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Unit Commitment Incorporating Spatial Distribution Control of Air Pollutant Dispersion

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Abstract--Air pollution problems are attracting increasing attention, especially among developing countries with frequent haze events. Renewable energy sources such as wind power are expected to help relieve such environmental concerns. However, air pollution issues under such a changing energy structure receive inadequate attention. Mostly, constraints for total pollutant emissions are considered in unit commitment (UC) and economic dispatch (ED) problems. In this paper, we propose a UC model with wind power that considers the dispersion of air pollutants. The dispersion process is described by models involving meteorological conditions and the system's geographical distribution, to estimate the spatial distribution of air pollutants, i.e. the concentration of ground-level air pollutants at monitored locations such as load centers. A penalty cost is introduced based on this estimation. Particulate matter 2.5 micrometers or less in diameter, the major air pollutant concerning most developing countries, is selected as the focus of this work. To properly estimate and sufficiently utilize the benefits of wind power for air pollutant dispersion control, robust optimization is applied to accommodate wind power uncertainty. Case studies justify this consideration of air pollutant dispersion, and demonstrate the effectiveness of the proposed model for improving load centers' air pollution control and utilizing wind power benefits.

Index Terms--Air pollutant dispersion, Gaussian plume model, robust optimization, unit commitment, wind power.

NOMENCLATURE

A. Indices:

i	Index of thermal units, $i=1, \dots, N_G$
w	Index of wind farms, $w=1, \dots, N_W$
j	Index of loads, $j=1, \dots, N_D$
l	Index of transmission lines, $l=1, \dots, N_L$
t	Index of time intervals, $t=1, \dots, T$

B. Parameters:

su_i/sd_i	Start-up/shut-down cost of thermal unit i
$\lambda_i/\gamma_i/\beta_i$	Fuel cost coefficients of thermal unit i
mu_i/md_i	Minimum up/down-time of thermal unit i
f_{il}	Power flow distribution factor (PFDF) of transmission line l due to thermal unit i
f_{wl}	PFDF of transmission line l due to wind farm w
f_{jl}	PFDF of transmission line l due to load j
F_l	Power flow limit of transmission line l
P_i^{max}/P_i^{min}	Upper/lower limit for real power output of thermal unit i
UR_i/DR_i	Ramp-up/down rate limit of thermal unit i
P_{jt}	Power demand of load j at time t
$\bar{P}_{wt}$	Forecasted mean power output of wind farm w at time t
$\hat{P}_{wt}$	Deviation from forecast of wind farm w at time t

C. Variables:

O_{it}	Binary on/off decision of thermal unit i at time t
SU_{it}	Binary start-up decision of thermal unit i at time t
SD_{it}	Binary shut-down decision of thermal unit i at time t
P_{it}^b	Real power dispatch decision of thermal unit i at time t in the base case
P_{it}^u	Adaptive real power dispatch decision of thermal unit i at time t considering wind power uncertainty
P_{wt}	Uncertain power output of wind farm w at time t

I. INTRODUCTION

MANY developing countries have witnessed frequent haze events in recent years. In China, for example, smog covered the major eastern cities of the country for over a week in winter 2013. More recently, severe haze hit Beijing in early December 2015, causing disruption for schools and companies, cancelled flights, and other issues. This kind of event has drawn worldwide attention to air pollution problems, as particulate matter 2.5 micrometers or less in diameter (PM2.5), the major cause of haze, is extremely harmful to human health due to its capability to deeply penetrate into human lungs and the blood stream. According to reports by the United Nations Environment Programme [1] and the World Health Organization (WHO) [2], air pollution is one of the world's worst environmental health risks, causing millions of premature deaths and trillions of US dollars in economic cost.

As a major consumer of fossil fuels, the electric system is responsible for a high proportion of air pollutants emissions, with coal-fired plants the major source of PM2.5 and secondary

PM2.5 formation elements SO_2 and NO_X. Dominant portion of power is supplied by coal in U.S., Germany, Australia, England, China, etc. Researchers and practitioners in power systems are accountable for the urgent need for better air pollution control.

In some pioneering research works, the total amount of emitted pollutants was considered, typically formulated as a quadratic function of the real power output of thermal units. Constraints or penalty costs were introduced based on this summation of pollutants emissions [3]-[6]. In [7], the operation of various flue gas desulfurization systems was also accounted for. However, one essential aim of emission regulations is to limit ground-level air pollutant concentration (GLAPC), especially at "monitored locations" such as load centers with a high population density—places where there is more concern or interest about air quality. Following U.S. government efforts in the 1960s and 1970s such as the Clean Air Act of 1970, considerable research has been devoted to studying the dispersion of emitted air pollutants, i.e., to consider the resulting GLAPC at monitored locations [8]-[10]. Environmental science models describing the dispersion process of pollutants emitted from thermal units have been introduced to estimate GLAPC. This estimation, as an index, has been included as constraints or as a penalty cost in optimization problems of power system operations.

Nevertheless, industry practice for emissions regulations in power systems is still normally based on total emission limits, rather than consideration of GLAPC. Also, the past several decades has seen only a limited number of papers published by power system researchers that study GLAPC issues. There are likely two reasons for this modest level of effort. First, as air pollutant dispersion is an extremely complex process involving atmospheric movement, chemical reactions, etc., obtaining an estimation with acceptable accuracy is not easy. Plus the fact that electric systems are just one of many sources of air pollutants such as traffic, wildfires, etc., thermal units' responsibilities are difficult to identify quantitatively, which is the second major reason. However, as we now have a much clearer understanding of the severe human health risks due to air pollution, these relevant topics deserve much more attention. As such, many mature and reliable dispersion models are now available. Governments are also much more willing to spend money in air pollution control. With the development of detection, computation and communication technologies for the emerging smart grid [11], air pollution control based on GLAPC information is important and can be practical for existing power systems.

Additionally, enormous renewable energy sources, especially wind power, has been integrated into power systems all over the world [12]. Besides relieving a potential energy crisis, wind power is also expected to reduce environmental pollution. One straightforward yet critical topic is to study the benefits of wind power integration in terms of CO_2 and air pollutants emissions reduction. To the best of the authors' knowledge, all recent papers are based on the amounts of emissions such as in [13]-[18], while the essential relief in terms of GLAPC has not been analyzed. Specifically, in [13]-[16] wind power benefits in terms

of carbon emission control were studied. On the other hand, in [17], a study based on the Ireland system indicates that wind power could be ineffective in SO_2 and NO_X emission reduction. A dispatch model minimizing NO_X emission is proposed for systems with stochastic wind power in [18].

