Generation Expansion Planning with Revenue Adequacy Constraints

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Abstract

Generation capacity expansion models have traditionally taken the vantage point of a centralized planner seeking to find cost-optimal generation capacity to reliably meet load over decadal time scales. Often assuming perfectly competitive players, these models attempt to provide guidance for system planners without necessarily ensuring that individual generators are adequately remunerated for their generation, flexibility, and capacity. In this work, we incorporate revenue adequacy constraints in a two-stage generation expansion planning model. After making generation investment decisions in the first stage, day-ahead unit commitment (UC) and dispatch decisions are made in the second stage, along with market-clearing pricing decisions. To approximate a market equilibrium, the duality gap between the second-stage non-convex UC problem and its linearly-relaxed dual is used as a regularizer. Case studies of a simplified California-ISO system are presented to contrast a traditional planning model with our revenue adequacy-constrained model.
Keywords: OR in Energy, generation expansion, mixed-integer bilinear programming, power system planning, profitability

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1. Introduction

Generation capacity expansion models are used regularly and globally to assist electricity sector planners, policy-makers and stakeholders in making more informed short- and long-term generation investment decisions. Surveying over 75 such decision support tools, the review papers by Gacitua et al. [14] and Ringkjøb et al. [33] reveal that there is no shortage of generation capacity expansion models. Traditional models take the vantage point of a centralized planner seeking to find cost-optimal generation capacity to reliably meet load over decadal time scales. Furthermore, a majority of models, including flagship models like ReEDS [36], US-REGEN [40], and IPM [37],

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whose results have influenced regional and national policies, assume a perfectly competitive market while ignoring non-convex cost structures that complicate day-ahead market clearing. By design, these models attempt to provide guidance for system planners without necessarily ensuring that individual generators are adequately remunerated for their generation, flexibility and capacity. In this work, we present a two-stage optimization model that determines optimal investment decisions in power generation capacity, while simultaneously ensuring that individual generators achieve a pre-specified revenue adequacy threshold.

In what follows, we review the literature on revenue adequacy in electricity markets (Section 1.1), discuss models for the generation expansion planning problem (Section 1.2), discuss the impact of non-convexity in models on market equilibria and the role of a regularizer used in our model (Section 1.3), present different paradigms for modeling behaviours of participants in generation expansion planning (Section 1.4), and then summarize the contributions of our work (Section 1.5).

1.1. Revenue Adequacy in Electricity Markets

Ensuring revenue adequacy for participants in a power system is important for providing incentive for production and investment, and has garnered increasing attention in recent years. The issue has become even more prominent due to the growing presence of variable renewable generation, which may ultimately drive marginal generation costs to zero in the future [13]. A market is deemed *revenue adequate* if individual service providers, who are instrumental in maintaining grid reliability through their capacity, energy, and flexibility, recover the fixed and variable costs associated with providing their services [17].

In electricity market modeling, due to the non-convex structure associated with start-up decisions, ramping limits, etc., it is difficult to ensure revenue adequacy for market participants [34]. Consequently, numerous improved models have been proposed. As far as day-ahead unit commitment (UC) models are concerned, Martin et al. [27] use a class of cutting planes to eliminate non-profitable solutions in a branch-and-cut framework. Ruiz et al. [34] derive revenue adequate prices from a primal-dual model. Fernández-Blanco et al. [11] introduce a revenue-constrained market-clearing procedure that can be recast as an equivalent single-level mixed-integer linear program. As for capacity expansion models, Dvorkin et al. [9] extend the work of Ruiz et al. [34], and propose a two-stage model that ensures the revenue adequacy of invested energy storage units. Levin and Botterud [23] strive to fill a void in the generation capacity expansion space by offering a mathematical model which recognizes that generation investment will be more likely to take place if such an investment is profitable.

Deriving a pricing scheme to ensure the revenue adequacy of generators has been a popular topic in the literature. Pricing schemes usually impact day-ahead UC markets, but it can also be relevant to expansion planning models, because the pricing scheme used in the day-ahead UC market should ultimately be reflected in the capacity expansion model as well. The current pricing schemes used by independent system operators (ISOs) may lead to revenue deficiencies. This market inefficiency stems from the non-convexity of the energy market. Convex markets with continuous goods can be modelled as a linear program (LP). As such, equilibrium prices can be calculated from a dual solution of the LP, and thus is also called the marginal prices. However, the electricity market is non-convex, as it includes discrete decisions such as commitment decisions. Therefore, it is not straightforward to compute equilibrium electricity prices. Several pricing schemes have been proposed to address this problem, the most popular of which is called the *locational marginal price (LMP)*, and is used by many ISOs in North America. LMPs are obtained from the duals for the demand constraints of a unit commitment problem with fixed binary variable values. This pricing scheme is easy to implement but generally does not guarantee revenue adequacy. In practice, such revenue inadequacy is compensated by *uplift payments*, which equals the difference between the total cost and revenue of a generator. This arrangement has raised questions about fairness [11]. To provide incentive-compatible prices, the *convex hull price (CHP)* scheme is proposed [18, 38]. However, CHP is computationally expensive, and its framework is making it difficult to incorporate additional modeling specifications such as investment decisions. To address these issues, an approximation of CHP, known as *approximated CHP (aCHP)*, can be employed where a tight unit commitment formulation is used and dual prices are obtained from the model's LP relaxation as in the LMP case. For a detailed comparison of different pricing schemes in non-convex markets, we refer the reader to [24]. In addition, the work [26] paints a nice picture concerning what is being considered in policy circles.

The pricing scheme that uses LMP and uplift payments is relatively computationally easier, but it may distort the market and cause price discrimination [11, 28]. On the other hand, the model that combines aCHP and revenue adequacy requirements in an energy-only market [11] is computationally more expensive, but it promotes fairness. In our work, we choose to use the aCHP. More importantly, to ensure revenue adequacy for each generator, instead of using the uplift payments, our model directly yields revenue adequate prices via revenue adequacy constraints, which ensure that a generator's revenue covers its total costs over the course of its lifetime. Note that when one refers to cost recovery in spot markets today, one is usually referring to daily constraints that exclude capital cost recovery. Although it is not the aim of our study to compare different pricing schemes, we compare our solutions to those obtained from a traditional model which incorporates the LMP as it is commonly used in practice.

The inadequacy of revenue from the wholesale markets creates the "missing money" problem, where the wholesale market prices are not enough to recover investment costs. In addition to non-convexities, causes of the "missing money" problem include price caps, subsidized or mandated renewable generation, and unstable regulatory environment, among others [3, 4]. Several market designs are proposed and adapted in practice to address the missing money problem, such as forward capacity markets and scarcity pricing, and we refer the interested readers to the survey paper by Bublitz et al. [4] on this topic. Despite the relatively large literature on market design for the missing money problem, there are few works that consider revenue adequacy in the planning stage. The goal of this work is to fill this void by proposing a generation expansion planning model that co-optimizes investment, operational and pricing decisions, and fully reimburses both short-run operational cost and long-run investment cost without requiring explicit capacity payments and only through the spot market. Our modeling setup is similar to that of the energy storage planning model by [9], which we discuss in more detail in Section 1.2.

Note that another cause of revenue inadequacy is the uncertainty in the market, e.g., the lack of long-term contracts with consumers [31]. We do not consider this issue in our work.

1.2. Generation Expansion Planning Problem Modeling

In this work we take the viewpoint of a central planner, who makes generation expansion decisions, and aims to ensure the revenue adequacy of the generators in the system via energy and reserve prices, and without uplift payments or capacity payments. Similar to Shavandi et al. [35], we include reserve markets, allowing generators to make revenue from both power and reserve markets. We recognize that there is an ongoing (and at times heated) debate concerning whether this is an optimal market design policy, but we do not consider other market revenue streams, e.g., capacity payments, here. Similar to Dvorkin et al. [9], we formulate a two-stage model. The first stage determines optimal generator investment decisions, while minimizing the long-term investment and fixed operational costs. In the second-stage problem, we include a standard security-constrained day-ahead UC model as presented in Anjos et al. [2], as well as the dual of the LP relaxation of UC constraints, and revenue adequacy constraints. We then combine the two stages into a single mixed-integer bilinear program (MIBLP), which we solve to simultaneously obtain the optimal investment, operational, and pricing decisions. Notice that in contrast to [9], we include the commitment decisions in the second stage instead of the first stage; thus our second-stage problem contains integer variables. We think this is a natural way to divide the model, as the first-stage investment decisions are made at the current time, while the second-stage commitment, production, and pricing decisions happen in a future target year. From this perspective, our setup is close to [34]. Another difference from [9] is that they use an aggregated revenue adequacy constraint for total energy storage capacity in the system, while we ensure revenue adequacy for each thermal generator in our system, which avoids profit redistribution and facilitates fairness. Note that our two-stage model optimizes all decisions together, and thus mathematically it can be reduced to a single stage. This setup is different from a bilevel leader-follower problem setup where the leader and the follower compete with each other, and generally cannot be optimized in a single-stage problem.

1.3. Market Equilibrium and Use of a Regularizer in Our Model

The primal-dual pricing model proposed by Ruiz et al. [34] provides a way to approach the market equilibrium in *non-convex* markets, despite the lack of strong duality in such markets. It is well known that in a convex market where each player's feasible region is a convex compact set, an equilibrium is guaranteed to exist. A primal-dual approach, in which one simultaneously formulates the primal and dual problems and then links them via a strong duality constraint, is often used to find equilibria. Indeed, many papers in the energy market literature incorporate this type of primal-dual approach in a two-stage framework [9, 11]. In these works, high-level decisions such as planning decisions are made in the first stage, then in the second stage operational decisions and pricing decisions are obtained via the primal-dual method. However, these two-stage models often assume a linear primal second-stage problem, in order to use strong duality to connect the primal and dual via bilinear equilibrium constraints. Then the nonlinear program is solved via linearization. In our model, however, the primal problem is an MILP. Explicitly modeling second-stage mixed-integer operational decisions poses several challenges, most notably the potential non-existence of a market equilibrium in the day-ahead market. Because there is no strong duality theorem for MILP, we cannot simply write a "primal objective equals dual objective" constraint as found in most primal-dual approaches. This means that there is no single direct way to link hourly generator production decisions and market prices to guarantee a market equilibrium. In the worst case, an equilibrium may not even exist. If there were no capacity expansion decisions to be made, then directly minimizing the duality gap is a suitable choice for simultaneously finding production levels and market-clearing prices. This is precisely the primal-dual approach introduced by Ruiz et al. [34] to determine market-clearing prices that avoid uplift payments. However, since our main objective (the first-stage objective) is to minimize total system cost (the sum of investment and operational costs), inspired by the primal-dual approach in [34], we treat duality gap minimization as a secondary objective. We introduce a regularization term in the objective to act as a tunable parameter for the modeler to control the trade-off between system costs and the deviation from market equilibrium. Without this regularizer, the model would minimize system costs while ensuring revenue adequacy, but have no incentive to achieve a second-stage market equilibrium.

