This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Co-Optimization of Battery Storage Investment and Grid Expansion in Integrated Energy Systems

Hossein Karimianfard, Hossein Haghighat, *Member, IEEE*, and Bo Zeng, *Member, IEEE*

***Abstract*—Battery storage is a flexible resource that can deliver a wide range of grid services quickly and efficiently. This article presents an investment planning model for battery storage, power transmission grid, and natural gas network in a stochastic gas–electric energy infrastructure. A bilevel stochastic optimization program is developed with an upper level investor and two interrelated lower level players. The investment decisions pertaining to the battery storage facilities and the expansion of power and gas systems are made by an independent investor anticipating the clearing results of gas and electricity markets, modeled as connected mixed-integer lower level programs. The nonconvexity of power generation and the randomness of power and gas demands, as well as renewable energy are considered in the formulation of the lower level problems. To compute this stochastic bilevel optimization with discrete decisions in both levels and interrelated lower level programs, we develop an exact solution methodology in a decomposed master-subproblem form. The application of the method is illustrated on two test systems. Experimental results show the modeling of gas and power grids' interaction and the nonconvex nature of power production using the proposed methodology significantly affects the optimal costs and expansion plans.**

***Index Terms*—Battery storage, grid expansion planning, power and gas systems, stochastic mixed-integer bilevel optimization.**

NOMENCLATURE

A. Set and Index

Δ	Set of network nodes, indexed by i.
$\Delta(i)$	Set of network nodes directly connected to node i.
Ω_H^E	Set of existing branches, indexed by ij.
Ω_H^C	Set of candidate branches, indexed by ij.
$\mathcal{Q}$	Set of gas-fired units, indexed by q.
$\mathcal{L}$	Set of non-gas-fired units.
$\mathcal{Q}(i)$	Set of gas-fire units connected to node i.
$\mathcal{L}(i)$	Set of non-gas-fired units connected to node i.
$\mathcal{K}$	Set of gas network nodes, indexed by k, n.
$\mathcal{K}$	Set of existing pipelines, indexed by nk.
$\mathcal{P}_L$	Set of candidate pipelines.
Λ	Set of gas network pipelines.
l	Index of a generator in the gas-fired or non-gas-fired sets.
$\mathcal{A}$	Set of battery storage ratings.
A_o	Elements of set $\mathcal{A}$, indexed by $o \in \mathcal{O}$.
H	Set of hours of a representative day in the target year, indexed by h.
W	Set of indexes of scenarios.
w	Index of scenarios $w \in W$.

B. Parameters

N_h	Number of hours in a representative day of the target year.
σ_w	Weight of each scenario.
B_{ij}	Series susceptance of line ij (p.u.).
D_i^a	Nodal real power demand (MW).
g_i^R	Real power output of a renewable resource (MW).
η_i^s	Battery efficiency (p.u.).
η_{kq}	Heat rate ratio of each gas-fired unit at node k (Mm^3/MWh).
$p_i^{\min}, p_i^{\max}$	Lower and upper bounds of active power generation (MW).
$p_{ij}^{\max}$	Upper limit of real power flow on line ij (MW).
$f_{kn}^{\max}$	Upper limit of gas flow of pipeline kn (Mm^3/h).
G_k^{smax}	Upper limit of gas supplied at each gas system node (Mm^3/h).
G_k^{pmax}	Upper limit of gas demand at a gas system node (Mm^3/h).
c_i^b	Capital cost of battery storage ($/MWh).
c_k^s	Marginal cost of gas supplied at a gas network node ($/Mm^3).
c_k^p	Bid price of a gas-fired unit ($/M^3).
G_k^d	Fixed gas demand (Mm^3/h).
$\hat{c}_i^b$	Annualized capital cost of battery storage [$/MWh/yr].
$\tilde{c}_i^s, c_i^s$	Costs of battery operation from the perspective of the planner and market operator ($/MWh).
$\tilde{c}_l^g, c_l^g$	Costs of power generation from the perspective of the planner and market operator ($/MWh).
$\tilde{c}_l^c, c_l^c$	Costs of power curtailment from the perspective of planner and market operator ($/MWh).
$\tilde{C}_l^{nl}, C_l^{nl}$	Costs of no-load power generation from the perspective of the planner and market operator ($/h).

Manuscript received June 3, 2021; revised September 29, 2021; accepted November 18, 2021. *(Corresponding author: Hossein Haghighat.)*

Hossein Karimianfard and Hossein Haghighat are with the Electrical Engineering Group, Islamic Azad University, Jahrom Branch, Jahrom 7419685768, Iran (e-mail: karimianfard@gmail.com; haghighat@jia.ac.ir).

Bo Zeng is with the Department of Industrial Engineering and the Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, PA 15260 USA (e-mail: bzeng@pitt.edu).

Digital Object Identifier 10.1109/JSYST.2021.3130057

$\tilde{C}_l^u, C_l^u$	Costs of start-up from the perspective of the planner and market operator ($).
$\tilde{C}_l^d, C_l^d$	Costs of shutdown from the perspective of the planner and market operator ($).
$\hat{k}_{ij}$	Annualized capital cost of transmission line ij ($/yr).
k_{ij}	Capital cost of transmission line ij ($).
$\hat{t}_{nk}$	Annualized capital cost of pipeline nk ($/yr).
t_{nk}	Capital cost of pipeline nk ($).
I_M	Expansion budget ($).

C. Variables

θ_i	Nodal voltage angle (rad).
r_i	Nodal active power curtailment (MW).
p_l	Active power output of a production unit (MW).
p_{ij}	Real power flow on line ij (MW).
X_i^s	Battery storage capacity (discrete-sized) (MWh).
e_i^s	Energy level of the battery storage (MWh).
$p_i^{\text{ch}}/p_i^{\text{dis}}$	Charge/discharge power of the battery storage (MW).
z_i	Binary variable used for modeling the charge/discharge operating mode of the battery.
G_k^s	Gas supplied at a gas network node (Mm^3/h).
G_k^p	Gas demand of a gas-fired unit at a gas network node (Mm^3/h).
f_{nk}	Gas flow in each pipeline (M^3/h).
v_l	Binary variables used for modeling commitment status of each generator.
α_{io}	Binary variable used for selection of each element $A_o \in \mathcal{A}$.
u_l	Binary variables used for modeling start-up of each generator.
s_l	Binary variables used for modeling shutdown of each generator.
x_{ij}	Investment status of transmission line ij.
y_{nk}	Investment status of pipeline line nk.

I. Introduction

A. Background and Motivations

WITH battery storage technology becoming more cost-effective, and given its flexibility, low standby cost, and fast response time, the recent trend in some power systems is to deploy commercial-scale battery storage facilities to complement the variability of renewable resources, like wind and solar power [1], [2]. According to [3], about 90% of large-scale battery storage capacity in the U.S. is installed in the regions covered by five of the ISOs or regional transmission organizations.

Beside renewables, power systems operate conventional technologies, like gas-fired units whose share has increased from 37% in 2019 to 39% in 2020, according to [4]. With the growing reliance on gas-fired units, the coupling between the natural gas and electricity infrastructures becomes intensified, which would affect the supply and demand balance of both systems and presents significant challenges for the operation and planning of them.

The current trend of using battery storage and the increasing share of gas-fired units in power grids indicate a necessity for utilities to produce unified expansion plans in which the interdependency of these energy systems and the deployment of battery storage, as a fast-acting dispatchable resource, are observed. This research aims to address battery storage investment with coordinated expansion planning of power and natural gas systems in a stochastic environment.

B. Literature Review

Acknowledging the necessity for coordinating electricity and natural gas systems, the technical literature on co-investment planning of power and gas systems offers us several approaches. Mixed-integer linear programming (MILP) [5], [6] and second-order cone programming techniques [7] have been applied to solve joint expansion planning problem of natural gas and electricity systems. They used a deterministic approach for computational tractability. To handle uncertainties, two-stage robust optimization [8], [9] and stochastic programming [10], [11] were proposed and solved using decomposition algorithms. Chen *et al.* [12] studied investment equilibria in electricity and gas markets using bilevel optimization. The investment decisions on gas storage facilities, power lines, and pipelines are made by the independent investor considering the clearing outcomes of connected gas and electricity markets modeled as coupled mixed-integer lower level programs. Chaudry *et al.* [13] proposed a combined gas and electricity network planning approach for making investment decisions on power units, power lines, pipelines, compressors, and gas-storage facilities. Cheng *et al.* [14] used a decentralized scheme for integrated energy system expansion planning considering carbon-emission constraints. The aforementioned works [5]–[14] developed expansion models for combined gas–electric systems, but do not consider the battery storage facility in the problem formulation. Ordoudis *et al.* [15] discussed the benefits of coordination between electricity and natural gas systems, where they compare the results obtained from decoupled and integrated market clearing models. Along this, decoupled market clearing models, to obtain the maximum social welfare for economic analysis of coordinated power and gas systems, are developed in [16], [17], [18], and [19].

