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The Effect of Natural-Gas Prices on Power-System Reliability

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Abstract
Purpose of Review Electricity production in United States of America is shifting from coal to natural gas. Much of this shift is driven by decreased natural-gas prices, which are resulting from hydraulic fracturing. Decreased natural-gas prices are causing a price reversal in the merit order between natural-gas- and coal-fired generators. Given that these fuel-price changes are anticipated to persist and are impacting power-system operations, a question is how these changes impact power-system reliability.
Recent Findings We survey literature that pertains to how fuel prices impact power-system reliability. Most existing works focus on long-term dynamics and power-system planning. Moreover, most reliability assessments assume that power-system resources are operated correctly to meet reliability requirements. Thus, they may not capture the impact on the availability of generating capacity of power-system operations changing due to fuel prices. We use a case study that is based on Texas's power system to show how operational decisions can impact power-system reliability.
Summary We demonstrate that the operational impact of fuel prices can have dramatic reliability effects. These findings illustrate the importance of capturing power-system operations in assessing power-system reliability.

Keywords Power-system reliability · power-system operations · unit commitment · economic dispatch

1 Introduction

For the first time in modern history United States of America (US) began producing more electricity from natural gas than it did from coal in April, 2015.[1] This shift in

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[1] https://www.eia.gov/electricity/monthly/

the fuel mix is due largely to sustained natural-gas-price decreases. These natural-gas-price decreases are spurred by the proliferation of hydraulic fracturing. These natural-gas-price decreases are causing a price reversal in the merit order between coal- and natural-gas-fired generating units.

This shift in how generators are operated can have short- and long-run impacts on power-system reliability. In the short-run, during which time the installed resource mix is fixed, fuel prices impact which units are online, operating, and available to provide energy and capacity. In the long-run, during which time capacity investment and retirement can be undertaken, the installed mix of generating resources can react to fuel-price changes.

This paper contributes to understanding the interplay between fuel prices and power-system reliability. We begin by surveying and reviewing the existing technical literature that studies this question. We find two common themes in this literature. Most existing works focus on the long-run impacts of fuel-price changes. In essence, their focus is on understanding how fuel prices may impact the evolution of the generation mix and the resultant impact on power-system reliability. An important limitation of these studies that we observe is that they do not account for the impacts of power-system operations on reliability. How a power system is operated can impact its reliability because generating capacity may not be online or available to address a reliability event. Much of the existing literature assumes that generating capacity is available, so long as it is not impacted by a forced or maintenance outage.

On the basis of these two observations regarding the existing literature, we illustrate the impacts of operational decisions on power-system reliability. These impacts are illustrated using a three-step methodology that we apply to a Texas-based case study [1]. The first step of the process uses a unit-commitment model, which includes operating-level constraints, to optimize daily power-system operations. Next, the solution of the unit-commitment model is used to determine the maximum amount of power that each generator can provide during each time step. The calculation in this step accounts for the generators' dispatch instructions and operating flexibility that is allowed by their ramping and start-up and shutdown capabilities. Finally, each generator's maximum potential output is combined with its effective forced outage rate (EFOR) to compute the loss of load probability (LOLP) during each time step and the loss of load expectation (LOLE) over the full model horizon.

We apply our modeling methodology to a case study that is based on the Electric Reliability Council of Texas (ERCOT) system. We consider two cases—one in which natural-gas prices are high and another in which they are low. The ERCOT system has a mix of coal- and natural-gas-fired units. Thus, the overall mix of generating fuels that is used to produce electricity differs substantively between the cases with high and low natural-gas prices. We find that if natural-gas prices are sufficiently low for the merit order between natural-gas- and coal-fired units to switch, operating-reserve requirements must be increased to maintain the same reliability level with low natural-gas prices. There are two underlying drivers of this result. First, natural-gas-fired units that are idle (due to economic reasons) with high natural-gas prices provide operational flexibility to the system. This flexibility is lost with low natural-gas prices, because these units are operated for economic reasons. Second, natural-gas-fired units tend to have higher EFORs than coal-fired generators. We consider also a case with a high penetration of wind generation. We find that wind generation mitigates, but does not eliminate, the reliability impact of fuel prices.

The remainder of our paper is organized as follows. First we provide our literature survey and review. Next we detail case-study methodology, data, and results. This is followed by conclusions.

