IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 30, 2020, accepted April 18, 2020, date of publication April 22, 2020, date of current version June 25, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2989514

Co-Optimization of Generation Self-Scheduling and Coal Supply for Coal-Fired Power Plants

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This work was supported in part by the National Key Research and Development Program of China under Grant 2016YFB0901900, in part by the National Natural Science Foundation of China under Grant 71402021, in part by the Major International Joint Research Project of the National Natural Science Foundation of China under Grant 71520107004, in part by the Major Program of National Natural Science Foundation of China under Grant 71790614, and in part by the 111 Project under Grant B16009.

ABSTRACT Generation self-scheduling and coal supply in coal-fired power plants are closely related but typically optimized separately. To enhance the optimal operation of power plants, we propose a coordinated optimal operation strategy of generation and coal management in this paper. Uncertainties in electricity prices and demands, coal prices, and coal inventory holding costs are captured and modeled by discrete scenarios. Emission constraints are introduced to control generation emissions. The heat loss caused by the weathering of coal during the storage is taken into account, which distinguishes the considered co-optimization problem from the previous ones. The proposed strategy is built on a mixed-integer linear programming-typed two-stage stochastic programming model, in which whether to purchase coal is determined in the first stage and the quantity of coal purchase, the coal inventory, and the economic generation dispatch are determined in the second stage. The objective is to maximize the expected profits. An improved Benders decomposition algorithm is developed to solve the problem where multiple Benders cuts are added in each iteration and valid inequalities are introduced to speed up the convergence of the algorithm. Numerical experiments demonstrate the effectiveness of the proposed strategy and algorithm.

INDEX TERMS Generation self-scheduling, coal supply, co-optimization, stochastic programming, Benders decomposition.

NOMENCLATURE

A. SETS AND INDICES

I, i	Set and index of generators
J, j	Set and index of days
S, s	Set and index of scenarios
T, t	Set and index of hours
M_i, m	Set and index of linear segments for the coal consumption curve of generator i
k	Index of number of storage days

B. PARAMETERS

NI	Number of generators
NJ	Number of days over the decision time horizon
NS	Number of scenarios
NT	Number of hours over the decision time horizon
NM_i	Number of linear segments for the coal consumption curve of generator i
R_i^D/R_i^U	Downward/upward ramp rate of generator i
P_i^L/P_i^U	Minimum/maximum power output of generator i
$G_i(\cdot)$	Coal consumption function of generator i
α_{im}/β_{im}	Slope/intercept of the mth segment line for the coal consumption curve of generator i
p_{i0}	Power output of generator i in hour 0
D_t^s	Electricity demand in hour t in scenario s
r_i	Emission coefficient of generator i
$E^{\max}$	Maximum allowance of emissions over the decision time horizon
λ_t^s	Unit electricity price in hour t in scenario s
Q_j	Setup cost of coal purchase in day j
c_j^s	Unit coal price in day j in scenario s
h_j^s	Unit coal inventory holding cost in day j in scenario s

The associate editor coordinating the review of this manuscript and approving it for publication was Bilal Alatas.

ρ Daily heat-loss rate of coal
θ Thermal efficiency of coal
C_0 Initial inventory of coal
ρ_0 Heat-loss rate of the initial inventory of coal
$C^{\max}$ Inventory capacity of the coal yard
$\underline{F}$ Minimum purchase requirement for coal purchase
$F_j^{\max}$ Supply capacity of the coal market in day j
π_s Probability of scenario s

C. DECISION VARIABLES

y_j Binary decision variable to indicate whether to purchase coal in day j
p_{it}^s Power output of generator i in hour t in scenario s
ψ_{it}^s Quantity of coal consumed by generator i in hour t in scenario s
ϕ_{it}^s Quantity of thermal energy consumed by generator i in hour t in scenario s
f_j^s Quantity of coal purchased at the beginning of day j in scenario s
C_j^s Coal inventory at the end of day j in scenario s
In_{j0}^s Quantity of coal purchased at the beginning of day j and consumed in day j in scenario s
In_{jk}^s Quantity of coal purchased at the beginning of day j and stored for k days in scenario s
In_{00}^s Initial inventory of coal consumed in day 1 in scenario s
In_{0k}^s Initial inventory of coal stored for k days within the planning horizon in scenario s
z_s Auxiliary variable to represent the lower bound of the optimal objective function value of the Benders subproblem corresponding to scenario s
$\xi 1_{itm}^s, \xi 2_{qit}^s, \xi 3_{qit}^s, \xi 4_t^s, \xi 5^s, \xi 6_j^s, \xi 7^s, \xi 8_j^s, \xi 9_{qj}^s$ Dual variables of the Benders subproblem corresponding to scenario s
$\boldsymbol{\xi}^s$ Vector composed of the dual variables of the Benders subproblem corresponding to scenario s

I. INTRODUCTION

Generation self-scheduling (GSS) and coal supply (CS) are two important parts in the operation of coal-fired power plants. GSS is to decide the hourly output levels of generators according to electricity prices and demands for maximizing the generation profits. CS is to optimize the purchase and storage plans of coal according to the power plant's coal demands and the coal market's prices and supply capacity for minimizing the cost. These two parts essentially have a mutual impact. That is, GSS determines the coal demands to be met in the CS plan, while CS provides adequate fuel to ensure the stable operations of GSS in power plants. Such a close relationship motivates us to investigate a coordinated optimal operation strategy of GSS and CS with the objective to maximize the total profits.

The market-based operational process of a coal-fired power plant is illustrated in Figure 1. As shown in the figure, the power plant first purchases coal from the coal market according to the CS plan. Then, the purchased coal is temporarily stored in an open-air coal yard. During the storage, coal will has oxidation loss, namely *weathering*, resulting in the decrease of the coal's calorific value (hereinafter this is briefly referred to as the heat loss of coal). Finally, the coal is burned for power generation according to the GSS, emitting a large amount of CO_2 as a by-product. The produced electricity is sold to the electricity market at market price. The decision period for GSS is one hour and for CS is one day. These decisions are affected by electricity prices and demands, coal prices, and coal inventory holding costs, which are full of uncertainty. The uncertainty may come from the impacts of changes of weather, economic situation, or government policies on energy. Therefore, the aforementioned coordinated operation of GSS and CS is a stochastic co-optimization problem of GSS and CS with features of coal weathering and generation emissions.