Extensive researches can be also found on the topic of joint optimization of transmission system and battery storage. Specifically, Zhang *et al.* [20] proposed a multilevel model, which decides on the storage allocation in the upper level and the expansion of transmission system is decided by the middle level problem. In [21], a single level formulation is developed with a linear approximation of transmission losses in the objective function. A bilevel program is developed in [22] for allocating storage units in a distribution system integrated with transmission network. The upper level represents the distribution system and the lower level accounts for the transmission network. A two-stage stochastic model for storage sizing is presented in [23], assuming a model predictive control scheme and inaccurate forecast of renewable resources. Pandžić *et al.* [24] proposed a three-stage planning scheme wherein the optimal location, rating, and operating of the storage are sequentially determined. Huang *et al.* [25] presented a comparative analysis on two joint market mechanisms on storage investment and operation: a socially optimal investment model with centralized operation and a profit-maximizing investment one with deregulated operation. Wogrin *et al.* [26], [27] formulated a storage planning model from a social planner perspective that minimizes the overall system operation and investment cost by selecting the site and/or size of the storage facilities. The investment problem faced by a strategic planner, based on a multilevel mathematical programming, is addressed in [28], wherein investment decisions are made by the upper level decision maker and the operational ones by a centralized market mechanism. Haghighat and Zeng [29] developed a bilevel stochastic optimization model for transmission expansion planning considering integrated gas-power grids in the lower level problem using MILP formulation. The above-mentioned works [20]–[29] consider the allocation of battery storage but ignore natural gas system and develop optimization models, in which network expansion is performed only for the power system and/or the interaction with the gas system is not accounted for.

We note that in the aforementioned research studies, joint investment planning of battery storage, power transmission lines, and gas pipelines in a connected and separately operated gas–electric system under uncertainty using multilevel optimization is not presented yet. Developing a bilevel co-investment framework, which supports interlinked optimization and decision-making tasks for a coordinated but independently cleared gas–electric market with uncertain demands and discrete decisions in both levels, and an exact solution method that computes the optimal decision for the stochastic problem, constitute the primary objectives of this article.

C. Objectives and Contributions

Different from the present literature, our approach considers a more complex situation and develops a stochastic bilevel optimization program, which is suitable for co-optimization of battery storage capacity, power transmission network, and natural gas grid in a coordinated gas-power system. Given that these energy systems interact hierarchically with little centrally controlled operations, and that the objectives of the controlling/planning authority can be different from those of power and gas markets' operators, bilevel optimization provides a more relevant and compelling tool in such a context. Moreover, because of uncertain factors that affect both markets and the discrete and interrelated decisions of the lower level players, the resulting problem is a complex stochastic optimization with mixed-integer programs (MIPs) in the top and bottom levels. Our contributions thus include the following.

1) We co-optimize storage investment and expansion planning of electricity and natural gas systems using multilevel programming with a probabilistic description of uncertain power and gas demands and renewable generation. Unlike the growing literature on multilevel programming where operational nonconvexities associated with generation units and binary commitment variables are often disregarded in market clearing, our approach exactly considers these critical factors and develops a stochastic multilevel optimization with interlinked linear MIP programs in the lower levels. This feature helps us accurately understand the interactions between these energy systems and assess the impacts of those critical factors on the planning results. To our best knowledge, similar complex stochastic bilevel model has not appeared or been solved exactly in the literature yet.
2) We present a solution method based on *reformulation-and-decomposition* strategy, which first reformulates this stochastic multilevel optimization with connected lower level MIP programs as a regular bilevel formulation. Subsequently, we develop and customize the *column-and-constraint-generation* algorithm to compute this stochastic problem in an exact fashion. The proposed solution methodology paves the way for efficient computing unresolved stochastic bilevel MIP optimizations with guaranteed convergence to the global optimality. The application is illustrated and discussed on two test systems.

The rest of this article is organized as follows. In Section II, the notation, the modeling assumptions, and the proposed multilevel optimization formulation are described. In Section III, the solution methodology involving formulations of the master problem and subproblems as well as the computing algorithm are outlined. In Section IV, experimental results are discussed. Section V concludes this article.

II. Problem Statement

In this section we present the optimization problem of the planning model. The assumptions are introduced first.

A. Market Structure and Assumptions

In the proposed co-investment model, we assume a multilevel structure. The upper level decision maker, which could be a private planner or a regional authority, minimizes the construction and operation costs constrained by two lower level problems. The lower level consists of interrelated natural gas and electricity markets that clear independently of one another and have complete information interchange. Indeed, the proposed structure for these energy markets simulates the current decoupled setup between electricity and natural gas markets. Note that they clear independently and mainly interact through the operation of gas-fired production units, meaning natural gas is an input fuel for some gas-fired generation units.

To manage the trade-off between accuracy and solvability, we make several key assumptions in our model. First, the investment decisions are derived for a single target year and optimization is carried out over a number of representative hours/days in the target year. Second, natural gas and power demands are assumed to be uncertain. The stochastic nature of demands is described through finite sets of scenarios. Third, the operating cost of renewable generation is zero and its uncertainty is described using a scenario-based method, similar to the modeling of uncertain demand. Fourth, we assume the two markets clear simultaneously, which facilitates the coordination and integration of these systems and improves efficiency of energy trade [30]. Fifth, to clear the power market, we use a mixed-integer linear power flow formulation, which is consistent with current practice in wholesale electricity markets. Moreover, we employ a linear steady-state gas system model where gas flows of pipelines are directly controllable. The gas system model that we assume is widely used in power system operating and planning studies (see [8], [10], [14], [16], [30], and [31] to name a few). A detailed mathematical description of modified gas system is provided in the subsequent section.

B. Stochastic and Multilevel Coordinated Investment Planning

The market-based planning problem is formulated as

$$\min \sum_{ij\in\Omega_L} \hat{k}_{ij}x_{ij} + \sum_{kn\in\mathcal{P}_L} \hat{t}_{kn}y_{kn} + \sum_{i\in\Delta} \hat{c}_i^b X_i^s$$
$$+ 365 \times \frac{24}{N_h} \sum_{w\in\mathcal{W}} \sigma_w \Bigg(\sum_{i\in\Delta,h\in H} \big[\tilde{c}_i^s (p_{ihw}^{\text{dis}}/\eta_i^s + p_{ihw}^{\text{ch}}\eta_i^s)\big] + \sum_{l\in\mathcal{Q}(i)\cup\mathcal{L}(i)} \Big[\tilde{c}_l^g p_{lhw} + \tilde{C}_l^{nl} v_{lhw} + \tilde{C}_l^u u_{lhw} + \tilde{C}_l^d s_{lhw}\Big] + \sum_{i\in\Delta} \tilde{c}_i^c r_{ihw} \Bigg) \tag{1a}$$

$$\text{s.t.}\quad X_i^s = \sum_{o\in\mathcal{O}} \alpha_{io}A_o, \quad \sum_{o\in\mathcal{O}} \alpha_{io} \le 1 \quad \forall i\in\Delta, o\in\mathcal{O}, A_o\in\mathcal{A} \tag{1b}$$

$$\sum_{ij\in\Omega_L} k_{ij}x_{ij} + \sum_{kn\in\mathcal{P}_L} t_{kn}y_{kn} + \sum_{i\in\Delta} c_i^b X_i^s \le I_M \tag{1c}$$

$$\alpha_{io},\, y_{kn},\, x_{ij} \in \{0,1\} \quad \forall i, o, kn\in\mathcal{P}_L, ij\in\Omega_L \tag{1d}$$

