Chance-constrained Scheduling of Variable Generation and Energy Storage in a Multi-Timescale Framework

Wen-Shan Tan*, Md Pauzi Abdullah[†] and Mohamed Shaaban**

Abstract – This paper presents a hybrid stochastic deterministic multi-timescale scheduling (SDMS) approach for generation scheduling of a power grid. SDMS considers flexible resource options including conventional generation flexibility in a chance-constrained day-ahead scheduling optimization (DASO). The prime objective of the DASO is the minimization of the daily production cost in power systems with high penetration scenarios of variable generation. Furthermore, energy storage is scheduled in an hourly-ahead deterministic real-time scheduling optimization (RTSO). DASO simulation results are used as the base starting-point values in the hour-ahead online rolling RTSO with a 15-minute time interval. RTSO considers energy storage as another source of grid flexibility, to balance out the deviation between predicted and actual net load demand values. Numerical simulations, on the IEEE RTS test system with high wind penetration levels, indicate the effectiveness of the proposed SDMS framework for managing the grid flexibility to meet the net load demand, in both day-ahead and real-time timescales. Results also highlight the adequacy of the framework to adjust the scheduling, in real-time, to cope with large prediction errors of wind forecasting.

Keywords: Multi-timescale scheduling, Energy storage, Mixed-integer linear programming, Unit commitment, Wind generation

1. Introduction

The main disadvantage of variable renewable generation resources relative to conventional generation is their high intermittency, unpredictable fluctuations and limited output control capability. Consequently, these cause existing power system operation paradigms, especially generation scheduling, to face profound challenges [1]. A grid system with extra flexibility resources is needed to even out the intermittency and variability of wind generation in order to enable the high penetration of variable generation into the grid system.

Different approaches have been proposed in the literature to investigate the effect of adding various levels of variable renewable generation into the generation mix [2-5]. Chance-constrained programming is an alternate option to the modelling of uncertainties in power systems, in which constraints can be violated with a predefined level of probability [6]. The chance constraints are often converted into deterministic equivalents and a standard solution technique is applied to solve the stochastic power system

problem, such as the optimal power flow [7] and transmission planning problem [8]. Throughout the literature, researchers have proposed chance-constrained optimization to solve the generation scheduling problem with only demand uncertainty [9, 10], only wind uncertainty [11, 12], or both simultaneously [13-15]. In [12], the authors proposed a generation scheduling problem, with uncertain wind power, formulated as a two-stage chance-constrained stochastic program; which ensures a large portion of the wind power output at each operating hour could be utilized. In [11], a chance constraint is proposed to restrict the probability of load imbalance. A sample average approximation (SAA) algorithm, [16], was ubiquitously proposed in the above generation scheduling models, [10-13], to replace the chance constraint, by a pointwise constraint that must hold at a finite number of sample points drawn randomly from the chance constraint distribution. However, the SAA algorithm requires repetitive iterations and multiple validation scenarios to calculate the optimality gap for solution validation. These drawbacks make the SAA unsuitable for large scale generation scheduling problem formulation that requires long processing time.

The prospect for deployment of the emerging energy storage has become much more possible in recent years. Storage devices are expected to have the potential to become competitive under high penetration levels of renewable generation. This, in turn, will improve power system reliability, meet real-time power demand, and enhance economic efficiency [17]. Successful cases of bulk

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energy storage installations are emerging [18]. The fast ramping capability provides energy storage the ability to better manage the variability of renewable generation in a smaller timescale as hour-ahead real-time scheduling optimization (RTSO). Several studies have addressed the importance and value of storage devices in power systems [17, 19]. The authors in [19] have introduced utility-scale energy storage as part of a set of control measures in a corrective form of the full stochastic security-constrained unit commitment (SCUC) problem.

Multi-timescale scheduling is already adopted in some power markets to accommodate large-scale variable renewable generation [1]. Economic benefits of considering stochastic nature of wind on multi-timescale generation scheduling and dispatch were examined through higher frequency of rolling reschedule with the most updated wind forecast [5]. In [20], multi-timescale scheduling that includes mid-term (few days) and day-ahead scheduling, is proposed for better scheduling of slow start-up coal generation in a wind-coal intensive power system. In this paper, a short-term day-ahead and intra-hour real-time online rolling scheduling framework is proposed, for reducing the search space of real-time scheduling. In [21], the authors proposed a multi-timescale coordinated automatic power dispatching system which provides incremental refinement in sequence timescale, according to the precision in predicting wind power in different timescales. The framework has been implemented in Jilin provincial power grid, China. Whereas a similar concept is implemented herein, wind generation uncertainty and energy storage are distinctively incorporated into the multi-timescale scheduling framework developed in this paper.