In summary, recent studies of wind's environmental benefits has concentrated on the total amount of carbon or other air pollutants emitted, while other essential benefits of wind power, such as GLAPC reduction, were not analyzed. As mentioned above, it is well recognized that it is critically important to look into the dispersion of air pollutants emitted by thermal units [8]-[10], [19]. Without consideration of air pollutant dispersion, wind power's benefits in terms of air pollution control can be greatly undermined.

As one of the most important power system operation problems, unit commitment (UC) models minimize cost by optimizing each power plant' on/off states and power dispatch [20]. Based on the above arguments, this work proposes a UC model that considers wind power benefits in terms of dispersion control of air pollutants. A dispersion model that considers meteorological conditions and the system's geographical distribution is applied to describe the dispersion of air pollutants emitted by thermal units. Thus, GLAPC at monitored locations (load centers in this paper) is estimated and rendered a cost. That is, the spatial distribution of air pollutants are considered. The cost can be in the form of penalty costs, taxes for thermal units, or subsidies for influenced customers in load centers, etc. As wind power is uncertain in nature, robust optimization is employed to ensure robust feasibility of commitment decisions [21]-[24]. Thus, the system can be relieved from harsh spinning reserve requirements to accommodate wind power uncertainty and to prevent even worse emissions results. That is, robust optimization is applied to appropriately accommodate wind power uncertainties in terms of spinning reserve scheduling, so that the benefits of wind power for air pollutant dispersion control can be properly estimated and sufficiently utilized. A modified IEEE 14-bus system and the real-world Guangdong Grid system are used to demonstrate the effectiveness of the proposed UC model and analyze how wind power can help control air pollutant dispersion. The main contributions of this paper are summarized as follows:

1) A novel UC model is proposed and studied, in which the dispersion of air pollutants emitted by thermal units is considered. A review of major dispersion models is also presented. Meteorological conditions and the system's geographical distribution are included in the applied plume model, to achieve better air pollution control in load centers, namely the spatial distribution control of air pollutant dispersion. Note that our method of air pollutant dispersion consideration can be easily extended for applications in problems such as economic dispatch (ED) and generation expansion planning.

2) Wind power benefits in air pollution control are studied. The reasons and methods to explicitly consider this issue are presented. Robust optimization is employed to handle wind power uncertainty to avoid its benefits being undermined by harsh spinning reserve requirements. The proposed model better

utilizes wind power benefits on this issue. The analysis focuses on PM2.5, which currently receives inadequate attention by power system researchers, with the aim of these results to provide advice and information for system operators and policy-makers.

The remaining parts of this paper are organized as follows. In Section II, air pollutant dispersion models are presented and discussed. In Section III, the proposed UC model is formulated. Section IV introduces the solution algorithm for the formulated problem. Case studies are included in Section V for illustration. Section VI concludes this paper.

II. AIR POLLUTANT DISPERSION MODELS

To estimate a thermal unit's contribution to the GLAPC of a specific monitored location, a model describing the dispersion of pollutants is necessary. First, the emission rate functions of thermal units for different kinds of pollutants are briefly summarized.

The NO_X emission rate function is highly non-linear in P (real power output). While most researchers generally apply a function with both polynomial and exponential terms, some use a second order polynomial function instead. For SO_X and particulate matter, including the focus of this work PM2.5, emission rates are normally seen as proportional to coal consumption, i.e., generally quadratic to P. Thus, the PM2.5 emission rate of unit i at time t can be described as:

$$E_{it} = c_i \cdot (P_{it}^b)^2 + b_i \cdot P_{it}^b + a_i \tag{1}$$

where a_i, b_i, and c_i denote emission coefficients.

Air pollutants are transported by atmospheric movements, i.e. dispersed, when emitted by thermal units at the above rate. From simple fixed-box models to the much more sophisticated plume and puff models, many different dispersion models have been developed to describe the dispersion process and predict the resulting GLAPC. For point sources including thermal units, both plume and puff models are extensively employed. As sketched in Fig. 1, a plume model describes air pollutants as a plume emitted from a stack, while a puff model regards thermal units as sources of a series of continuously overlapping puffs. Both models may assume some types of distribution for the dispersion in the cross-wind direction (y) and the vertical direction (z).

In the literature, some studies have used the plume model for its maturity, while others have used the puff model as it is more flexible for considering the non-steady state of meteorological conditions. To assert that one model is superior to the other is unreasonable and unnecessary. As mentioned, air pollutant dispersion is an extremely complex process related to complicated atmospheric movements, chemical reactions, meteorological conditions, etc. In environment science, it is believed that the critical point is to select a suitable and applicable model for the specific application. In this paper, based on literature ([4], [8]-[10], and [25]-[29]), a relatively comprehensive comparison of these two types of popularly used models is summarized and presented in Table I. Note that the practical application of these models normally demands efforts
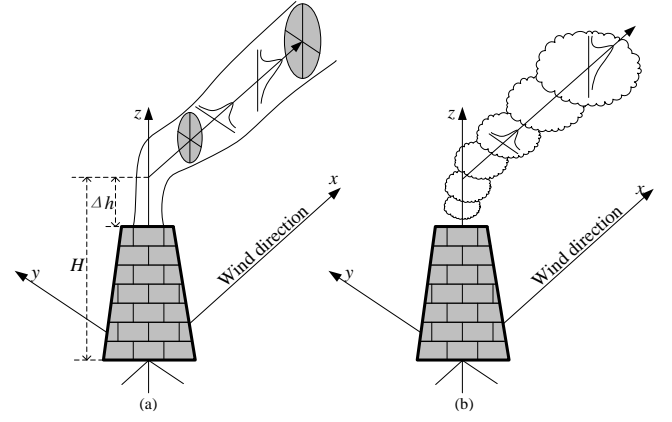

Fig. 1. Schematics for two major dispersion models: (a) Plume model; (b) Puff model.