$$\mathbf{p_l}, \mathbf{p_i^{dis}}, \mathbf{p_i^{ch}}, \mathbf{v_l}, \mathbf{u_l}, \mathbf{s_l} \in \operatorname{argmin}\Bigg\{$$

$$\sum_{h\in H} \Bigg(\sum_{i\in\Delta} \big[c_i^s (p_{ihw}^{\text{dis}}/\eta_i^s + p_{ihw}^{\text{ch}}\eta_i^s)\big] + \sum_{l\in\mathcal{Q}(i)\cup\mathcal{L}(i)} \big[c_l^g p_{lhw} + C_l^{nl} v_{lhw} + C_l^u u_{lhw} + C_l^d s_{lhw}\big] + \sum_{i\in\Delta} c_i^c r_{ihw} \Bigg) \tag{1e}$$

$$\sum_{l\in\mathcal{L}(i)} p_{lhw} + \sum_{q\in\mathcal{Q}(i)} p_{qhw} + r_{ihw} - p_{ihw}^{\text{ch}} + p_{ihw}^{\text{dis}} + \sum_{j\in\Delta(i)} p_{jihw} - \sum_{j\in\Delta(i)} p_{ijhw} = D_{ihw}^a - g_{ihw}^R \;\forall i\in\Delta, h \tag{1f}$$

$$\big|p_{ijhw} = B_{ij}(\theta_{ihw} - \theta_{jhw})\big| \le p_{ij}^{\max} \;\forall ij\in\Omega_E, h\in H \tag{1g}$$

$$\big|p_{ijhw} = x_{ij}B_{ij}(\theta_{ihw} - \theta_{jhw})\big| \le p_{ij}^{\max} \forall ij\in\Omega_L, h\in H \tag{1h}$$

$$v_{lhw}p_l^{\min} \le p_{lhw} \le v_{lhw}p_l^{\max} \quad \forall l\in\mathcal{Q}\cup\mathcal{L}, h\in H \tag{1i}$$

$$v_{lhw} - v_{l,h-1,w} = u_{lhw} - s_{lhw} \quad \forall l\in\mathcal{Q}\cup\mathcal{L}, h\in H \tag{1j}$$

$$0 \le 1/\eta_i^s p_{ihw}^{\text{dis}} \le z_{ihw}X_i^s \quad \forall i\in\Delta, h\in H \tag{1k}$$

$$0 \le \eta_i^s p_{ihw}^{\text{ch}} \le (1 - z_{ihw})X_i^s, \quad \forall i\in\Delta, h\in H \tag{1l}$$

$$e_{ihw}^s = e_{i,h-1,w}^s + p_{ihw}^{\text{ch}}\eta_i^s - p_{ihw}^{\text{dis}}/\eta_i^s \;\forall i\in\Delta, h\in H \tag{1m}$$

$$0 \le e_{ihw}^s \le X_i^s \quad \forall i\in\Delta, h\in H \tag{1n}$$

$$0 \le r_{ihw} \le D_{ihw}^a \quad \forall i\in\Delta, h\in H \tag{1o}$$

$$G_{khw}^p = \eta_{kq}p_{qhw} \quad \forall k\in\mathcal{K}, q\in\mathcal{Q}, h\in H \tag{1p}$$

$$\theta_{ihw} = 0 \quad i = \text{ref.}, h\in H \tag{1q}$$

$$\left.\begin{array}{l} v_{lhw},\, u_{lhw},\, s_{lhw},\, z_{ihw} \in \{0,1\} \\ \quad \forall l\in\mathcal{Q}\cup\mathcal{L}, i\in\Delta, h\in H \end{array}\right\} \forall w\in\mathcal{W} \tag{1r}$$

$$\mathbf{G_{khw}^p} \in \operatorname{argmax}\Bigg\{ \sum_{h\in H,k\in\mathcal{K}} (c_k^p G_{khw}^p - c_k^s G_{khw}^s) \tag{1s}$$

$$\text{s.t.}\quad G_{khw}^s - G_{khw}^p + \sum_{n\in\mathcal{K}(n)} f_{nkhw} - \sum_{n\in\mathcal{K}(n)} f_{knhw} = G_{khw}^d \;:\lambda_{khw} \quad \forall k\in\mathcal{K}, h\in H \tag{1t}$$

$$\big|f_{knhw}\big| \le f_{kn}^{\max} \;:(\mu_{knhw}^{f_E,l}, \mu_{knhw}^{f_E,u}) \;\forall kn\in\mathcal{P}_E, h \tag{1u}$$

$$\big|f_{knhw}\big| \le y_{kn}f_{kn}^{\max} \;:(\mu_{knhw}^{f_L,l}, \mu_{knhw}^{f_L,u}) \;\forall kn\in\mathcal{P}_L, h \tag{1v}$$

$$G_k^{s\min} \le G_{khw}^s \le G_k^{s\max} \;:(\mu_{khw}^{s,l}, \mu_{khw}^{s,u}) \;\forall k\in\mathcal{K}, h \tag{1w}$$

$$\left.G_k^{p\min} \le G_{khw}^p \le G_k^{p\max} \;:(\mu_{khw}^{p,l}, \mu_{khw}^{p,u}) \;\forall k\in\mathcal{K}, h \right\} \forall w\in\mathcal{W}. \tag{1x}$$

The first two terms of (1a) are the annualized costs of building transmission line, gas pipelines, and storage facilities. The rest of the terms represent the operating costs of convectional generators and storage facilities, as well as the load curtailment cost. In objective function (1a), investment variable X_i^s denotes the storage capacity in MWh. We assume that this capacity is converted to charge/discharge rate (i.e., power capacity) using a fixed energy-to-power ratio set to 1 hour here, for each battery storage.

The running cost of conventional production units comprises fixed and variable costs. The fixed cost terms consist of the costs of no-load operation, start-up, and shutdown included in the objective with binary variables v_{lhw}, u_{lhw}, and s_{lhw}, respectively. It is assumed that the storage capacity variable X_i^s is discrete-sized, which is enforced by (1b) where set $\mathcal{A}$ defines the available discrete ratings. Budget constraint is given by (1c), and constraint (1d) declares binary variables of the top problem.

There are two interrelated lower level programs. The first one, given in (1e)–(1r), represents the power market clearing, and the gas market is modeled by (1s)–(1x). The objective function (1e) is analogous to that in (1a). As mentioned earlier, the transmission system constraints are represented using a standard dc power flow model in (1f)–(1h) for new and existing transmission lines. The output limits of generating units are defined by (1i) where upper and lower bounds are multiplied by a binary variable representing the on/off status of the unit. The governing equations of the storage operation, including charge/discharge power limits (1k) and (1l), energy balance (1m), and energy limit (1n), are provided in this formulation. To prevent simultaneous charging and discharging of stored energy, binary variable z_{ihw} is introduced in (1k) and (1l). Load curtailment limit is enforced by (1o). Observe that the the right-hand sides of (1k) and (1l) involve the product of a (lower level) binary and an (upper level) integer variable. The relationship between the power production and gas consumption of gas-fired units is defined by (1p) through its heat-rate efficiency. We assume a linear relationship for simplicity. Constraint (1q) defines the reference voltage angles, and (1r) declares binary variables.

To model gas network, we assume that the gas market operator collects offers and bids from gas suppliers (wells) and consumers together with their technical constraints. Here, we consider fixed demands and gas-fired units as the main gas consumers, where only bids from gas-fired units are considered. The gas market operator maximizes the social welfare of suppliers and consumers stated by (1s). The gas balance constraint is given by (1t). Bounds on the flow of existing and new pipelines are stated in (1u) and (1v). Limits on the consumption levels of gas-fired units and production of gas suppliers (wells) are modeled in (1w) and (1x). As previously indicated, we use a linear transportation gas flow model, where nodal pressure variables are omitted and the gas flow in each pipeline is directly controllable assuming a maximum flow limit. This linear model is widely used in planning studies and economic analysis problems of gas–electric systems (for instance, refer to [8], [10], [14], [16], [30], and [31]). With this linear format of gas flow constraints, we can develop a computable bilevel optimization model with discrete decisions being in the top problem and in only one of the bottom level problems [i.e., the power market clearing problem (1e)–(1r)]. Such modeling approach allows us to replace the gas market clearing problem (1s)–(1x) with its primal–dual equivalent counterpart, which leads to an augmented linear MIP program in the lower level. We mention that when a detailed MILP gas flow model with practical factors of a real system (e.g., linearized Weymouth equations) is employed, the bilevel optimization model will have interrelated lower level MIP programs, which currently lacks of well-established results to ensure the existence and to further capture the equilibrium between them. Hence, gas flow model is modified here into a simpler linear one for tractability reasons. Certainly, an alternative approach is to use a linear power market clearing with an MILP model of gas system, and apply a similar primal–dual transformation to the power market problem (1e)–(1r) to build an alternative mixed-integer bilevel formulation. Since both approaches are fundamentally similar, the latter one is not considered in this article.

