A Novel Approach for Multi-Area Power System Day-ahead Scheduling under Uncertainties

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***Abstract*—The uncertainties of renewable energy and load demand challenge the short-term operation of power system. Although robust unit commitment has been extensively studied, we propose a novel approach for day-ahead scheduling in multi-area power system, which is in compliance with the operation pattern of hierarchically-organized system operators such as in China. The problem is formulated as a two-stage robust optimization, in which the first-stage problem minimizes a quadratic function to decide an interval of daily generation, and the second-stage problem works out generation and transmission power profiles while guaranteeing the robust feasibility of the pre-decision with regard to any realization within the uncertainty set. Column-and-constraint generation method are adopted in the solution procedure. We carry out numeric experiment based on China Southern Grid, after which the performance of our algorithm is assessed, and the effectiveness and feasibility of the proposed approach are verified.**

***Index Terms*—Day-ahead power scheduling, interval, multi-area, renewable energy, robust optimization.**

NOMENCLATURE

A. Deterministic Parameters

$\mathcal{S}$ Set of indices of sending-end power systems.
$\mathcal{R}$ Set of indices of receiving-end power systems.
$\mathcal{T}$ Set of indices of scheduling intervals.
N_S Number of sending-end power systems.
N_R Number of receiving-end power systems.
N_T Number of scheduling interval (15 min/ interval).
ω_i Weighting factor which is inversely proportional to the load demand level.
ε The daily energy trading error that is permitted.
E_i^{N} Daily energy trading plan of area i.
$\bar{p}_{Ri,t}$ Predicted renewable generation of area i at period t.
$\bar{p}_{Li,t}$ Predicted load demand of area i at period t.

B. Deterministic Decision Variables

$p_{Gi,t}^{\min}$ Lower bound of generation interval.
$p_{Gi,t}^{\max}$ Upper bound of generation interval.
$p_{Gi,t}$ Generation power of area i at period t.
$p_{Ti,t}$ Net transmission power of area i at period t.
$r_{Gi,t}^{\pm}$ 15-minute up/down-regulation reserve.

C. Uncertain Parameters and Variables

$\mathcal{A}$ Set of indices of uncertain power injection types including renewable generation and load demand.
$\mathcal{U}$ The budgeted uncertainty set.
$u_{\alpha i,t}$ Possible power injection of type α uncertain parameter of area i at period t.
$\Gamma_{\alpha t}$ Budget parameter for type α uncertain parameter of area i at period t.

I. INTRODUCTION

Integration of renewable energy resources has been dramatically increased due to its advantages in saving fossil fuels and environment protection. The installed capacity of renewable energy has reached 171.48 GW by the year of 2015 in China, ranked first in the world [1]. However, the uncertainty and fluctuation of very high penetration renewables bring great challenges to the balance between generation and load, as well as the economic operation of the power system.

Take Yunnan province of China Southern Grid (CSG) as an example, in 2016 the installed capacity of renewable energy was more than 18% of its total capacity, of which 85% was wind power. Despite sharing an annual incremental installed capacity of 1,613 MW, 4.17% of the wind power in Yunnan Power Grid, namely 641,000 GWh was discarded, and the environmental cost has reached up to 14.7 million dollars. In addition to the uncertainty of renewable generation, the uncertainty of load demand appeals to more operation reserve, more generation adjustment which results in lower economic efficiency and less reliability of the system.

In China, several provincial power grids are interconnected to form a large-scale regional power grid. One of the task of the interconnection is to transfer power energy from resource center to load center according to trade contract [2], and the other objective is to save operation cost by taking advantage of the complementarity of load characteristics and the geographical dispersion of renewable generation [3]. Novel approach for operation optimization which is able to consider uncertainties, and more importantly in line with the dispatching and operating mechanism, is essential for interconnected power systems.