TABLE I
COMPARISON OF PLUME AND PUFF MODELS

	Plume model	Puff model
State assumption	Straight-line, steady-state	Non-steady state
Model features	Fits seen & experience	More abstract modeling
Applicable range	Limited to 50km	Long range (200-300km)
Pollutant sources	Point/line/area sources	Point/line/area sources
Applicable pollutant types	Particulate matter, NO_X, SO_2, CO	Particulate matters, NO_X, SO_2, CO
Emission description	Continuous release	Quasi-instantaneous, short-term release
Dispersion coefficients setup	Relatively more available & mature references	Limited available references
Data requirements	Need less data	Need more detailed data (spatial/temporal effects)
Time step/scale	Release time much greater than transition time from source to receptor	Release/sampling time very short compared to transition time
Preferable applications	When simple output required, maximum concentration considered	Complex terrain scenarios (coastal effects, etc.)
Major shortcomings	Naturally not for varying meteorological conditions	Difficulty in coefficients setup, overlook in-puff fluctuations
EPA-recommended scenarios	Near-field	Long-range, complex wind-field
EPA-approved model developments	AERMOD, ISC3, BLP, OCD, etc.	CALPUFF, etc.

* EPA: U.S. Environmental Protection Agency

such as model adjustments, parameters tuning, grid cell modelling, etc.

In this paper, the Gaussian plume model, which is the most widely used model for describing the dispersion of continuous-release plumes, is applied for the following reasons:

1) Thermal units are point sources with a continuous release of pollutants. Their emissions can be better described by a contaminated plume. The release time is also greater than the transition time of the plume.

2) The plume model considers emissions as a plume starting from the stack of each thermal unit, while the puff model considers emissions as puffs independent of their source. Thus, it

is much more straightforward to use the plume model to describe the effect of thermal units on the air pollution of monitored locations.

3) This work considers a predicted GLAPC on load centers in a day-ahead UC problem. A model with simple inputs and simple outputs is preferred and desired for possible practice, since the much more detailed data necessary for the puff model can be inaccurate or unavailable.

Based on the applied plume model, as sketched by Fig. 1(a), a thermal unit's contribution at time t_r to the GLAPC of a load center, which is the monitored locations in this study, can be summarized as:

$$C_{ijt_r} = \frac{1}{w} \cdot \frac{E_{it}}{\pi \cdot I_y \cdot I_z \cdot d_x^{\;2}} \cdot \exp\left(-\frac{d_y^{\;2}}{2 \cdot I_y^2 \cdot d_x^{\;2}} - \frac{H^2}{2 \cdot I_z^2 \cdot d_x^{\;2}} \right) \quad (2)$$

where w represents wind speed, d_x and d_y are the downwind direction and cross-wind direction distances between load j and thermal unit i, I_y and I_z are emission constants determined by many factors such as geographical/meteorological conditions and air pollutant dissipation situations, and H is the effective stack height of the thermal units. Interested readers may refer to [25] for more details. In this work, the aforementioned parameters are all assumed known. Equation (2) actually estimates the spatial distribution of air pollutants quite conservatively. Such a conservative estimation in turn leads to decisions that are sufficiently effective in terms of air pollutant dispersion control for the future day. Note that the time indices of C_{ijt_r} and E_{it} are different due to the transition time of the emitted pollutants from a thermal unit to a load center. In this work we consider our study in a geographical area where the longest transition time is about one hour [10]. In addition, the polluting coal units normally supply the base load and do not significantly change their power output in each hour. More importantly, the responsibility of each thermal unit towards GLAPC at load centers is given a linear cost in this paper. Thus, it is not necessary to explicitly model this transition time into our UC formulation. For simplicity and clarity, denote K_{ij} as the "air pollutants dispersion coefficient" between generation i and load j under specific meteorological conditions, which means we can re-write (2) and apply (1) to get:

$$C_{ijt_r} = K_{ij} \cdot E_{it} = K_{ij} \cdot [c_i \cdot (P_{it}^b)^2 + b_i \cdot P_{it}^b + a_i] \quad (3)$$

Equation (3) reveals a roughly quadratic relationship under specific conditions. Note that if thermal unit i is on the downwind side of load center j, K_{ij} should be zero. Although a basic plume model is based on a steady-state assumption, it can actually be modified to handle scenarios with varying meteorological conditions, complex terrain, and other special cases such as calm winds, stagnation conditions, and variable wind direction. Wind speed is one of the major factors influencing the air pollutant dispersion process. It is worth mentioning that as shown in [10], one day can be approximately split into two halves, i.e. day and night, to have two different wind scenarios, each with a different relatively stable wind speed and wind direction. This conforms to the steady-state assumption of the plume model and justifies its application here. In this

paper, average wind speeds and directions for day and night are used. To consider more spatially or temporally varying meteorological conditions, the plume model can be adjusted for better performance, and the puff model may be more applicable in some cases. Techniques or models such as grid cell partitioning [30] or the RNG k-ε turbulence model [31], may also be necessary.

III. PROBLEM FORMULATION

In this section, a novel UC model with wind power that considers air pollutant dispersion is formulated, with the aim of ensuring the benefits that wind power provides for the spatial distribution control of air pollutants. The first part presents and explains the objective function. The second part describes the constraints, including a robust feasibility check.

A. Objective Function

A deterministic form of the objective function is adopted here to avoid over-conservativeness of the worst-case cost of robust optimization. The objective function (4) consists of three parts: 1) the commitment costs (CC) corresponding to start-up and shut-down operations of thermal units; 2) the base-case dispatch cost (BDC) under the nominal scenario with forecasted mean wind power outputs; and 3) the air pollutant dispersion cost (APDC) with the "price" α_j.

$$\min(CC + BDC) + APDC$$

$$CC = \sum_{t=1}^{T} \sum_{i=1}^{N_G} (su_i \cdot SU_{it} + sd_i \cdot SD_{it})$$

$$BDC = \sum_{t=1}^{T} \sum_{i=1}^{N_G} [\lambda_i \cdot (P_{it}^b)^2 + \gamma_i \cdot P_{it}^b + \beta_i \cdot O_{it}]$$

$$APDC = \sum_{t=1}^{T} \sum_{j=1}^{N_D} \sum_{i=1}^{N_G} \alpha_j \cdot K_{ij} \cdot [c_i \cdot (P_{it}^b)^2 + b_i \cdot P_{it}^b + a_i \cdot O_{it}] \quad (4)$$

Thus, the objective function considers both the common UC cost (UCC, including CC and BDC) and the proposed APDC introduced below.

As for the APDC, this cost actually exists even though industry practice does not normally have a tax or charge in this form. For example, reference [32] estimates the cost resulting from environmental damage caused by NO_X, SO_2 and PM_{10}, including human health impacts. However, to completely determine the real economic cost of human health harm and environmental pollution resulting from the dispersion of emitted air pollutants is far too difficult, and would involve issues such as policy-making, pollution remediation, public health, etc. Thus, APDC is introduced as a penalty cost in this paper instead. This cost is different from the UCC as it is not really an existing charge. Instead, the APDC is mathematically included to drive changes in UC decisions and costs. However, we do incorporate some practical considerations, including population density and background pollution, when setting this penalty cost. This approach means that the APDC has correlated relationships with damage costs due to the impact of air pollutants on the environment and human health, and with pollution treatment costs typically shouldered by the government.