1.4. Behaviour of Market Participants in Generation Expansion Planning

There is a rich literature on the generation expansion planning problem under various settings [14, 20, 21, 22, 33]. The monograph by Conejo et al. [7] provides an informative discussion pertaining to investment problems in electric energy. There are at least two major modeling paradigms to represent player behavior: The first assumes all players are treated as price takers having no market power. The second assumes that some players may exert market power and are usually formulated as two-stage Stackelberg games in which the strategic player plays (i.e., invests) first, and then the market is cleared, as in Wogrin et al. [39] and Kazempour et al. [19]. As has been widely documented, electricity markets exhibit myriad characteristics that "prevent them from functioning as a purely competitive market" due at least in part to non-convexities [13]. Despite this fact, we augment the first approach to ensure revenue adequacy because price-taker assumptions are so widely used. More precisely, we propose a central planning model with truthful cost disclosure by market participants. Taking liberties with terminology, from here on, we will refer to the model as a "price-taker" model, rather than the more precise but longer phrase "central planner with truth-telling agents" model. Note that because of non-convexities, we do not necessarily have market equilibrium despite price-taker assumptions.

Our modeling approach is meant as a practical compromise between a traditional deterministic centralized planning model that assumes a market with price takers and a more sophisticated game-theoretic model that attempts to model a range of imperfect competition scenarios. Our motivation for this compromise is founded on three main practical difficulties. First, it is difficult to determine historical levels of market power. While it may be conceptually easy within a mathematical model to represent each market participant as a strategic player endowed with a certain degree of market power, from a practical perspective, it can be extremely difficult to ascertain the parameter settings needed to calibrate such a model. For analysts maintaining a centralized planning model, there are numerous sources from which one can obtain cost improvement assumptions, load profiles, weather forecasts, and other information needed to populate a deterministic LP or MILP. On the other hand, there are far fewer outlets publishing the degree of market power for various market participants. Second, even if historical market power data could be obtained easily, the main purpose of a generation expansion planning tool is to project *future* electricity resource needs. Thus, a centralized planner is still left with the task of conjecturing the future degree of market power for each market participant. Is it true that a market participant who exhibited a large amount of market power in the past will have the ability or inclination to exert the same degree of market power in the future? In short, projecting strategic behavior into the future is a challenging exercise. Third, as articulated well by Ralph and Smeers [32], "... market power is a complex issue that requires a lot of assumptions to be modeled. The effect of this multiplicity of assumptions on the final result clearly requires careful elaboration." Because of the reasons stated above, even though a number of planning models take the form of a mathematical program with equilibrium constraints (MPECs) or an equilibrium problem with equilibrium constraints (EPECs), in which players act in a strategic manner and an equilibrium is sought, we choose not to adapt those approaches. Instead, we assume the viewpoint of a central planner, and use profit constraints to ensure the revenue adequacy of individual participants.

1.5. Our Contributions

We summarize three key features of generation expansion planning models in Figure 1, based on our literature review in Sections 1.2 and 1.4. Those key features include the details of operational decisions, the modeling methodologies, and the behaviour of market participants. In our setting, we consider a unit commitment with economic dispatch (UCED) problem with both reserve decisions and binary decisions. Our model is based on a primal-dual approach which leads to a mixed-integer nonlinear program (MINLP). We assume the market participants follow the instructions of a central planner; however similar to perfect competition markets, the profitability of those market participants are ensured.

The contributions of our study are as follows:

(1) To our knowledge, this is the first generation capacity expansion model combining the

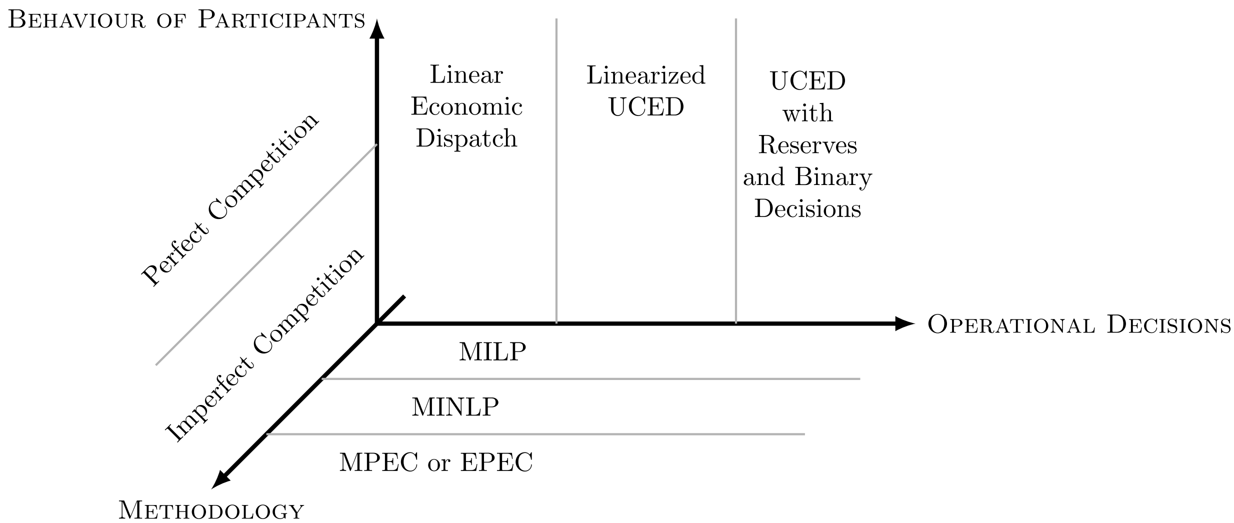


Figure 1: Features of generation expansion planning models

investment problem with revenue adequacy constraints. By ensuring revenue adequacy in the planning stage, we make more informed investment decisions in a market without uplift payments or capacity payments.

(2) In addition to minimizing total costs, we propose to add a regularizer to the objective that represents the magnitude of market disequilibrium or, equivalently, the duality gap between the second-stage primal and dual objectives. The goal of including this regularizer is to offer the modeler a tunable term to balance the trade-off between minimizing system costs and deviation from a market equilibrium. That is to say, we assume a multi-objective perspective. By increasing the regularizer penalty parameter, one can drive the second-stage solution closer to a market equilibrium, thereby producing more reasonable prices. Otherwise, the minimization of total cost is prioritized. It is up to the modeler to decide the weight of each objective. Our regularizer is novel for expansion planning problems and can be viewed as a departure from the more common two-stage primal-dual models (e.g., [9, 11]) that assume a linear second-stage primal problem.

(3) We compare alternative solution methods for our MIBLP model. Although linearization is the most commonly used approach to solve primal-dual models, our experiments reveal that Gurobi 9.0.0 [16], which is the first MIBLP solver from Gurobi and guarantees convergence to a global optimum, is competitive in its performance. Gurobi is a widely-used MILP solver, and our work is one of the first to use the Gurobi as a MIBLP solver since its release. The promising results are meaningful because practitioners prefer maintaining models, not algorithms. We believe showing the efficacy of the new solver technology increases the viability of primal-dual models.

2. Problem Formulation

We propose a two-stage model for the generation capacity expansion problem, where in the first stage we make long-term investment decisions on the new generators to build, and in the second stage we take the existing and new generators in the system as given, and make daily operational and pricing decisions, under the operational constraints, LP dual constraints, and additional constraints to ensure generator revenue adequacy. The structure of our model is illustrated in Fig. 2.

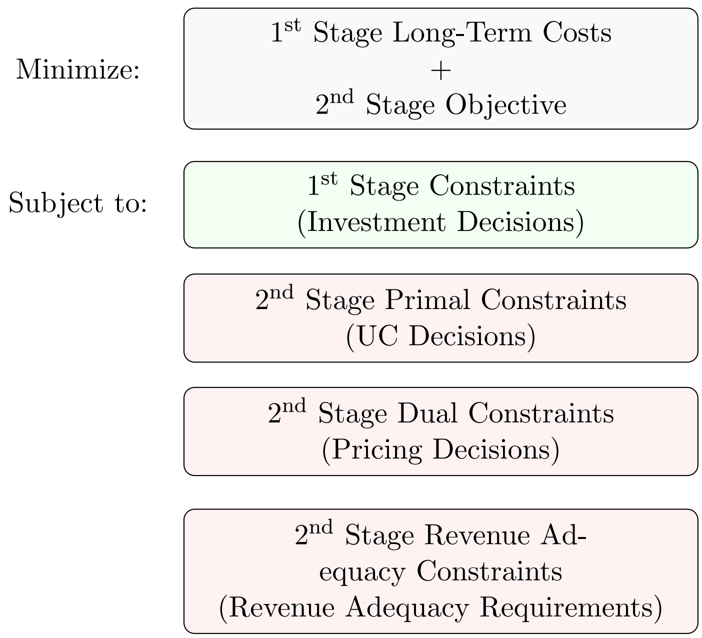


Figure 2: The two-stage revenue adequacy model

Next, we explain each component of our model in detail, using the notation given in Table 1.

Table 1: Nomenclature

Sets and indices:	
$\mathcal{G}$	Set of generators, indexed by g.
$\mathcal{G}^{\text{Thermal}}$	Set of thermal generators.
$\mathcal{G}^{\text{Renew}}$	Set of renewable generators.
$\mathcal{G}^{O}$, $\mathcal{G}^{N}$	Set of existing/candidate generators.
$\mathcal{T}$	Set of time periods, indexed by t.
$\mathcal{D}$	Set of representative days, indexed by d.
In what follows, "in (d,t)" is shorthand for "in time period t on representative day d".	
Parameters:	
C_g^{VOM}	Variable operational cost of generator g, \$/MWh.
C_g^{Fuel}	Fuel cost of generator g, \$/MWh.
C_g^{FOMG}	Annual fixed operational cost of generator g, \$/MW.

C_g^{Startup}	Startup cost of generator g, \$/startup.
C_g^{V}	Annually amortized investment cost of generator g, \$/MW.
C^l	Cost of unmet load, \$/MW.
$C^{\text{Spin}}, C^{\text{QS}}$	Cost of unmet spinning/quick-start reserve, \$/MW.
Δt	Duration of time period t, hour.
D^{Peak}	Peak load for the future year, MW.
D_{dt}	Load in (d, t), MW.
F_{gdt}^{CF}	Capacity factor for renewable generator g in (d, t).
F_g^{CV}	Capacity value of generator g.
$F^{\text{Op}}, F^{\text{Spin}}$	Fraction of load that must be met by total/spinning reserves.
$F_g^{\text{Spin}}, F_g^{\text{QS}}$	Fraction of generator g's excess capacity that can be allocated to spinning/quick-start reserves.
P_g^{CapUB}	The capacity upper bound for building new renewable generator g, MW.
$P_g^{\max}, P_g^{\min}$	Max/minimum power from generator g, MW.
Q	Minimum rate of return.
R_g^{Up}	Ramp up limit of generator g, MW/time step.
Δ_g^{MinUp}	Minimum up duration of generator g.
Γ	Planning reserve margin.
ρ	Scalar of regularizer in second-stage objective.
Variables:	
DOB	Objective value of dual second-stage problem.
OC	Total operating cost in the target future year, \$.
p_{gdt}^{Gen}	Power output of generator g in (d, t), MW.
$p_{gdt}^{\text{Spin}}, p_{gdt}^{\text{QS}}$	Power from generator g allocated to spinning/quick-start reserves in (d, t), MW.
p_{dt}^{Unmet}	Unmet load in (d, t), MW.
$p_{dt}^{\text{UnmetSpin}}$	Unmet spinning reserve in (d, t), MW.
p_{dt}^{UnmetQS}	Unmet quick-start reserve in (d, t), MW.
q_g^{Renew}	New capacity for renewable generator g, MW.
u_{gdt}, v_{gdt}	Binary variables that take value 1 if generator g is started up/shut down in (d, t); 0 otherwise.
w_g	Binary variable that takes value 1 if generator g is invested in; 0 otherwise.
y_{gdt}^{Gen}	Binary variable that takes value 1 if generator g is turned on in (d, t); 0 otherwise.