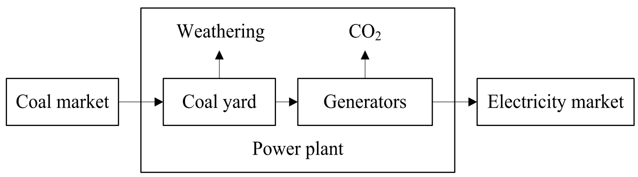

FIGURE 1. Market-based operational process of a coal-fired power plant.

There has been extensive research for GSS and CS in the literature. However, these works typically optimize GSS and CS separately, while the research on the aforementioned coordinated operation still lacks. Studies on GSS problems can be found in [1]–[9]. In [1], a worst-case robust economic dispatch strategy for the GSS with uncertain electricity prices was presented. In [2] and [3], the authors addressed the tradeoffs between profit and risk for the GSS. In [4], information-gap decision theory based GSS models were proposed. In [5], the GSS model considering carbon tax was presented. In [6], a data-driven risk-averse approach was developed for the GSS problem of combined-cycle units. In [7], a mixed integer linear programming (MILP) model was proposed for the GSS problem in pay-as-bid electricity markets. In [8], a stochastic adaptive robust optimization GSS model was presented for a virtual power plant. In [9], the GSS horizon for a wind farm and compressed air energy storage combined system was optimized. These works on GSS only focused on optimizing the generation schedules without considering fuel supply decisions. On the other hand, studies on CS in power plants can be found in [10]–[13]. In [10], a general decision analysis formulation of coal inventory for power plants was presented to assess optimal purchase and storage decisions. In [11], a two-phase dynamic procedure was proposed for fuel procurement of electricity utilities under demand and market price uncertainties. In [12], an economic order quantity model incorporating stochastic programming and interval parameters was proposed for power plant planning. In [13], a risk management model was proposed for the coal inventory problem under uncertainty and emission constraints. These works on CS only focused on optimizing the procurement and storage plans of coal without considering the impact and effect of GSS.

Although there were works on the co-optimization of generation and fuel supply, related studies typically concentrated on power-gas co-optimization, i.e., the coordinated scheduling of power generation and natural gas supply. A stochastic formulation for hedging between natural gas and electricity markets was discussed in [14]. A deterministic coordinated scheduling of security-constrained unit commitment and natural gas transmission was studied in [15]. A stochastic programming model that simultaneously determined the trading quantities of natural gas and electricity and the generation schedule was proposed in [16]. An hourly demand response was incorporated in the scheduling of integrated electricity and natural gas networks in [17]. MILP formulations for coupled power and gas networks were proposed in [18] and [19]. An integrated stochastic model of natural gas and wind energy generators was proposed in [20]. An interval optimization based model for gas-power integrated systems was proposed in [21]. Robust optimization models for addressing the day-ahead coordinated operations of interdependent power and gas systems were proposed in [22] and [23]. A distributionally robust scheduling model of gas-electricity integrated system considering wind power uncertainty was proposed in [24]. Bi-level optimization models for gas-electricity systems were proposed in [25] and [26]. Since natural gas is well preserved in pipelines, the models for power-gas co-operations do not consider fuel weathering. However, coal is easy-to-be weathered due to its open storage. Therefore, the models for power-gas co-operations reviewed above cannot precisely describe the actual operation of CS and be directly applied to the problem of GSS and CS coordinated operation.

To address the aforementioned problem, in this paper, we propose a GSS and CS coordinated optimal operation strategy in the view point of a coal-fired power plant who acts as a price-taker. The proposed strategy is built on a two-stage stochastic programming model, in which emission constraints are introduced to control generation emissions and the heat loss caused by the weathering of coal is taken into account for representing the plant's practical operation. The proposed strategy will enable the coal-fired power plant to decide the optimal coal purchase and generation scheduling for maximizing the operation profits, while satisfying practical operational constraints including the capacity limits of coal market supply and coal purchase and storage, generator operating requirements, and constraints for electricity demands and emissions. The major contributions of the paper can be summarized as follows:

1) In view of the mutual effect between GSS and CS in coal-fired power plants, we propose a co-optimization strategy of GSS and CS for enhancing the optimal operation and coordination of power plants.

2) The proposed strategy is built on a two-stage stochastic programming model which considers the effects of coal weathering and the control of generation emissions, and uses scenarios to describe uncertainties in electricity prices and demands, coal prices, and coal inventory holding costs.

3) An improved Benders decomposition algorithm is developed to solve the proposed problem where multiple Benders cuts are added in each iteration and valid inequalities are introduced to speed up the convergence of the algorithm.

4) Numerical experiments are conducted to demonstrate the effectiveness of the proposed strategy and algorithm. A sensitivity analysis is carried out to discuss the impact of coal weathering on the operation decision.

The rest of the paper is organized as follows. Section II formulates the proposed co-optimization strategy. Section III develops a Benders decomposition algorithm to solve the problem. The effectiveness of the proposed strategy and the algorithm efficiency are verified by case studies in Section IV. Finally, Section V concludes the paper.

II. STRATEGY DESCRIPTION AND FORMULATION

In this section, we present the framework of the proposed co-optimization strategy, the expression of uncertain parameters, the thermal energy consumption functions of generators, and the formulation of the proposed strategy.

A. FRAMEWORK OF THE CO-OPTIMIZATION STRATEGY

Figure 2 depicts the framework of the proposed co-optimization strategy of GSS and CS. As illustrated in the figure, the proposed strategy coordinates optimizations for GSS and CS in a two-stage decision framework. Whether to purchase coal is determined in the first stage, and the quantity of coal purchase, the coal inventory, and the economic generation dispatch are determined in the second stage. The objective of the strategy is to maximize the total operation profits. Under the strategy, the mutual effect between GSS and CS is taken into account and the information in electricity and coal markets is balanced in the decision-making.