In optimization model (1), the top problem is constrained by two interrelated lower level stochastic programs. That is,

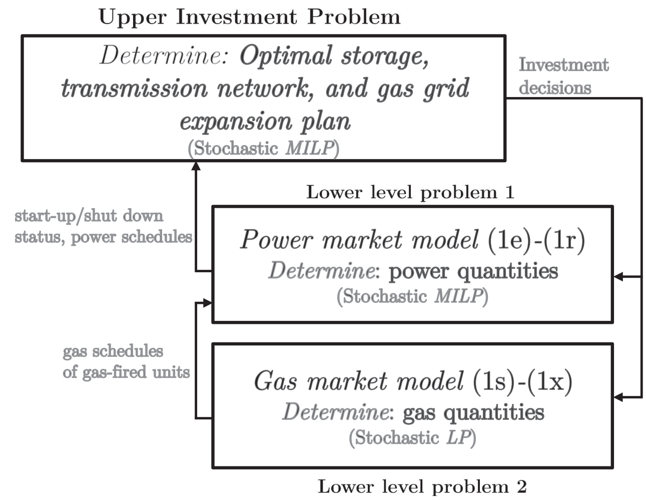

Fig. 1. Structure of the proposed model.

the mixed-integer linear program (1e)–(1r), which is connected to the linear program (1s)–(1x) through (1p). Observe that optimization problem (1) is a stochastic program, in which the uncertainty of power and gas demands as well as renewable generation is described through a finite set of scenarios indexed by $w \in \mathcal{W}$.

In Fig. 1, the proposed framework and information exchange between the top and bottom level problems are depicted.

Remark 1: The nonlinear inequality (1h) can be reformulated as a linear one by $\left|p_{ijhw} = B_{ij}(\theta_{ihw} - \theta_{jhw})\right| \leq (1 - x_{ij})M$, where *M* is a big positive constant.

III. Solution Methodology

Given the interdependency of the lower level problems and the mixed-integer nature of power market decisions, this problem cannot be computed in a straightforward fashion unless some preliminary reformulations for algorithmic development are applied, as described next. Therefore, we first derive the primal–dual formulation of the gas market model (1s)–(1x), and place it as a set of constraints into the power market problem. This reformulation will produce a single lower level problem, which is mixed-integer linear. The primal–dual counterpart of the gas market model, for every scenario $w \in \mathcal{W}$, reads as

$$[\text{Constraints}(1t) - (1x)] \quad \forall k \in \mathcal{K}, h \in H \tag{2a}$$

$$-\lambda_{khw} + \mu^{p,u}_{khw} - \mu^{p,l}_{khw} - c^p_k = 0 \quad \forall k \in \mathcal{K}, h \in H \tag{2b}$$

$$\lambda_{khw} + \mu^{s,u}_{khw} - \mu^{s,l}_{khw} + c^s_k = 0 \quad \forall k \in \mathcal{K}, h \in H \tag{2c}$$

$$\mu^{f_E,u}_{knhw} - \mu^{f_E,l}_{knhw} + \lambda_{khw} - \lambda_{nhw} = 0 \qquad \forall k, n \in \mathcal{K} : kn \in \mathcal{P}_E, h \in H \tag{2d}$$

$$\mu^{f_L,u}_{knhw} - \mu^{f_L,l}_{knhw} + \lambda_{khw} - \lambda_{nhw} = 0 \qquad \forall k, n \in \mathcal{K} : kn \in \mathcal{P}_L, h \in H \tag{2e}$$

$$\sum_{h \in H, k \in \mathcal{K}} (c^g_k G^p_{khw} - c^s_k G^s_{khw}) = \sum_{h \in H, k \in \mathcal{K}} \Big(\lambda_{khw} G^d_{khw}$$

$$+ G_k^{\text{pmax}} \mu_{khw}^{p,u} - G_k^{\text{pmin}} \mu_{khw}^{p,l} + G_k^{\text{smax}} \mu_{khw}^{s,u} + G_k^{\text{smin}} \mu_{khw}^{s,l} \Big)$$
$$+ \sum_{kn \in \mathcal{P}_E} f_{kn}^{\max} \left(\mu_{knhw}^{f_E,u} + \mu_{knhw}^{f_E,l} \right)$$
$$+ \sum_{kn \in \mathcal{P}_L} y_{kn} f_{kn}^{\max} \left(\mu_{knhw}^{f_L,u} + \mu_{knhw}^{f_L,l} \right) \tag{2f}$$

where (2a) is the primal constraint of the gas market clearing, (2b)–(2e) are dual constraints, and (2f) is the primal–dual constraint. Next, we augment the lower power market clearing problem (1e)–(1r) with this equivalent primal–dual formulation (2a)–(2f) to form the stochastic optimization as follows:

$$\min \ (1a) \tag{3a}$$
$$\text{s.t.} \ \ [\text{Constraints (1b)–(1d)}] \tag{3b}$$
$$\min \ (1e) \tag{3c}$$
$$\text{s.t.} \ \ [\text{Constraints (1f)–(1r)}] \tag{3d}$$
$$[\text{Constraints (2a)–(2f)}] \ . \tag{3e}$$

Bilevel optimization (3) consists of the following.

1) The constraints of the original upper level investment problem (3b).
2) The constraints of the lower level power market clearing problem (3c) and (3d).
3) The equivalent counterpart of gas market clearing problem (3e), which is written as a set of constraints for the original power market clearing problem.

Observe that problem (3) is an instance of stochastic bilevel optimization with mixed-integer linear programs in both upper and lower levels. Given that the conventional reformulation methods that employ Karush–Kuhn–Tucker (KKT) conditions or strong duality (to replace the lower level problem with its equivalent optimality conditions) are not applicable to problem (3), we use and extend the *reformulation-decomposition* strategy [32] with *column-and-constraint-generation* method [33] being the decomposition algorithm, to compute it in an iterative fashion. The complete solution procedure partitions (3) to a master problem and two subproblems, and solves them iteratively, as described next.

A. Subproblem Formulation

The first subproblem, i.e., $\text{SP}^1{}_w$, computes an upper bound of the objective function. It is written below for every scenario $w \in \mathcal{W}$ (the dual variables are indicated in (1s)-(1x) before each constraint after a colon)

$$\mathbf{SP}_w^1: \ \Gamma_w^{sp} = \min_{\boldsymbol{Y_L}} \sum_{h \in H} \Bigg(\sum_{i \in \Delta} \left[c_i^s \left(\eta_i^s p_{ihw}^{\text{ch}} + p_{ihw}^{\text{dis}} / \eta_i^s \right) \right.$$
$$\left. + c_i^c r_{ihw} \right] + \sum_{l \in \mathcal{Q}(i) \cup \mathcal{L}(i)} \left[c_l^g p_{lhw} + C_l^{nl} v_{lhw} \right.$$
$$\left. + C_l^u u_{lhw} + C_l^d s_{lhw} \right] \Bigg) \tag{4a}$$
$$\text{s.t.} \ \ [\text{Constraints (1f)–(1r)}] \tag{4b}$$
$$[\text{Constraints (2a)–(2f)}] \tag{4c}$$

where we denote the vector of lower level variables by $\boldsymbol{Y_L} = [\boldsymbol{\lambda}, \boldsymbol{\mu^f}, \boldsymbol{\mu^s}, \boldsymbol{\mu^p}, \boldsymbol{G^s}, \boldsymbol{G^p}, \boldsymbol{f}, \boldsymbol{p}, \boldsymbol{r}, \boldsymbol{p}^{\text{dis}}, \boldsymbol{p}^{\text{ch}}, \boldsymbol{\theta}, \boldsymbol{v}, \boldsymbol{z}]$. Subproblem (4) is a standard stochastic MILP problem, which can be efficiently computed for every scenario. It provides an optimal solution of the lower level model (3c)–(3e) for the investment decision $(x_{ij}^*, y_{kn}^*, X_i^{s*})$. However, it might have multiple solutions. The second subproblem, i.e., SP^2, derives one that is in favor of the upper level model, as follows:

$$\mathbf{SP}^2: \quad \widehat{\Gamma}^{sp} = \min \ \ [(1a)] \tag{5a}$$
$$\text{s.t.} \ \ [\text{Constraints (4b)–(4c)}] \quad \forall w \in \mathcal{W} \tag{5b}$$
$$\sum_{h \in H} \Bigg(\sum_{i \in \Delta} \left[c_i^s \left(\eta_i^s p_{ihw}^{\text{ch}} + p_{ihw}^{\text{dis}} \eta_i^s \right) + c_i^c r_{ihw} \right]$$
$$+ \sum_{l \in \mathcal{Q}(i) \cup \mathcal{L}(i)} \left[c_l^g p_{lhw} + C_l^{nl} v_{lhw} + C_l^u u_{lhw} + C_l^d s_{lhw} \right] \Bigg)$$
$$\leq \Gamma_w^{sp,*} \quad \forall w \in \mathcal{W}. \tag{5c}$$

Observe that SP^2 is a regular stochastic MILP problem.

B. Master Problem

The master problem computes a lower bound estimate of the original objective function (1a) iteratively and dynamically improves it by adding new variables and constraints to the master problem until convergence is reached. Specifically, it is constructed by the following.

1) Duplicating the lower level variables $\boldsymbol{Y_L}$ and constraints (3d)–(3e) in the upper level problem. That is, constraints in (6c), which are indicated with superscript "$\sim$" meaning all variables involved in these constraints are duplicated variables and indexed by ν.
2) Replacing the lower level problem (3c)–(3e), in iteration ν, of fixed realizations of binary variables $z_{ihw}^{*,(\nu)}$, $v_{lhw}^{*,(\nu)}$, $u_{lhw}^{*,(\nu)}$, and $s_{lhw}^{*,(\nu)}$ by its KKT conditions. That is, constraints in (6d), which are linearized with the help of Big-M method.
3) Augmenting constraint in (6e), to enforce master problem MP to be equivalent to the original problem (1). Again, superscript "$\sim$" on the right-hand side of (6e) means variables in this constraint are duplicated ones.

Let us denote by $\boldsymbol{X_U}$ the vector of the upper level variables. The master problem is written in the compact form as follows:

$$\mathbf{MP}: \quad \Gamma^{\text{mp}} = \min_{\boldsymbol{X_U}} \ \ (1a) \tag{6a}$$
$$\text{s.t.} \ \ [\text{Constraints (1b)–(1d)}] \tag{6b}$$
$$[\text{Constraints } \widetilde{(3d)}\text{–}\widetilde{(3e)}] \tag{6c}$$
$$\text{KKT of [Constraints (3c)–(3e)]} \tag{6d}$$
$$(1e) \leq \widetilde{(1e)}. \tag{6e}$$

Algorithm for solving stochastic optimization (1)

1: **Step 1**. Set LB $= 0$, UB $= \infty$, and $\tau = 0$.

2: **Step 2**. Solve MP. Report optimal $\boldsymbol{X}_{\boldsymbol{U}}^{*}$ and update LB $= \max\{\Gamma^{mp}, \mathrm{LB}\}$.

3: **Step 3**. Given optimal $\boldsymbol{X}_{\boldsymbol{U}}^{*}$, solve SP_w^1 for every w and report optimal $\Gamma_w^{sp,*}$.

4: **Step 4**. Given $\Gamma_w^{sp,*}$, solve SP^2 and report optimal $z_i^{*,(\tau)}, v_l^{*,(\tau)}, u_l^{*,(\tau)}, s_l^{*,(\tau)}, G_k^{p*,(\tau)}$, and $\widehat{\Gamma}^{sp,*}$. Update UB $= \min\{\widehat{\Gamma}^{sp,*}, \mathrm{UB}\}$.

5: **Step 5**. If UB $-$ LB $\leq \epsilon$, stop with a solution associated with UB. Otherwise, go to step 6

6: **Step 6**. Let $\tau = \tau + 1$, create variables and constraints indexed by ν, and add them to MP. Go back to step 2.

We remark that the bilinear terms that appear in the master problem are product of binary and continuous variables, which can be readily linearized to convert MP to a standard stochastic MILP program.

Let LB and UB be the lower and upper bounds, respectively, τ be the iteration index, and ϵ be the optimality tolerance. The algorithm steps are sketched as follows.

This algorithm dynamically provides stronger upper bounds (from subproblems) and lower bounds (from the master problem) and, in each iteration, adds new variables and constraints to the master problem until the difference between bounds is not larger than optimality tolerance ϵ. The mathematical proof of finite convergence of this algorithm to the optimal value is provided in [32] (see also [34] for a recent application).

IV. Experimental Results

In this section, we illustrate the proposed method on two test systems assuming that the annual load growth is 5% and the interest rate is 10% per annum. The uncertainties of electricity and gas demand as well as the renewable generation (treated as negative demand) are considered using a discrete scenario approach. For simplicity and to introduces nontrivial uncertainties into the model, it is assumed that electric and gas loads can differ by up to $\pm 20\%$ relative to the assumed baseline level.

Experiments were done by a MATLAB platform in Gurobi solver on a laptop computer with Intel Core (TM) i7-2670QM CPU (2.2 GHz) and 8 GB memory. The MIP optimality gap is set to 0.0001.

A. Example System

The first test system is composed of a six-node power system and a four-node gas network, as shown in Fig. 2. The power system has four existing generators and three existing transmission lines. We consider ten candidate transmission lines involving seven new lines 2–3, 2–4, 3–4, 3–6, 4–6, and 5–6 and three existing lines 1–2, 1–3, and 5–4 (see Fig. 2). The storage can be installed at each bus with discrete ratings of {50, 75, 100, 125, 150} MWh. The gas network has two gas suppliers (wells) and five candidate pipelines. The gas-fired units at Nodes 5 and 6 are connected to gas network Nodes 1 and 3, respectively. The

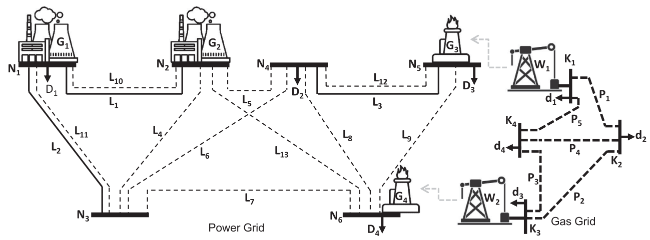

Fig. 2. Example system: 6- and 4-node power and gas grids.

network is planned for target year 10. The investment costs of transmission lines and pipelines are in the range of [0.84, 2.1] M$ and [1.5, 1.8] M$, respectively. The battery investment and operating costs are 100 $/kWh and 0.5 $/MWh, respectively. Load shedding is penalized at a price of 500 $/MWh. The rest parameters of this gas–electric system is provided in the link.[1]

To reduce the problem size and improve computing speed and solution accuracy, we considered three representative days in the target year with a total duration of 72 h. Hourly loading factors for each day were chosen from [35]. They correspond to three different seasons and week days. To model the uncertainty of the gas and power demands, we assumed that nodal demands exhibit uniform probability distributions, and can deviate by $\pm 20\%$ from the nominal forecast. In doing so, 50 equiprobable scenarios were created to account for unpredictable variations of gas and power demands in the target year. The investment budget is 100 M$. The following six cases are studied.