This paper proposes a hybrid stochastic deterministic multi-timescale scheduling (SDMS) framework. The framework is composed of a generation scheduling model which considers two flexible resource component options. The first is the chance-constrained day-ahead scheduling optimization (DASO) with conventional generation. Its main objective is to minimize the daily production cost in a power system with variable renewable energy resources. The second is the deterministic hour-ahead online rolling RTSO with energy storage scheduling. The proposed SDMS framework avoids the dimensionality problem associated with full stochastic formulation. Wind curtailment is included in the DASO, as a decision variable that reshapes the probability density function (PDF) of the predicted wind power [22], and as a variable in the RTSO. A discrete distribution chance constrained formulation is applied, which can be theoretically solved to optimality, by employing a linearization approach. The proposed chance constrained formulation does not require an approximation approach, such as the sample approximation average (SAA) [12, 13], that deals with continuous distribution formulation and requires multiple iterations and long computation time. An MILP formulation, called the extended approach [16], is proposed to linearize the chance constraint in the DASO problem. The contribution of this paper is listed as follows:

1) The chance-constrained scheduling is formulated in a multi-timescale framework. The use of a chance-constrained model averts the need for the computationally demanding scenario-based solutions; typically needed for full stochastic optimization.

2) Unlike other multi-timescale scheduling approaches that consider fully deterministic or fully stochastic models in all timescales, the proposed SDMS framework uniquely adopts a discrete distribution chance-constrained DASO that takes full consideration of inter-temporal ramping constraints as well as transmission line thermal constraints, and a deterministic RTSO with energy storage. The main objective of RTSO is to balance out the net load deviation between different timescales. RTSO utilizes the DASO results as boundary conditions, to further reduce the search space and the computational requirements. This makes the formulation more intuitive and practical from the standpoint of industrial realization, while preserving the same features of stochastic optimization.

3) As operational uncertainties can be large through the DASO dispatch, the 15-min interval, completely deterministic, RTSO formulation utilizes the newly updated wind and load forecast information to provide accurate dispatch through online rolling scheduling. The combination of stochastic and deterministic models is the distinguishing feature that singles out the proposed framework from others.

4) The adoption of discrete distribution in the chance constrained DASO promotes the use of linearization to transform the chance-constrained problem into a more tractable form, of an MILP structure. The latter warrants solution of the problem efficiently, using available optimization solvers.

The remaining structure of the paper is as follows: Section 2 expounds the multi-timescale scheduling framework. Section 3 describes the flexibility chance-constrained DASO formulation and the linearization of the formulation to a mixed-integer linear form. Section 4 models the RTSO with energy storage constraints. Section 5 presents the case studies and results. Finally, Section 6 concludes.

2. A Multi-Timescale Scheduling Framework

2.1 Nomenclature

Functions

C_{gen}	Generation cost
$C_{startup}$	Startup cost
NDR	Net demand ramp

Indices

h	15 minutes scheduling interval $\in \{1 \ldots H\}$
i, k	Generator $\in \{1 \ldots I\}$
j	Storage $\in \{1 \ldots J\}$
l	Stair-wise intervals number of unit $i \in \{1 \ldots L\}$
m	Constraint $\in \{1 \ldots M\}$
s	Net demand discrete level $\in \{1 \ldots S\}$
t, n	Hourly scheduling interval $\in \{1 \ldots 24\}$

Continuous variables at time t or h

dG_{ih}	Generation deviation for unit i [MW]
$\overline{D}_t^{net}$	Scheduled mean value of net demand [MW]
e_{jt}	State of charge (SOC) of storage j [%]
$flex_{it}^{up}$	Scheduled up flexibility of unit i [MW]
$flex_{it}^{on,up}$	Schedule up flexibility of online unit i [MW]
$flex_{it}^{off,up}$	Schedule up flexibility of offline unit i [MW]
$flex_{it}^{dn}$	Scheduled down flexibility of unit i [MW]
G_{it} / G_{ih}	Scheduled generation of unit i [MW]
G_h^W	Wind generation [MW]
p_{st}^{net}	Probability of net demand being equal to d_t^{net} when wind power is curtailed
q_{jt}^c / q_{jt}^d	Charge/discharge of energy storage j [MW]
x_{st}	Linearization variable of discrete level s

Binary variables at time t

A_{it}^{on}	Availability to be online of generation units i
A_{it}^{off}	Availability to be offline of generation units i
I_{it}	On/off status of generation units i
J_{jt}	Charge/discharge status of storage j
z_{st}, u_{st}	Probabilistic auxiliary variable of discrete level s

Parameters

$D_t^{total} / D_h^{total}$	Predicted total demand at time t or h [MW]
$\underline{D}_{st}^{net}$	Discrete realizations of level s at time t [MW]
dG_{it}	Generation deviation limit for unit i [MW]
e_j^{min} / e_j^{max}	Min/max state of charge of storage j [MW]
$e_{jh}^{up} / e_{jh}^{dn}$	Up/down limit for SOC of storage j at time h [%]
E_j^0	Initial SOC of storage j at initial time [%]
G_{ih}^{Sch}	Previous iteration hour-ahead scheduled generation result of unit i [MW]
$G_{it}^{min} / G_{it}^{max}$	Min/max power output of unit i at time t [MW]
Hr_i	Incremental heat rate of unit i [Btu/kWh]
η_j^c / η_j^d	Efficiency rate to charge/discharge of storage j
T_i^{on} / T_i^{off}	Minimum on/off time of unit i [hr]
$q_{jh}^{min,c} / q_{jh}^{max,c}$	Min/max charge power of storage j at time h [MW]
$q_{jh}^{min,d} / q_{jh}^{max,d}$	Min/max discharge power of storage j at time h [MW]
r_i^{up} / r_i^{dn}	Ramp up/down rate limit of unit i [MW]
SR_t	Spinning reserve at time t [MW]
SU_{il}	Startup cost of stair-wise level l of unit i [$]
W_t^0	Expected wind generation at time t [MW]
π_i^{gen}	Incremental fuel cost of unit i [$/Btu]
π_j^c / π_j^d	Charge/discharge cost of storage j [$/MWh]
ε	Confidence level of chance constraint
Δ	Real-time slot [hr]