PM2.5 µg/m³	Air quality category	Remarks	BP_j
~12	Good	EPA annual primary standard protecting public health	1
~15	Moderately good	EPA annual secondary standard protecting public welfare	2
~25	Moderate	EC annual PM2.5 standard, WHO 24-hour standard, EPA 24-hour primary & secondary standard	3
~35	Moderate	Should take immediate measures	4
~55	Unhealthy for sensitive groups	Much higher long-term mortality risk indicated by WHO	5
>55	Unhealthy	Severe pollution	6

Based on the applied plume model described by equations (2) or (3), for each load center j located in different geographical positions, an estimation of each thermal unit's contribution to the GLAPC is obtained and endowed a cost on the "price" of α_j. For each load center, α_j can be set as a different value. Major considerations in choosing a reasonable value for α_j can include: 1) the population NP_j at load center j; and 2) the background pollution level BP_j at load center j.

Air pollution is a sophisticated problem resulting from not only thermal unit power generation, but also other sources such as vehicle fuel consumption, kitchen fumes and atmospheric transport, which cause a background pollution. In fact, there are many locations with relatively severe background air pollution and it would be necessary to set a higher α_j in these locations to avoid even worse health risks for people who live there. Based on the PM2.5 regulation standards or guidelines of WHO [2], the U.S. Environmental Protection Agency (EPA) [33] and the European Commission (EC) [34], BP_j is introduced to indicate background PM2.5 pollution level with those values shown in Table II. Note that "annual" and "24-hour" mean the averaging time in the table. While a linearly incremental BP_j was set here for this work, more complicated policies for setting the value can be applied according to one's preference.

Based on the above two considerations, we can describe α_j using:

$$\alpha_j = s \cdot NP_j \cdot BP_j^2 \tag{5}$$

where s is a parameter indicating the penalty cost per person per exposure to PM2.5. Tuning of this parameter is required to obtain UC decisions with desired air pollution control effects and acceptable costs. Note that the second power of BP_j is used here to limit serious air pollution.

Thus, the APDC, indicated by (4) and (5) is a penalty for the total exposure of influenced people to PM2.5 that also considers the background pollution. The proposed UC model minimizes both the common UCC and peoples' exposure to air pollutants, which is PM2.5 in this paper. We focus on PM2.5 since it is a major type of air pollutant, especially in developing countries, such as China.

Note that our method of air pollutant dispersion consideration can be easily extended to other pollutants such as PM10, NO$_X$ and SO$_2$, as well as other problems such as ED and generation expansion planning. Generally, a dispersion model should be selected first according to the spatial and temporal considerations of the studied or applied problem, followed by necessary modifications. Then the problem can be formulated and revised. For example, if the atmosphere is of the temperature inversion condition, the Gaussian plume dispersion model has to be refined to incorporate the reflection effect of the inversion layer. References [35], [36] and [37] are examples for considering air pollutant dispersion in different power system optimization problems. Interested readers can also refer to [25] for more systematic instructions on air pollution control.

B. Constraints

The constraints in the proposed UC model are presented and explained as follows:

$$O_{it} - O_{i(t-1)} - O_{ih} \leq 0, \forall i, \forall t \geq 2, \forall t+1 \leq h \leq \min(mu_i + t - 1, T) \tag{6}$$

$$O_{i(t-1)} - O_{it} + O_{ih} \leq 1, \forall i, \forall t \geq 2, \forall t+1 \leq h \leq \min(md_i + t - 1, T) \tag{7}$$

$$O_{i(t-1)} - O_{it} + SU_{it} \geq 0, \forall i, \forall t \geq 2 \tag{8}$$

$$O_{it} - O_{i(t-1)} + SD_{it} \geq 0, \forall i, \forall t \geq 2 \tag{9}$$

$$O_{it}, SU_{it}, SD_{it} \in \{0,1\}, \forall i, \forall t \tag{10}$$

$$\sum_{i=1}^{N_G} P_{it}^b + \sum_{w=1}^{N_W} \overline{P}_{wt} = \sum_{j=1}^{N_D} P_{jt}, \forall t \tag{11}$$

$$P_i^{\min} \cdot O_{it} \leq P_{it}^b \leq P_i^{\max} \cdot O_{it}, \forall i, \forall t \tag{12}$$

$$P_{it}^b - P_{i(t-1)}^b \leq UR_i \cdot O_{i(t-1)} + P_i^{\min} \cdot (O_{it} - O_{i(t-1)}) + P_i^{\max} \cdot (1 - O_{it}), \\ \forall i, \forall t \geq 2 \tag{13}$$

$$P_{i(t-1)}^b - P_{it}^b \leq DR_i \cdot O_{it} + P_i^{\min} \cdot (O_{i(t-1)} - O_{it}) + P_i^{\max} \cdot (1 - O_{i(t-1)}), \\ \forall i, \forall t \geq 2 \tag{14}$$

$$-F_l \leq \sum_{i=1}^{N_G} f_{il} \cdot P_{it}^b + \sum_{w=1}^{N_W} f_{wl} \cdot \overline{P}_{wt} - \sum_{j=1}^{N_D} f_{jl} \cdot P_{jt} \leq F_l, \forall l, \forall t \tag{15}$$

$$O_{it} \in \{O_{it} : \forall P_{wt} \in W, \exists P_{it}^u \in \Omega(O_{it}, P_{wt})\} \tag{16}$$

where:

$$W := \{P^{N_W \times T} : P_{wt} \in [\overline{P}_{wt} - \hat{P}_{wt}, \overline{P}_{wt} + \hat{P}_{wt}], \forall w, \forall t;$$

$$\sum_{w}^{N_W} \frac{|P_{wt} - \overline{P}_{wt}|}{\hat{P}_{wt}} \leq \Delta^s, \forall t; \sum_{t}^{T} \frac{|P_{wt} - \overline{P}_{wt}|}{\hat{P}_{wt}} \leq \Delta^t, \forall w\} \tag{17}$$