2 Literature Survey

A long-standing electricity-industry challenge is ensuring reliable electricity supply. Garver [2] presents a graphical approach to assessing power-system reliability. Garver's proposed methodology is based on estimating a relationship between a power system's reliability, which he measures using LOLP, and its installed-reserve margin. The reliability contributions of incremental generation resources can be assessed from this relationship. Billinton and Allan [3] extend Garver's formative work in numerous ways. Most importantly, Billinton and Allan develop analytic methods, which do not rely upon graphical analysis [2], to assess power-system reliability and the resource-adequacy contribution of resources.

A recently growing area of interest in assessing power-system reliability is understanding the impacts of generation-mix changes. This interest is driven by the shift towards natural gas as a generating fuel and the growing use of renewable energy sources. US Department of Energy (DOE) [4] discusses tools that the US electricity industry could use to maintain reliability as power systems shift away from coal-fired generation towards increasing use of natural-gas-fired units and nondispatchable renewable energy. DOE [4] does not conduct formal reliability analyses. Rather, DOE provides trends in generation-capacity additions and retirements and power-system planning-reserve margins and reliability events. Indeed, the study can be viewed through a political lens. The study provides weak (if any) support for claims that US power systems are suffering reliability and resilience issues. Nevertheless, its conclusions were used by the energy secretary to propose a rule to Federal Energy Regulatory Commission (FERC)[2] to establish a tariff mechanism providing for cost recovery and return on equity for what the rule terms 'reliability and resilience resources.' The proposed rule defines reliability and resilience resources as facilities that provide essential reliability services and that have a 90-day fuel supply on-site.

North American Electric Reliability Corporation (NERC) [5] examines needed reserve margins and resource-adequacy requirements to maintain power-system reliability in the face of similar types of capacity-mix changes to those that DOE examines. NERC [5] focuses on the potential reliability impacts of Clean Power Plan, which was a policy proposed by US Environmental Protection Agency (EPA) to decarbonize the US electricity-supply mix. Nevertheless, issues surrounding growing use of natural gas as a generation fuel are discussed. NERC [5] does not conduct technical analyses of the reliability impacts of these capacity-mix changes. Rather, it provides power-system planners with important reliability considerations under EPA's proposed policy changes.

[2] *cf.* FERC docket number RM18-1-000 for details regarding the proposed rule and FERC proceeding.

An analysis of the PJM Interconnection system [6] examines power-system reliability given the prevalence of natural-gas-fired generation, increase in renewable resources, and potential future retirements of coal-fired and nuclear units. The analysis finds that these long-run generation-mix changes may result in less fuel assurance but greater flexibility and ramping attributes. A similar analysis of the ISO New England system[3] finds that low natural-gas prices led to increasing use of natural gas as a generating fuel over a 16-year period preceding the study. This shift in the energy mix reduces the use of less efficient oil- and coal-fired units. Contemporaneously, ISO New England contends with fuel assurance as a long-run reliability issue.

A common theme of these works [4–6] is their focus on fuel-price changes impacting the installed mix of resources and the resultant effect on power-system reliability. To a large extent, these works neglect shorter-term reliability impacts, whereby fuel prices change the operation of a fixed mix of resources. One way to address short-term reliability impacts of fuel prices is through the adjustment of operating reserves. A standard way of setting operating-reserve levels is through deterministic heuristic methods, for instance based on the size of the largest system contingency, a fixed percentage of load, or to meet a reliability criterion (*e.g.*, $N-1$). Another approach employs probabilistic methods to compute operating-reserve levels in a more endogenous manner that accounts for the likelihood of reliability events. Anstine *et al*. [7] develop a methodology whereby operating-reserve requirements are calibrated to achieve a desired level of power-system reliability using a post-processing algorithm that is applied to a unit-commitment solution. Another set of works [8–12] incorporate reliability indices directly into the unit-commitment model. These reliability-constrained unit-commitment models determine operating-reserve levels endogenously so the power system achieves a desired reliability level. A major challenge that is raised by reliability-constrained unit commitment is the computational cost of the resultant model. These challenges are address using a variety of approaches, including Lagrangian relaxation [8], simplifications that consider limited failure types [9], and metaheuristic algorithms [10, 12].

3 Case-Study Methodology

The existing literature does not address how fuel prices affect power-system operations and reliability. Relative fuel-price changes can alter the merit order between generation technologies. Merit-order changes can yield differences in power-system operations, which impact the system's ability to react to reliability events. We develop and apply a three-step methodology to demonstrate these operational and reliability impacts of fuel-price changes. This section details the three steps of our methodology.