2.2 Multi-timescale scheduling

The hybrid stochastic deterministic multi-timescale scheduling (SDMS) framework is comprised of two components interacting with each other; namely DASO and RTSO. The SDMS framework, advocated in this study, is illustrated in Fig. 1. In reality, the day-ahead wind prediction error could be large, whereas the real-time prediction error is insignificant, and mostly consists of small wind variations. Therefore, DASO is formulated as a chance-constrained scheduling problem to accommodate substantial wind and load uncertainty, while RTSO is expressed as pure deterministic problem to deal with the limited deviation between the hourly-ahead simulation and actual net demand. Specifically, system operators obtain energy supply from both conventional and wind generation, and manage the demand of energy users via day-ahead and real-time scheduling respectively. Conventional generation, in order, is drawn from two sources: base-load generators (e.g., nuclear and hydro units) and fast-start generators (gas turbines). Energy supply procurement is performed in two stages, i.e., day-ahead and real-time scheduling, at different timescales.

In day-ahead scheduling, which runs every 24 h, at 1-hour time resolution, with prediction information of wind generation and traditional energy user demand, system operator decides on the generation scheduling for the next day. The real-time or hourly-ahead online rolling scheduling is performed every 1-hour, to determine the generation output of all units in the upcoming 3-hours, with a time resolution of 15-min. Fig. 2 shows the day-
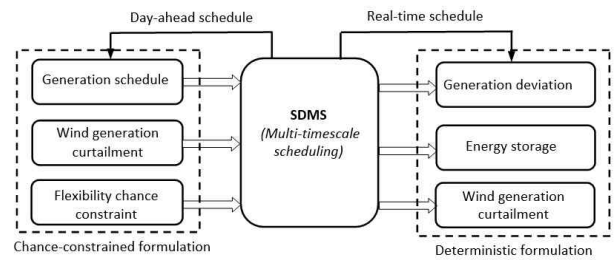

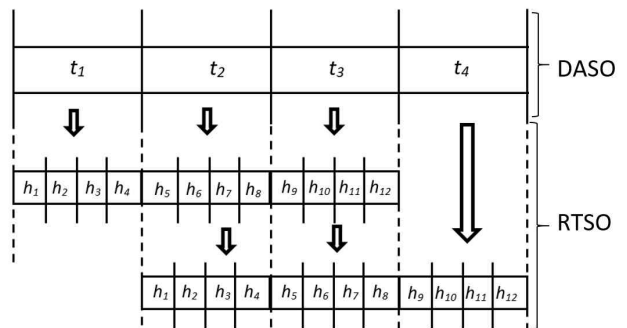**Fig. 1.** Stochastic determinstic multi-timescale scheduling (SDMS) framework

Fig. 2. Scheduling horizon and timescales

ahead hour t_1 to t_3 DASO results, to be used as real-time scheduling based results, for 12 intra-hour intervals h_1 to h_{12}. The combination of t_2 and t_3 hour intervals with the DASO t_4 schedule are used for the next online rolling real-time scheduling. The process continues throughout the day.

Upon realization of wind generation and demand, SDMS will re-dispatch real-time generation based on the simulated DASO results, to close the deviation gap between demand and supply. The utilization of DASO results, which include scheduled generation and the on/off status, reduces the search space of the real-time problem formulation. It, therefore, becomes amenable to be cast in a deterministic form, to further reduce the computational requirements. Energy storage is implemented to balance out the large deviation gap, as well as to avoid wind curtailment. It is worth noting that the above framework, which consists of day-ahead and real-time scheduling, is developed based on the state-of-the-art scheduling schemes of power system market [1].

3. Day-Ahead Scheduling Optimization (DASO)

The first component of the SDMS framework is the day-ahead scheduling optimization (DASO). DASO is a chance-constrained optimization problem that models the flexibility of conventional generation as a chance constraint, with wind power availability and load demand uncertainty. The details of the DASO formulation are given as:

$$\min \sum_{i,t} \left[C_{gen,it} + C_{startup,it} \right] \quad \forall i,t \tag{1}$$

s.t.