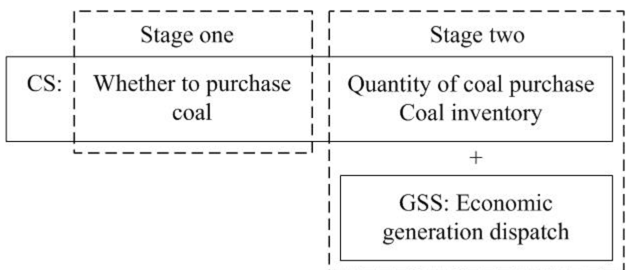

FIGURE 2. Framework of the co-optimization strategy of GSS and CS.

B. EXPRESSION OF UNCERTAIN PARAMETERS

Electricity prices and demands, coal prices, and coal inventory holding costs are uncertain and approximated by a finite number of discrete scenarios with certain probabilities of occurrence. These scenarios and their probabilities can be available from historical data. A common approach to obtain the scenarios is to generate a large number of scenarios using the Monte Carlo sampling method and then reduce the number of scenarios using the cluster analysis method. The scenario-based approach has been widely used in dealing with uncertainties. Examples for modeling uncertainties based on scenarios in generation scheduling problems can be found in [27]–[30].

C. THERMAL ENERGY CONSUMPTION FUNCTIONS

For each generator, the quantity of thermal energy consumption is proportional to the quantity of coal consumption:

$$\phi_{it}^s = \theta G_i(p_{it}^s), \quad i \in I,\ t \in T,\ s \in S \tag{1}$$

where θ represents the quantity of thermal energy provided by each unit of coal, and $G_i(p_{it}^s)$ is a quadratic function of p_{it}^s. By approximating $G_i(p_{it}^s)$, $i \in I$, $t \in T, s \in S$, using the following piecewise linear functions:

$$\psi_{it}^s \geq \alpha_{im} p_{it}^s + \beta_{im}, \quad m \in M_i,\ i \in I,\ t \in T,\ s \in S, \tag{2}$$

one can obtain the piecewise linear approximation for the thermal energy consumption functions of generators as follows:

$$\begin{aligned} &\phi_{it}^s \geq \theta(\alpha_{im} p_{it}^s + \beta_{im}), \\ &m \in M_i, \quad i \in I,\ t \in T,\ s \in S. \end{aligned} \tag{3}$$

D. MATHEMATICAL FORMULATION OF THE STRATEGY

Based on the above discussion, the co-optimization strategy of GSS and CS is formulated as follows:
(P)

$$\max \ -\sum_{j=1}^{NJ} Q_j y_j + \sum_{s=1}^{NS} \pi_s [\sum_{t=1}^{NT} \lambda_t^s \sum_{i=1}^{NI} p_{it}^s - \sum_{j=1}^{NJ} (c_j^s f_j^s + h_j^s C_j^s)] \tag{4}$$

subject to constraints (3) and

$$P_i^L \leq p_{it}^s \leq P_i^U, \quad i \in I,\ t \in T,\ s \in S \tag{5}$$

$$-R_i^D \leq p_{it}^s - p_{i,t-1}^s \leq R_i^U, \quad i \in I,\ t \in T,\ s \in S \tag{6}$$

$$\sum_{i=1}^{NI} p_{it}^s \leq D_t^s, \quad t \in T,\ s \in S \tag{7}$$

$$\frac{1}{\theta} \sum_{t=1}^{NT} \sum_{i=1}^{NI} r_i \phi_{it}^s \leq E^{\max}, \quad s \in S \tag{8}$$

$$f_j^s = \sum_{k=0}^{NJ-j+1} In_{jk}^s, \quad j \in J,\ s \in S \tag{9}$$

$$\begin{aligned} \sum_{t=24(j-1)+1}^{24j} \sum_{i=1}^{NI} \phi_{it}^s &= \theta\, [In_{0,j-1}^s (1-\rho_0)(1-\rho)^{j-1} \\ &\quad + \sum_{j'=1}^{j} In_{j',j-j'}^s (1-\rho)^{j-j'}], \quad j \in J,\ s \in S \end{aligned} \tag{10}$$

$$C_j^s = \sum_{k=j}^{NJ} In_{0k}^s + \sum_{j'=1}^{j} \sum_{k=j+1-j'}^{NJ-j'+1} In_{j'k}^s, \quad j \in J,\ s \in S \tag{11}$$

$$C_0 = \sum_{k=0}^{NJ} In_{0k}^s, \quad s \in S \tag{12}$$

$$C_j^s \leq C^{\max}, \quad j \in J,\ s \in S \tag{13}$$

$$y_j \underline{F} \leq f_j^s \leq y_j F_j^{\max}, \quad j \in J,\ s \in S \tag{14}$$

$$y_j \in \{0, 1\}, \quad j \in J \tag{15}$$

$$\phi_{it}^s, p_{it}^s \geq 0, \quad i \in I,\ t \in T,\ s \in S \tag{16}$$

$$f_j^s, C_j^s \geq 0, \quad j \in J,\ s \in S \tag{17}$$

$$In_{0k}^s \geq 0, \quad k \in \{0\} \cup J,\ s \in S \tag{18a}$$

$$In_{jk}^s \geq 0, \quad j \in J,\ k = 0, \ldots, NJ - j + 1,\ s \in S \tag{18b}$$