3.1 Unit-Commitment Model

The first step of our approach uses a unit-commitment model to determine the planned operation of the power system. Lowery [13] and Muckstadt and Koenig [14] provide

[3] https://www.iso-ne.com/rsp

pioneering works in unit-commitment modeling and literature surveys [15–19] summarize the state-of-the-art.

3.1.1 Model Notation

Sets and Indices

i	index of generators.
I	set of generators.
t	time index.
T	set of time periods.

Sets and Parameters

c_i^N	generator i's no-load cost ($).
c_i^S	generator i's start-up cost ($).
$c_i^V(\cdot)$	generator i's power-output-dependent cost function ($).
D_t	time-t demand (MW).
K_i^-	generator i's minimum operating point (MW).
K_i^+	generator i's maximum operating point (MW).
R_i^-	generator i's ramp-down limit (MW).
R_i^+	generator i's ramp-up limit (MW).
η	total-reserve margin (p.u.).
η^S	spinning-reserve margin (p.u.).
$\bar{\rho}_i^N$	generator i's non-spinning-reserve capacity (MW).
$\bar{\rho}_i^S$	generator i's spinning-reserve capacity (MW).
τ_i^-	generator i's minimum-down time (time steps).
τ_i^+	generator i's minimum-up time (time steps).

Variables

$h_{i,t}$	equals 1 if generator i is shutdown at time t and equals 0 otherwise.
$q_{i,t}$	generator i's time-t production (MW).
$s_{i,t}$	equals 1 if generator i is started up at time t and equals 0 otherwise.
$u_{i,t}$	equals 1 if generator i is online at time t and equals 0 otherwise.
$\rho_{i,t}^N$	time-t non-spinning reserves provided by generator i (MW).
$\rho_{i,t}^S$	time-t spinning reserves provided by generator i (MW).

3.2 Model Formulation

Our unit-commitment model is formulated as the mixed-integer linear optimization problem:

$$\min \sum_{t\in T}\sum_{i\in I}[c_i^V(q_{i,t}) + c_i^N u_{i,t} + c_i^S s_{i,t}]; \tag{1}$$

$$\text{s.t.} \sum_{i\in I} q_{i,t} = D_t; \qquad \forall t \in T; \tag{2}$$

$$\sum_{i\in I}(\rho_{i,t}^S + \rho_{i,t}^N) \geq \eta D_t; \qquad \forall t \in T; \tag{3}$$

$$\sum_{i \in I} \rho^S_{i,t} \geq \eta^S \eta D_t; \qquad \forall t \in T; \qquad (4)$$

$$K^-_i u_{i,t} \leq q_{i,t}; \qquad \forall i \in I, t \in T; \qquad (5)$$

$$q_{i,t} + \rho^S_{i,t} \leq K^+_i u_{i,t}; \qquad \forall i \in I, t \in T; \qquad (6)$$

$$q_{i,t} + \rho^S_{i,t} + \rho^N_{i,t} \leq K^+_i; \qquad \forall i \in I, t \in T; \qquad (7)$$

$$0 \leq \rho^S_{i,t} \leq \bar{\rho}^S_i u_{i,t}; \qquad \forall i \in I, t \in T; \qquad (8)$$

$$0 \leq \rho^N_{i,t} \leq \bar{\rho}^N_i; \qquad \forall i \in I, t \in T; \qquad (9)$$

$$R^-_i \leq q_{i,t} - q_{i,t-1}; \qquad \forall i \in I, t \in T; \qquad (10)$$

$$q_{i,t} - q_{i,t-1} + \rho^S_{i,t} + \rho^N_{i,t} \leq R^+_i; \qquad \forall i \in I, t \in T; \qquad (11)$$

$$\sum_{y=t-\tau^+_i}^{t} s_{i,y} \leq u_{i,t}; \qquad \forall i \in I, t \in T; \qquad (12)$$

$$\sum_{y=t-\tau^-_i}^{t} h_{i,y} \leq 1 - u_{i,t}; \qquad \forall i \in I, t \in T; \qquad (13)$$

$$s_{i,t} - h_{i,t} = u_{i,t} - u_{i,t-1}; \qquad \forall i \in I, t \in T; \qquad (14)$$

$$u_{i,t}, s_{i,t}, h_{i,t} \in \{0,1\}; \qquad \forall i \in I, t \in T. \qquad (15)$$

Objective function (1) minimizes total generation costs. $c^V_i(\cdot)$ is a convex piecewise-linear function $\forall i \in I$, making (1) linear in the decision variables. Constraints (2) ensure load balance in each time step. Constraints (3) and (4) enforce operating-reserve requirements.