2.1. First-stage Problem

The first-stage objective is:

$$\min \sum_{g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}}} (C_g^{\text{V}} + C_g^{\text{FOMG}}) P_g^{\max} w_g + \sum_{g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Renew}}} (C_g^{\text{V}} + C_g^{\text{FOMG}}) q_g^{\text{Renew}} + \sum_{g \in \mathcal{G}^O} C_g^{\text{FOMG}} P_g^{\max} \tag{1}$$

which minimizes annualized long-term costs. The first (second) term is the total investment and fixed operational costs for new thermal (renewable) generators. The third term is the fixed operational cost for existing generators in the system. Note that the parameter C_g^{V} is amortized and represents the present value of the annual investment cost. We use the binary variable w_g for the investment decision of a thermal generator in $\mathcal{G}^{\text{Thermal}}$, and the continuous variable q_g^{Renew} for invested capacity of a renewable generation in $\mathcal{G}^{\text{Renew}}$. The set $\mathcal{G}^{\text{Thermal}}$ is for candidate thermal generators, while the set $\mathcal{G}^{\text{Renew}}$ is for possible locations to build renewable generation, as the choice of location is an important consideration for renewable generators. Although we consider locations for renewable generators, we do not incorporate transmission networks in the model for computational purposes. Also for simplicity, we do not consider uncertainty of renewable generation. Instead, we use representative days to capture seasonal variability.

In the first stage, we have a planning reserve constraint (2a), which ensures that the total generator capacity in the future target year exceeds the peak load by a threshold, and bound constraints (2b) for new renewable generators:

$$\sum_{g\in\mathcal{G}^O} F_g^{\text{CV}} P_g^{\max} + \sum_{g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Thermal}}} F_g^{\text{CV}} P_g^{\max} w_g + \sum_{g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Renew}}} F_g^{\text{CV}} q_g^{\text{Renew}} \geq (1+\Gamma) D^{\text{Peak}} \tag{2a}$$

$$0 \leq q_g^{\text{Renew}} \leq P_g^{\text{CapUB}}, \ \forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Renew}} \tag{2b}$$

2.2. Primal Constraints in Second-stage Problem

The primal constraints of the second-stage problem are conventional unit commitment constraints. Note that the variable in parentheses at the end of each constraint is the corresponding *dual variable*. Also note that in constraints where multiple time periods are involved, such as the ramping constraints (6a),(6b) and minimum up time constraints (9d), we link the first hour with the last hour in each day.

(1) *Operational Cost Constraint (i.e., Primal Objective):*

$$\begin{aligned} OC = &\sum_{g\in\mathcal{G}^{\text{Thermal}}} \sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \left[(C_g^{\text{VOM}} + C_g^{\text{Fuel}})\Delta t\right] p_{gdt}^{\text{Gen}} + \sum_{g\in\mathcal{G}^{\text{Thermal}}} \sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} C_g^{\text{Startup}} u_{gdt} \\ &+ \sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \left(C^l p_{dt}^{\text{Unmet}} + C^{\text{Spin}} p_{dt}^{\text{UnmetSpin}} + C^{\text{QS}} p_{dt}^{\text{UnmetQS}} \right) \end{aligned} \tag{3a}$$

where the first term is the total variable operational and management costs, and the second term is the total startup cost. The remaining terms correspond to the penalty due to unmet load, unmet spinning and quick-start reserves, respectively.

$$p_{dt}^{\text{Unmet}}, p_{dt}^{\text{UnmetSpin}}, p_{dt}^{\text{UnmetQS}} \geq 0, \quad \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{4}$$

(2) *Load Constraints ($\forall d \in \mathcal{D}, t \in \mathcal{T}$):* For each hour in each day, the total generation should satisfy the demand, or we record the unsatisfied portion as the unmet load:

$$\sum_{g \in \mathcal{G}} p_{gdt}^{\text{Gen}} + p_{dt}^{\text{Unmet}} \geq D_{dt} \qquad (\lambda_{dt}) \tag{5}$$

(3) *Ramping Constraints ($\forall g \in \mathcal{G}^{\text{Thermal}}, d \in \mathcal{D}, t \in \mathcal{T}$):* When ramping up or down a thermal generator's output change should be within the ramp up/down limits, except for the hours when turning on/off the generator, in which case the upper bound on ramping is the minimum production level or the ramping limit, whichever is higher:

$$p_{gdt}^{\text{Gen}} - p_{gd,t-1(\text{mod } |\mathcal{T}|)}^{\text{Gen}} \leq R_g^{\text{Up}}(1 - u_{gdt}) + \max\{R_g^{\text{Up}}, P_g^{\min}\} u_{gdt} \qquad (-\beta_{gdt}^{\text{RU}}) \tag{6a}$$

$$p_{gd,t-1(\text{mod } |\mathcal{T}|)}^{\text{Gen}} - p_{gdt}^{\text{Gen}} \leq R_g^{\text{Down}}(1 - v_{gdt}) + \max\{R_g^{\text{Down}}, P_g^{\min}\} v_{gdt} \qquad (-\beta_{gdt}^{\text{RD}}) \tag{6b}$$

(4) *Production Constraints ($\forall d \in \mathcal{D}, t \in \mathcal{T}$):* Constraints (7a) ensure that if a thermal generator is turned on, the production is at least at the minimum production level. Constraints (7b) ensure that a thermal generator that is not invested in should not produce any electricity. Constraints (7c) and (7d) provide the renewable production levels:

$$p_{gdt}^{\text{Gen}} \geq P_g^{\min} y_{gdt}^{\text{Gen}}, \quad \forall g \in \mathcal{G}^{\text{Thermal}} \qquad (\underline{\alpha}_{gdt}) \tag{7a}$$

$$p_{gdt}^{\text{Gen}} \leq P_g^{\max} w_g, \quad \forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}} \qquad (-\pi_{gdt}) \tag{7b}$$

$$p_{gdt}^{\text{Gen}} = F_{gdt}^{\text{CF}} P_g^{\max}, \quad \forall g \in \mathcal{G}^O \cap \mathcal{G}^{\text{Renew}} \qquad (\alpha_{gdt}^{\text{Renew}}) \tag{7c}$$

$$p_{gdt}^{\text{Gen}} = F_{gdt}^{\text{CF}} q_g^{\text{Renew}}, \quad \forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Renew}} \qquad (\alpha_{gdt}^{\text{Renew}}) \tag{7d}$$

(5) *Reserve Constraints ($\forall d \in \mathcal{D}, t \in \mathcal{T}$):* Constraints (8a) and (8b) provide upper bounds for production levels, spinning reserve levels, and quick-start reserve levels of thermal generators. Constraints (8c) and (8d) prevent getting reserves from generators that are not invested in. Constraints (8e) and (8f) ensure that the spinning reserve requirement and the total reserve requirement are

met.

$$
\begin{aligned}
&p_{gdt}^{\text{Gen}} + p_{gdt}^{\text{Spin}} \leq P_g^{\max} y_{gdt}^{\text{Gen}}, && \forall g \in \mathcal{G}^{\text{Thermal}} && (-\alpha_{gdt}^{\text{Spin}}) && (8a)\\
&p_{gdt}^{\text{QS}} \leq P_g^{\max}(1 - y_{gdt}^{\text{Gen}}), && \forall g \in \mathcal{G}^{\text{Thermal}} && (-\alpha_{gdt}^{\text{QS}}) && (8b)\\
&0 \leq p_{gdt}^{\text{Spin}} \leq P_g^{\max} w_g, && \forall g \in \mathcal{G}^{N} \cap \mathcal{G}^{\text{Thermal}} && (-\pi_{gdt}^{\text{Spin}}) && (8c)\\
&0 \leq p_{gdt}^{\text{QS}} \leq P_g^{\max} w_g, && \forall g \in \mathcal{G}^{N} \cap \mathcal{G}^{\text{Thermal}} && (-\pi_{gdt}^{\text{QS}}) && (8d)\\
&\sum_{g \in \mathcal{G}^{\text{Thermal}}} F_g^{\text{Spin}} p_{gdt}^{\text{Spin}} + p_{dt}^{\text{UnmetSpin}} \geq F^{\text{Spin}} D_{dt} && && (\varrho_{dt}^{\text{Spin}}) && (8e)\\
&\sum_{g \in \mathcal{G}^{\text{Thermal}}} (F_g^{\text{Spin}} p_{gdt}^{\text{Spin}} + F_g^{\text{QS}} p_{gdt}^{\text{QS}}) + p_{dt}^{\text{UnmetSpin}} + p_{dt}^{\text{UnmetQS}} \geq F^{\text{Op}} D_{dt} && && (\varrho_{dt}^{\text{OP}}) && (8f)
\end{aligned}
$$

(6) *Startup Shutdown Decisions ($\forall d \in \mathcal{D}, t \in \mathcal{T}$):* Constraints (9a) link the startup/shutdown decisions with the on/off status of generators. Constraints (9b) and (9c) ensure that we do not simultaneously start up and shut down a generator in the same hour. Minimum up time constraints (9d) ensure that once a generator is started up, it will remain on for the next Δ_g^{MinUp} hours. Constraints (9e), (9f), (9g), and (9h) explicitly specify binary variable upper bounds, for the convenience of linear relaxation and dualization in Section 2.3:

$$
\begin{aligned}
&u_{gdt} - v_{gdt} = y_{gdt}^{\text{Gen}} - y_{gd,t-1(\text{mod } |\mathcal{T}|)}^{\text{Gen}}, && \forall g \in \mathcal{G}^{\text{Thermal}} && (\sigma_{gdt}) && (9a)\\
&u_{gdt} + v_{gdt} \leq 1, && \forall g \in \mathcal{G}^{O} \cap \mathcal{G}^{\text{Thermal}} && (-\zeta_{gdt}) && (9b)\\
&u_{gdt} + v_{gdt} \leq w_g, && \forall g \in \mathcal{G}^{N} \cap \mathcal{G}^{\text{Thermal}} && (-\zeta_{gdt}) && (9c)\\
&y_{g,d,\tau(\text{mod}|\mathcal{T}|)} \geq y_{gdt}^{\text{Gen}} - y_{gd,t-1(\text{mod}|\mathcal{T}|)}^{\text{Gen}}, && \forall g \in \mathcal{G}^{\text{Thermal}}, \tau \in [t+1, t+\Delta_g^{\text{MinUp}} - 1] && (\mu_{gdt,\tau(\text{mod}|\mathcal{T}|)}) && (9d)\\
&0 \leq y_{gdt} \leq 1, && \forall g \in \mathcal{G}^{O} \cap \mathcal{G}^{\text{Thermal}} && (-\xi_{gdt}) && (9e)\\
&0 \leq y_{gdt} \leq w_g, && \forall g \in \mathcal{G}^{N} \cap \mathcal{G}^{\text{Thermal}} && (-\xi_{gdt}) && (9f)\\
&0 \leq u_{gdt} \leq 1, && \forall g \in \mathcal{G}^{\text{Thermal}} && (-\upsilon_{gdt}) && (9g)\\
&0 \leq v_{gdt} \leq 1, && \forall g \in \mathcal{G}^{\text{Thermal}} && (-\nu_{gdt}) && (9h)
\end{aligned}
$$

2.3. Dual Constraints in Second-stage Problem

The primal constraints in Section 2.2 contain binary variables u_{gdt}, v_{gdt} and y_{gdt}. We relax those binary variables, then take the dual of the linearly relaxed second-stage primal constraints.