$$\Omega(O_{it}, P_{wt}) := \{P_{it}^u :$$

$$\sum_{i=1}^{N_G} P_{it}^u + \sum_{w=1}^{N_W} P_{wt} = \sum_{j=1}^{N_D} P_{jt}, \forall t \tag{18}$$

$$P_i^{\min} \cdot O_{it} \leq P_{it}^u \leq P_i^{\max} \cdot O_{it}, \forall i, \forall t \tag{19}$$

$$P_{it}^u - P_{i(t-1)}^u \leq UR_i \cdot O_{i(t-1)} + P_i^{\min} \cdot (O_{it} - O_{i(t-1)}) + P_i^{\max} \cdot (1 - O_{it}), \\ \forall i, \forall t \geq 2 \tag{20}$$

$$P_{i(t-1)}^u - P_{it}^u \leq DR_i \cdot O_{it} + P_i^{\min} \cdot (O_{i(t-1)} - O_{it}) + P_i^{\max} \cdot (1 - O_{i(t-1)}), \\ \forall i, \forall t \geq 2 \tag{21}$$

$$-F_l \leq \sum_{i=1}^{N_G} f_{il} \cdot P_{it}^u + \sum_{w=1}^{N_W} f_{wl} \cdot P_{wt} - \sum_{j=1}^{N_D} f_{jl} \cdot P_{jt} \leq F_l, \forall l, \forall t\} \tag{22}$$

Among these constraints, inequalities (6)-(10) are constraints for commitment decision variables. Constraints (6) and (7) are minimum up-time and minimum down-time limits. Inequalities (8) and (9) are the logic constraints for start-up and shut-down operations, respectively. Constraint (10)

enforces commitment decision variables be binary. Constraints (11)-(15) are for base-case dispatch variables. Equation (11) represents the power balance for each time interval. Constraint (12) limits the power output of thermal units within its upper and lower bound. Constraints (13) and (14) indicate ramp-up and ramp-down rate limits. Inequality (15) is the power flow capacity constraints for the transmission lines. Constraint (16) is the robust feasibility check for the on/off state variables of the thermal units to guarantee existence of feasible adaptive dispatch strategies under any scenario within the wind power outputs' uncertainty set W defined by (17). Here, $\Omega(O_{it}, P_{it})$ is the feasible set of adaptive dispatch variables indicated by (18)-(22). In (17), Δ^s is the "spatial budget" to limit wind power deviations at each time interval t, while Δ^t is the "temporal budget" to limit deviations during the whole time window for each wind farm w. Constraints (18)-(22) represent power balance, thermal unit power output limits, ramp-up and ramp-down rate limits, and transmission line capacities, respectively.

Specifically, the robust feasibility check constraint is added for two major reasons. First, wind power uncertainties have to be considered appropriately, so that adequate spinning reserve is set, to avoid over-estimating and in turn under-utilizing wind power benefits for air pollutant dispersion control. That is, if UC decisions are determined based on forecasted mean values of wind power outputs, inadequate spinning reserve can lead to frequent start-up/shut-down of flexible units and environmentally unfriendly real-time operations of more polluting coal-fired units, which can cause much higher operational costs and even worse air pollutant dispersion results. In such cases, wind power becomes cost-ineffective or even ineffective for air pollutant dispersion control. Second, here robust optimization [21]-[23], [38] is more appropriate compared to deterministic and stochastic optimization methods [39]-[40]. If the distribution information of uncertainties is available, which is often not the case, stochastic optimization can be preferable. Otherwise, instead of setting intuitive criteria based spinning reserve, robust optimization should be applied to optimally schedule spinning reserve, so that wind power benefits in air pollutant dispersion control can be estimated properly and thus utilized sufficiently.

IV. SOLUTION ALGORITHM

The proposed UC model results in a mixed integer quadratic programing (MIQP) problem with a robust feasibility check. For simplicity and clarity in presenting the solution algorithm, its compact matrix formulation is derived as:

$$\min_{\mathbf{x}, \mathbf{y}_1} \mathbf{q}_0^T \mathbf{x} + (1/2)\mathbf{y}_1^T \mathbf{Q} \mathbf{y}_1 + \mathbf{q}_1^T \mathbf{y}_1 \tag{23}$$

$$s.t. \quad \mathbf{R}\mathbf{x} + \mathbf{G}\mathbf{y}_1 + \mathbf{D}\mathbf{u}_0 \le \mathbf{e} \tag{24}$$

$$\forall \mathbf{u} \in \mathbf{U}, \exists\, \mathbf{y}_2 : \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{y}_2 + \mathbf{E}\mathbf{u} \le \mathbf{g} \tag{25}$$

where $\mathbf{x}$, $\mathbf{y}_1$, $\mathbf{y}_2$, $\mathbf{u}_0$, $\mathbf{u}$, and $\mathbf{U}$ denote commitment variables, base-case dispatch variables, adaptive dispatch variables, forecasted mean wind power outputs, uncertain wind power outputs, and their uncertainty set, respectively. Other vectors and matrices are cost parameters or coefficients in the constraints.

The solution algorithm is in an iterative master-sub-problem framework. First, the robust feasibility check (25) is implemented by a sub-problem (SP) written as:

$$\text{SP:} \quad \max_{\mathbf{u} \in \mathbf{U}} \min_{\mathbf{y}_2, \, \mathbf{s}^+, \, \mathbf{s}^-} \mathbf{1}^T \mathbf{s}^+ - \mathbf{1}^T \mathbf{s}^- \tag{26}$$

$$s.t. \quad \mathbf{A}\mathbf{x}_K + \mathbf{B}\mathbf{y}_2 + \mathbf{E}\mathbf{u} + \mathbf{I}\mathbf{s}^+ + \mathbf{I}\mathbf{s}^- \le \mathbf{g} \tag{27}$$

where $\mathbf{I}$, $\mathbf{1}$, $\mathbf{s}^+$, $\mathbf{s}^-$, and $\mathbf{x}_K$ denote the identity matrix, all-ones vector, positive slack vector, negative slack vector, and the current solution of $\mathbf{x}$ in the Kth iteration, respectively.

The SP can be solved in one of two ways: 1) first taking the dual of the inner minimization problem and then linearizing the resulting bilinear terms in the objective function via McCormick envelopes [38], [41]; or 2) first employing the Karush-Kuhn-Tucker conditions for the inner minimization problem and then linearizing the complementary slackness constraints via big-M linearization [23], [42]. Both approaches lead to a mixed integer linear programming (MILP) problem that can be solved by off-the-shelf solvers such as Gurobi. We apply the first method in this work.