Multiarea power system robust scheduling has been concerned about in some literatures. In [4], a decentralized robust optimization approach is proposed to jointly schedule the hourly commitment of generation and tie-line interchanges considering the limitations on private data exchange and model management. [5] optimizes tie-line power flows across

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areas that are independently operated by different system operators using multi-parametric linear programming, which allows privacy reservation as well global optimization. However, both of the methods need a central coordinator and the procedures are not straightforward (need iterations).

It is observed that if the interarea power transmission plan is discordant with the load demand of an area, its generation needs to adjust repetitively and even inversely with the load variance, the burden of its peak load regulation gets increased as well. The objective of multiarea power scheduling can simply be smoothing the daily generation curve, which can be obtained by minimizing the standard deviation of the daily generation series [6]. Because, intuitively the start-up cost and regulation cost of its thermal units can be reduced if the output level is steady, or ideally a straight line. Another motivation to choose this objective is that when the scheduled generation is plain, more regulation resources are left to handle uncertainty.

Hence, in the multiarea power system power scheduling frame, one alternative approach is to decide a near-optimal interarea 15-minute power transmission plan based on the nominal condition, and set the interval of generation for each area which is immune to uncertainty. The generation interval could be adopted as boundary information when area are carrying out UC/ED.

In this paper, we propose a two-stage optimization model for the multiarea power system robust scheduling (MARS) problem, where the first-stage problem gives a decision of generation interval, and the second-stage problem is for robust feasibility checking. Interarea power transmission decision on the nominal condition can also be obtained by solving the problem. Only limited data is required to formulate the model. MARS is quite different from classic model in terms of the objective function and the equivalence process for an area. The main contributions of our paper are summarized as below.

1) We formulate a novel model for multiarea power system day-ahead power scheduling on the background of China's regional power grid, in which the objective is a quadratic function used to seek smooth generation profile and compact generation interval. Furthermore, we investigate its uncertainty form (the MARS problem) through a two-stage robust optimization model.
2) We conduct numerical experiments on a real world regional power system combined with four provincial power grids. We study the performance of our algorithm and verify its efficiency. Comparison of the economic efficiency and robustness between results of MARS and that of current practice is presented.

The paper is organized as follows. Section II proposes a deterministic multiarea scheduling model. Section III develops the multiarea robust scheduling model and present the numerical algorithm. Test results on China Southern Grid are presented in Section IV. Section V concludes with discussions.

II. Deterministic Multiarea Scheduling Model

For dispatching center of a regional power grid, it is not necessary to work out UC. Instead, it should formulate a reasonable day-ahead power exchange plan, to ensure the execution of daily contract and allow economic operation of provincial power grids. For each provincial power grid, the following equality holds,

$$\boldsymbol{P}_{generation} + \boldsymbol{P}_{renewables} = \boldsymbol{P}_{demand} + \boldsymbol{P}_{transaction} \qquad (1)$$

where $\boldsymbol{P}_{generation}$, $\boldsymbol{P}_{renewables}$, $\boldsymbol{P}_{demand}$ and $\boldsymbol{P}_{transaction}$ are $N_T \times 1$ vectors. $\boldsymbol{P}_{generation}$ is the dispatchable generation without the proportion of renewables. $\boldsymbol{P}_{transaction}$ is the net transaction power of an area. When $\boldsymbol{P}_{demand}$ and $\boldsymbol{P}_{renewables}$ are settled as predicted values, $\boldsymbol{P}_{generation}$ can be optimized by adjusting $\boldsymbol{P}_{transaction}$. We choose minimizing the standard deviation of daily generation series as the common objective of each area.

Before UC is carried out, the on/off status of generators remain unknown, and thus the generation capacity is unsettled. To tackle this problem, two types of decision variables indicating the interval of generation are introduced. The variances of generation series are then minimized in the objective function. It is obviously that if the generation profile is smooth and the interval is compact, less units should be turned on or shut off during the day, less reserves are required, and therefore operation cost can be saved.