The objective for the dual problem, DOB, is included in the model as constraint (10):

$$DOB = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\Bigg(D_{dt}\lambda_{dt} + F^{\text{Spin}}D_{dt}\varrho_{dt}^{\text{Spin}} + F^{\text{Op}}D_{dt}\varrho_{dt}^{\text{Op}} + \sum_{g\in\mathcal{G}^{\text{Thermal}}}(-R_g^{\text{Up}}\beta_{gdt}^{\text{RU}} - R_g^{\text{Down}}\beta_{gdt}^{\text{RD}} - P_g^{\max}\alpha_{gdt}^{\text{QS}} - \upsilon_{gdt} - \nu_{gdt}) + \sum_{g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Thermal}}}(-P_g^{\max}w_g\pi_{gdt} - P_g^{\max}w_g\pi_{gdt}^{\text{Spin}} - P_g^{\max}w_g\pi_{gdt}^{\text{QS}} - w_g\zeta_{gdt} - w_g\xi_{gdt}) + \sum_{g\in\mathcal{G}^O\cap\mathcal{G}^{\text{Thermal}}}(-\zeta_{gdt} - \xi_{gdt}) + \sum_{g\in\mathcal{G}^O\cap\mathcal{G}^{\text{Renew}}}F_{gdt}^{\text{CF}}P_g^{\max}\alpha_{gdt}^{\text{Renew}} + \sum_{g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Renew}}}F_{gdt}^{\text{CF}}q_g^{\text{Renew}}\alpha_{gdt}^{\text{Renew}}\Bigg) \tag{10}$$

Note that (10) contains *bilinear* terms, which are the products of an investment decision variable w_g or q_g^{Renew}, and a dual variable. They appear in the objective because when dualizing the second-stage primal constraints, we assume the investment decisions w_g and q_g^{Renew} are given, and treat them as constants.

The rest of the second-stage dual constraints are linear ($\forall d\in\mathcal{D}, t\in\mathcal{T}$):

$$\lambda_{dt} - \beta_{gdt}^{\text{RU}} + \beta_{gd(t+1)}^{\text{RU}} + \beta_{gdt}^{\text{RD}} - \beta_{gd(t+1)}^{\text{RD}} + \underline{\alpha}_{gdt} - \alpha_{gdt}^{\text{Spin}} \le (C_g^{\text{VOM}} + C_g^{\text{Fuel}})\Delta t, \ \forall g\in\mathcal{G}^O\cap\mathcal{G}^{\text{Thermal}} \tag{11a}$$

$$\lambda_{dt} - \beta_{gdt}^{\text{RU}} + \beta_{gd(t+1)}^{\text{RU}} + \beta_{gdt}^{\text{RD}} - \beta_{gd(t+1)}^{\text{RD}} + \underline{\alpha}_{gdt} - \alpha_{gdt}^{\text{Spin}} - \pi_{gdt} \le (C_g^{\text{VOM}} + C_g^{\text{Fuel}})\Delta t, \quad \forall g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Thermal}} \tag{11b}$$

$$\lambda_{dt} + \alpha_{gdt}^{\text{Renew}} \le 0, \quad \forall g\in\mathcal{G}^{\text{Renew}} \tag{11c}$$

$$\left(\max\{R_g^{\text{Up}}, P_g^{\min}\} - R_g^{\text{Up}}\right)\beta_{gdt}^{\text{RU}} + \sigma_{gdt} - \zeta_{gdt} - \upsilon_{gdt} \le C_g^{\text{Startup}}, \quad \forall g\in\mathcal{G}^{\text{Thermal}} \tag{11d}$$

$$\left(\max\{R_g^{\text{Down}}, P_g^{\min}\} - R_g^{\text{Down}}\right)\beta_{gdt}^{\text{RD}} - \sigma_{gdt} - \zeta_{gdt} - \nu_{gdt} \le 0, \quad \forall g\in\mathcal{G}^{\text{Thermal}} \tag{11e}$$

$$- P_g^{\min}\underline{\alpha}_{gdt} + P_g^{\max}(\alpha_{gdt}^{\text{Spin}} - \alpha_{gdt}^{\text{QS}}) - \sigma_{gdt} + \sigma_{gd,t+1(\text{mod }|\mathcal{T}|)} + \sum_{t'=t-\Delta_g^{\text{MinUp}}+1}^{t-1}\mu_{gd,t'(\text{mod }|\mathcal{T}|),t} - \sum_{\tau=t+1}^{t+\Delta_g^{\text{MinUp}}-1}\mu_{gdt,\tau(\text{mod }|\mathcal{T}|)} + \sum_{\tau=t+2}^{t+\Delta_g^{\text{MinUp}}}\mu_{gd,t+1(\text{mod }|\mathcal{T}|),\tau(\text{mod }|\mathcal{T}|)} - \xi_{gdt} \le 0, \ \forall g\in\mathcal{G}^{\text{Thermal}} \tag{11f}$$

$$- \alpha_{gdt}^{\text{Spin}} + F_g^{\text{Spin}}(\varrho_{dt}^{\text{Spin}} + \varrho_{dt}^{\text{OP}}) \le 0, \quad \forall g\in\mathcal{G}^O\cap\mathcal{G}^{\text{Thermal}} \tag{11g}$$

$$- \alpha_{gdt}^{\text{Spin}} + F_g^{\text{Spin}}(\varrho_{dt}^{\text{Spin}} + \varrho_{dt}^{\text{OP}}) - \pi_{gdt}^{\text{Spin}} \le 0, \quad \forall g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Thermal}} \tag{11h}$$

$$- \alpha_{gdt}^{\text{QS}} + F_g^{\text{QS}}\varrho_{dt}^{\text{OP}} \le 0, \quad \forall g\in\mathcal{G}^O\cap\mathcal{G}^{\text{Thermal}} \tag{11i}$$

$$-\alpha_{gdt}^{\text{QS}} + F_g^{\text{QS}} \varrho_{dt}^{\text{OP}} - \pi_{gdt}^{\text{QS}} \leq 0, \qquad \forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}} \tag{11j}$$

$$\lambda_{dt} \leq C^l \tag{11k}$$

$$\varrho_{dt}^{\text{Spin}} + \varrho_{dt}^{\text{OP}} \leq C^{\text{Spin}} \tag{11l}$$

$$\varrho_{dt}^{\text{OP}} \leq C^{\text{QS}} \tag{11m}$$

where the signs of the dual variables are as follows: $\{\lambda_{dt},\ \beta_{gdt}^{\text{RU}},\ \beta_{gdt}^{\text{RD}},\ \underline{\alpha}_{gdt},\ \pi_{gdt},\ \alpha_{gdt}^{\text{Spin}},\ \alpha_{gdt}^{\text{QS}},\ \varrho_{dt}^{\text{Spin}},\ \varrho_{dt}^{\text{OP}},\ \pi_{gdt}^{\text{Spin}},\ \pi_{gdt}^{\text{QS}},\ \zeta_{gdt},\ \mu_{gdt\tau},\ \xi_{dgt},\ \upsilon_{gdt},\ \nu_{gdt} \geq 0;\ \alpha_{gdt}^{\text{Renew}},\ \sigma_{gdt}\ \text{free}\}$.

2.4. Revenue Adequacy Constraints in Second-stage Problem

Revenue adequacy constraints ensure that for all the thermal generators, the total revenue is no less than some multiple of the total cost:

$$\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} \Big(\lambda_{dt} p_{gdt}^{\text{Gen}} + (\varrho_{dt}^{\text{Spin}} + \varrho_{dt}^{\text{Op}}) F_g^{\text{Spin}} p_{gdt}^{\text{Spin}} + \varrho_{dt}^{\text{Op}} F_g^{\text{QS}} p_{gdt}^{\text{QS}}\Big) \geq (1+Q)\Bigg(\frac{C_g^{\text{FOM}}|\mathcal{D}|}{365} + \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} [(C_g^{\text{VOM}} + C_g^{\text{Fuel}})\Delta t] p_{gdt}^{\text{Gen}} + \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} C_{gt}^{\text{Startup}} u_{gdt}\Bigg), \qquad \forall g \in \mathcal{G}^O \cap \mathcal{G}^{\text{Thermal}} \tag{12a}$$

$$\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} \Big(\lambda_{dt} p_{gdt}^{\text{Gen}} + (\varrho_{dt}^{\text{Spin}} + \varrho_{dt}^{\text{Op}}) F_g^{\text{Spin}} p_{gdt}^{\text{Spin}} + \varrho_{dt}^{\text{Op}} F_g^{\text{QS}} p_{gdt}^{\text{QS}}\Big) \geq (1+Q)\Bigg(\frac{(C_g^{\text{V}} + C_g^{\text{FOM}})|\mathcal{D}|}{365} w_g + \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} [(C_g^{\text{VOM}} + C_g^{\text{Fuel}})\Delta t] p_{gdt}^{\text{Gen}} + \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} C_{gt}^{\text{Startup}} u_{gdt}\Bigg), \qquad \forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}} \tag{12b}$$

Constraints (12) ensure that generators make a minimum rate of return Q. The left-hand-side of constraints (12a) and (12b) is the total revenue from energy and reserve markets. We assume two types of reserve markets in this problem: the spinning reserve market and the operating reserve market. The right-hand-side of those constraints is a multiple of the total cost, which represents the minimum return. Total cost includes variable operational cost, startup cost, fixed operational cost, and the investment cost if the generator is newly invested in.

Constraints (12) contain bilinear terms in the left-hand-side, because we need to multiply the price and production variables in order to calculate the revenue.

Note that even though we include the planning reserve constraint (2a) in our model, we choose not to include its shadow price as a revenue stream. In the literature, there are both pricing schemes that use the shadow price of the planning reserve constraint [10], and pricing schemes that do not [19]. To compare those two different pricing schemes would be an interesting topic for future works.