By dualizing the inner minimization problem and incorporating the derived dual formulation with the outer maximization problem, the SP becomes a bilinear program (BLP) sub-problem:

$$\text{BLP-SP:} \quad \max_{\mathbf{u} \in \mathbf{U}, \, \boldsymbol{\eta}} \boldsymbol{\eta}^T (\mathbf{g} - \mathbf{A}\mathbf{x}_K) - \boldsymbol{\eta}^T \mathbf{E}\mathbf{u} \tag{28}$$

$$s.t. \quad \boldsymbol{\eta}^T \mathbf{B} \le \mathbf{0}^T \tag{29}$$

$$-\mathbf{1}^T \le \boldsymbol{\eta}^T \le \mathbf{0}^T \tag{30}$$

where $\boldsymbol{\eta}$ and $\mathbf{0}$ denote the dual variables and all-zero vector, respectively. As the BLP-SP is non-convex, its global optimum is difficult to obtain. Thus, we transform the problem into an equivalent MILP instead by first representing each uncertain variable u_m with:

$$u_m = \bar{u}_m + (u_m^+ - u_m^-) \cdot \hat{u}_m \tag{31}$$

where $\bar{u}_m$ and $\hat{u}_m$ denote the forecasted mean value and deviation of u_m, respectively, and u_m^+ and u_m^- are binary variables. The matrix $\mathbf{E}$ is sparse in our case. Then we eliminate each bilinear term in the BLP-SP by using an auxiliary continuous variable and four linear constraints. For example, the bilinear term $\eta_m \cdot u_n^+$ can be represented by v_{mn}^+ and constrained by:

$$v_{mn}^+ \le 0, \ \eta_m \le v_{mn}^+, \ -u_n^+ \le v_{mn}^+, \ v_{mn}^+ \le \eta_m - u_n^+ + 1. \tag{32}$$

As in (32), the bounds for dual variables are explicitly known, so appropriately pre-specified big-M values are not necessary to linearize the BLP-SP. The resulting MILP is parameter-free.

If the objective of the SP is zero or less than a pre-set threshold δ, we conclude that the current $\mathbf{x}_K$ satisfies the robust feasibility check (25). Otherwise, based on the identified "worst scenario" $\mathbf{u}_K$, cuts should be added to form the master-problem (MP) with (23)-(24) and previously added cuts:

$$\text{MP:} \quad \min_{\mathbf{x}, \mathbf{y}_1, \mathbf{y}_{2,k}} \mathbf{q}_0^T \mathbf{x} + (1/2)\mathbf{y}_1^T \mathbf{Q} \mathbf{y}_1 + \mathbf{q}_1^T \mathbf{y}_1 \tag{33}$$

$$s.t. \quad (24)$$

$$\mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{y}_{2,k} + \mathbf{E}\mathbf{u}_k \le \mathbf{g}, \forall k \le K \tag{34}$$

Here, $\mathbf{y}_{2,k}$ is the introduced dispatch variables under the scenario $\mathbf{u}_k$. The MP is a MIQP problem with a positive semi-definite $\mathbf{Q}$ matrix involving only positive diagonal elements. Thus, the MP can be efficiently solved by off-the-shelf solvers as well. Note that cuts can also be generated in terms of dual variables based on Benders cutting plane algorithms [21]-[22]. Here we add cuts in terms of primal variables based on the idea of the column-and-constraint generation (C&CG) algorithm [23], [42]. Although the C&CG algorithm adds not only more constraints but also new variables into the MP, it shows better performance in terms of computational time and required number of iterations [23], [42].

The iterative algorithm is presented as follows:
1) Set the number of iterations $K=0$. Choose a tolerance $\delta(>0)$ for the robust feasibility check.
2) Solve the MP to update the current optimal solution ($\mathbf{x}^*$, $\mathbf{y_1}^*$, $\mathbf{y}_{2,1}^*$,…, $\mathbf{y}_{2,K}^*$).
3) $K=K+1$. Solve the SP with $\mathbf{x}_K=\mathbf{x}^*$, to obtain $\mathbf{u}_K$.
4) If *objective_of_SP* $\leq \delta$, return ($\mathbf{x}^*$, $\mathbf{y_1}^*$) and terminate. Otherwise, go to step 2).

Theoretically, the maximum iteration number of the above algorithm is the number of extreme points of the uncertainty set. However, this method normally acquires the optimum solution within several iterations.

V. ILLUSTRATIVE CASES

Case studies were conducted on a modified IEEE 14-bus system and the real-world Guangdong Grid system to demonstrate the need for air pollutant dispersion consideration and the effectiveness of the proposed UC model. Gurobi 6.0.4 was used to solve related MIQP and MILP problems.

A. The Modified IEEE 14-Bus System

This system has 5 thermal units, the data for which are shown in Table III. Note that gas units hardly emit any PM2.5. One wind farm with 10% penetration on average was introduced to bus 14, with its hourly forecasted mean power output and the system load given in Fig. 2. Wind power uncertainties were set as ±10% of forecasted values, with $\Delta^s=1$ and $\Delta^t=16$. Transmission line data were obtained from MATPOWER [43]. The geographic distribution of the thermal units and load centers was based on [35]. The background PM2.5 pollution, and the corresponding BP_j and NP_j, are listed in columns 1-4 in Table IV. As for meteorological conditions, we set the average wind speed and direction to be 4.2 m/s from the south during the day and 9.3 m/s from the southwest at night. The atmospheric stability class was set to D, i.e., neutral stability. This determines the two meteorological parameters I_y and I_z to be 0.147 and 0.811, respectively.

Four cases were studied for illustration: Case 1: this case does not include the wind farm at bus 14, nor the APDC in the objective function; Case 2: in this case the wind farm is considered, while the APDC is still absent from the objective function; Case 3: a constraint for total PM2.5 emission is added based on Case 2; Case 4: the exact proposed UC model is applied for this case, where *s* is set as 0.01 \$ m^3/μg.