- *Case 1:* This is the base stochastic case involving 50 equiprobable scenarios. We assume that nodal natural gas and power demands exhibit uniform probability distributions, and can deviate by $\pm 20\%$ from baseline values.
- *Case 2:* The offer parameters of the two gas suppliers change by $\pm 12.5\%$ with respect to the base case.
- *Case 3:* A 60-MW wind farm is placed at node 3. As indicated earlier, marginal generation cost of renewable generation is zero and it is treated as negative demand. The uncertainty of wind generation is handled similar to demand uncertainty using a finite set of scenarios.
- *Case 4:* The gas network is ignored assuming gas-fired units will supply power according to their operational capacities.
- *Case 5:* A simplified power flow model, which is frequently used in investment planning studies, is employed by lifting the restrictions on simultaneous charging/discharging of storage devices and ignoring the nonconvex cost components of the production units. Observe that binary variables v_{ihw}, u_{ihw}, s_{ihw}, and z_{ihw} are eliminated from the first lower level program rendering a linear market clearing problem.
- *Case 6:* The investment budget assumed in case 1 decreases to 40 M$. The rest parameters remain unchanged.

The optimal investment decisions involving annual costs, installed power lines, and gas pipelines, as well as battery storage facilities are given in Table I. The outcomes of these case studies

[1]zenodo.org/record/5483014

TABLE I
OPTIMAL PLAN OF EXAMPLE SYSTEM WITH 50 SCENARIOS

costs (M$)	case 1	case 2	case 3	case 4	case 5	case 6
Power line	6.2	4.7	7.7	7.2	6.6	2.6
Pipeline	4.8	6.4	4.8	–	6.1	3.4
Storage investment	2.8	4.9	3.7	1.6	0	0
Storage operation	0.7	2.9	1.0	0.2	0	0
Production	3617	3435	3305	3370	2830	3811
Budget	85	98	99	54	72	37
Total	3632	3454	3322	3379	2842	3817
Storage node (MWh)	3(75), 4(50) 5(50)	2(100), 3(100) 4 (100)	4(50), 5(125) 6(50)	4(50), 6(50)	–	–
Power lines	2–4, 3–6 2–3, 5–6 2–6	3–6, 4–6 5–6, 2–6	3–4, 2–4 3–6, 4–6 2–6	2–4, 3–6 4–6, 5–6 1–2, 2–6	2–4, 3–4 4–6, 2–3 2–6	2–4, 2–6
Pipelines	1–2, 3–4 2–4	1–2, 3–4 2–4, 1–4	1–2, 3–4 2–4	–	2–3, 3–4 1–4	2–3, 1–4

are compared to Case 1, wherein five new transmission lines and three pipelines are installed in the electric and gas systems, respectively. In addition, three storage devices are added to the power grid. The required budget is nearly equal to 85 M$with an objective value of 3632 M$. In Case 2, offers of gas suppliers change by $\pm 12.5\%$, which affect the investment decisions on both energy systems. It is seen that the expansion plan of both network changes due to changes in the gas market clearing results, which affect the dispatch results of the gas-fired units in the power market. The storage capacity increases by 125 MWh, which reduces the production cost as well as the overall planning cost. In Case 3, the impact of adding a wind farm at node 3 is analyzed. Observe that it increases the overall investment costs of all assets while the overall planning cost decreases. Detailed experimental results show that the expansion decisions will depend on the location of the wind generation. However, in all cases studied, it decreases the planning cost due to reduction of the net system load. In Case 4, the gas system is not modeled, giving rise to a higher investment in the transmission system and a lower investment in storage capacity. We note that by ignoring the gas system, gas-fired units will generate according to the operational capacities with no fuel and dispatch restrictions being imposed on their operation by the gas system. Consequently, the production and the total planning costs are reduced because the share of gas-fired units in supplying the system demand increases owing to lower start-up and no-load costs.

The least expensive investment plan is achieved in Case 5, in which a simplified power flow model is used. It is clearly seen that no storage facility is installed, and the objective function and the required investment budget decrease by 22% and 15%, respectively. Note that the expansion plan of the gas network also differs from that obtained in Case 1. It is worth mentioning that the expansion plan achieved in this case represents an approximate (more exactly, inaccurate) one as it was unrealistically assumed that the nonconvex cost components of power production are zero and the storage devices can simultaneously charge and discharge. These simplifications represent a cheaper investment and expansion plan. Finally, in Case 6, the impact of reducing the investment budget to 40 M$ is analyzed. This case gives the most expensive objective and planning costs. Observe

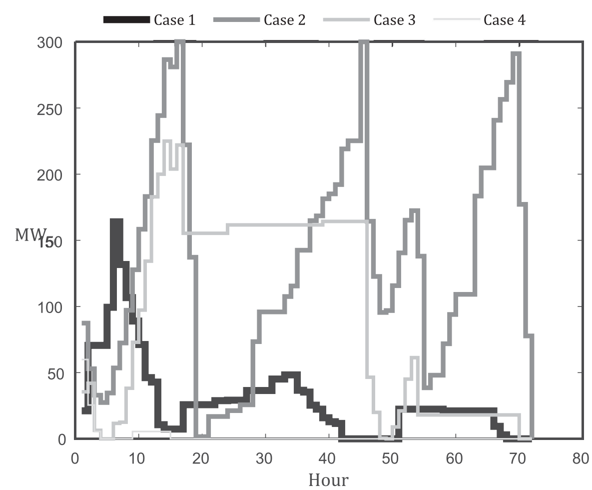

Fig. 3. Average energy level of batteries in the example system.

that the production cost reaches its highest amount due to the fact that costlier units must supply the system loads.

Fig. 3 shows the average energy levels (i.e., $e^s_{ih\omega}$) of all batteries installed in the example power system for the seven cases. Note that the energy levels of different storage devices are aggregated over the 50 scenarios for a compact presentation. Cases 5 and 6 are not shown in the figure because no storage is invested in these two cases. For the rest cases, it is seen that the highest energy level is associated with Case 2, which is consistent with the results of battery storage investment in Table I where the largest storage investment and operation take place. Moreover, the second largest energy level (and hence, storage dispatch) corresponds to Case 3 for the same reason, as given in Table I.

Results from these case studies and test system clearly show that modeling critical factors in an integrated gas–electric system plays an instrumental role in joint co-optimization of power and gas systems, which are considered in the proposed formulation and solution methodology.

TABLE II
DEMAND SCALING FACTORS

scenario	1	2	3	4	5	6	7	8
power	1.05	1.13	0.9	1.0	0.95	1.1	0.85	0.8
gas	0.90	1.03	1.1	0.95	1.02	1.0	0.94	1.05

B. 118-Node System

The second test system is a modified IEEE 118-node system. There are nine gas-fired generators in this system supplied from a 20-node natural gas system. The gas network is essentially the Belgium natural gas system, frequently used in expansion planning studies. The candidate power lines and gas pipelines considered are similar to the existing ones in both systems, meaning there are 138 transmission lines and 25 pipelines that can be installed. The investment cost of transmission line is assumed to be 200 K$/Km, and the cost of gas pipeline is proportionate to its capacity. Analogous to the previous test system, the battery investment and operating costs are 100 $/kWh and 0.5 $/MWh, respectively. Load shedding is penalized at a price of 500 $/MWh. The complete list of gas–electric parameters and their values are provided in the link.[2]

The transmission capacity of electrical branches was decreased by 60%. The planning is carried out for target year 10. For simplicity, each day of the target year was modeled by a representative 24-h day. The hourly load data and the parameters of the gas system were adopted from [36]. Load shedding is penalized at 1000 $/MWh. For simplicity, we only consider the variable and the no-load costs of power generation. The battery storage is available at discrete ratings as given in the previous test system. To describe uncertain natural gas and power demands, we created eight scenarios with the scaling factors given in Table II. They are applied to the gas and power demands. The investment budget is 220 M$. Seven cases are studied next.

- *Case 1:* This is the base stochastic case with eight equiprobable scenarios. Scaling factors for natural gas and power demands are given in Table II.
- *Case 2:* The gas system is not modeled.
- *Case 3:* The capacity of each gas pipeline decreases by 20% comparing with the original network.
- *Case 4:* The weights (probability) of the scenarios change to $\{0.15, 0.25, 0.08, 0.1, 0.09, 0.2, 0.07, 0.06\}$. Note that the average scenario weight is equal to 0.125, which is identical with that of the base case.
- *Case 5:* A simplified power market clearing is used by eliminating all binary variables from the model.
- *Case 6:* The base case budget is reduced by 20%.
- *Case 7:* The load shedding is priced at 100 $/MWh.