$$C_{gen,it} = G_{it} * Hr_i * \pi_i^{gen} \quad \forall i,t \tag{2}$$

$$C_{startup,it} \geq 0 \quad \forall i,t \tag{3}$$

$$C_{startup,it} \geq SU_{il} \left[I_{it} - \sum_{n=1}^{l} I_i(l-n) \right] \quad \forall l,i,t \tag{4}$$

$$W_t^0 + \sum_i G_{it} = D_t^{total}, \quad \forall i,t \tag{5}$$

$$\overline{D}_t^{net} = \sum_i G_{it}, \quad \forall i,t \tag{6}$$

$$\Pr\left(-\sum_i flex_{it}^{dn} \leq NDR_{st} \leq \sum_i flex_{it}^{up} \right) \geq 1-\varepsilon, \ \forall s,i,t \tag{7}$$

$$NDR_{st} = D_{s(t+1)}^{net} - \overline{D}_t^{net}, \quad \forall s,t \tag{8}$$

$$flex_{it}^{up} = flex_{it}^{on,up} + flex_{it}^{off,up}, \quad \forall i,t \tag{9}$$

$$flex_{it}^{on,up} = \min\left(r_i^{up}, G_{it}^{max} - G_{it} \right) * I_{it}, \quad \forall i,t \tag{10}$$

$$flex_{it}^{off,up} = \min\left(r_i^{up}, G_{it}^{max} \right) * \left(1 - I_{it} \right) * A_{it}^{on}, \quad \forall i,t \tag{11}$$

$$flex_{it}^{dn} = \min\left(r_i^{dn}, G_{it} - \left(G_{it}^{min} * \left(1 - A_{it}^{off} \right) \right) \right) * I_{it}, \quad \forall i,t \tag{12}$$

$$\sum_{i=1}^{NG} G_{it}^{max} * I_{it} \geq D_t^{total} + SR_t, \quad \forall i,t \tag{13}$$

$$G_{it} - G_{i(t-i)} \leq r_i^{up}, \quad \forall i,t \tag{14}$$

$$G_{i(t-1)} - G_{it} \leq r_i^{dn}, \quad \forall i,t \tag{15}$$

$$-I_{i(t-1)} + I_{it} - I_k \leq 0, \quad (1 \leq k-(t-1) \leq T_i^{on}), \forall i,k,t \tag{16}$$

$$I_{i(t-1)} - I_{it} + I_k \leq 1, \quad (1 \leq k-(t-1) \leq T_i^{off}), \forall i,k,t \tag{17}$$

$$G_{it}^{min} * I_{it} \leq G_{it} \leq G_{it}^{max} * I_{it}, \quad \forall i,t \tag{18}$$

The objective function (1) consists of electricity production fuel cost (2), and startup cost (3) - (4), over a 24-hour scheduling horizon. The hourly scheduling constraints listed above denote the following:

- Eq. (5) is the system power balance constraint;
- Eq. (6) is the hourly power balance between expected value of net demand and scheduled generation;
- Eq. (7) entails that the probability of net demand ramp (NDR) remains within the up and down flexibility limits. In other words, generation ramping and reserve capability should be greater than or equal to a threshold value $1-\varepsilon$;
- Eq. (8) is the NDR formulation, defined as the difference between discrete realizations of the net demand at hour $t+1$ and expected value of the net demand at hour t;
- Eq. (9)-(12) define the up and down flexibility indices [18];
- Eq. (13)-(18) consist of system spinning reserve requirement, unit ramping up and ramping down limits, unit minimum on/off time limit, and unit maximum/minimum generation limits.

The nonlinear production cost of thermal generating units is approximated by a piecewise linear function. A stair-wise startup cost function (3) – (4) is implemented to discretize the startup cost formulation [23]. By replacing constraints (7) and (10) through (12) with equivalent linear forms, the proposed formulation can be expressed in the MILP form. Details of the linearization can be found in [22], and [24].

Big-M formulation [22, 24], is a conventional linearization technique used to transform (7) into a discrete linear formulation as:

$$\sum_i flex_{it,l}^{dn} + D_{s(t+1),l}^{net} - \overline{D}_{st,l}^{net} + z_{st,l} M \geq 0 \tag{19}$$

$$\sum_i flex_{it,l}^{up} - D_{s(t+1),l}^{net} + \overline{D}_{st,l}^{net} + z_{st,l} M \geq 0 \tag{20}$$

$$\sum_s z_{st,l} p_{s(t+1),l}^{net} \leq \varepsilon \tag{21}$$

where M is a very large positive number.

A computationally efficient extended formulation for linearizing the chance constraint (7) is proposed to solve the DASO [16]. The extended formulation is expressed by adding the star-inequalities, as described below:

$$\sum_i flex_{it,m}^{dn} - \overline{D}_{t,m}^{net}$$

$$+\sum_{s=1}^{S-1} u_{st,m}\left(D_{s(t+1),m}^{net} - D_{s+1(t+1),m}^{net}\right) \geq -D_{1(t+1),m}^{net}, \quad \forall i,s,t,m \tag{22}$$

$$\sum_i flex_{it,m}^{up} + \overline{D}_{t,m}^{net}$$

$$+\sum_{s=1}^{S-1} u_{st,m}\left(D_{s(t+1),m}^{net} - D_{s+1(t+1),m}^{net}\right) \geq D_{1(t+1),m}^{net}, \quad \forall i,s,t,m \tag{23}$$

$$u_{st,m} - u_{(s+1)t,m} \geq 0, \quad \forall s,t,m \tag{24}$$

$$z_{st,m} - u_{st,m} \geq 0, \quad \forall s,t,m \tag{25}$$

$$u_{st,m} = 0, \quad \forall s,t,m \tag{26}$$

$$\sum_s z_{st,m} p_{st,m}^{net} \leq \varepsilon, \quad \forall s,t,m \tag{27}$$

$$0 \leq x_{st,m} \leq z_{st,m}, \quad \forall s,t,m \tag{28}$$

$$0 \leq p_{st,m}^{net} - x_{st,m} \leq 1 - z_{st,m}, \quad \forall s,t,m \tag{29}$$

Since the extended formulation requires the discrete realization to be arranged in descending form, without loss of generality, net demand is arranged in descending format for (22), and ascending format for (23).