In the above model, the objective function (4) is to maximize the expected profits over all scenarios. The profits under each scenario are determined by coal purchase startup costs, the electricity sales revenue, coal purchase linear costs, and coal inventory holding costs. The decision is made in two stages. The first stage is to decide whether to purchase coal (y_j) in each day. The second stage is to decide the quantity of coal purchase (f_j^s) and the coal inventory (C_j^s) in each day and the generation level of each generator (p_{it}^s) in each hour. Constraints (5) represent the power output ranges of generators. Constraints (6) represent the upward and downward ramp-rate constraints of generators. Constraints (7) represent electricity demand constraints in the electricity market. Constraints (8) limit the total quantity of emissions over the decision time horizon within the maximum allowance. Constraints (9) represent the balance constraints on the purchase, consumption, and storage of coal. Constraints (10) represent thermal energy balance constraints for coal-fired power generation in each day, which connect GSS and CS decisions. Constraints (11) represent that the coal inventory in each day consists of the coal initial inventory stored to the day and the coal purchased no later than the day and stored to the day. Constraints (12) represent the relationship between the consumption and storage of coal initial inventory. It can be noted from constraints (9)-(12) that variables In_{j0}^s, In_{jk}^s, In_{00}^s, and In_{0k}^s are introduced to model the heat loss of coal and the relationships between the introduced variables and f_j^s, C_j^s, and C_0 are presented in constraints (9), (11), and (12), respectively. Constraints (13) represent the capacity limits for inventory holding of the coal yard. Constraints (14) represent the capacity limits for coal purchase in each day, which are determined by not only the minimum purchase requirement of the power plant itself, but also the supply capacity of the coal market in that day. Constraints (15)-(18b) define the value fields of decision variables.

III. SOLUTION METHODOLOGY

(P) is a large-scale mixed integer linear programming (MILP) problem with multiple scenarios. Considering the structure of (P), we develop a Benders decomposition algorithm in this section to solve it.

A. TRANSFORMATION OF THE PRIMARY PROBLEM

First, we can reduce the number of decision variables in (P) by replacing C_j^s and f_j^s in (4), (13), (14), and (17) with equations (9) and (11). Second, we transform (P) equivalently into a minimization problem for convenience of expression. The obtained equivalent transformation of (P) is given below:

(P1)

$$\begin{aligned}\min & \sum_{j=1}^{NJ} Q_j y_j + \sum_{s=1}^{NS} \pi_s \{ \sum_{j=1}^{NJ} [c_j^s (\sum_{k=0}^{NJ-j+1} In_{jk}^s) \\ & + h_j^s (\sum_{k=j}^{NJ} In_{0k}^s + \sum_{j'=1}^{j} \sum_{k=j+1-j'}^{NJ-j'+1} In_{j'k}^s)] - \sum_{t=1}^{NT} \lambda_t^s \sum_{i=1}^{NI} p_{it}^s \} \\ = & \sum_{j=1}^{NJ} Q_j y_j + \sum_{s=1}^{NS} \pi_s \{ \sum_{k=1}^{NJ} (\sum_{j=1}^{k} h_j^s) In_{0k}^s + \sum_{j=1}^{NJ} c_j^s In_{j0}^s \\ & + \sum_{j=1}^{NJ} \sum_{k=1}^{NJ-j+1} (c_j^s + \sum_{j'=j}^{k+j-1} h_{j'}^s) In_{jk}^s - \sum_{t=1}^{NT} \lambda_t^s \sum_{i=1}^{NI} p_{it}^s \} \end{aligned} \quad (19)$$

subject to constraints (3), (5)-(8), (10), (12), (15), (16), (18a), (18b), and

$$\sum_{k=j}^{NJ} In_{0k}^s + \sum_{j'=1}^{j} \sum_{k=j+1-j'}^{NJ-j'+1} In_{j'k}^s \leq C^{\max}, \quad j \in J, \ s \in S \quad (20)$$

$$y_j \underline{F} \leq \sum_{k=0}^{NJ-j+1} In_{jk}^s \leq y_j F_j^{\max}, \quad j \in J, \ s \in S \quad (21)$$

B. THE BENDERS SUBPROBLEM

By fixing the integer variable $y_j = \bar{y}_j$ in (P1), we can obtain the Benders subproblem as follows:

(SP)

$$\begin{aligned}\min & \sum_{s=1}^{NS} \pi_s \{ \sum_{k=1}^{NJ} (\sum_{j=1}^{k} h_j^s) In_{0k}^s + \sum_{j=1}^{NJ} c_j^s In_{j0}^s \\ & + \sum_{j=1}^{NJ} \sum_{k=1}^{NJ-j+1} (c_j^s + \sum_{j'=j}^{k+j-1} h_{j'}^s) In_{jk}^s - \sum_{t=1}^{NT} \lambda_t^s \sum_{i=1}^{NI} p_{it}^s \} \end{aligned} \quad (22)$$

subjective to constraints (3), (5)-(8), (10), (12), (16), (18a), (18b), (20), and

$$\bar{y}_j \underline{F} \leq \sum_{k=0}^{NJ-j+1} In_{jk}^s \leq \bar{y}_j F_j^{\max}, \quad j \in J, \ s \in S. \quad (23)$$

C. THE BENDERS MASTER PROBLEM

The Benders master problem is:

(MP)

$$\min \sum_{j=1}^{NJ} Q_j y_j + \sum_{s=1}^{NS} \pi_s z_s \quad (24)$$

subject to constraints (15).

(MP) is an MILP problem and can be effectively solved by an MILP solver. As (MP) is a relaxation of (P1), the optimal objective function value of (MP) provides a lower bound for (P1).

D. BENDERS CUTS

The lower bound provided by (MP) can be tightened by adding Benders cuts that include Benders feasibility cuts and Benders optimality cuts into (MP). In the typical Benders decomposition algorithm, Bender cuts are constructed based on the dual of the Benders subproblem and only one Benders cut is added into the Benders master problem in each iteration. In this paper, instead of constructing Benders cuts according to the typical Benders decomposition algorithm, we construct multiple Benders cuts in each iteration to improve the convergence of the algorithm [31], [32].

First, noting that (SP) is separable in scenarios, we decompose (SP) into NS subproblems where the sth subproblem is:

(SP_s)

$$\begin{aligned}\min & \sum_{k=1}^{NJ} (\sum_{j=1}^{k} h_j^s) In_{0k}^s + \sum_{j=1}^{NJ} c_j^s In_{j0}^s \\ & + \sum_{j=1}^{NJ} \sum_{k=1}^{NJ-j+1} (c_j^s + \sum_{j'=j}^{k+j-1} h_{j'}^s) In_{jk}^s - \sum_{t=1}^{NT} \lambda_t^s \sum_{i=1}^{NI} p_{it}^s \end{aligned} \quad (25)$$

subjective to constraints (3), (5)-(8), (10), (12), (16), (18a), (18b), (20), and (23) corresponding to scenario s.