Constraints (5)–(7) ensure that each generator's power output is between its minimum and maximum when it is online and that its output is zero when it is offline. Constraints (6) account for additional power that generators produce *if* spinning reserves are called in real-time. Constraints (7) account for non-spinning reserves that a generator provides. Constraints (8) and (9) enforce generators' reserve limits. The commitment variables appear in the right-hand sides of (8) to ensure that a generator be online to provide spinning reserves. Constraints (10) and (11) enforce generators' ramping limits. Constraints (11) account for reserves that may be called in real-time in enforcing upward ramping limits. In doing so, (11) are conservative relative to how some market models handle the provision of operating reserves in enforcing ramping constraints. Constraints (12) and (13) enforce minimum up- and down-time restrictions, respectively, whenever a generator is switched on or off and (14) define the start-up and shutdown variables in terms of intertemporal changes in the $u_{i,t}$ variables. Constraints (15) impose integrality restrictions.

3.3 Maximum Potential Generation

The maximum potential power output of a generator during each time step depends on its planned operating status, which is determined by the unit-commitment model, and its technical capabilities [20]. A generator's planned operating status affects its potential output in two ways. The first is that unless a generator has fast start-up capability, it must be online to produce power. Second, a generator's maximum potential time-t output is limited by its time-$(t-1)$ output through its ramping capability.

For all $i \in I, t \in T$, we account for the effect of generator i's online status by making its maximum time-t potential output, $\bar{q}_{i,t}$, dependent on the optimized values of $u^*_{i,t-1}$ and $u^*_{i,t}$, which are determined by the unit-commitment model. We define:

$$\bar{q}_{i,t} = \begin{cases} \min\{K_i^+, q^*_{i,t-1} + R_i^+\}; & \text{if } u^*_{i,t-1} = 1; \\ \max\{K_i^-, R_i^+\}; & \text{if } u^*_{i,t-1} = 0 \text{ and } u^*_{i,t} = 1; \\ \max\{K_i^-, R_i^+\}; & \text{if } u^*_{i,t-1} = 0,\ u^*_{i,t} = 0, \text{ and } \bar{\rho}_i^N > 0; \\ 0; & \text{otherwise;} \end{cases} \tag{16}$$

where the $*$ superscripts in the right-hand side of (16) denote optimized variable values from the unit-commitment model. Equation (16) defines $\bar{q}_{i,t}$ in four cases. The first is if generator i is scheduled to be online during time step $(t-1)$. If so, generator i can remain online at time t (*i.e.*, even if $u^*_{i,t} = 0$ in the unit-commitment solution) and $\bar{q}_{i,t}$ is limited by whichever of its maximum-output and ramping capacities are more restrictive. The second case is if generator i is started-up at time t in the unit-commitment schedule. In this case, $\bar{q}_{i,t}$ is limited by generator i's ramping and minimum-load constraints. The third case is if generator i is offline at time $(t-1)$ and not scheduled to start-up at time t in the unit-commitment solution. If such a generator has fast start-up capability it can be started at time t and its output is governed (as in the second case) by its ramping and minimum-load constraints. By assumption, only generators with fast start-up capability can provide non-spinning reserves. Thus, this third case arises only if $\bar{\rho}_i^N > 0$. The fourth case in (16) covers all remaining circumstances, in which case $\bar{q}_{i,t} = 0$.

Equation (16) combines the unit-commitment solution with technical generator constraints to determine the maximum amount that each generator can contribute towards serving load reliably. The logic that underlies (16) can be likened to a similar approach to analyzing power-system reliability that Patton *et al.* [21] and Singh *et al.* [22] employ. The computation in (16) assumes that a generator may be called by the system operator to provide more energy than its day-ahead schedule indicates. Some markets limit the amount of energy that a generator must provide in real-time based on the day-ahead schedule. We assume in our analysis that if power-system reliability is threatened, the system operator has the authority to increase the output of generators, so long as their technical capabilities are respected, even if a day-ahead schedule is violated. Additional remuneration may be needed to operate generators in such a way, which we neglect.