The basic model for multiarea power system day-ahead power scheduling can be formulated as the following deterministic optimization:

$$\min_{p_G, p_T, r_G, p_G^{\max}, p_G^{\min}} \sum_{i \in \mathcal{R} \cup \mathcal{S}} \sum_{t \in \mathcal{T}} \omega_i [(p_{Gi,t} - \overline{p}_{Gi})^2 + (p_{Gi,t}^{\max} - \overline{p}_{Gi})^2 + (p_{Gi,t}^{\min} - \overline{p}_{Gi})^2] \qquad (2a)$$

$$\text{s.t.} \quad p_{Gi,t} + \overline{p}_{Ri,t} - p_{Ti,t} - \overline{p}_{Li,t} = 0, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \in \mathcal{T} \qquad (2b)$$

$$\sum_{i \in \mathcal{R} \cup \mathcal{S}} p_{Ti,t} = 0 \qquad (2c)$$

$$(1-\varepsilon) E_i^{\mathrm{N}} \le 24 / N_T \sum_{t \in \mathcal{T}} \left| p_{Ti,t} \right| \le (1+\varepsilon) E_i^{\mathrm{N}}, \ \ \forall i \in \mathcal{R} \cup \mathcal{S} \qquad (2d)$$

$$P_{Ti}^{\min} \le p_{Ti,t} \le P_{Ti}^{\max}, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \in \mathcal{T} \qquad (2e)$$

$$-r_{Gi,t}^{-} \le p_{Gi,(t+1)} - p_{Gi,t} \le r_{Gi,t}^{+}, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \& t+1 \in \mathcal{T} \qquad (2f)$$

$$r_{Gi,t}^{+}, r_{Gi,t}^{-} \ge 0, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \in \mathcal{T} \qquad (2g)$$

$$p_{Gi,t}^{\min} + r_{Gi,t}^{-} \le p_{Gi,t} \le p_{Gi,t}^{\max} - r_{Gi,t}^{+}, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \in \mathcal{T} \qquad (2h)$$

$$P_{Gi}^{\min} \le p_{Gi,t}^{\min} \le p_{Gi,t}^{\max} \le P_{Gi}^{\max}, \ \ \forall i \in \mathcal{R} \cup \mathcal{S}, \ t \in \mathcal{T} \qquad (2i)$$

In the objective function (2a), $\bar{P}_{Gi} = \sum_{t \in T} P_{Gi,t} / N_T$, represents the average output level of area i during the day. (2b) is the power balance condition for each area, (2c) is the power balance condition for total power exchange. (2d) is the energy trading constraint. (2e) is transmission capacity limit. (2f)-(2g) are ramping rate limits. (2h) is constraint on generation, in which $P_{Gi}^{\max}$ is the installed capacity excluding maintenance capacity, and $P_{Gi}^{\min}$ is the minimum production level of must-on units.

We set the scheduling interval as 15 minutes considering the fact that the transmission plan is at the 15-minute level, and we can also recall that it is within the tertiary regulation interval. In (2h), the 15-minute operation reserve is defined and then associated with ramping limit according to (2f), which means that the reserve can be dispatched at the current period is equivalent to the maximum ramping rate. In power system operation, this kind of reserve is supplied mainly by spinning reserve and quick-start units such as gas turbine units, hydro units and pumped-storage units.

In the above deterministic model (2), renewable generation and load demand are presumed to be accurately forecasted, and this deterministic model is a particular case of the robust model developed in Section III.