For the fixed $\bar{y}_j$, each (SP_s) is a linear programming (LP) model and its dual formulation is:

(DSP_s)

$\max f(\bar{y}_j, \ \boldsymbol{\xi}^s)$

with

$$\begin{aligned} f(\bar{y}_j, \ \boldsymbol{\xi}^s) = & \sum_{i=1}^{NI} \sum_{t=1}^{NT} (\theta \sum_{m=1}^{NM} \beta_{im} \xi 1_{itm}^s + P_i^L \xi 2_{1it}^s - P_i^U \xi 2_{2it}^s \\ & - R_i^D \xi 3_{1it}^s - R_i^U \xi 3_{2it}^s) + \sum_{i=1}^{NI} p_{i0} (\xi 3_{1i1}^s - \xi 3_{2i1}^s) \\ & - \sum_{t=1}^{NT} D_t^s \xi 4_t^s - E^{\max} \xi 5^s + C_0 \xi 7^s - C^{\max} \sum_{j=1}^{NJ} \xi 8_j^s \\ & + \sum_{j=1}^{NJ} (\underline{F} \xi 9_{1j}^s - F_j^{\max} \xi 9_{2j}^s) \bar{y}_j \end{aligned} \quad (26)$$

subjective to

$$\sum_{m=1}^{NM_i} \xi 1_{itm}^s - \frac{1}{\theta} r_i \xi 5^s + \xi 6_j^s \leq 0,$$
$$i \in I, \quad t = 24(j-1)+1, \ldots, 24j, \ j \in J \quad (27)$$

$$\begin{aligned} & -\theta \sum_{m=1}^{NM_i} \alpha_{im} \xi 1_{itm}^s + \xi 2_{1it}^s - \xi 2_{2it}^s + \xi 3_{1it}^s - \xi 3_{2it}^s \\ & - \delta_{(t \leq T-1)} (\xi 3_{1i,t+1}^s - \xi 3_{2i,t+1}^s) - \xi 4_t^s \leq -\lambda_t^s, \quad i \in I, \ t \in T \end{aligned} \quad (28)$$

$$-\theta(1-\rho_0)\xi 6_1^s + \xi 7^s \leq 0 \tag{29a}$$

$$-\delta_{(k\leq J-1)}\theta(1-\rho_0)(1-\rho)^k \xi 6_{k+1}^s + \xi 7^s - \sum_{j=1}^{k} \xi 8_j^s \leq \sum_{j=1}^{k} h_j^s, \quad k \in J \tag{29b}$$

$$-\theta \xi 6_j^s - \xi 9_{1j}^s + \xi 9_{2j}^s \leq c_j^s, \quad j \in J \tag{30a}$$

$$-\delta_{(1\leq j\leq NJ-1,\ 1\leq k\leq NJ-j)}\theta \xi 6_{k+j}^s (1-\rho)^k + \sum_{j'=j}^{j+k-1} \xi 8_{j'}^s - \xi 9_{1j}^s + \xi 9_{2j}^s \leq c_j^s + \sum_{j'=j}^{j+k-1} h_{j'}^s, \quad j \in J,\ k = 0, \ldots, NJ-j+1 \tag{30b}$$

$$\xi 1_{itm}^s \geq 0, \quad i \in I,\ t \in T,\ m \in M_i \tag{31}$$

$$\xi 2_{qit}^s \geq 0, \quad \xi 3_{qit}^s \geq 0,\ q = 1,\ 2,\ i \in I,\ t \in T \tag{32}$$

$$\xi 4_t^s \geq 0, \quad t \in T \tag{33}$$

$$\xi 5^s \geq 0, \quad \xi 7^s \in R \tag{34}$$

$$\xi 6_j^s \in R, \quad \xi 8_j^s \geq 0,\ j \in J \tag{35}$$

$$\xi 9_{qj}^s \geq 0, \quad q = 1, 2,\ j \in J \tag{36}$$

where $\xi 1_{itm}^s, \xi 2_{qit}^s, \xi 3_{qit}^s, \xi 4_t^s, \xi 5^s, \xi 6_j^s, \xi 7^s, \xi 8_j^s, \xi 9_{qj}^s$ are dual variables corresponding to constraints (3), (5)-(8), (10), (12), (20), and (23), respectively, and $\delta_{(A)}$ is an indicative function to represent whether event A is true or not. Each (DSP$_s$) is an LP model and can be conveniently solved by an LP solver.

Second, we construct Benders cuts based on (DSP$_s$), $s \in S$, as follows. If (DSP$_s$) is infeasible for a given scenario s, determine an extreme ray $\tilde{\boldsymbol{\xi}}^s$ of the polyhedron composed of constraints (27)-(36) corresponding to scenario s and produce the following Benders feasibility cut:

$$f(y_j,\ \tilde{\boldsymbol{\xi}}^s) \leq 0. \tag{37}$$

Otherwise, if (DSP$_s$) is feasible for all scenario s, obtain the optimal solution $\hat{\boldsymbol{\xi}}^s$ to each (DSP$_s$), $s \in S$, and generate multiple Benders optimality cuts as follows:

$$f(y_j,\ \hat{\boldsymbol{\xi}}^s) \leq z^s, \quad s \in S. \tag{38}$$

E. VALID INEQUALITIES

To speed up the convergence of the algorithm, we construct the following supply capacity valid inequalities based on the constraints in (P) and add them into the Benders master problem:

$$\sum_{i=1}^{n}\sum_{t=1}^{24j} x_{it} \leq C_0 + \sum_{j'=1}^{j} y_{j'} \min\{F_{j'}^{\max},\ C^{\max} + \sum_{i=1}^{n}\sum_{t=24j'-23}^{24j'} x_{it}\}, \quad j \in J \tag{39}$$

where

$$x_{it} = \begin{cases} \alpha_{im_{it}} \max\{p_{i0} - tR_i^D, P_i^L\} + \beta_{im_{it}}, & t \leq \tau_i, \\ G_i(P_i^L), & t > \tau_i, \end{cases} \tag{40}$$

$$\tau_i = \max\{0,\ (p_{i0} - P_i^L)/R_i^D\}, \tag{41}$$

$$m_{it} = \min\{m \in M_i : P_i^L + (m-1)\Delta p_i \leq \max\{p_{i0} - tR_i^D, P_i^L\} \leq P_i^L + m\Delta p_i\}, \tag{42}$$

and

$$\Delta p_i = (P_i^U - P_i^L)/M_i. \tag{43}$$

Valid inequalities (39) is used to insure that the minimum quantity of coal consumption is no more than the maximum supply of coal, where the latter is determined by the initial inventory, coal-purchase decisions, the supply capacities of the coal market, and the inventory capacity of the coal yard.