The optimal stochastic results including costs and investment decisions on transmission lines, pipelines, and storage capacity are given in Table III. These results are compared to Case 1 representing the base case. In Case 1, the power and gas networks are expanded by installing 15 power lines and ten pipelines. The invested storage capacity is 625 MWh (at 7 nodes), and the required investment budget is 164 M$. In Case 2, gas system is not modeled. The overall investment in the power system (involving power lines and storage capacity) and the production cost decreases. As expected, the required budget and the objective function are reduced compared to the base case and a different power system expansion plan is achieved. In Case 3, the investment cost of natural gas pipelines as well as the required budget increase owing to the reduced pipeline capacity. Moreover, the storage capacity and, consequently, its operating cost approximately double. A different expansion plan with larger indices values given in Table III is attained in Case 4 when the scenario weights change. Note that the average scenario weights (probability) of Case 4 and base case are identical, but scenarios with higher loading levels are given higher priorities (weights). Consequently, the allocation and expansion costs in Case 4 nearly increase by 20% (equal to percent reduction in gas pipeline capacity). Note that a different expansion plan for both systems is obtained compared to the base case. The role of modeling power flow details in investment results is assessed in Case 5, where a simplified power market model is applied. It is clearly seen that the smallest numbers of storage and transmission lines are installed in this case while the gas system expansion remains almost the same as that in Case 1. The least expensive investment, and hence an approximate plan, is achieved in this case. In Case 6, we reduce the budget, which mostly affects the investment decisions in the power system where the production cost, and thus, the objective function value increase due to budget limitation. In Case 7, the impact of decreasing the price of load shedding is investigated where the price is reduced to allow for more load curtailment. Detailed results show that some load shedding takes place at two system nodes in the second scenario (with the highest loading factor given in Table II). The required investment and budget are reduced but the overall objective function slightly increases in this case.

Fig. 4 shows the average energy levels of batteries installed in the 118-bus system for the seven cases given in Table IV. For a

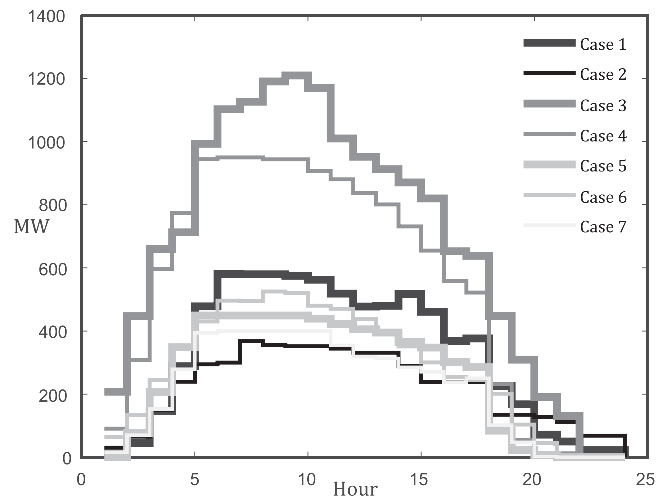

Fig. 4. Average energy level of batteries in IEEE 118-bus system.

[2]zenodo.org/record/5403292

TABLE III
OPTIMAL STOCHASTIC INVESTMENT PLAN OF IEEE 118-BUS SYSTEM

costs (M$)	case 1	case 2	case 3	case 4	case 5	case 6	case 7
Power lines	10.4	9.7	8.4	11.2	5.0	6.5	8.0
Gas pipelines	6.1	-	7.0	6.5	6.5	6.2	7.0
Storage investment	10.2	6.5	20.3	15.5	8.1	8.5	6.5
Storage operation	5.6	3.3	10.9	8.3	3.9	4.6	3.6
Production	15259	15088	15354	15755	14382	15341	15272
Budget	164	100	219	204	120	131	132
Total	15291	15207	15401	15797	14406	15367	15297
Storage node (MWh)	4 (75), 6 (50) 5 (250), 9 (50) 56 (25), 77 (150) 83 (25)	3 (25), 30 (250) 83 (25), 84 (75) 118 (25)	30 (125), 32 (250) 56 (25), 75 (250) 77 (250), 83 (25) 114 (250), 115 (75)	6 (100), 3 (250) 30 (100), 38 (250) 56 (250)	5 (250), 77 (250)	32 (250), 114 (175) 115 (100)	56 (75), 114 (250) 118 (75)
Power lines	12–11, 12–7 17–15, 17–30 32–23, 59–63 64–63, 65–64 79–78, 81–68 95–94, 99–80 100–94, 100–99 113–17	5–8, 32–23 65–64, 68–65 79–78, 81–68 80–81, 82–77 83–82, 92–89 94–93, 95–94 95–94, 99–80 100–94	5–4, 5–8 11–5, 17–30 59–63, 65–64 68–65, 78–77 81–68, 95–94 99–80, 100–94 100–99	5–8, 27–25 56–54, 78–77 82–77, 83–82 85–84, 95–94 98–80, 100–94 100–98, 100–99	17-30, 99-80 100-94, 100-99	5–8, 17–30 65–64, 81–68 95–94, 99–80 100–94, 100–99	5–4, 5–8 17-30, 30-26 81–68, 95–94 99–80, 100–94 100–99
Gas pipelines	4–3, 6–5 7–6, 14–4 11–10, 15–14 16–15, 17–11 19–18, 20–19	–	4–3, 6–5 10–9, 11–10 15–14, 16–15 17–11, 19–18 20–19, 7–9	4–3, 6–5 7–6, 4–7 14–4, 11–10 15–14, 16–15 17–11, 19–18 20–19, 7–9	4–3, 6–5 7–6, 14–4 15–14, 16–15 17–11, 19–18 20–19, 14–10	4–3, 6–5 4–7, 14–4 11–10, 15–14 16–15, 17–11 19–18, 20–19 7–9	4–3, 6–5 7–6, 4–7 10–9, 11–10 15–14, 16–15 17–11, 19–18 20–19, 7–9

TABLE IV
MODEL STATISTICS AND COMPUTATIONAL PERFORMANCE

	six-bus system		118-bus system
	10 scenarios	50 scenarios	8 scenarios
number of variables	144051	720051	460423
number of constraints	103691	518411	361384
number of iterations	3	3	3
solver time (sec)	639	11340	5836

compact presentation, energy levels of different storage devices are aggregated over the scenarios. Clearly and as previously observed, Case 3 yields the largest energy level, which is also given in Table IV where the largest storage investment and operating takes place. Note that in Case 3, the capacity of the gas system is reduced compared to the base case, which restricts the production of gas-fired units and consequently increases the dispatch of storage facilities. Finally, in Fig. 5, we compare the investment decisions with respect to the required budget versus the total production cost. In this figure, the ratio of production cost to the investment budget for each case is calculated and depicted. It is seen that Case 3 provides the most appropriate investment decision, while Case 2 is a very expensive plan in so far as the production cost is concerned.

The statistics of the model and its computational performance are given in Table IV. As expected, the problem size and the computing time markedly increase with the number of scenarios while the iteration number of the solution method remains unchanged.

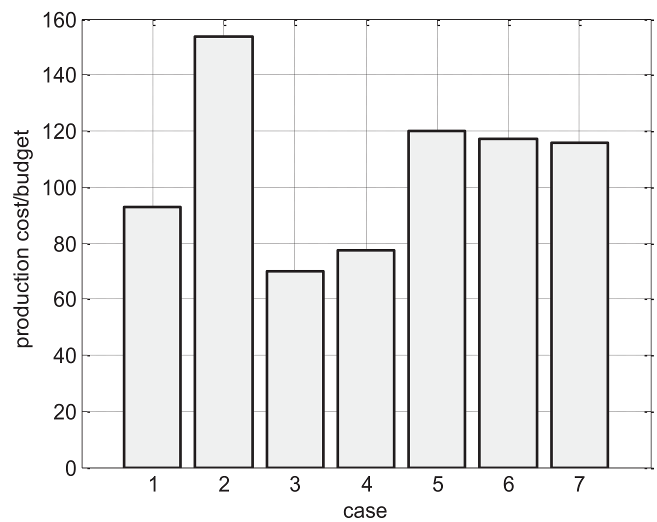

Fig. 5. Production cost to investment budget in IEEE 118-bus system.