Model (2) is a QP, and its compact matrix formulation is as follows:

$$\min_{\boldsymbol{x},\,\boldsymbol{y}} \boldsymbol{x}^{\mathrm{T}}\boldsymbol{Q}_1\boldsymbol{x} + \boldsymbol{f}_1^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{y}^{\mathrm{T}}\boldsymbol{Q}_2\boldsymbol{y} + \boldsymbol{f}_2^{\mathrm{T}}\boldsymbol{y} \tag{3a}$$

$$\text{s.t. } \boldsymbol{Gx} \le \boldsymbol{g} \tag{3b}$$

$$\boldsymbol{Hy} \le \boldsymbol{h} \tag{3c}$$

$$\boldsymbol{Ax} + \boldsymbol{By} \le \boldsymbol{0} \tag{3d}$$

$$\boldsymbol{Cu} + \boldsymbol{Dy} = \boldsymbol{0} \tag{3e}$$

where $\boldsymbol{x}, \boldsymbol{y}$ are vectors of decision variables defined as below according to model (2), and $\boldsymbol{u}$ is the vector of parameters acquired from day-ahead power forecast.

$$\begin{cases} \boldsymbol{x} = \{p_{Gi,t}^{\max},\ p_{Gi,t}^{\min},\ \ \forall i \in \mathcal{R} \cup \mathcal{S},\ t \in \mathcal{T}\} \\ \boldsymbol{y} = \{p_{Gi,t},\ r_{Gi,t}^{+},\ r_{Gi,t}^{-},\ p_{Ti,t},\ \ \forall i \in \mathcal{R} \cup \mathcal{S},\ t \in \mathcal{T}\} \\ \boldsymbol{u} = \{p_{Ri,t},\ p_{Li,t},\ \ \forall i \in \mathcal{R} \cup \mathcal{S},\ t \in \mathcal{T}\}. \end{cases}$$

Decision variables and parameters are classified in such way in order to furtherly develop an uncertainty model.

III. Two-Stage Multiarea Robust Scheduling Model Formulation

The first step to build a robust model is to defined an uncertainty set. In our paper, the typical budget set is adopted to generate an uncertainty set [7].

$$\mathcal{U}(\bar{\boldsymbol{u}}, \boldsymbol{u}, \boldsymbol{\Gamma}) = \Big\{ \boldsymbol{u} \in \mathbb{R}_{+}^{2(N_S+N_R)\times N_T} \ \Big|\, u_{\alpha i,t} \in [\bar{u}_{\alpha i,t} - u_{\alpha i,t}, \bar{u}_{\alpha i,t} + u_{\alpha i,t}] \\ \textstyle\sum_{\forall i \in \mathcal{R}\cup\mathcal{S}} | u_{\alpha i,t} - \bar{u}_{\alpha i,t} | / u_{i,t} \le \Gamma_{\alpha t},\ \ \forall \alpha \in \mathcal{A},\ i \in \mathcal{R} \cup \mathcal{S},\ t \in \mathcal{T} \Big\}. \tag{4}$$

where $\bar{u}_{\alpha i,t}$ is the forecasting value of power injection type α of area i at period t ($\alpha = R$ for renewable generation and L for load demand), $\hat{u}_{\alpha i,t}$ is the deviation from the predicted value of area i at period t, $u_{\alpha i,t}$ can take any value from the range $[\bar{u}_{\alpha i,t} - \hat{u}_{\alpha i,t}, \bar{u}_{\alpha i,t} + \hat{u}_{\alpha i,t}]$. $\Gamma_{\alpha t}$ is the uncertainty budget of power injection type α at period t used to restrict the total deviation of power injection of all areas. A larger $\Gamma_{\alpha t}$ would enlarge the uncertainty set, and is therefore more conservative but less economic effective. Statistical analysis of historical data on renewable generation and load demand of the system we operate, gives us the knowledge that the error rate of power forecast (relative deviation from the predicted value) varies with areas, seasons, workdays or holidays, as well as periods of a day, which is meaningful for us to determine an appropriate value of $\Gamma_{\alpha t}$.

