In this paper, a stochastic optimization problem is formulated for optimal sizing of energy storage devices and fast-ramping units taking into account uncertainties, e.g., wind generation and demand fluctuations. We model and integrate the capability of the storage to provide multiple services for the system. The proposed problem minimizes the investment and operation/maintenance costs. The considered planning problem is divided into two time perspectives: hourly and intra-hour time intervals. In the hourly time perspective, fast-ramping generators and the existing thermal units are scheduled to provide adequate capacity to support hourly load. The charge/discharge power of energy storages as well as adjustments in the power provided by fast-ramping and the existing thermal units ensure that the system is capable of load following in intra-hour time intervals with respect to the wind power and demand forecast errors. Furthermore, the proposed optimal sizing problem is formulated with respect to having sufficient ramping capability for regulation purposes in intra-hour intervals. This ramping capability guarantees that the system is able to alleviate the impact of short-term wind power output and demand fluctuations. Power balance, network security, and power system ramping capability are modeled as chance constraints.

The simulation results show that when we neglect sub-hourly time intervals, optimal sizes of the newly deployed energy storages and fast-ramping units are considerably different from the values determined in the case including both hourly and sub-hourly time intervals. The total investment cost of the case with only hourly time intervals (Case 1) is less than that determined in the case with sub-hourly time intervals (Case 2). However, the newly added ramping capability in Case 1 might not be adequate to guarantee the system reliability and security in response to wind power and demand short-term fluctuations and forecast errors.

The results also indicate that increasing the wind power penetration reduces the needs for deploying new generation resources because wind generation can supply the demand when the confidence levels of the chance constraints are small. However, to meet the requirement for supply and ramping while ensuring the system reliability, reasonably large confidence levels need to be selected. On the other hand, increasing the confidence levels of the chance constraints increases the capacity of the newly deployed energy storages and fast-ramping units.

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