4. Real-Time Scheduling Optimization (RTSO)

The second component of the SDMS framework is concerned with the real-time deterministic scheduling formulation of wind power generation. The main objective is to neutralize the deviations of the day-ahead predicted load demand and predicted wind generation with the more accurate real-time prediction data. The detailed formulation can be listed as follows:

$$\min \sum_{i,h} \Delta\pi_i^{gen} G_{ih} Hr_i + \sum_{j,h} \Delta\pi_j^c q_{jh}^c + \Delta\pi_j^d q_{jh}^d \quad \forall i,j,h \tag{30}$$

s.t.

$$\sum_i dG_{ih} - \Delta q_{jh}^c + \Delta q_{jh}^d = D_h^{total} - G_h^W - G_{ih}^{sch}, \quad \forall i,j,h \tag{31}$$

$$dG_{ih} \geq \max\left(G_{ih}^{\min} I_{ih} - G_{ih}^{Sch}, G_{ih} - G_{ih}^{Sch} - \overline{dG}_{ih}\right), \quad \forall i,h \tag{32}$$

$$dG_{ih} \leq \min\left(G_{ih}^{\max} I_{ih} - G_{ih}^{Sch}, G_{ih} - G_{ih}^{Sch} + \overline{dG}_{ih}\right), \quad \forall i,h \tag{33}$$

$$\left(G_{ih} + dG_{ih}\right) - \left(G_{i(h-1)} + dG_{i(h-1)}\right) \leq \Delta r_i^{up}, \quad \forall i,h \tag{34}$$

$$\left(G_{i(h-1)} + dG_{i(h-1)}\right) - \left(G_{ih} + dG_{ih}\right) \leq \Delta r_i^{dn}, \quad \forall i,h \tag{35}$$

$$G_{ih}^{\min} * I_{ih} \leq G_{ih} + dG_{ih} \leq G_{ih}^{\max} * I_{ih}, \quad \forall i,h \tag{36}$$

$$q_{jh}^{\min,c}\left(1 - J_{jh}\right) \leq \Delta q_{jh}^c \leq q_{jh}^{\max,c}\left(1 - J_{jh}\right), \quad \forall j,h \tag{37}$$

$$q_{jh}^{\min,d} J_{jh} \leq \Delta q_{jh}^d \leq q_{jh}^{\max,d} J_{jh}, \quad \forall j,h \tag{38}$$

$$e_{jh} = e_{j,h-1} + \Delta\left[\eta_j^c q_{jh}^c - \frac{1}{\eta_j^d} q_{jh}^d\right]\frac{1}{e_j^{\max}}, \quad \forall j,h \tag{39}$$

$$\frac{e_j^{\min}}{e_j^{\max}} \leq e_{jh} \leq 1, \quad \forall j,h \tag{40}$$

$$e_{j,0} = e_{j,H} = E_j^0, \quad \forall j,h \tag{41}$$

$$e_{jh}^{dn} \leq e_{jh} \leq e_{jh}^{up}, \quad \forall j,h \tag{42}$$

The objective function (30) consists of electricity production fuel cost, and energy storage charging/discharging cost over a 3-hour online rolling scheduling horizon. Each hour is divided into four intervals, 15 minutes each. The hourly scheduling constraints can be described as:
- Eq. (31) is the system power balance constraint, to ensure that generation deviation and energy storage charging or discharging should be equal to the total deviation between the current and former net demand;
- Eq. (32) and (33) are the generation deviation constraints;
- Eq. (34) and (35) are the ramp up and ramp down limits;
- Eq. (36) is the maximum/minimum generation limits;
- Eq. (37) and (38) are the upper and lower bounds of charging and discharging constraints for energy storage;
- Eq. (39) is the state of charge (SOC) constraint;
- Eq. (40) is the maximum and minimum SOC limit;
- Eq. (41) suggests that the SOC at the initial and at the last period (h = NH) should be the same; while (42) limits the SOC within upper and lower bounds. These bounds are called cone shape constraints, and will be explained in the next subsection.