Based on model (3) and the uncertainty set, we sign $\boldsymbol{y}$ and $\boldsymbol{u}$ in model (3) as $\boldsymbol{y}_0$ and $\boldsymbol{u}_0$ and hereafter we can formulate the two-stage multiarea robust scheduling model as follows:

$$\min_{\boldsymbol{x},\,\boldsymbol{y}} \max_{\boldsymbol{u} \in \mathcal{U}} \boldsymbol{x}^{\mathrm{T}}\boldsymbol{Q}_1\boldsymbol{x} + \boldsymbol{f}_1^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{y}_0^{\mathrm{T}}\boldsymbol{Q}_2\boldsymbol{y}_0 + \boldsymbol{f}_2^{\mathrm{T}}\boldsymbol{y}_0 \tag{5a}$$

$$\text{s.t. } \boldsymbol{Gx} \le \boldsymbol{g} \tag{5b}$$

$$\boldsymbol{Hy}_0 \le \boldsymbol{h},\ \boldsymbol{Hy} \le \boldsymbol{h} \tag{5c}$$

$$\boldsymbol{Ax} + \boldsymbol{By}_0 \le \boldsymbol{0},\ \boldsymbol{Ax} + \boldsymbol{By} \le \boldsymbol{0} \tag{5d}$$

$$\boldsymbol{Cu}_0 + \boldsymbol{Dy}_0 = \boldsymbol{0},\ \boldsymbol{Cu} + \boldsymbol{Dy} = \boldsymbol{0}\ \ \forall \boldsymbol{u} \in \mathcal{U} \tag{5e}$$

The objective function takes the profit of first-stage decision and that of second-stage decision under nominal state into account. From (5d) and (5e), we can find that $\boldsymbol{y}$ is a function of $\boldsymbol{x}$ and $\boldsymbol{u}$, thus (5) can be recast in the following equivalent form:

$$\min_{\boldsymbol{x}} \max_{\boldsymbol{u} \in \mathcal{U}} \min_{\boldsymbol{y} \in \Omega(\boldsymbol{x},\boldsymbol{u})} \boldsymbol{x}^{\mathrm{T}}\boldsymbol{Q}_1\boldsymbol{x} + \boldsymbol{f}_1^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{y}_0^{\mathrm{T}}\boldsymbol{Q}_2\boldsymbol{y}_0 + \boldsymbol{f}_2^{\mathrm{T}}\boldsymbol{y}_0 \tag{6a}$$

$$\text{s.t. } \boldsymbol{x} \in \mathrm{X} \cap \mathrm{X}_R \tag{6b}$$

where $\mathrm{X} = \{\boldsymbol{x} \mid \boldsymbol{Gx} \le \boldsymbol{g},\ \boldsymbol{Hy}_0 \le \boldsymbol{h},\ \boldsymbol{Ax} + \boldsymbol{By}_0 \le \boldsymbol{0},\ \boldsymbol{Cu}_0 + \boldsymbol{Dy}_0 = \boldsymbol{0}\}$ is the inherent constraint of first-stage decision variable $\boldsymbol{x}$, and $\mathrm{X}_{\mathrm{R}} = \{\boldsymbol{x} | \forall \boldsymbol{u} \in \mathcal{U}, \Omega(\boldsymbol{x}, \boldsymbol{u}) \neq \emptyset\}$ is the robust feasible region of $\boldsymbol{x}$ in which $\Omega(\boldsymbol{x}, \boldsymbol{u})$ is the set of feasible scheduling solutions for any fixed first-stage decision and certain power injection realization, given as

$$\Omega(\boldsymbol{x}, \boldsymbol{u}) = \{\boldsymbol{y} \mid \boldsymbol{Hy} \le \boldsymbol{h},\ \boldsymbol{Ax} + \boldsymbol{By} \le \boldsymbol{0},\ \boldsymbol{Cu} + \boldsymbol{Dy} = \boldsymbol{0}\}. \tag{7}$$

From this formulation, we can see that the non-adjustable variables $\boldsymbol{x}$ take into account all possible values of uncertain parameters, thus for each realization of $\boldsymbol{u}$ within the uncertainty set, $\boldsymbol{y}$ is feasible, which means the generation interval is fully adaptive to the uncertain or variance of renewable energy and load demand.