F. ALGORITHM FRAMEWORK

Based on the above discussion, the proposed Benders decomposition algorithm can be implemented based on the following steps:

Step 0. Initialize $l = 1$, $y_j^{(1)} = 0$, and $Z^U = +\infty$, where l is the index of iteration and Z^U is the upper bound of the optimal objective function value of (P1). Add valid inequalities (39) to (MP).

Step 1. Fix $y_j = y_j^{(l)}$ in (DSP$_s$), $\forall s \in S$, and add Benders cuts to (MP) as follows:

- Step 1.0. Initialize $s = 1$ and $w = 1$, where w is a binary variable to indicate whether all (DSP$_s$), $\forall s \in S$, are feasible in the current iteration.
- Step 1.1. Solve (DSP$_s$) using an LP solver. If (DSP$_s$) is infeasible, add a Benders feasibility cut (37) to (MP) and set $w = 0$. If (DSP$_s$) is feasible, record the optimal objective function value of (DSP$_s$) as g^s.
- Step 1.2. If $s \leq NS - 1$, let $s = s + 1$ and go to Step 1.1.
- Step 1.3. If $w = 1$, add Benders optimality cuts (38) to (MP), calculate $B^U = \sum_{j=1}^{NJ} Q_j y_j + \sum_{s=1}^{NS} \pi_s g^s$, and update Z^U with B^U if $B^U < Z^U$.

Step 2. Solve (MP) by an MILP solver and obtain its optimal solution $y_j^{(l+1)}$ and its optimal objective function value B^L.

Step 3. If either of the following criteria is met, stop the iteration. Otherwise, let $l = l + 1$ and go back to Step 1:

1) The relative gap $(Z^U - B^L)/|B^L|$ is zero;
2) The maximum iteration number is reached.

IV. NUMERICAL RESULTS

In this section, the proposed strategy and algorithm are validated by extensive numerical experiments implemented in Visual C++ under the computing environment of 3.40 GHz and 16.0 GB memory. The MILP and LP involved are completed by using CPLEX 12.5 callable library. The maximum iteration number is set to 50 in the experiments.

The numerical experiments are performed in four parts. First, we use test cases of different sizes to test

TABLE 1. Settings for partial parameters.

Parameter	Setting
$\underline{F}$	$168\sum_{i=1}^{NI} G_i(P_i^U)$
$C^{\max}$	$\eta_C \sum_{i=1}^{NI} G_i(P_i^U), \eta_C \sim U(168, 236)$
$E^{\max}$	$672\,[\sum_{i=1}^{NI} r_i G_i(P_i^L) + \eta_E(\sum_{i=1}^{NI} r_i G_i(P_i^U) - \sum_{i=1}^{NI} r_i G_i(P_i^L))], \eta_E \sim U(0.4, 1)$
D_t^s	$\eta_D \sum_{i=1}^{NI} P_i^U, \eta_D \sim U(0.8, 1)$

TABLE 2. Value ranges for partial parameters.

Parameter (Unit)	Value Range
λ_t^s (\$/MWh)	(10, 60)
c_j^s (\$/t)	(70, 100)
h_j^s (\$/t)	(0.12, 0.15)
Q_j (\$)	(1000, 1200)
r_i	(2.0, 2.8)
ρ	(0.0005, 0.0015)

the performance of the proposed Benders decomposition algorithm. Second, we test the effectiveness of the co-optimization strategy by comparing the strategy with the separated optimization strategy that optimizes GSS and CS separately. Third, we provide the sensitive analysis of the heat-loss rate of coal. Finally, the impact of emission constraints on the solution is tested.

Test cases are generated randomly based on IEEE data and the real data of a coal-fired power plant located in Northeastern China. The decision time horizon is set to be 28 days (672 hours), the numbers of generators are 4, 7, and 10, respectively, and the numbers of scenarios are 5, 10, 15, and 20, respectively. The combination of the configurations forms 12 different problem sizes. For each problem size, ten test cases are generated randomly where each test case is described as follows. Generators are sampled randomly from the 33 generators in the modified IEEE 118-bus system. Parameters for coal consumption curves of the sampled generators are adjusted so that the average coal consumption for power generation is 0.22 t/MWh. Settings for parameters $\underline{F}$, $C^{\max}$, $E^{\max}$, and D_t^s are shown in Table 1. $F_j^{\max}$ is set to be $672\sum_{i=1}^{NI} G_i(P_i^U)$ if the coal market can supply sufficient coal and 0 otherwise. Without loss of generality, C_0 is set to be $24\sum_{i=1}^{NI} G_i(P_i^U)$ and ρ_0 is 0.01. Other parameters' values are generated randomly from the ranges given in Table 2. For each generator, a five-piece piecewise linear function is utilized to approximate the quadratic coal consumption function. In the second, third, and fourth parts of the experiments, the cases under different numbers of scenarios demonstrate similar patterns of results; so only the results of test cases with ten scenarios will be shown for the sake of brevity.

TABLE 3. Numerical results of CPLEX solver and algorithms BD and MVBD.