Although one could include similar constraints for solar and wind generators, we omit them as revenue adequacy issues can be a more near-term concern for conventional thermal generators, since they have non-zero marginal costs. In fact, variable renewable energy (VRE) generators are also making money through government subsidies, known in the US as an "Investment Tax Credit" for solar and a "Production Tax Credit" for wind. These subsidies implicitly appear in a unit commitment problem through a VRE generator's bid price. A VRE generator may even bid a negative price (i.e., signal to the ISO that it is willing to pay a small amount of money to produce energy) because it knows that it will receive a tax credit from the government that will make it revenue adequate.

2.5. Second-stage Problem Objective

For the second-stage overall objective, we minimize (variable) operational costs plus a scaled version of duality gap:

$$\min \; OC + \rho * (OC - DOB) \tag{13}$$

where OC is the value of the primal second-stage objective defined by constraint (3a), DOB is the value of the second-stage dual objective defined by constraint (10), and ρ is a scalar. The duality gap is the difference between the second-stage primal problem objective which minimizes the operational costs, and the objective of the dual for the LP relaxation of the second-stage problem. We can also regard this scaled duality gap as a regularizer for the second-stage problem.

The addition of the scaled duality gap is inspired by the primal-dual method of [34] where the deviation from a solution satisfying Karush-Kuhn-Tucker (KKT) conditions is minimized. The economic intuition behind the minimization of the duality gap is as follows: if strong duality holds, then the optimal primal and dual solutions, which satisfy KKT conditions, establish a market equilibrium [8]. In other words, a zero duality gap corresponds to market equilibrium. However, in our model there are non-convexities because of the commitment decisions, which means strong duality does not necessarily exist. Therefore, we minimize the duality gap between a MILP primal and its LP relaxation dual to drive the obtained solution as close to the market equilibrium as possible. Instead of using a regularizer in the form of the weighted objective (13), lexicographical optimization and multiobjective optimization can also be considered. Note that in similar works, e.g., [9] and [11], such a regularizer is not necessary, as their second-stage primal problems do not contain any integer variables, thus strong duality can be directly enforced by KKT conditions.

If our model does not have a regularizer, then it can theoretically set very high prices at all hours, as long as the revenue adequacy constraints are satisfied. By minimizing the regularizer, we try to drive prices towards more reasonable values that are closer to the market equilibrium prices.

3. Solution Method

We can combine the two stages into one optimization problem:

$$\min \quad \frac{1}{365}\text{eq. (1)} + \frac{1}{|\mathcal{D}|}\text{eq. (13)} \tag{14a}$$

$$\text{s.t.} \quad \text{eqs. } (2), (3) - (12) \tag{14b}$$

The monolithic formulation (14) is a MIBLP, as the second-stage dual objective (10) and revenue adequacy constraints (12) contain bilinear terms. To solve this problem, we experiment with linearization techniques, as well as solving it directly with the Gurobi 9.0 solver.

To linearize the bilinear terms in the revenue adequacy constraints (12), we can use both McCormick relaxation and the discretization technique in [9]. More specifically, we use the McCormick relaxation for the dual objective (10), which is computationally less expensive than discretization, but it is a relaxation and may generate infeasible solutions. As such, we instead use discretization for revenue adequacy constraints, since the satisfaction of those constraints is key to our model. For a more detailed description of the linearization method, please refer to A. We find that solving the MILP model after linearization is faster than solving the MIBLP model directly with Gurobi 9.0 for small instances. However, for larger instances, direct computation of the MIBLP becomes faster. In addition, linearization methods require imposing bounds on some variables. As bounds may not be readily available for certain variables, such as the dual variables, it renders the obtained solutions less accurate. Therefore, in the case studies of Section 4.1 and Section 4.2, we use the results from solving the MIBLP model directly with Gurobi for our detailed analysis.

Notice that some of the bilinear terms in our model are the products of two unbounded continuous variables. This type of bilinear model is particularly hard to solve. Unlike bilinear terms with integer variables which can be linearized exactly using standard techniques, bilinear terms where both variables are continuous can only be linearized approximately. In addition to linearization and the commercial solver used in this work, other MIBLP solution methods include constructing linear relaxations of bilinear terms in a branch-and-bound framework [12], and the Reformulation-Linearization Technique [1]. However, those methods are not readily applicable to our problem structure. It is worth to mention that we also experimented with the generalized Benders decomposition method [15], which can be used as an approximation method for MIBLP, however, did not obtain any promising results.

4. Case Studies

4.1. Small Case Study

1) Data and Experimental Setup: We first show the test results of our model (14) on a small test case. We use the data from Section 5.4 of [41], More specifically, we use the data corresponding to their first seven clustered nodes and simplify them for the small case study.

We assume that there are two types of thermal generators - coal and natural gas combined cycle (NGCC) - and two types of VRE generators - solar and wind. For illustrative purposes, there are two units of each thermal generator type, while VRE generators are represented as continuous decision variables, located at nodes one and two. We list the cost parameters and some other parameters of thermal and VRE generators in Table 2. Total existing capacity is 8.1 GW, which breaks down as follows: coal 1.1 GW, NGCC 1.2 GW, solar 3.6 GW, and wind 2.2 GW. Data for wind and solar capacity factors and renewable generator capacities are based on [30, 29, 6]. We use the hourly load data from [5]. We assume a 30-year planning horizon where load grows at an annual rate of 1.7%. The peak load is obtained as the maximum of all projected loads. As we only have a portion of all generators from [41] in the test case, we reduce the load accordingly, using one seventh of the total load. Capital costs and operational parameters are taken from [25]. The scalar of the regularizer is $\rho = 1$ and we assume the minimum rate of return is $Q = 0$.[1] For the second-stage problem, we use two representative days to capture some seasonal variability. The days are selected via the K-means clustering method on a concatenated vector of solar capacity factor, wind capacity factor and load.

In Figure 3 we present the data for capacity factors of wind and solar generators. Comparing the two representative days in Figure 3 (a), the first day has a higher wind capacity factor, with an average of 0.61, while the average wind capacity factor of the second day is only 0.01. The different wind capacity factors show the pronounced seasonal difference between two representative days, which belong to September and February respectively.

[1] The detailed description of the data is available online: https://chengg04.github.io/docs/profitability_dataDocumentation.pdf.

Table 2: Parameters of thermal and renewable generators

	Thermal Generators		Renewable Generators	
Parameter	NGCC	Coal	Wind	Solar
C_g^{V} [$/MW]	159694.92	79448.22	136139.92	119771.19
C_g^{FOMG}[$/kW](existing)	26.87	13.96	30.82	42.48
C_g^{FOMG}[$/kW] (new)	62	10	29	24
F_g^{CV}	1	1	0.15	0.6
Minimum generation fraction (existing)	0.48	0.32		
Minimum generation fraction (new)	0.3	0.4		
C_g^{Startup} [$/MW]	140.94	86.31		
F_g^{Spin}	0.1	0.1		
F_g^{QS}	0	1		
$\Delta_g^{\mathrm{MinUp}}$	24	6		

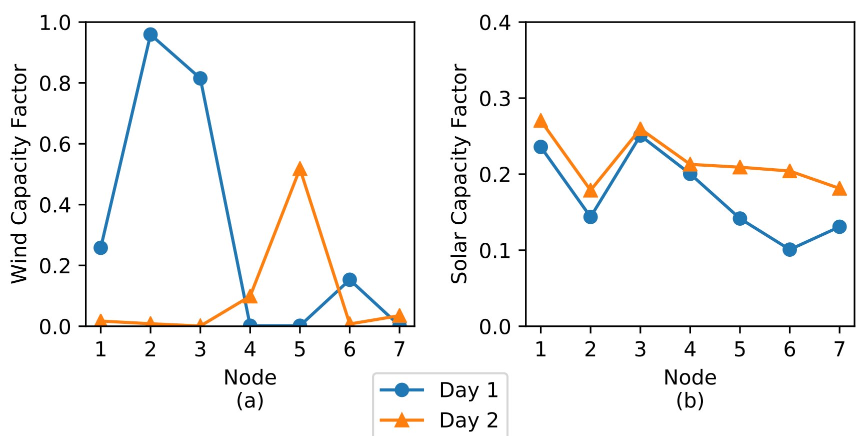


Figure 3: Capacity factors at each node for: (a) wind generators, (b) solar generators.

We compare the results of model (14) with a traditional generation planning model (15) which only includes investment and operational decisions with their associated constraints, i.e., does not enforce revenue adequacy for thermal generators:

$$\min \quad \frac{1}{365}\text{eq. } (1) + \frac{1}{|\mathcal{D}|}OC \tag{15a}$$

$$\text{s.t.} \quad \text{eqs. } (2), (3) - (9) \tag{15b}$$

2) Optimal Investment Decisions: Fig. 4 shows the invested new capacities for different types of generators (coal, natural gas (NG), solar and wind). We observe that the traditional model invests in more coal capacities, while our model invests in more solar capacities. This demonstrates that adding revenue adequacy requirements can lead to different planning decisions. Also, as the traditional model does not ensure revenue adequacy, the fact that more coal capacities are invested indicates that it builds coal power plants that lose money.

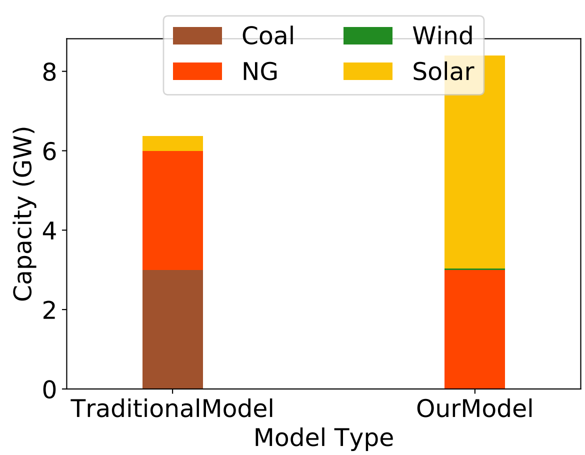
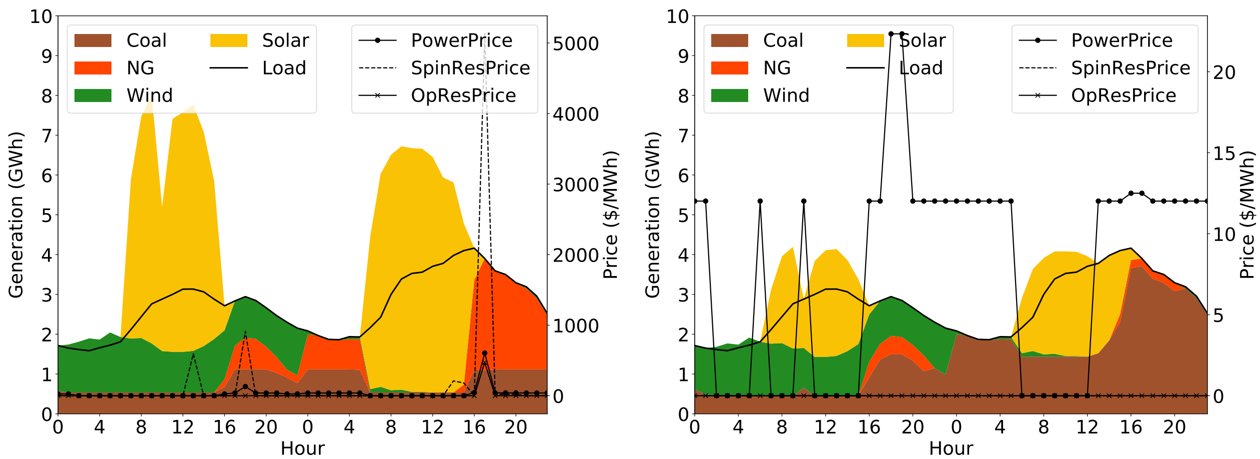


Figure 4: Breakdown of additional capacity investments

3) Optimal Production Profile and Pricing: Fig. 5a shows the optimal generation dispatch profile from our model, as well as the load and the optimal power price (PowerPrice), spinning reserve price (SpinResPrice), and the operating reserve price (OpResPrice). In each of the representative days, the load has peaks in the middle of the day. These peak loads correspond to the peak solar productions, so thermal productions are relatively low during those hours. Net load, i.e., load satisfied by the thermal generators, peaks around hour seventeen each day when the solar production drops, resulting in the widely documented "duck curve." Noticeably, we see more NG production at those hours. This is expected as NG generators have low startup cost and high variable cost, making them ideal for supplying the peak net load. The power price and reserve prices also peak around hour seventeen, when power becomes more scarce, while in the morning when there is abundant power supply, the price is close to zero.