3.4 Reliability Model

We use two indices—LOLP and LOLE—to measure power-system reliability [3, 23, 24]. LOLP is the probability that the system has insufficient generating capacity to serve load during a given time step. LOLPs are agnostic to the duration of time periods that are modeled. For instance, one could compute daily LOLPs (based on daily peak load) or hourly LOLPs. LOLE is defined as the sum of LOLPs over a time horizon and measures the expected number of periods within that horizon during which a shortage occurs. LOLPs and LOLEs are modeled in our case study at the same time step and over the full optimization horizon that are used in the unit-commitment model.

Using the values of $\bar{q}_{i,t}$, we compute the time-t LOLP, π_t, as:

$$\pi_t = \text{Prob}\left\{\sum_{i \in I} \bar{q}_{i,t} < D_t\right\}; \forall t \in T. \tag{17}$$

The Prob$\{\cdot\}$ in (17) can capture any type of uncertainty that would affect the system's ability to serve load. Our analysis considers generator failures only. We model generator failures using EFORs, which represent the steady-state probability of a generator failure, taking account of the recovery time from a failure. LOLPs are computed in each time step from the $\bar{q}_{i,t}$'s and EFORs by calculating a capacity outage probability table [3, 23, 24]. The LOLE, Λ, is computed as:

$$\Lambda = \sum_{t \in T} \pi_t. \tag{18}$$

4 Case-Study Data

We analyze a case study that is based on the ERCOT system [1] and modeled at hourly time steps over a one-year horizon.

4.1 Unit-Commitment-Model Data

Our base case models all of the conventional generators that were operational in ERCOT during 2005. Generation costs are computed based on fuel prices, heat rates, variable operation and maintenance (VOM) costs, SO_2-emissions rates, and SO_2-permit prices. Heat rates, VOM costs, average output-based SO_2-emissions rates, and year-2005 SO_2-permit prices are obtained from Global Energy Decisions (GED).

We model two fuel-price cases. The first uses actual fuel prices from 2005, which are obtained from GED and Platts Energy. Fig. 1 shows a standard box plot of year-2005 monthly natural-gas prices. Each box gives the 25th, 50th, and 75th percentiles, which we denote Q_{25}, Q_{50}, and Q_{75}, respectively. The whiskers represent the range of non-outlier observations, where outliers are defined as being less than $Q_{25} - 1.5(Q_{75} - Q_{25})$ or greater than $Q_{75} + 1.5(Q_{75} - Q_{25})$. Outliers are indicated with plus signs. Natural-gas prices in this case are relatively high, with a simple average price over the year of about \$9/MMBTU. The other case uses actual year-2005 prices for all fuels except for natural gas, which we assume to cost \$2/MMBTU throughout the year.

The four nuclear generators in ERCOT are modeled as must-run units, *e.g.*, they are assumed to be online and operating at nameplate capacity throughout the year.