No.	Size	CPLEX		BD			MVBD		
	($NI \times NS$)	N^o	RT (s)	N^o	N^i	RT (s)	N^o	N^i	RT (s)
1	4×5	10	227.92	10	19	31.69	10	11	19.41
2	7×5	8	713.26	10	15	46.44	10	11	31.99
3	10×5	3	435.19	10	17	88.56	10	11	58.29
4	4×10	1	388.56	10	25	82.70	10	12	40.52
5	7×10	4	1147.94	9	35	198.51	10	17	97.81
6	10×10	0	-	10	22	229.15	10	13	127.99
7	4×15	1	1979.18	10	31	145.11	10	13	64.05
8	7×15	0	-	10	33	284.61	10	14	122.40
9	10×15	0	-	9	32	505.41	10	14	223.23
10	4×20	3	2026.39	8	28	180.64	10	13	85.14
11	7×20	0	-	9	36	425.75	10	15	180.42
12	10×20	0	-	7	37	791.61	10	16	334.22
	Avg.	3	-	9	27	250.85	10	13	115.46

A. PERFORMANCE OF THE PROPOSED BENDERS DECOMPOSITION ALGORITHM

To benchmark the performance of the proposed Benders decomposition algorithm, CPLEX solver and the typical Benders decomposition algorithm are used to solve the test cases. For simplicity, hereinafter the typical Benders decomposition algorithm and the proposed algorithm are referred to as BD and MVBD, respectively. Table 3 shows the numerical results in which the following three indices of the algorithm performance are compared:

1) N^o, which is the number of test cases that can be solved optimally.

2) N^i, which is the number of iterations of algorithms BD and MVBD.

3) RT, which is the average computation time of each solution method. (If a solution method is out of memory for a certain test case, the computation time of that case in the corresponding RT is not included. If a solution method is out of memory for all test cases for a certain problem size, the average computation time of this method for this problem size is not shown).

From Table 3, one can obtain the following observations:

1) When CPLEX solver is used to solve the test cases directly, all small-size test cases (i.e., size 1) and some of the medium-size cases (i.e., sizes 2-5, 7, and 10) can be solved optimally. For large-size problems (i.e., sizes 6, 8, 9, 11, and 12), CPLEX solver is out of memory for all test cases. The average number of solvable test cases under the same problem size is 3.

2) When algorithm BD is used to solve the test cases, there are eight test cases that are not solved to optimality. The average number of iterations and computation time and the longest computation time are 27, 250.85 s, and 791.63 s, respectively.

3) For algorithm MVBD, it can solve all the test cases under all problem sizes to optimality. The average number of iterations and computation time and the longest computation

time are 13, 115.46 s, and 334.22 s, respectively. The computation time increases linearly as the problem size increases. The results indicate that algorithm MVBD can solve the considered test cases to optimality in a reasonable time.

4) A comparison of the results between algorithm BD and algorithm MVBD shows that the introduced multi-cut generation strategy and valid inequalities can effectively reduce both the number of iterations and the computation time of the Benders decomposition algorithm. A comparison of the results between algorithm MVBD and CPLEX solver indicates that algorithm MVBD is more effective than CPLEX solver for solving the considered test cases.

B. EFFECTIVENESS OF THE CO-OPTIMIZATION STRATEGY

To verify the effectiveness of the proposed co-optimization strategy (hereinafter referred as the CO strategy), we apply the separated optimization strategy (referred to as the SO strategy, in which GSS is optimized first, and then CS is optimized based on the obtained self-scheduling) as a benchmark. The following two situations are considered:

1) *Situation 1*: the base situation where the coal market can supply sufficient coal during the decision horizon.

2) *Situation 2*: the situation where the coal market is out of stock for several consecutive days during the decision time horizon. The duration of the coal shortage, denoted by $Dout$, is set to be 7, 14, and 21 days, respectively, and the beginning day of the coal shortage is generated randomly form day 2 to day $NJ - Dout + 1$. For the convenience of comparing the solution performances, we introduce a linear penalty item in the expected profits for any unsatisfied coal demand where the unit penalty cost is set to be 200\$/t.

Tables 4 and 5 show the numerical results in which the following four indices are compared:

TABLE 4. Comparison of the solutions between the SO and CO strategies in situation 1.

NI	N^n		Profits (\$)		PI (\$)	RPI (%)
	SO	CO	SO	CO		
4	0	0	8273945.33	8756316.69	482371.36	5.83
7	0	0	16066978.58	16431531.12	364552.54	2.27
10	0	0	20431841.23	21983127.48	1551286.25	7.59
Avg.	0	0	14924255.05	15723658.43	799403.38	5.23

TABLE 5. Comparison of the solutions between the SO and CO strategies in situation 2.

$Dout$ (d)	NI	N^n		Profits (\$)		PI (\$)	RPI (%)
		SO	CO	SO	CO		
7	4	1	0	8074437.45	8737933.14	663495.69	8.22
	7	0	0	15852433.74	16408345.87	555912.13	3.51
	10	1	0	20019092.92	21791033.72	1771940.80	8.85
	Avg.	1	0	14648654.70	15645770.91	997116.21	6.86
14	4	6	0	6195017.05	8621393.67	2426376.62	39.17
	7	5	0	12415002.51	16263451.36	3848448.85	31.00
	10	7	0	17612139.91	21568060.21	3955920.30	22.46
	Avg.	6	0	12074053.16	15484301.75	3410248.59	30.88
21	4	10	0	1974363.48	8511838.17	6537474.69	331.12
	7	10	0	6296397.68	15973603.41	9677205.73	153.69
	10	10	0	8614464.27	21256595.71	12642131.44	146.75
	Avg.	10	0	5628408.48	15247345.76	9618937.29	210.52

1) N^n, the number of test cases in which no solution can be found by the SO strategy or the CO strategy.

2) The expected profits under the SO strategy and the CO strategy, in which each result is the average of the ten test cases under the same problem size.

3) PI, the profit increment obtained from the expected profits under the CO strategy minus those under the SO strategy.

4) RPI, the relative profit increment calculated by PI/expected profits under the SO strategy $\times$ 100%.

From Tables 4 and 5, one can have the following observations:

1) The SO strategy cannot find a solution for some of the test cases in situation 2. This is because the SO strategy ignores the supply capacity of the coal market in the optimization of GSS, so that it may not be able to buy enough coal to meet the demand of power generation. The number of test cases in which the SO strategy cannot find a solution increases as the duration of coal shortage increases. When the duration of coal shortage increases to 21 days, the SO strategy is infeasible for all the test cases. The CO strategy, in contrast, can find solutions for all the test cases under all coal-shortage durations.