(a) Our model

(b) Traditional model

Figure 5: Optimal production profiles and prices

Comparing the two representative days, the first day (first twenty four hours in Fig. 5) has more wind production. This is because, as we mentioned before, the first day has a higher average wind capacity factor, which helps to reduce the production from thermal generators. Finally, note that the unusual dip in solar production at around hour ten in the first day is likely a consequence of the clustering procedure. Namely, the centroid of the first cluster contained a solar profile with this sudden capacity factor drop.

Fig. 5b shows the optimal generation dispatch profile and prices from the traditional model. The prices here are obtained by fixing the binary variables in the model (15), re-solving it and taking the dual solutions for load constraints (5) and reserve requirement constraints (8e) and (8f). Compared with our model, the traditional model has more coal plant generation and less solar power generation, as it invests in more coal capacities. The power and reserve prices in the traditional model are much lower than those in our model. The reserve prices in the traditional model are always zero in this case study, while the peak power price is around \$25/MWh. Meanwhile, uplift payments are substantial as shown in Table 3. Thus, the tradeoff for keeping low hourly prices is potentially large make-whole payments. In contrast, in our model the peak power price is around \$600/MWh, and the reserve prices are not always zero. Lastly, we note that although investing in more solar generation might seem to contradict revenue adequacy, it is chosen by the model to reduce the total cost.

For our model, we additionally experiment with imposing a price cap of \$500/MWh. The optimal generation dispatch profile and prices are similar to what we see in Fig. 5a.

4) Evaluation of Profit and System Payment: In Fig. 6 we compare the daily average profit of each thermal generator including existing coal (CoalOld) and NG (NGOld) generators as well as new coal (CoalNew) and NG (NGNew) generators, two units for each. The profit is calculated as the total revenue from power production and reserves, minus the total cost of investment and operation. All thermal generators have nonnegative profit in our model, while in the traditional model they all have negative profit. In fact, for thermal generators in the traditional model, the negative profits are as high as 77% to 100% of their total costs. This demonstrates that by setting prices satisfying revenue adequacy constraints (12), our model ensures the revenue adequacy of each thermal generator in circumstances where the traditional model fails.

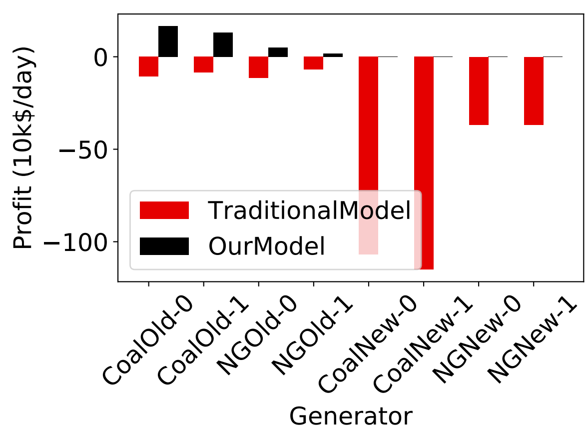


Figure 6: Profit of thermal generators

We further show the benefit of our model by comparing the daily total system payment for thermal generators in Table 3. We also experiment with adding a \$500/MWh price cap to the prices in our model. The payments are calculated as follows:

- Uplift Payment: the total positive difference between a thermal generator's cost and its revenue. For an existing generator this value can be calculated by deducting the left-hand side of constraint (12a) from its right-hand side at the optimal solution (if negative, then the uplift payment is 0). The same can be done for newly-invested thermal generators with constraint (12b).
- Power Revenue: the total revenue from thermal power production. Obtained by summing up

the optimal value of $\lambda_{gt} p_{gdt}^{\mathrm{Gen}}$ over all thermal generators, days and time periods.

- Res Revenue: the total revenue from reserves. Obtained by summing up the optimal value of $(\varrho_{dt}^{\mathrm{Spin}} + \varrho_{dt}^{\mathrm{Op}}) F_g^{\mathrm{Spin}} p_{gdt}^{\mathrm{Spin}} + \varrho_{dt}^{\mathrm{Op}} F_g^{\mathrm{QS}} p_{gdt}^{\mathrm{QS}}$ over all thermal generators, days and time periods.

- Total Revenue: the sum of Power Revenue and Res Revenue.

- Total Payment: the sum of Total Revenue and Uplift Payment.

- Total Cost: the total costs of investment and operations.

Table 3: Thermal generator costs and revenues

Cost/Revenue (100k$)	TraditionalModel	OurModel	OurModel(PriceCap)
Uplift Payment	33.3	0.0	0.0
Power Revenue	3.7	21.5	21.2
Res Revenue	0.0	4.3	2.9
Total Revenue	3.7	25.8	24.1
Total Payment	37.0	25.8	24.1
Total Cost	37.0	20.6	20.7

The system needs to pay the generators for the power and reserves they provide, and this amount is listed as "Revenue" in Table 3. When the revenue cannot recover a generator's cost, the system also needs to pay an uplift payment to the generator. Compared with the traditional model, the thermal generators in our model receive a much higher revenue, which can be explained by the higher prices from our model. However, the traditional model needs to pay a high uplift cost, while our model needs not. As a result, the total payment of the system is lower in our model. The addition of price caps in our model also pushes down the total payment.

Another interesting observation from Table 3 is that, for our model, the generators make much more revenue from the electricity market (Power Revenue) than from the reserve markets (Res Revenue). Therefore, even though the reserve prices can be very high in certain hours in Fig. 5a, they do not result in a significantly high revenue.

The total costs for thermal generators is lower in our model, which is to be expected as our model invests in less thermal capacity. On the other hand, the total costs of all generators is $4.45 million in the traditional model, while our model has slightly more costs of $4.79 million.

4.2. Large-scale Case Study

In this section we investigate a large-scale case study. All the data sources and setups in this section are the same as Section 4.1, except that here we include all seven nodes and their corresponding coal, NGCC, solar and wind capacities, with a total existing generation capacity of 47.9 GW, which consists of 12.5 GW coal, 17.9 GW NGCC, 11.2 GW solar, and 6.3 GW wind generations.

The investment decisions are shown in Fig. 7. Again, we see different investment decisions between the two models with our model again investing in more renewable generators. In particular, in our model solar generators are built in two nodes - SCE and SDG&E - which have the highest solar capacity factors out of all seven nodes.

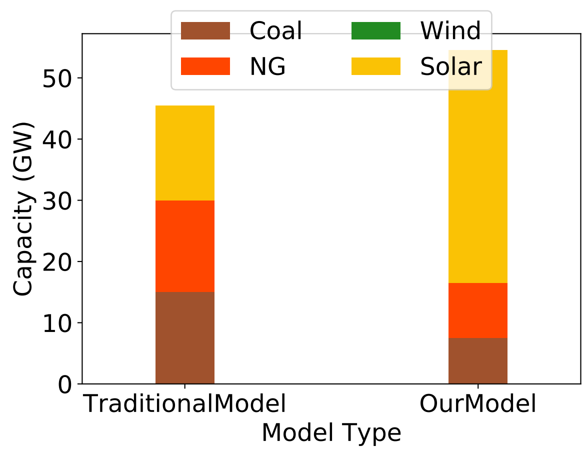


Figure 7: Breakdown of additional capacity investments in the large-scale case study

Production profiles, prices and profit are similar in the large-scale case study as in its smaller-scale counterpart. The net load peaks in the late afternoon each day, around which time we have the highest power and reserve prices; most thermal generators in the traditional model are losing money, while in our model they are profitable.

In Table 4 we show the costs and revenue of thermal generators in the large-scale case study. Similar to the small case study, generators in our model receive higher revenue. Also, in the traditional model thermal generators earn more revenue from uplift costs than from power and reserves prices. In our model, the total costs of thermal generators are lower, while the total costs of all generators again have a slight increase: from \$30.48 million in the traditional model to \$33.91million in our model.

4.3. Computational Details and Performance Analysis

All experiments are conducted on Linux workstations with 3.6GHz Intel Core i9 CPUs and 128GB memory. The traditional model and our model are respectively solved with CPLEX 12.10

Table 4: Thermal generator costs and revenues for the large-scale case study

Cost/Revenue (100k$)	TraditionalModel	OurModel	OurModel(PriceCap)
Uplift Payment	153.8	0.0	0.0
Power Revenue	66.0	1467.8	227.8
Res Revenue	5.8	369.9	127.7
Total Revenue	71.8	1837.7	355.5
Total Payment	225.7	1837.7	355.5
Total Cost	225.4	171.1	187.0

and Gurobi 9.0. The optimality gaps of the solvers are set to 1%. All experiments are completed within 168 hours.

One technique we use to speedup the computation is to use the optimal integer solutions from the traditional model as a warm start for our model. We also give the branching priority to the investment decisions.

When the time limit is reached, our model is not solved to optimality. For example, for the small case there is a 3.95% optimality gap. To make sure that the obtained investment decisions are still better than the investment decisions from the traditional model, we fix the investment decisions in our model as provided by the traditional model (actually we fixed some of them, as fixing all of them leads to infeasibility), and this gives us a worse objective value. This shows that even though we are not able to solve our model to optimality, the investment decisions from our model is still better than those from the traditional model.

Next, we show the experiment results on the comparison of computational performance, as well as the benefit of our solution approach over the common practice.