V. CONCLUSION

In this article, a bilevel co-investment framework, which supports interlinked optimization and decision making tasks for a coordinated but independently cleared gas–electric market, was developed. The uncertainty of demands in both markets and the discreteness of decisions in the top and bottom level problems were modeled. An exact solution method, based on a reformulation-and-decomposition procedure, was proposed to iteratively compute the optimal decision for the stochastic problem.

We illustrated the method on two test systems assuming various case studies. It was shown that ignoring gas system in the planning problem can produce cheaper but erroneous plans as gas-fired units restrictions are not properly captured in such interlinked systems. We also examined the impacts of using a simplified power market clearing model in which power generation nonconvexities, such as start-up/no-load costs and/or minimum generation levels, are neglected and showed that such simplifications lead to approximate and unrealistic expansion plans with zero storage investment.

For future studies, the model can be extended to include reliability criteria to ensure the security of power and gas systems under contingency conditions.

REFERENCES

[1] U.S. electric company investment and innovation in energy storage. 2018. [Online]. Available: http://www.eei.org/issuesandpolicy/Energy%20Storage/Energy_Storage_Case_Studies.pdf
[2] Australian energy market operator, "Hornsdale wind farm 2 FCAS trial," 2018. [Online]. Available: http://www.aemo.com.au/-/media/Files/Electricity/NEM/StrategicPartnerships/2018/HWF2-FCAS-trial-paper.pdf
[3] U.S. battery storage market trends, U.S. Energy Inf. Admin., Washington, DC, USA, Tech. Rep., 2018. [Online]. Available: https://www.eia.gov/analysis/studies/electricity/batterystorage/archive/2018/pdf/battery_storage.pdf
[4] U.S. energy information administration, "Short-term energy outlook," 2020. [Online]. Available: http://https://www.eia.gov/outlooks/steo/report/electricity.php
[5] Y. Zhang, Y. Hu, J. Ma, and Z. Bie, "A mixed-integer linear programming approach to security-constrained co-optimization expansion planning of natural gas and electricity transmission systems," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6368–6378, Nov. 2018.
[6] J. Qiu *et al.*, "A linear programming approach to expansion co-planning in gas and electricity markets," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3594–3606, Sep. 2016.
[7] R. Bent, S. Blumsack, P. Van Hentenryck, C. Borraz-Sánchez, and M. Shahriari, "Joint electricity and natural gas transmission planning with endogenous market feedbacks," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6397–6409, Nov. 2018.
[8] C. Shao, M. Shahidehpour, X. Wang, X. Wang, and B. Wang, "Integrated planning of electricity and natural gas transportation systems for enhancing the power grid resilience," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4418–4429, Nov. 2017.
[9] C. He, L. Wu, T. Liu, and Z. Bie, "Robust co-optimization planning of interdependent electricity and natural gas systems with a joint N-1 and probabilistic reliability criterion," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2140–2154, Mar. 2018.
[10] B. Zhao, A. J. Conejo, and R. Sioshansi, "Coordinated expansion planning of natural gas and electric power syst," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3064–3075, May 2018.
[11] T. Ding, Y. Hu, and Z. Bie, "Multi-stage stochastic programming with nonanticipativity constraints for expansion of combined power and natural gas systems," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 317–328, Jan. 2018.
[12] S. Chen, A. J. Conejo, R. Sioshansi, and Z. Wei, "Investment equilibria involving gas-fired power units in electricity and gas markets," *IEEE Trans. Power Syst.*, vol. 35, no. 4, pp. 2736–2747, Jul. 2020.
[13] M. Chaudry, N. Jenkins, M. Qadrdan, and J. Wu, "Combined gas and electricity network expansion planning," *Appl. Energy*, vol. 113, pp. 1171–1187, 2014.
[14] Y. Cheng, N. Zhang, Z. Lu, and C. Kang, "Planning multiple energy systems toward low-carbon society: A decentralized approach," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 4859–4869, Sep. 2019.
[15] C. Ordoudis, P. Pinson, and J. M. Morales, "An integrated market for electricity and natural gas systems with stochastic power producers," *Eur. J. Oper. Res.*, vol. 272, no. 2, pp. 642–654, 2019.
[16] C. Wang, W. Wei, J. Wang, F. Liu, and S. Mei, "Strategic offering and equilibrium in coupled gas and electricity markets," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 290–306, Jan. 2018.
[17] S. Chen, A. J. Conejo, R. Sioshansi, and Z. Wei, "Equilibria in electricity and natural gas markets with strategic offers and bids," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 1956–1966, May 2020.
[18] Z. Ji and X. Huang, "Day-ahead schedule and equilibrium for the coupled electricity and natural gas markets," *IEEE Access*, vol. 6, pp. 27530–27540, 2018.
[19] C. Wang, W. Wei, J. Wang, L. Wu, and Y. Liang, "Equilibrium of interdependent gas and electricity markets with marginal price based bilateral energy trading," *IEEE Trans. Power Syst.*, vol. 33, no. 5, pp. 4854–4867, Sep. 2018.
[20] F. Zhang, Z. Hu, and Y. Song, "Mixed-integer linear model for transmission expansion planning with line losses and energy storage systems," *IET Gener., Transmiss. Distrib.*, vol. 7, no. 8, pp. 919–928, 2013.
[21] Y. Dvorkin *et al.*, "Co-planning of investments in transmission and merchant energy storage," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 245–256, Jan. 2018.
[22] A. Hassan and Y. Dvorkin, "Energy storage siting and sizing in coordinated distribution and transmission systems," *IEEE Trans. Sustain. Energy*, vol. 9, no. 4, pp. 1692–1701, Oct. 2018.
[23] K. Baker, G. Hug, and X. Li, "Energy storage sizing taking into account forecast uncertainties and receding horizon operation," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 331–340, Jan. 2017.
[24] H. Pandžić, Y. Wang, T. Qiu, Y. Dvorkin, and D. S. Kirschen, "Near-optimal method for siting and sizing of distributed storage in a transmission network," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2288–2300, Sep. 2015.
[25] Q. Huang, Y. Xu, and C. Courcoubetis, "Financial incentives for joint storage planning and operation in energy and regulation markets," *IEEE Trans. Power Syst*., vol. 34, no. 5, pp. 3326–3339, Sep. 2019.
[26] S. Wogrin and D. F. Gayme, "Optimizing storage siting, sizing, and technology portfolios in transmission-constrained networks," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3304–3313, Nov. 2015.
[27] B. Xu *et al.*, "Scalable planning for energy storage in energy and reserve markets," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4515–4527, Nov. 2017.
[28] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, "Strategic sizing of energy storage facilities in electricity markets," *IEEE Trans. Sustain. Energy*, vol. 7, no. 4, pp. 1462–1472, Oct. 2016.
[29] H. Haghighat and B. Zeng, "Stochastic network investment in integrated gas-electric systems," *Electric Power Syst. Res.*, vol. 197, 2021, Art. no. 107219.
[30] M. Gil, P. Dueñas, and J. Reneses, "Electricity and natural gas interdependency: Comparison of two methodologies for coupling large market models within the european regulatory framework," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 361–369, Jan. 2016.
[31] A. Martinez-Mares and C. R. Fuerte-Esquivel, "A unified gas and power flow analysis in natural gas and electricity coupled networks," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2156–2166, Nov. 2012.
[32] B. Zeng and Y. An, "Solving bilevel mixed integer program by reformulations and decomposition," Univ. South Florida, Tampa, FL, USA, Tech. Rep. 4455, 2014. [Online]. Available: http://www.optimizationonline.org/DB_HTML/2014/07/4455.html
[33] B. Zeng and L. Zhao, "Solving two-stage robust optimization problems using a column-and-constraint generation method," *Operations Res. Lett.*, vol. 41, no. 5, pp. 457–461, 2013.
[34] H. Haghighat, H. Karimianfard, and B. Zeng, "Integrating energy management of autonomous smart grids in electricity market operation," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4044–4055, Sep. 2020.
[35] Probability Methods Subcommittee, "IEEE reliability test system," *IEEE Trans. Power App. Syst.*, vol. PAS-98, no. 6, pp. 2047–2054, Nov. 1979.
[36] G. Sun, S. Chen, Z. Wei, K. W. Cheung, and H. Zang, "Corrective security-constrained optimal power and gas flow with binding contingency identification," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 1033–1042, Apr. 2020.