To obtain the robust feasible region of $\boldsymbol{x}$, we can substitute the extreme points of the uncertainty set into the equality constraints without regard to its dimension. Unfortunately for our MARS model, the number of extreme points is large as $2^{2(N_S+N_R)\times N_T}$. One alternative method to solve the problem is to utilize merely some active critical scenarios identified from the second-stage problem, known as column-and-constraint generation method (C&CG) [8]. It has similar philosophy with that behinds critical-scenario method proposed or applied in [9], [10].

Next, the overall algorithm is presented. In the description, LB denotes the lower bound, UB denotes the upper bound, k is the counter of iterations and $\varepsilon (> 0)$ is an outer level convergence tolerance level.

Algorithm 1: Column-and-constraint Generation

Step 1 *Initialization.*

Set $LB = -\infty$, $UB = +\infty$ and $k = 0$.

Step 2 *Solving the outer minimizing problem.*

$$\min_{\boldsymbol{x}} \boldsymbol{x}^{\mathrm{T}}\boldsymbol{Q}_1\boldsymbol{x} + \boldsymbol{f}_1^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{y}_0^{\mathrm{T}}\boldsymbol{Q}_2\boldsymbol{y}_0 + \boldsymbol{f}_2^{\mathrm{T}}\boldsymbol{y}_0$$

$$\text{s.t. } \boldsymbol{Gx} \le \boldsymbol{g}$$

$$\boldsymbol{H}\boldsymbol{y}_l \le \boldsymbol{h},\ \ \forall l \le k$$
$$\boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y}_l \le \boldsymbol{0},\ \ \forall l \le k$$
$$\boldsymbol{C}\boldsymbol{u}_l^* + \boldsymbol{D}\boldsymbol{y}_l = \boldsymbol{0},\ \ \forall l \le k$$

Derive an optimal solution $\tilde{\boldsymbol{x}}_{k+1}$ and update $LB = \tilde{\boldsymbol{x}}_{k+1}^{\mathrm{T}}\boldsymbol{Q}\tilde{\boldsymbol{x}}_{k+1} + \boldsymbol{f}^{\mathrm{T}}\tilde{\boldsymbol{x}}_{k+1}$.

Step 3 *Solving the inner max-min problem.*
Based on the $\tilde{\boldsymbol{x}}_{k+1}$ derived from Step 2, solve a max-min problem and donate the slack solution under critical scenario $\boldsymbol{u}_{k+1}^*$ as η. Update $UB = \min\{UB, \eta\}$.

Step 4 *Convergence Checking.*
If $UB - LB \le \varepsilon$, return $\tilde{\boldsymbol{x}}_{k+1}$ and terminate. Otherwise, update $k = k + 1$ and go to Step 2 with addition of the following decision variables and their constraints to the model.

$$\boldsymbol{H}\boldsymbol{y}_{k+1} \le \boldsymbol{h},\ \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y}_{k+1} \le \boldsymbol{0},\ \boldsymbol{C}\boldsymbol{u}_{k+1}^* + \boldsymbol{D}\boldsymbol{y}_{k+1} = \boldsymbol{0}$$

To solve the max-min problem on Step 2, we can transform it into a MILP by using reformulation-linearization technique [3]. The outer approximation algorithm proposed in [7] seems to be an efficient way as well.

IV. Case Studies

To validate the feasibility and effectiveness of the prosed model and algorithm, numeric experiments are carried out on the realistic four-area southern China power system.