TABLE III
DATA FOR THERMAL UNITS

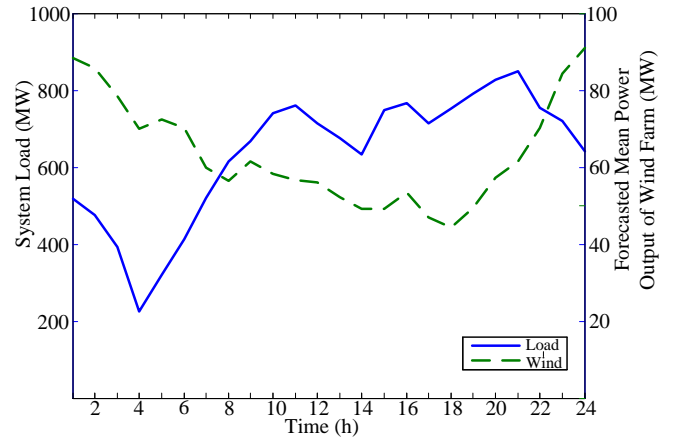| Bus No.	1	2	3	6	8
Unit Type	Coal	Coal	Coal	Gas	Gas
P_i^{max} (MW)	250	200	200	100	100
P_i^{min} (MW)	100	100	100	10	10
UR_i & DR_i (MW/h)	125	100	100	50	50
mu_i (h)	4	4	3	1	1
md_i (h)	4	4	2	1	1
su_i (\$)	120	220	300	0	0
sd_i (\$)	60	110	150	0	0
λ_i (\$/MW^2)	0.0045	0.004	0.004	0.005	0.005
γ_i (\$/MW)	13.5	12	12	16.5	16.5
β_i (\$)	175	155	155	130	130
c_i (g/MW^2 s)	0.006	0.0065	0.006	0	0
b_i (g/MW s)	0.45	0.55	0.5	0	0
a_i (g/s)	24	65	55	0	0
H (m)	456	448	461	—	—

Fig. 2. System load profile and forecasted mean power outputs of the wind farm.

TABLE IV
LOAD CENTER BP_j, NP_j, PGLAPC AND AGLAPC FOR THE FOUR CASES

Bus No.	Background PM2.5 μg/m^3	BP_j	NP_j	PGLAPC μg/m^3 Case No.				AGLAPC μg/m^3 Case No.			
				1	2	3	4	1	2	3	4
4	22	3	9203	22.00	22.00	22.00	22.00	20.00	22.00	22.00	22.00
5	50	5	1463	70.32	70.32	64.79	56.07	59.97	59.15	56.04	52.53
7	22	3	320	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00
9	22	3	5680	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00
10	30	4	1733	30.02	30.02	30.02	30.01	30.01	30.01	30.00	30.00
11	36	5	674	53.28	53.28	53.28	53.28	46.14	46.01	46.13	46.75
12	23	3	1174	32.36	32.36	31.99	31.46	28.60	28.34	27.71	27.61
13	18	3	2600	21.02	21.02	20.97	20.90	20.57	20.37	19.73	19.97
14	13	2	2869	13.13	13.13	13.13	13.13	13.06	13.06	13.02	13.06

In Table IV, the resulting peak GLAPC (PGLAPC) and average GLAPC (AGLAPC) of each load center under the four cases are listed. In Table V, total PM2.5 emissions (TPME), total exposure (TE, sum of NP_j $GLAPC_{jt}$ for all load centers and all time intervals), UCC, and the system's PGLAPC and AGLPAC are shown. The on/off states of the thermal units under the four cases are given in Table VI, where the grey-colored data are the ones that are different between the cases. From these results, several points can be drawn:

TABLE V
COST AND EMISSION RESULTS FOR THE FOUR CASES (IEEE 14-BUS SYSTEM)

	UCC k\$	TPME ton	PGLAPC μg/m^3	AGLAPC μg/m^3	TE ·10^5 μg/m^3
Case 1	224.58	100.25	70.32	29.37	150.92
Case 2	200.19	93.43	70.32	29.22	150.42
Case 3	213.38	65.00	64.79	28.29	148.09
Case 4	209.79	67.90	56.07	28.10	145.81

TABLE VI
ON/OFF STATE COMPARISON OF THE FOUR CASES

Hour	Case 1					Case 2					Case 3					Case 4				
	Unit Bus No.					Unit Bus No.					Unit Bus No.					Unit Bus No.				
	1	2	3	6	8	1	2	3	6	8	1	2	3	6	8	1	2	3	6	8
1	1	1	1	0	0	0	1	1	1	0	1	0	0	1	1	0	1	1	0	1
2	1	1	1	0	0	0	1	1	1	0	1	0	0	1	1	0	1	1	0	1
3	0	1	1	0	0	0	1	1	1	0	1	0	0	1	1	0	1	1	0	1
4	0	1	1	0	0	0	1	0	1	0	1	0	0	1	1	0	1	0	0	1
5	0	1	1	0	0	1	1	0	0	0	1	0	0	1	1	0	1	0	0	1
6	0	1	1	1	1	1	1	1	0	0	1	0	0	1	1	0	1	1	1	1
7	1	1	1	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	1	1
8	1	1	1	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	1	1
9	1	1	1	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
13	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1
14	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1
15	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1
24	1	1	1	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	1	1
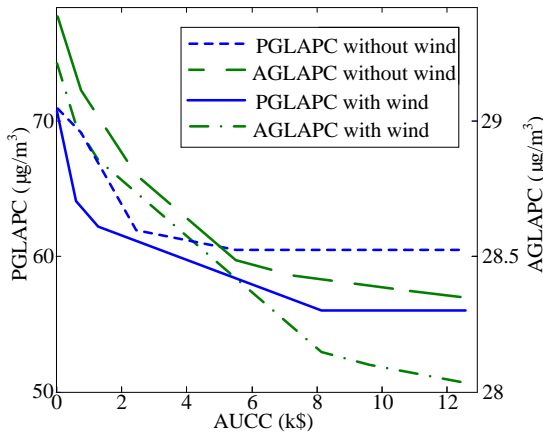
Fig. 3. Curves of AUCC-PGLAPC and AUCC-AGLAPC with and without wind power (IEEE 14-bus system).

although TPME decreases due to 10% less power demand from the thermal units. The system's PGLAPC stays the same at 70.32 μg/m^3, which is classified as severe pollution. This is because the system still uses more power from cheaper but more polluting coal units, as indicated in Table VI.

2) The measure for limiting the total amount of air pollutant emissions, i.e., TPME in this paper, can be less cost-effective than our proposed method in terms of air pollution control with wind power integration. From Cases 3 and 4, we can see that, if emission is explicitly considered, wind power is helpful in improving the effects of air pollution control. However, comparing Case 4 to Case 3, the results of the system's PGLAPC, AGLAPC, and TE are 13.46%, 0.67%, and 1.54% better, respectively, with \$3590 less UCC in Case 4. Note that in Case 3, TPME is limited to 65 tons, which is actually less than that of Case 4. This demonstrates our argument that meteorological conditions and the system's geographical distribution are critical factors for environmental generation scheduling.