2) In both situations, the CO strategy leads to higher expected profits compared with the SO strategy. This indicates the advantage of the proposed CO strategy that it can contribute to higher profits for the power plant.

3) Compared with Situation 1, Situation 2 shows higher values of PI and RPI. This is not only because the CO strategy can find the global optimum but also because the occurrence of unsatisfied coal demand introduces a penalty cost in Situation 2. In Situation 2, as the duration of coal shortage increases, both PI and RPI increase. This indicates that the advantage of the CO strategy over the SO strategy is more obvious with the increase of the duration of coal shortage.

The above observations demonstrate the advantages of the CO strategy over the SO strategy.

C. SENSITIVITY ANALYSIS OF THE HEAT-LOSS RATE

To show how the change of the heat-loss rate of coal affects the solution, we set the heat-loss rates to be 0.0005, 0.0010, and 0.0015, respectively, and present the total quantity of coal purchase and the expected profits under these different heat-loss rates. The numerical results are reported in Tables 6 and 7, from which the following observations can be made:

TABLE 6. Quantity of coal purchase (t) under different heat-loss rates of coal.

NI	$\rho = 0.0005$	$\rho = 0.0010$	$\rho = 0.0015$
4	90360.01	92541.98	93997.56
7	166134.70	169052.96	172133.70
10	207706.28	212226.29	217039.04
Avg.	154733.66	157940.41	161056.77

TABLE 7. Profits ($) under different heat-loss rates of coal.

NI	$\rho = 0.0005$	$\rho = 0.0010$	$\rho = 0.0015$
4	8788606.40	8752955.47	8718052.20
7	16493969.43	16435499.59	16380855.16
10	22063844.31	21981297.24	21904758.44
Avg.	15782140.05	15723250.77	15667888.60

TABLE 8. Profits ($) for problems with (W) and without (WO) emission constraints.

NI	WO	W	RD [a] (%)
4	8810959.74	8756316.69	0.62
7	16565704.77	16431531.12	0.81
10	22443501.66	21983127.48	2.05
Avg.	15940055.39	15723658.43	1.36

[a]Relative difference.

TABLE 9. Quantity of emissions (t) for problems with (W) and without (WO) emission constraints.

NI	WO	W	RD [a] (%)
4	238103.33	231774.77	2.66
7	422796.76	417319.96	1.30
10	564341.58	545976.87	3.25
Avg.	408413.89	398357.20	2.46

[a]Relative difference.

1) As the heat-loss rate increases, the total quantity of coal purchase increases. This indicates that the power plant needs to buy more coal to compensate for the increased thermal energy loss of coal.

2) The expected profits decrease with the increase of the heat-loss rate. This indicates that the heat-loss rate of coal is one of the key factors affecting the power plant's profits. Therefore, it is advisable for power plants to better manage the coal storage so as to obtain higher profits.

D. IMPACT OF EMISSION CONSTRAINTS ON THE SOLUTION

In the proposed strategy, emission constraints are introduced to control emissions from power generation. The following comparative studies are preformed to show the impact of emission constraints on the solution. First, we compare the solutions for problems with and without emission constraints. Second, we consider four sets of value range for emission coefficients, denoted by R_l, $l = 1, 2, 3, 4$, and compare the solutions corresponding to different value-range settings for emission coefficients. Other parameter settings remain unchanged. Numerical results of the first comparison are presented in Tables 8 and 9, and those of the second comparison are presented in Table 10.

From Tables 8 and 9, one can have the following observations:

1) The expected profits reduce by 1.36% when emission constraints are considered. This is because the emission constraints reduce the feasible region of the problem.

2) The quantity of emissions reduces by 2.46% with emission constraints included. This indicates the effectiveness of emission constraints in emission reduction.

TABLE 10. Expected profits for problems under different value-range settings for emission coefficients.

NI	Profits ($)			
	R_1 : (2.0, 2.2)	R_2 : (2.2, 2.4)	R_3 : (2.4, 2.6)	R_4 : (2.6, 2.8)
4	8801416.97	8767457.01	8706151.90	8604407.81
7	16551487.81	16505362.59	16413904.17	16214604.48
10	22342233.65	22142665.13	21807543.54	21339372.99
Avg.	15898379.48	15805161.58	15642533.20	15386128.43

From Table 10, it can be seen that the expected profits increase with the decrease of emission coefficients. In other words, under the restriction of emission constraints, power plants with low emission generators can obtain more profits. This indicates that the introduction of emission constraints can stimulate coal-fired power plants to develop efficient clean-generation technologies to improve their economic profits within the maximum emission allowance.

V. CONCLUSION

In this paper, we propose a co-optimization strategy of GSS and CS for coal-fired power plants in deregulated electricity markets. Electricity prices and demands, coal prices, and coal inventory holding costs are stochastic and expressed by scenarios. The heat loss due to the weathering of coal during the storage and emission constraints are taken into account. The proposed strategy is built on a two-stage stochastic programing model with the objective of maximizing the expected profits, in which the first stage determines whether to purchase coal and the second stage optimizes the quantity of coal purchase, the coal inventory, and the power scheduling of each generator. To solve this model, we develop a Benders decomposition algorithm which decomposes the original problem into a master problem and multiple subproblems. Multiple Benders cuts are added into the master problem in each iteration and valid inequalities are constructed to improve the convergence of the algorithm. The numerical experimental results indicate that 1) the proposed Benders decomposition algorithm can solve the considered problem effectively, 2) for GSS and CS, the co-optimization strategy is advantageous over the separated optimization strategy, 3) power plants can increase their profits by improving the coal storage, and 4) the proposed model which considers emission constraints can help coal-fired power plants to manage their emissions and can incentivize them to develop low-carbon generation methods.

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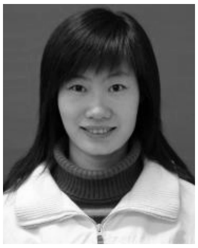

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