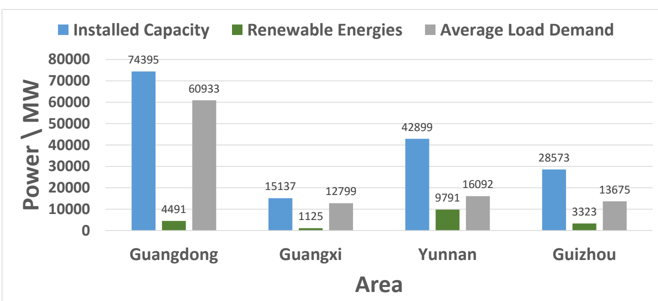


Fig. 1. Summarized information of each area in China Southern Grid.

Information of total installed capacity, renewables capacity and average load demand on a normal winter day for each area are summarized in Fig. 1. The installed capacities of YN and GZ are much higher than their demand, and the surplus power is delivered to GD and GX. We can also see that the penetrations of renewable energy of YN and GZ are very high, respectively 18.3% and 11.0% of their installed capacity.

A. Generation and Transmission Power Scheduling Results

The deterministic multiarea scheduling model proposed in Section II is the foundation of MARS. We can inspect its effectiveness through the solution result of $\boldsymbol{y}_0$ in MARS.

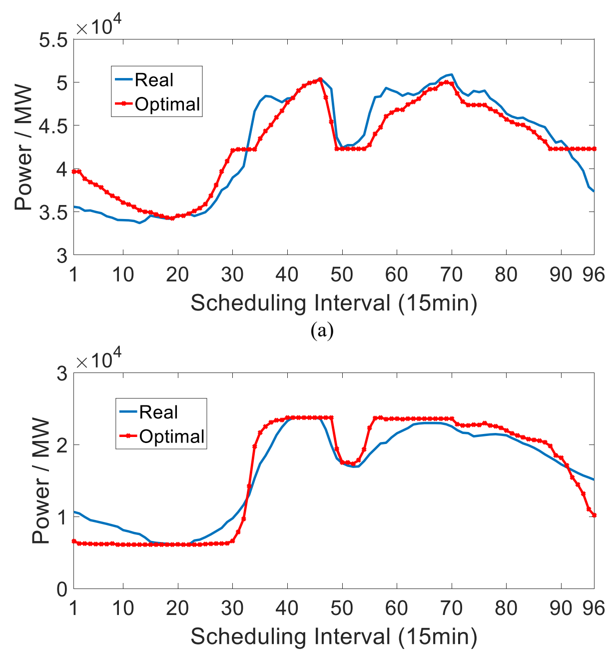
Realistic data on a normal winter day of CSG in 2016, which is partly showed in Table I, is adopted to verify the performance our model, and compare the optimal power scheduling with the real one. According to our operation experiment, two aspects of GD, the load center of CSG, requires immediate attention: with nearly 1/3 of its load demand supplied by sending-ends, whether the transmission plan is reasonable seriously influences GD's economic operation; because 86.3% of GD's capacity comes from thermal plants, the burden of its peak load and frequency regulation is heavy especially when the uncertainty of renewables and load emerges. Following, the optimization result of GD is presented.

Table I
Model Parameters for the China Southern Grid Case.

	$P_G^{\min}$/MW	$P_G^{\max}$/MW	$P_T^{\min}$/MW	$P_T^{\max}$/MW	E^{N}/MWh
GD	20,667	77,806	6,090	23,749	356,643
GX	3,489	16,357	400	2,500	33,365
YN	7,909	48,505	6,640	19,520	354,336
GZ	9,682	27,118	1,420	3,030	60,002

In Fig. 2(a), the blue line shows the daily generation curve of GD which is the original one scheduled empirically by system operators, and the red dotted line is that after optimization.

The improvement is obvious: near interval 40, 60 and 70, reverse regulations can be observed in the real one, but the optimal one is smooth without inefficient adjustments. Statistically, the std (standard variation) is decreased from 6096.4 MW to 4855.0 MW, while the peak-valley deviation is declined from 17197 MW to 16056 MW. With such improvement, there is no doubt that the thermal units of GD can be operated much more efficiently. From the power transmission curves depicted in Fig. 2(b), we can realize that is the discordance of transmission plan and load demand in an area that worsen the generation property, and our contribution relies on a reasonable transmission scheduling.