3) Our proposed UC model can be quite helpful in realizing wind power benefits in air pollution control, especially for a system with locations with severe background pollution. In this system, the load center on bus 5 had the highest background PM2.5 concentration. Cases 1, 2, and 3 all resulted in much worse PGLAPC and AGLAPC, while in Case 4 they were both much lower. As shown in Table VI, the coal unit at bus 1, which is exactly in the upwind direction of bus 5, is turned on much less in Case 4 to ensure better air quality for the load center on bus 5. Compared to Case 3, this leads to a relatively slight increase in AGLAPC for the load centers on buses 11, 13, and 14, where the background PM2.5 pollutions are not as severe as at the load center on bus 5. This is an acceptable compromise.

We further explored the cost and effectiveness of reducing a system's PGLAPC and AGLAPC with and without wind power. First, based on Case 4, s was gradually increased from 0.0001 to 0.1 \$·m^3/μg, to obtain relationships between additional UCC (AUCC) and the PGLAPC, as well as between the AUCC and the AGLAPC. The AUCC is the increased UCC compared to Case 2. Secondly, similar work was done with wind power outputs set to zero such that the AUCC became the increased UCC compared to Case 1. As shown is Fig. 3, the system can be much more cost-effective in reducing the PGLAPC and AGLAPC when wind power is accommodated and proper consideration is given to air pollutant dispersion. This capability is also strengthened by wind power, since both the convergent PGLAPC and AGLAPC with AUCC increased are smaller with wind power compared to without wind power. These quantitative relationships can guide system operators in environmental generation scheduling according to their cost budget and air pollution control objective, and help governments in making corresponding subsidies or tax policies for air pollution control.

B. The Guangdong Grid System

The Guangdong Grid system has 1117 buses and 116 thermal units, with 6 planned wind farms reaching about 15% penetration. Reducing air pollution (GLAPC) in Guangzhou was the focus of this simulation. Monitored locations were

1) With wind power integrated, we still need to explicitly consider emissions during operations to utilize the benefits of wind power for air pollution control. Take Case 2 as an example, where TE and the system's AGLAPC only decrease by 0.33% and 0.49%, respectively, compared to Case 1,

TABLE VII
COST AND EMISSION RESULTS OF THE FOUR CASES (GUANGDONG GRID)

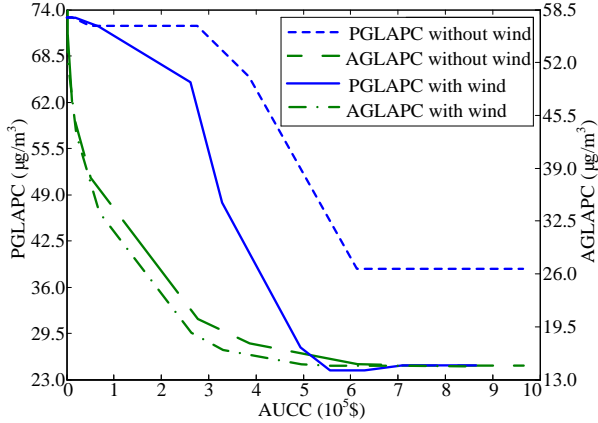|	UCC $\cdot 10^7$ \$	TPME ton	PGLAPC $\mu g/m^3$	AGLAPC $\mu g/m^3$	TE $\cdot 10^8 \mu g/m^3$
Case 1	1.6254	26640.70	74.36	58.88	133.59
Case 2	1.4596	24183.33	74.36	55.43	124.21
Case 3	1.5290	11500.00	74.36	33.60	66.54
Case 4	1.5158	19228.48	24.36	14.52	16.93

Fig. 4. Curves of AUCC-PGLAPC and AUCC-AGLAPC with and without wind power (Guangdong Grid)

selected among its 11 districts. The simulation assumed a summer day with a 2.44m/s southeast wind and neutral atmospheric stability. The applied plume model was also modified to consider the special temperature inversion condition prevalent in the area. Based on the meteorological and geographical conditions, 44 coal units out of the total 116 units were identified as directly influencing the GLAPC in Guangzhou and were specifically considered for air pollutant dispersion control. The other units in the system were only included in the UC model for on/off operational planning.

Similar to the previous study, four cases were simulated, with the TPME limit of Case 3 and s of Case 4 set as 11500.00 tons and 0.003 \$·m³/µg, respectively. A part of results are shown in Table VII and Fig. 4. Note that the PGLAPC and AGLAPC in cases 1, 2 are over 70 and 55 µg/m³, respectively, which are values actually seen in Guangzhou on some summer days. In Case 2, air pollution is not quite relieved by integrated wind power, although the AGLAPC decreases slightly. This again demonstrates the need to explicitly consider emission issues for air pollution control. As indicated by Case 3, only limiting TPME is not an effective measure in air pollution control. In Case 4, the proposed UC model explicitly considers the dispersion of emitted air pollutants, resulting in better air pollution control with less cost, as wind power's environmental benefits are better realized. Fig. 5 again proves that wind power makes a system more cost-effective and more capable of air pollution control.

Note that this paper studied measures for limiting total emissions and the proposed method separately for comparison. In practice, both have to be considered, since total emissions are mostly limited by laws or regulations. The proposed method will help to achieve better and more cost-effective air pollution control in this case.

VI. CONCLUSIONS

This paper proposed a UC model that considered the dispersion of air pollutants emitted by thermal units via a plume model involving meteorological conditions and the system's geographical distribution to utilize wind power benefits in air pollution control. The GLAPC at monitored locations was modeled and rendered a cost to achieve the spatial distribution control of air pollutants. Robust optimization was applied to appropriately accommodate wind power uncertainties in terms of spinning reserve scheduling, so that the benefits of wind power for air pollutant dispersion control could be properly estimated and sufficiently utilized. Illustrative cases showed that wind power benefits in air pollution control should be explicitly considered as they were not fully utilized by only limiting total air pollutants emissions. This highlights the need to consider air pollutant dispersion. The proposed model proved to be quite effective in controlling air pollution, utilizing wind power benefits, and providing useful information for system operators and policy-makers to conduct environmental generation scheduling. We also showed that wind power makes a system more cost-effective and more capable of air pollution control. For future research, it may be beneficial to develop an intro-day economic dispatch framework to consider localized meteorological conditions, which are unknown or only known with great uncertainty in day ahead scheduling but which are available in real time or near real-time.

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