4.1 Cone shape constraints

To ensure that the initial and the last hour SOC are equal to a predetermined value(s), and the energy storage SOC follows a daily cycle, a storage SOC constraint is imposed [17, 19]. In SDMS, energy storage is implemented in the RTSO. To achieve the same energy storage SOC daily cycle, the cone shaped constraint is proposed. The cone-shaped constraint, Fig. 3, gives full freedom to the energy storage to ramp-up or ramp-down in the initial hours of the day. After a preset time, (e.g. 12 hours) the maximum and minimum SOC limits starts to shrink and this continues until it reaches the daily cycle initial SOC level, which is set to 50% SOC in the SDMS framework.
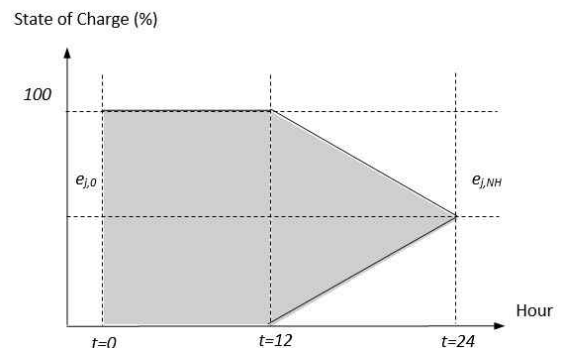

Fig. 3. Cone shape energy storage state of charge constraint

5. Case Studies

The proposed SDMS framework is applied to the IEEE Reliability Test System RTS-96; that consists of 24 buses and 32 generating units [25]. The U400 nuclear units and U50 hydro units are assumed to be always ON for simplicity. The coal-fired plant U350 is closed down and replaced by 800 MW and 1600 MW wind generation (25% and 50% penetration level) [22]. The load demand of the first day of the year is utilized. We have considered a horizon of 24 hours, each hour is divided into 4 periods of 15 min each to represent the real time, i.e., $\Delta = 1/4$. For the sake of simplicity, we have considered two equal energy storage units, with 800 MWh capacity each. The initial energy level of the storage units is set to 50% of their capacities (400 MWh). The maximum and minimum limits for power charging or discharging are both 400 MW. The cost of charging or discharging in the storage unit is $0.5/MWh and $0.1/MWh, respectively. The efficiency rates are set to 90% [17].

5.1 Wind generation and load prediction errors

For DASO, the day-ahead load prediction error is assumed to be following a normal distribution with zero mean value. Its standard deviation is 2% of the daily peak load. The hourly day-ahead wind power prediction is simulated by a time series autoregressive moving average (ARMA) forecast model, with mean average error up to 16%, based on hourly wind measurements for the province of Ontario, Canada [26]. The hourly wind power prediction is fitted into a probability density function (PDF) with generalized extreme value distribution for low predicted wind power (< 0.3 p.u.). Beta distribution is used to fit the remaining wind power prediction [22]. Fig. 4 illustrates the PDF for several levels of wind power forecast. The PDFs are converted into 19 discrete level PDF, with 0.05 p.u., or 40 MW sampling rate.

For the RTSO, the real-time load and wind generation data are assumed to be perfectly predicted for the first hour and the ARMA forecast model is applied for the second
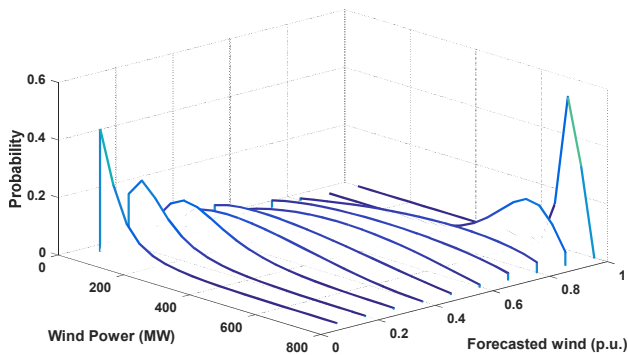
and third hour-ahead simulation. The maximum deviation limit is set to 15% of maximum generation for each generator.

We have chosen a day where the deviation of wind is considerable, with a mixture of under-prediction and over-prediction of wind generation, as the case study in this paper. The predicted and actual wind generation and load demand curves across 24 hours are illustrated in Fig. 5, and the resultant net demand curve is shown in Fig. 6. The actual net demand curve is captured after the end of the day. Fig. 6 shows the amount of deviation between day-ahead prediction and real-time actual data. The sizeable deviation in 5th hour (about 400 MW) will require energy storage to compensate for the shortfall, since conventional generation are constrained not to exceed 15% deviation from the day-ahead generation scheduling results. The SDMS framework will update the net demand prediction every hour in the RTSO with 3 hour-ahead prediction, thus the deviation will be gradually reduced in each iteration to be countered by conventional generation ramp as well as the energy storage.

The resulting mixed-integer optimization problems, are coded in C++ and solved using CPLEX 12.6 optimization package, on a computer with Intel Core i5 3.20 GHz and 10 GB memory.