(b)

Fig. 2. Comparison on real and optimal power scheduling of GD, (a) generation power and (b) transmission power.

B. Economic Efficiency and Reliability of MARS

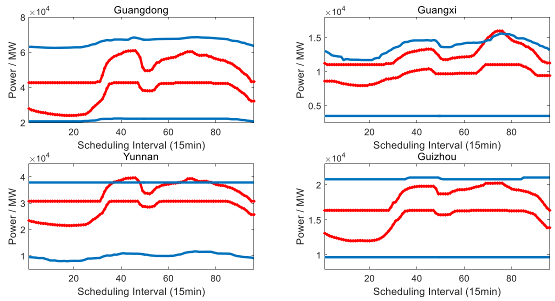


Fig. 3 Comparison on day-ahead power generation range in the case of CSG.

Data in Table I is also utilized in the MARS model. The day-ahead load forecast and renewables power forecast are adopted as the nominal of uncertain parameters $\bar{u}_{\alpha i,t}$, and the deviation $\hat{u}_{\alpha i,t}$ is set as $0.1\bar{u}_{\alpha i,t}$ to meet the realistic. In fact, for every single $\bar{u}_{\alpha i,t}$, an unique deviation can be defined based on our confidence of the prediction of the area at that dispatching interval.

The task of MARS is to give a tightest range of generation ability, that is robust against any renewable generation and load demand realization within the predefined uncertainty set. We carried out numeric experiments on various instances from $\Gamma_{\alpha t}=1$ to 4, and Fig. 3 gives the result of the most conservative one ($\Gamma_{\alpha t}=4$). The inner red dotted lines indicate the interval of generation derived from MARS, while the outer blue lines from real data. The improvement of GD is apparent because it is a thermal-dominant system and we have increased its weighted factor.

The advantages of MARS can be concluded as: *i*) by minimizing the variance of the series of $p_{Gi,t}^{\min}$ and $p_{Gi,t}^{\max}$ a tighter generation interval is obtained, which allows the provincial power grid to save operation cost by committing less units or units more economic efficient (the lower $p_{Gi}^{\max}$), and operating units near its economic point (the higher $p_{Gi}^{\min}$); *ii*) MARS is superior to the current method in reliability, because the pre-decision of MARS immunes from any perturbation within the uncertainty set, while the commitment state based on current method may requires load shedding or renewables discarding during intra-day operation (these are most likely to occur in YN near interval 40 and 70 where the red dotted line is slightly higher than the blue one as shown in Fig. 3); *iii*) this approach meets the hierarchical architecture in which power systems in China are organized, and the results it generates are more intuitional, visually and practical for system operators.

Even though the effect of MARS can't be measured by cost, the improvement is undoubted if we notice that less reserve is needed, the generation output is more stable, and emergency measures are less likely to be taken.

V. Conclusion

The MARS problem considering uncertain power injections, renewable energy and load demand, was formulated as a two-stage robust optimization. This model is distinct with robust unit commitment, in terms of that it provides the interarea power transmission scheduling, and the interval of daily generation (concerned with operation reserve) instead of on/off status of units in each area. The C&CG method are used to develop a practical solution algorithm. Numeric experiment demonstrates that the algorithm performance well, and hopefully can tackle multiarea power system day-ahead scheduling problem even with great uncertainty. We compared the results with the realistic operation data in CSG, which demonstrates that MARS provides the day-ahead power scheduling with higher economic efficiency and reliability.

The novel framework we proposed can address the needs of system operators which are hierarchically-organized, such as the regional and provincial dispatching centers in China. Future research may be carried out on collaborating the UC of each with the given robust generation interval, to further verify that the pre-decision derived from MARS allows lower-level power systems to withstand uncertainties.

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