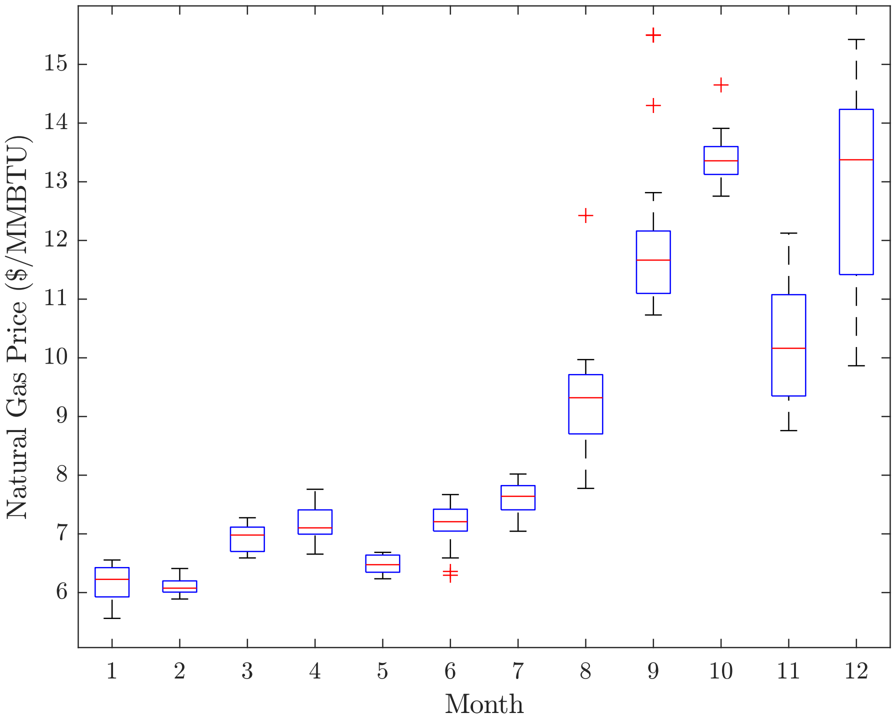

Fig. 1 Standard box plot of monthly year-2005 natural-gas prices

The remaining generators are modeled as being dispatchable, subject to their operating constraints. Constraint data for these generators are obtained from GED.

Our sensitivity case assumes 18 GW of wind, which provides 20% of total annual energy demand (absent wind curtailment), is added to the system. Capacity factors for the added wind are obtained from Eastern Wind Data Set and Western Wind Data Set, which are maintained by National Renewable Energy Laboratory. These two data sets provide modeled wind speeds at 10-minute temporal and 2-km spatial resolutions. The modeled wind speeds are combined with composite turbine-power curves to simulate power outputs of hypothetical wind generators. We use the simple average of the capacity factors for all of the locations in the ERCOT footprint to compute system-wide-average capacity factors of wind during each 10-minute time step during the year 2005. The six 10-minute system-wide-average capacity factors that correspond to each hour are averaged to obtain hourly-averaged system-wide-average capacity factors, which are used to model hourly wind availability.

Our case study uses hourly historical load data from 2005 for ERCOT, which are obtained from Public Utility Commission of Texas. Table 1 summarizes the supply and demand characteristics of the system that is modeled in our case study.

The unit-commitment model is solved using a rolling-horizon approach. We optimize these decisions 24 hours at a time using a 48-hour optimization horizon. Hours 25–48 are included in the unit-commitment model to ensure that sufficient

Table 1 Summary of supply and demand characteristics of case study

Natural-Gas-Fired Generation	
Number of Units	324
Total Nameplate Capacity (GW)	59.045
Coal-Fired Generation	
Number of Units	28
Total Nameplate Capacity (GW)	16.081
Nuclear Generation	
Number of Units	4
Total Nameplate Capacity (GW)	4.920
Load Summary Statistics (GW)	
Maximum	59.947
Minimum	20.893
Average	34.419

generating capacity is kept online at the end of each day to serve the following day's load [25]. As our model rolls through each day of the year, the starting generation level and commitment status of each generator are updated to specify (10)–(13) in the next day's unit-commitment model properly.

4.2 Reliability-Model Data

We obtain EFORs of the generator fleet in our case study using NERC's year-2005 Generating Availability Data System (GADS). GADS reports fleet-average EFORs across NERC's footprint based on generating technology and nameplate capacity. We combine the GADS data with the generation technology and nameplate capacity of each generator that are reported by GED. The EFORs that are used range between 3.57% and 80.66% and have a capacity-weighted average of 11.20%. Unit aging [26] and cycling [27], which can affect generating-unit reliability, are neglected in our analysis.

4.3 Reserve Calibration

We determine the total reserve levels (*i.e.*, the value of η) endogenously to achieve an annual LOLE of 2.4 hours. 2.4 hours corresponds to NERC's standard reliability target of one expected outage-day every 10 years [28]. We fix $\eta^S = 0.5$. In setting reserve requirements this way, we are adapting the technique that is proposed by Anstine *et al.* [7] to set operating-reserve requirements to achieve a desired system-reliability level.

We use the bisection technique that is outlined in Algorithm 1 to calibrate η. The algorithm takes two inputs, η_L and η_H. η_L is a reserve level that underachieves the desired annual system LOLE of $\Lambda = 2.4$. This means that if the unit-commitment model is solved with $\eta = \eta_L$, hourly maximum potential generation is computed using (16), and the system LOLE is computed using (17) and (18), we have $\Lambda < 2.4$. η_H is a reserve level that overachieves the desired LOLE.