5.2 Numerical results

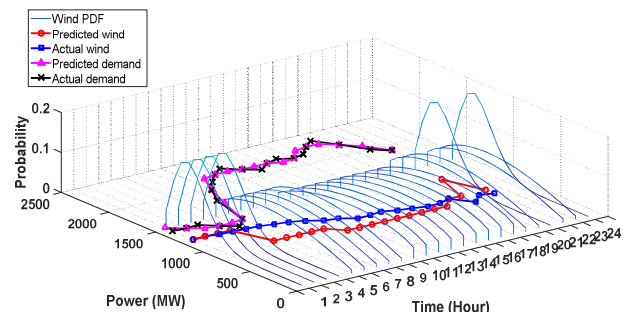The proposed SDMS framework is implemented on

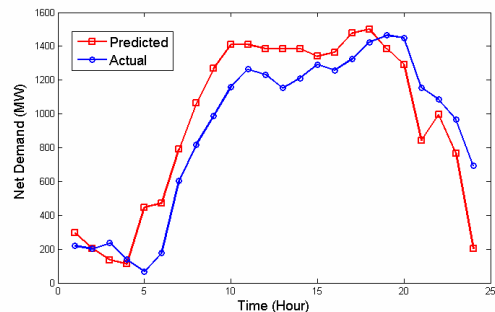**Fig. 5.** Predicted vs. actual wind generation and load demand for day-ahead, with 50% wind penetration.

Fig. 6. Predicted day-ahead net demand vs. real-time actual net demand, with 50% wind penetration

Fig. 4. Probabilistic density function for various levels of wind power forecast

Table 1. Results for the RTS-96 in the DASO with Various Wind Penetration

Wind (%)	1-ε (%)	Prod. Cost ($)	Wind Curt. (%)	Flex-up (MW)	Flex-dn (MW)	Comp. Time	
						Ext. (sec)	Big-M (sec)
0	-	**369,580**	-	-	-	5.03	
25	95	215,160	0.00	20,513	19,930	**28.31**	38.83
	80	215,160	0.00	20,513	19,930	**27.44**	37.22
	50	215,160	0.00	20,513	19,930	**22.14**	33.31
	30	215,160	0.00	20,513	19,930	**16.00**	27.63
50	95	123,235	12.35	23,228	13,849	366.58	**533.94**
	80	122,153	11.74	23,297	13,706	274.41	**337.33**
	50	122,009	11.63	23,407	13,784	184.83	**212.95**
	30	121,928	11.55	24,372	12,389	176.75	**210.84**

Table 2. Results for the RTS-96 in the RTSO

Wind (%)	Prod. Cost ($)	ES Cost ($)	Total Cost ($)	Wind Curt. (%)	Time (s)
0	**368,892**	-	**368,892**	-	2.84
25	**210,441**	566	211,007	**0.00**	**2.45**
50	**111,651**	762	112,413	**0.00**	**2.31**

multiple test cases to verify the effectiveness and robustness of the multi-timescale scheduling model. Four test cases are considered: 1) DASO base case with thermal units only. 2) Impact of increasing wind penetration level on DASO thermal unit operation. 3) Effect of increasing confidence levels of the chance constraint in DASO. 4) DASO and RTSO results are contrasted and discussed.

Case 1. The base case is run without wind generation, to provide a comparison platform for other test cases. As shown in Table 1, the day-ahead production cost is $369,580 which includes $366,996 fuel cost, and $2584 start-up cost.

Case 2. Optimality gap value of 0.05% and various reliability levels, 1-ε, are set for the chance-constrained DASO. An Optimality gap defines the gap or difference between the upper bound and lower bound of the simulation results, while a reliability level defines the probability that the flexibility chance constraints are enforced on the proposed problem.

Table 2 clearly indicates there is a substantial decrease in total production cost, when a higher level of wind penetration is implemented. The production cost drops to $215,160 and $123,235 for 25% and 50% wind penetration with 95% confidence level respectively. Wind curtailment occurs in case of 50% wind penetration, because of the insufficient grid flexibility from thermal generation. Whereas upward flexibility has increased, downward flexibility has decreased when wind penetration level increases from 25% to 50%; reflecting the effect of less conventional generation commitment, along with higher wind penetration.

Case 3. In this test case, the confidence level of the proposed flexibility based chance constraint is set to various percentage levels, to verify the effect of the flexibility requirement on the DASO generation scheduling. The chance constraints in the DASO are dealing with discrete and finite distribution of the net load, which can be

theoretically solved to optimality, by utilizing a linearization approach. Therefore, both linearization approaches, the Big-M and the proposed extended formulation, precisely linearize the chance constraint, without utilizing any approximation throughout the process. In addition, the same MILP solver, CPLEX, is employed, which ensures both approaches converge to the same scheduling results. At 25% wind penetration level, all confidence levels came out with the same results and zero wind curtailment. This implies that the chance constraint is redundant in this case and the power system has adequate flexibility. Moreover, results also corroborate that current system operation practices are still efficient enough to cope with the variability and uncertainty from low penetration levels of variable renewable generation. In case of the higher 50% wind penetration level, as the confidence level increases, indicating a stiffer flexibility requirement, the production cost increases. This is mainly due to the increase in wind curtailment, as the system has insufficient downward flexibility. Additionally, the decrease of upward flexibility, and increase of downward flexibility, shown in 50% wind penetration level in Table 1, as confidence level increases, further enlarges the production cost. The rise of production cost is attributed to the opportunity cost involved when expensive generation is scaled up to provide for the downward flexibility.