1) Computational Performance and Disadvantage of Linearization: We compare the computational performance of solving directly with the Gurobi 9.0 bilinear solver (Direct) and the linearization technique (Linearize). For the purpose of benchmarking, we set the time limit for this experiment to 24 hours. The results are presented in Table 5. We report the solution time (in hours) if the problem is solved within the time limit, otherwise provide the optimality gap obtained at the end of the time limit. For each instance we emphasize the fastest algorithm / algorithm with the smallest optimality gap with boldface. The two small instances ("small_1" and "small_2") have the same setup as the small case study in Section 4.1, except for the load values of "small_2", which are set to higher values. The "full" instance uses the same data as the experiment in Section 4.2. The instances "medium_1" and "medium_2" are two simplified versions of the instance "full", with fewer candidate generators than "full". We use "-" in the table if the solver cannot find any integer solution within the 24-hour time limit.

Table 5: Computational performance comparison (Time Limit: 24 Hours)

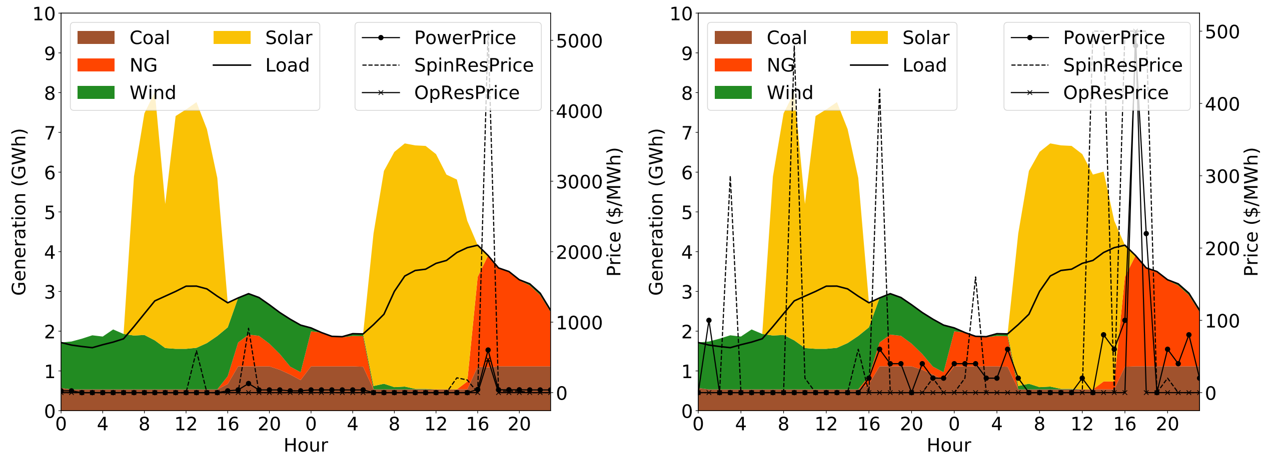
	Time/Gap	
Instance	Direct	Linearize
small_1	8.59%	**12.84 h**
small_2	4.91%	**0.02 h**
medium_1	**13.16%**	-
medium_2	**5.26 h**	5.45 h
full	**26.41%**	-

Table 5 shows that for small instances, the linearization method is able to solve both instances to optimality within the time limit, while if we use the bilinear solver directly, there is still optimality gap when the time runs out. However, for medium-sized instances and the full-sized case study, direct solving the model outperforms the linearization technique.

Also note that the linearization method imposes restrictions on dual prices, including addition of extra bounds and restriction of possible dual values to a finite set via discretization. The latter type of restriction can be relaxed by increasing the granularity of discretization, but the increased granularity also creates larger models after linearization, which can be problematic for large instances. In our linearization implementations, we set the bounds of discretized dual prices as 500, also divided the range for discretization evenly and set the cardinality of discretization sets at 50. We observe that the prices we obtain from linearization display a more restricted pattern than the prices from direct solving the model with Gurobi. This is why we use results from the direct approach in Sections 4.1, even though the optimality gap is 3.95% after a 168-hour time limit, while linearization solves the restriction of the same instance to optimality much faster.

2) Advantage of Our Solution Method over Common Practice: As we mentioned in Section 1.3, previous models using primal-dual approach do not include regularizers in the objective, and are usually solved by means of linearization. To compare our implementation with this common practice, we run an additional experiment on the small case study, where we reformulate the problem without the regularizer, and solve it by linearization, as commonly done in the literature. In Figure 8b we show the optimal production profiles and prices from this experiment, while Figure 8a is a copy of Figure 5a, and is repeated here for the convenience of comparison.

Comparing Figure 8a and Figure 8b, we see that the prices in Figure 8b do not follow the expected pattern, and the utility may charge high prices when the net load is low, such as in hours 20 to 24 of the second day. This may be because without the regularizer, the trend of dual prices is not forced to sync with the trend of the load, and prices could take higher values in non-peak



(a) (b)

Figure 8: Optimal production profiles and prices from (a) our method (with regularizer, solved directly by bilinear solver), (b) common practice (without regularizer, solved by linearization).

hours in order to satisfy the profitability constraints.

4.4. Value of the Regularizer

Our model assumes a multi-objective perspective, and a modeller can prioritize the minimization of the duality gap by increasing the value of the regularizer ρ. We report the investment decisions under different values of ρ in Table 6, where we list the optimality gap at termination, the number of invested NGCC and coal generators, as well as invested capacity of wind and solar generators. All experiments are run with a 168-hour time limit.

Table 6: Investment Decisions under Different ρ

		Thermal Generators		Renewable Generators	
ρ	Gap	NGCC (#)	Coal (#)	Wind (MW)	Solar (MW)
1	3.95%	2	0	43	5358
2	12.83%	2	0	193	5322
4	9.22%	2	0	1258	5054
8	26.06%	2	0	1328	5037

We observe that with the increase of ρ, the investment in renewable generators increases. This behaviour is to be expected, as a larger ρ means less weight on the minimization of (investment) cost. In practice, modellers should pick the value of ρ that best suits their planning goal. We envision that most practitioners will continue to use a traditional model as a reference point given their familiarity with such models. This amounts to first setting ρ to zero in our model. After observing the corresponding uplift payments needed to make thermal generators "whole", a practitioner could then begin gradually increasing ρ to understand how the results change as greater emphasis is placed on achieving a market equilibrium with non-convexities. An alternative approach would be to employ our model in a multi-objective optimization framework to obtain the so-called Pareto frontier, which would fully illustrate the trade-off between the system costs and the duality gap, thus eliminate the need to predetermine the value ρ.

5. Conclusion

We present a two-stage generation expansion planning model with revenue adequacy constraints. With energy and reserve payments as the only revenue source, we ensure revenue adequacy of all thermal generators in the system without uplift payments or capacity payments.

Through case studies, we show the impact of revenue adequacy constraints on investment and pricing decisions. Compared with a traditional model, our model invests in more renewable and flexible thermal generators. Also, our model generates revenue via power and reserve prices, while the traditional model obtains most payments through uplift costs.

In the computational experiments, we also demonstrate the advantage of solving the bilinear model directly over using the commonly used linearization technique for large instances. In addition, we show that by using the market equilibrium regularizer we propose, and solving the MIBLP model directly, our practice produces a more reasonable price trend. These results provide tools for future works that need to address problems with similar structures.

There are several interesting directions for future research. It would be interesting to explore the benefits of a multi-stage version of our two-stage model to understand the impact of revenue adequacy constraints over the evolution of expansion decisions. In addition, incorporating uncertainty into the model can lead to different investment and pricing decisions. Energy storage and transmission network can also be incorporated. Finally, in terms of methodology, decomposition may yield computational accelerations.

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A. Linearization of Bilinear Terms

The second stage dual objective (10) and profit constraints (12a), (12b) contain bilinear terms. We use a combination of the discretization method and the McCormick relaxation method to linearize the bilinear term.

1) Linearize the profit constraints: All the bilinear terms in profit constraints are products of two continuous variables. Generally speaking, when both variables in a bilinear term are continuous, we discretize one of the variables by restricting its value to a set of discrete values. More specifically, for bilinear terms $\lambda_{dt} p^{\text{Gen}}_{gdt}$, $\varrho^{\text{Spin}}_{dt} p^{\text{Spin}}_{gdt}$, $\varrho^{\text{Op}}_{dt} p^{\text{Spin}}_{gdt}$, and $\varrho^{\text{Op}}_{dt} p^{\text{QS}}_{gdt}$ in constraints (12a) and (12b), we discretize the dual variables in those terms, and assume that λ_{dt}, $\varrho^{\text{Spin}}_{dt}$ and ϱ^{Op}_{dt} can only take values in the sets $\{\Delta\lambda_{r_1} | r_1 \in \mathcal{R}_1\}$, $\varrho^{\text{Spin}}_{dt} \in \{\Delta\varrho^{\text{Spin}}_{r_2} | r_2 \in \mathcal{R}_2\}$, and $\varrho^{\text{Op}}_{dt} \in \{\Delta\varrho^{\text{Op}}_{r_3} | r_3 \in \mathcal{R}_3\}$, respectively. This assumption is a restriction on the original problem, but the accuracy of this method can be improved by increasing the granularity of discretization in the sets above.

Additionally, we introduce binary variables $z^1_{gdr_1}$, $z^2_{gdr_2}$, and $z^3_{gdr_3}$, which equal 1 if and only if $\lambda_{dt} = \Delta\lambda_{r_1}$, $\varrho^{\text{Spin}}_{dt} = \Delta\varrho^{\text{Spin}}_{r_2}$, and $\varrho^{\text{Op}}_{dt} = \Delta\varrho^{\text{Op}}_{r_3}$, respectively. Also, we define variables $h^1_{gdtr_1} := p^{\text{Gen}}_{gdt} z^1_{dtr_1}, h^2_{gdtr_2} := p^{\text{Spin}}_{gdt} z^2_{dtr_2}, h^3_{gdtr_3} := p^{\text{Spin}}_{gdt} z^3_{dtr_3}, h^4_{gdtr_3} := p^{\text{QS}}_{gdt} z^3_{dtr_3}$. Then constraints (12a) and (12b) can be replaced with the following mixed integer linear constraints:

$$
\begin{aligned}
&\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\Big(\sum_{r_1\in\mathcal{R}_1}\Delta\lambda_{r_1} h^1_{gdtr_1} + \sum_{r_2\in\mathcal{R}_2}\Delta\varrho^{\text{Spin}}_{r_2} h^2_{gdtr_2}\Big)\\
&\quad + \sum_{r_3\in\mathcal{R}_3}\Delta\varrho^{\text{Op}}_{r_3}(h^3_{gdtr_3} + h^4_{gdtr_3}) \geq \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}(C^{VOM}_{gdt}\\
&\quad + C^{\text{Fuel}}_g) p^{\text{Gen}}_{gdt} + \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} C^{\text{Startup}} u_{gdt} + \frac{C^{FOM}_g |\mathcal{D}|}{365},\\
&\quad \forall g \in \mathcal{G}^O \cap \mathcal{G}^{\text{Thermal}} \qquad \text{(A.16a)}
\end{aligned}
$$