Algorithm 1 Reserve calibration

1: **input:** η_L and η_H
2: $\eta \leftarrow \frac{1}{2}(\eta_L + \eta_H)$
3: **repeat**
4: $\quad (h^*, q^*, s^*, u^*, \rho^*) \leftarrow \arg\min$ (1) s.t. (2)–(15)
5: $\quad$ compute $\bar{q}$ using (16)
6: $\quad$ compute π and Λ using (17) and (18)
7: $\quad$ **if** $\Lambda > 2.4$ **then**
8: $\quad\quad \eta_H \leftarrow \eta$
9: $\quad$ **else if** $\Lambda < 2.4$ **then**
10: $\quad\quad \eta_L \leftarrow \eta$
11: $\quad$ **end if**
12: $\quad \eta \leftarrow \frac{1}{2}(\eta_L + \eta_H)$
13: **until** $|\Lambda - 2.4| < \varepsilon$
14: **output:** η

Line 2 initializes η to the arithmetic mean of η_L and η_H. Lines 3–13 are the iterative loop. The unit-commitment model is solved in Line 4. Line 5 computes maximum potential capacities using (16) and these values are used in Line 6 to determine the system's LOLE. Lines 7–12 are the bisective update. This iterative procedure repeats until Λ is within some tolerance level, ε, which we take to equal 0.1, of the target LOLE level.

5 Case-Study Results

Table 2 summarizes the operation of the system in the base case under three different combinations of fuel prices and operating reserves. The first column provides results using year-2005 natural-gas prices and Algorithm 1 to calibrate the operating-reserve margin to achieve the target 2.4-hour LOLE. This target is achieved with a total reserve margin of 12.35% (giving a 6.18% spinning-reserve margin). The case with year-2005 natural-gas prices and calibrated operating reserves yields an annual system operation cost of approximately \$21.7 billion. Because of the relatively high price of natural gas, coal-fired units have a high fleet-average capacity factor of 93% and coal-fired generation provides 43% of the system's energy.

The second column of Table 2 provides results using the same 12.35% operating-reserve margin that is calibrated for the case that is reported in the first column, but with \$2/MMBTU natural-gas prices. The system's annual LOLE increases to 8.2 hours in the case that is reported in the second column. Although the lower cost of natural gas increases natural-gas-fired generation significantly to over 61% of total energy supplied, the natural-gas-fired fleet operates at a capacity factor of only 36%. This relatively low capacity factor stems from natural-gas-fired units providing operating reserves. Table 3 summarizes the total amount of spinning and non-spinning reserves that are provided annually by coal- and natural-gas-fired units in the base case under the three combinations of fuel prices and operating reserves. Table 3 shows that natural-gas-fired units provide all of the non-spinning reserves, because the coal-fired fleet does not have the fast-start capability to provide it. Moreover, Table 3 shows that even with \$2/MMBTU natural-gas prices, the natural-gas-fired fleet provides over

Table 2 Reserve margin, LOLE, operation cost, and dispatch in base case with different natural-gas prices and operating reserves

Natural-Gas Prices Operating Reserves	Year-2005 Calibrated	\$2/MMBTU Uncalibrated	\$2/MMBTU Calibrated
η	0.1235	0.1235	0.1378
Λ	2.4	8.2	2.4
Operation Cost (\$ billion)	21.7	12.3	12.4
Generation (%)			
Coal	43.28	23.16	22.82
Natural Gas	40.96	61.05	61.38
Capacity Factor (%)			
Coal	92.86	50.02	48.97
Natural Gas	23.92	35.59	35.87

71% of the system's spinning reserves. This is because the coal-fired fleet has limited reserve capability relative to natural-gas-fired units, which have faster ramping capabilities.

Table 3 Operating reserves provided by coal- and natural-gas-fired units (GW-h) in base case with different natural-gas prices and operating reserves

Natural-Gas Prices Operating Reserves	Year-2005 Calibrated	\$2/MMBTU Uncalibrated	\$2/MMBTU Calibrated
Spinning Reserves			
Coal	1914	9039	9956
Natural Gas	27036	22000	25335
Non-spinning Reserves			
Coal	0	0	0
Natural Gas	8456	6577	6614

Table 2 shows that the shift in the energy mix from coal- to natural-gas-fired generation has a marked impact on system reliability. Decreased power-system reliability with low natural-gas prices is due to two factors. First, the natural-gas-fired fleet has a lower overall reliability compared to coal-fired units. Coal-fired generators in our case study have a capacity-weighted fleet-average EFOR of 6.25% as opposed to 12.55% for the natural-gas-fired units. The greater reliance (for economic reasons) on natural-gas-fired generation with \$2/MMBTU natural-gas prices means that less-reliable units are being dispatched to serve a larger portion of the load. Natural-gas-fired units may become more reliable if they are operated in a baseloaded manner [27], for which we do not account.