Case 4. DASO deterministic result (no wind) and the result with 95% confidence level, in Table I, are chosen as the base input for the RTSO. The optimality gap for the RTSO is set to 0.01%. DASO and RTSO results for 0% wind are $369,580 and $368,892 respectively. The minor cost variations are mainly due to load demand forecast error. On the other hand, the DASO and RTSO results for 50% wind penetration are $123,235 and $111,651. The lower cost of real-time scheduling is mainly due to the lower values of actual net demand in real-time as compared to the day-ahead predicted net demand, as depicted in Fig. 6. 12.35% of wind is curtailed for 50% wind penetration in the DASO, whereas there is no wind curtailment in the RTSO case. This is due to the flexibility provided by the energy storage to counter the deviation, as well as the variability of wind generation. In addition, the computation time required by the DASO is 366 seconds, whereas for the
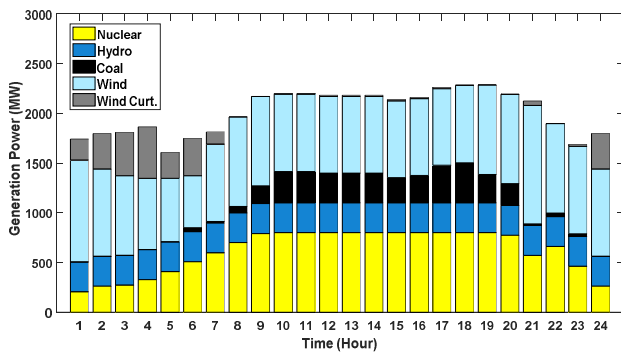
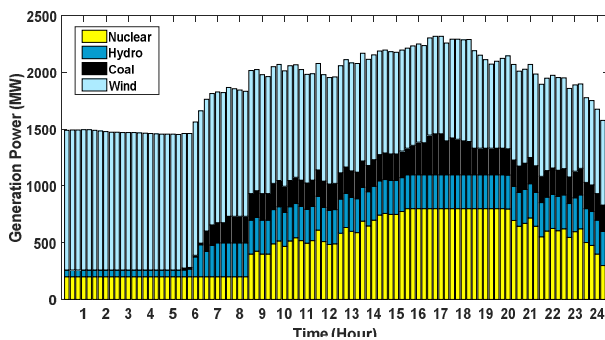**Fig. 7.** Day-ahead generation, for 50% wind penetration

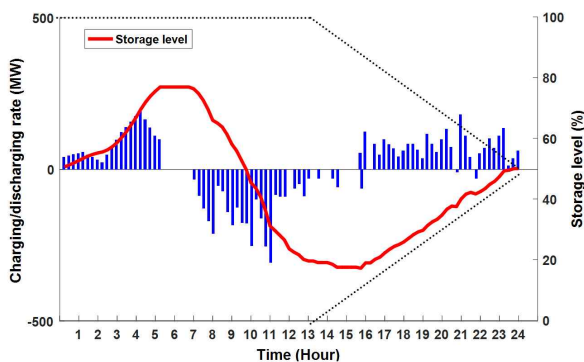**Fig. 8.** Real-time generation, for 50% wind penetration

Fig. 9. Energy storage charging and discharging rate vs. storage percentage level for RTSO, for 50% wind penetration

RTSO, it takes about 2.5 seconds only.

Detailed generation amount of each type of conventional generation, as well as the wind generation and curtailment, for 50% wind penetration, are illustrated in Fig. 7. In the selected case study, wind generation is significant throughout the day, therefore, wind curtailments occur to ensure the power system has enough flexibility from conventional generation ramping and reserve to cope with the net demand ramp (NDR). Furthermore, Fig. 8 depicts the generation mix of the RTSO, for 50% wind penetration. Due to the inclusion of energy storage to provide extra flexibility to the power system, wind curtailment did not occur. Essentially, the total conventional generation from

nuclear, hydro and coal generation should match the actual net demand curve as shown in Fig. 6. However, the curve in Fig. 8 shows some distortion and peaks. These are actually the effects of energy charging or discharging of energy storage, as clearly illustrated in Fig. 9.

Fig. 9 also includes energy storage percentage level across the 24-hours simulation. The dotted line shows the cone shape constraint implemented. It shows that energy storage size may be reduced, while it is still able to provide enough flexibility. Nonetheless, sizing of the energy storage is beyond the scope of this paper, and will be discussed in a future publication.

6. Conclusions

A new tool, called SDMS, is introduced in this paper, to schedule generators in a grid system, with high proportions of wind generation, in multiple timescales. The flexibility representation of conventional generation is pinned down to a nonlinear chance constraint inculcated in SDMS's DASO or day-ahead formulation. The chance constraint is linearized to maintain the computational tractability of the proposed DASO component of the SDMS model. RTSO or the SDMS'S component of the real-time rolling scheduling includes energy storage to provide another level of flexibility to balance out the deviations caused by net demand prediction error. RTSO also utilizes the day-ahead stochastic results, to further reduce the search space and the computational requirements of the proposed SDMS framework. Results show the robustness of the proposed framework in managing the generation scheduling, despite the high intermittency of wind generation. It also managed to reduce wind curtailment and compensate for large wind prediction errors, with the extra flexibility acquired from the energy storage.

Acknowledgements

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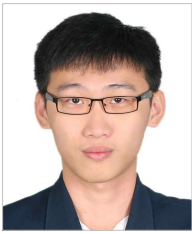
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