$$\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\Big(\sum_{r_1\in\mathcal{R}_1}\Delta\lambda_{r_1}h^1_{gdtr_1}+\sum_{r_2\in\mathcal{R}_2}\Delta\varrho^{\text{Spin}}_{r_2}h^2_{gdtr_2}$$
$$+\sum_{r_3\in\mathcal{R}_3}\Delta\varrho^{\text{Op}}_{r_3}(h^3_{gdtr_3}+h^4_{gdtr_3})\Big)\geq\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}(C^{VOM}_{gdt}$$
$$+C^{\text{Fuel}}_g)p^{\text{Gen}}_{gdt}+\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}C^{\text{Startup}}u_{gdt}$$
$$+\frac{(C^V_g+C^{FOM}_g)|\mathcal{D}|}{365}w_g,\forall g\in\mathcal{G}^N\cap\mathcal{G}^{\text{Thermal}} \tag{A.16b}$$

with the following mixed-integer linear constraints to make sure that the discretization is valid ($\forall d\in\mathcal{D},t\in\mathcal{T}$):

$$h^1_{gdtr_1}\leq P^{\max}_g z^1_{dtr_1},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_1\in\mathcal{R}_1 \tag{A.17a}$$
$$0\leq h^1_{gdtr_1}\leq p^{\text{Gen}}_{gdt},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_1\in\mathcal{R}_1 \tag{A.17b}$$
$$h^1_{gdtr_1}\geq p^{\text{Gen}}_{gdt}-P^{\max}_g(1-z^1_{dtr_1}),$$
$$\forall g\in\mathcal{G}^{\text{Thermal}},r_1\in\mathcal{R}_1 \tag{A.17c}$$
$$\lambda_{dt}=\sum_{r_1\in\mathcal{R}_1}\Delta\lambda_{r_1}z^1_{dtr_1} \tag{A.17d}$$
$$\sum_{r_1\in\mathcal{R}_1}z^1_{dtr_1}=1 \tag{A.17e}$$
$$h^2_{gdtr_2}\leq P^{\max}_g z^2_{dtr_2},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_2\in\mathcal{R}_2 \tag{A.17f}$$
$$0\leq h^2_{gdtr_2}\leq p^{\text{Spin}}_{gdt},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_2\in\mathcal{R}_2 \tag{A.17g}$$
$$h^2_{gdtr_2}\geq p^{\text{Spin}}_{gdt}-P^{\max}_g(1-z^2_{dtr_2}),$$
$$\forall g\in\mathcal{G}^{\text{Thermal}},r_2\in\mathcal{R}_2 \tag{A.17h}$$
$$\varrho^{\text{Spin}}_{dt}=\sum_{r_2\in\mathcal{R}_2}\Delta\varrho^{\text{Spin}}_{r_2}z^2_{dtr_2} \tag{A.17i}$$
$$\sum_{r_2\in\mathcal{R}_2}z^2_{dtr_2}=1 \tag{A.17j}$$
$$h^3_{gdtr_3}\leq P^{\max}_g z^3_{dtr_3},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_3\in\mathcal{R}_3 \tag{A.17k}$$
$$0\leq h^3_{gdtr_3}\leq p^{\text{Spin}}_{gdt},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_3\in\mathcal{R}_3 \tag{A.17l}$$
$$h^3_{gdtr_3}\geq p^{\text{Spin}}_{gdt}-P^{\max}_g(1-z^3_{dtr_3}),$$
$$\forall g\in\mathcal{G}^{\text{Thermal}},r_3\in\mathcal{R}_3 \tag{A.17m}$$
$$h^4_{gdtr_3}\leq P^{\max}_g z^3_{dtr_3},\qquad\forall g\in\mathcal{G}^{\text{Thermal}},r_3\in\mathcal{R}_3 \tag{A.17n}$$

$$0 \le h^4_{gdtr_3} \le p^{\text{QS}}_{gdt}, \qquad \forall g \in \mathcal{G}^{\text{Thermal}}, r_3 \in \mathcal{R}_3 \tag{A.17o}$$

$$h^4_{gdtr_3} \ge p^{\text{QS}}_{gdt} - P^{\max}_g(1 - z^3_{dtr_3}),$$
$$\forall g \in \mathcal{G}^{\text{Thermal}}, r_3 \in \mathcal{R}_3 \tag{A.17p}$$

$$\varrho^{\text{Op}}_{dt} = \sum_{r_3 \in \mathcal{R}_3} \Delta\varrho^{\text{Op}}_{r_2} z^3_{dtr_3} \tag{A.17q}$$

$$\sum_{r_3 \in \mathcal{R}_3} z^3_{dtr_3} = 1 \tag{A.17r}$$

2) Linearize the second stage dual objective: The right-hand side of constraint (10) contains bilinear terms $w_g\pi_{gdt}$, $w_g\pi^{\text{Spin}}_{gdt}$, $w_g\pi^{\text{QS}}_{gdt}$, $w_g\zeta_{gdt}$, $w_g\xi_{gdt}$, and $q^{\text{Renew}}_g\alpha^{\text{Renew}}_{gdt}$. Notice that the terms containing w_g is easier to discretize as w_g is a binary variable, and require no further discretization. To discretize those terms containing w_g, we assume the dual variables respectively have the upper bounds Π^{UB}, $\Pi^{\text{Renew, UB}}$, $\Pi^{\text{QS, UB}}$, Z^{UB}, and Ξ^{UB}, and define $h^{w_1}_{gdt} := w_g\pi_{gdt}$, $h^{w_2}_{gdt} := w_g\pi^{\text{Spin}}_{gdt}$, $h^{w_3}_{gdt} := w_g\pi^{\text{QS}}_{gdt}$, $h^{w_4}_{gdt} := w_g\zeta_{gdt}$, and $h^{w_5}_{gdt} := w_g\xi_{gdt}$.

To linearize $q^{\text{Renew}}_g\alpha^{\text{Renew}}_{gdt}$, we use McCormick relaxation, as it requires fewer new variables and constraints than linearization. Plus, unlike for profit constraints, using McCormick to relax terms in the dual objective does not affect the feasibility of the solution. to implement McCormick relaxation, we first need to impose bounds for the free dual variable $\alpha^{\text{Renew}}_{gdt}$. However, due to constraint (11c), $\alpha^{\text{Renew}}_{gdt}$ has a natural upper bound of 0. Thus, we only need to assume an additional lower bound for it as $A^{\text{Renew, LB}}$. Next, we define the variable $h^{\text{Renew}}_{gdt} := \alpha^{\text{Renew}}_{gdt}q^{\text{Renew}}_g$. Then the McCormick relaxation of $\alpha^{\text{Renew}}_{gdt}q^{\text{Renew}}_g$ can be written as in constraints (A.20).

The linearized constraint (10) is as follows:

$$\begin{aligned}
DOB = \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} \Big(& D_{dt}\lambda_{dt} + F^{\text{Spin}} D_{dt}\varrho^{\text{Spin}}_{dt} + F^{\text{Op}} D_{dt}\varrho^{\text{Op}}_{dt} \\
& + \sum_{g \in \mathcal{G}^{\text{Thermal}}} (-R^{\text{Up}}_g\beta^{\text{RU}}_{gdt} - R^{\text{Down}}_g\beta^{\text{RD}}_{gdt} - P^{\max}_g\alpha^{QS}_{gdt} - \upsilon_{gdt} \\
& - \nu_{gdt}) + \sum_{g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}}} (-P^{\max}_g h^{w_1}_{gdt} - P^{\max}_g h^{w_2}_{gdt} \\
& - P^{\max}_g h^{w_3}_{gdt} - h^{w_4}_{gdt} - h^{w_5}_{gdt}) + \sum_{g \in \mathcal{G}^O \cap \mathcal{G}^{\text{Thermal}}} (-\zeta_{gdt} \\
& - \xi_{gdt}) + \sum_{g \in \mathcal{G}^O \cap \mathcal{G}^{\text{Renew}}} F^{\text{CF}}_{gdt} P^{\max}_g \alpha^{\text{Renew}}_{gdt} + \sum_{g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Renew}}} F^{\text{CF}}_{gdt} h^{\text{Renew}}_{gdt} \Big)
\end{aligned} \tag{A.18}$$

Additionally the following constraints are needed to ensure the correctness of the linearization

$(\forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Thermal}}, d \in \mathcal{D}, t \in \mathcal{T})$:

$$h_{gdt}^{w_1} \leq \Pi_{gdt}^{\text{UB}} w_g \tag{A.19a}$$

$$0 \leq h_{gdt}^{w_1} \leq \pi_{gdt} \tag{A.19b}$$

$$h_{gdt}^{w_1} \geq \pi_{gdt} - \Pi_{gdt}^{\text{UB}}(1 - w_g) \tag{A.19c}$$

$$h_{gdt}^{w_2} \leq \Pi_{gdt}^{\text{Spin, UB}} w_g \tag{A.19d}$$

$$0 \leq h_{gdt}^{w_2} \leq \pi_{gdt} \tag{A.19e}$$

$$h_{gdt}^{w_2} \geq \pi_{gdt} - \Pi_{gdt}^{\text{Spin, UB}}(1 - w_g) \tag{A.19f}$$

$$h_{gdt}^{w_3} \leq \Pi_{gdt}^{\text{QS, UB}} w_g \tag{A.19g}$$

$$0 \leq h_{gdt}^{w_3} \leq \pi_{gdt} \tag{A.19h}$$

$$h_{gdt}^{w_3} \geq \pi_{gdt} - \Pi_{gdt}^{\text{QS,UB}}(1 - w_g) \tag{A.19i}$$

$$h_{gdt}^{w_4} \leq Z_{gdt}^{\text{UB}} w_g \tag{A.19j}$$

$$0 \leq h_{gdt}^{w_4} \leq \pi_{gdt} \tag{A.19k}$$

$$h_{gdt}^{w_4} \geq \pi_{gdt} - Z_{gdt}^{\text{UB}}(1 - w_g) \tag{A.19l}$$

$$h_{gdt}^{w_5} \leq \Xi_{gdt}^{\text{UB}} w_g \tag{A.19m}$$

$$0 \leq h_{gdt}^{w_5} \leq \pi_{gdt} \tag{A.19n}$$

$$h_{gdt}^{w_5} \geq \pi_{gdt} - \Xi_{gdt}^{\text{UB}}(1 - w_g) \tag{A.19o}$$

(A.19p)

and $(\forall g \in \mathcal{G}^N \cap \mathcal{G}^{\text{Renew}}, d \in \mathcal{D}, t \in \mathcal{T})$:

$$h_{gdt}^{\text{Renew}} \geq A^{\text{Renew, LB}} q_g^{\text{Renew}} \tag{A.20a}$$

$$h_{gdt}^{\text{Renew}} \geq P_g^{\text{CapUB}} \alpha_{gdt}^{\text{Renew}} \tag{A.20b}$$

$$h_{gdt}^{\text{Renew}} \leq A^{\text{Renew, LB}} q_g^{\text{Renew}} + P_g^{\text{CapUB}} \alpha_{gdt}^{\text{Renew}} - A^{\text{Renew, LB}} P_g^{\text{CapUB}} \tag{A.20c}$$