The second factor that results in the system being more reliable with year-2005 natural-gas prices is due to having excess capacity available from idle natural-gas-fired units to respond to reliability events. Natural-gas-fired units tend to have greater operational flexibility compared to coal-fired generators. Indeed, 76 natural-gas-fired units with a total capacity of about 1.1 GW have fast-start capability, meaning that they can be switched on from an offline state in a matter of minutes. Because operating these units is relatively expensive with year-2005 natural-gas prices, these units tend to be idle in the solution of the unit-commitment model. However, due to their fast-start capability, they contribute to system reliability, insomuch as they have strictly positive $\bar{q}_{i,t}$ values. Conversely, with \$2/MMBTU natural-gas prices, these units are dispatched. Although the system maintains the same level of reserves (*i.e.*, the value of η is the same in the cases that are reported in the first two columns of Tables 2 and 3), idle natural-gas-fired units with fast-start capability provide excess reserve capacity that can be used to mitigate a capacity shortfall with year-2005 natural-gas prices. Table 4 summarizes this impact of natural-gas prices by showing total maximum potential generation, which is defined as:

$$\sum_{t\in T, i\in I} \bar{q}_{i,t};$$

in the base case under the three combinations of fuel prices and operating reserves. The table shows that with year-2005 natural-gas prices idle natural-gas-fired units with fast-start capability provide an average of 270 MW of extra capacity during each hour compared to having \$2/MMBTU natural-gas prices and a 12.35% operating-reserve margin.

Table 4 Maximum potential generation from coal- and natural-gas-fired units (GW-h) in base case with different natural-gas prices and operating reserves

Natural-Gas Prices Operating Reserves	Year-2005 Calibrated	\$2/MMBTU Uncalibrated	\$2/MMBTU Calibrated
Coal	133 971	86 866	87 405
Natural Gas	197 335	244 073	249 294
Total	378 960	376 593	384 354

The third column of each of Tables 2–4 report results using \$2/MMBTU natural-gas prices and Algorithm 1 to determine the required operating-reserve margin to achieve a 2.4-hour LOLE. This reliability target is attained with a 13.78% total operating-reserve margin, which increases annual system-operation costs slightly to \$12.4 billion (relative to having \$2/MMBTU natural-gas prices and not increasing the operating-reserve margin). Table 4 shows that the system needs more maximum potential generation to achieve the same reliability level with \$2/MMBTU natural-gas prices than it does with year-2005 prices. This higher capacity requirement stems from the power system being more reliant on natural-gas-fired generators with \$2/MMBTU natural-gas prices. The natural-gas-fired units have higher EFORs than their coal-fired counterparts, increasing the system's flexibility requirements.

Tables 5–7 summarize for the case with added wind generation the same results that are presented in Tables 2–4 for the base case. All of the results that are reported in Tables 5–7 assume an operating-reserve margin of 12.35%, which achieves the 2.4-hour target LOLE with year-2005 natural-gas prices in the base case. As such, the LOLE with year-2005 natural-gas prices and wind generation is lower than the

2.4-hour LOLE that is achieved in the base case with these prices. This decreased LOLE is due to wind generators providing energy, which improves system reliability.

Table 5 Reserve margin, LOLE, operation cost, and dispatch with wind generation and different natural-gas prices

Natural-Gas Prices	Year-2005	\$2/MMBTU
η	0.1235	0.1235
Λ	1.1	3.1
Operation Cost (\$ billion)	16.2	9.4
Generation (%)		
Coal	38.26	18.52
Natural Gas	27.08	46.80
Wind	18.9	18.9
Capacity Factor (%)		
Coal	82.09	39.73
Natural Gas	15.82	27.35

Table 6 Operating reserves provided by coal- and natural-gas-fired units (GW-h) with wind generation and different natural-gas prices

Natural-Gas Prices	Year-2005	\$2/MMBTU
Spinning Reserves		
Coal	3995	9057
Natural Gas	24788	21686
Non-spinning Reserves		
Coal	0	0
Natural Gas	8881	7062

Table 7 Maximum potential generation from coal- and natural-gas-fired units (GW-h) with wind generation and different natural-gas prices

Natural-Gas Prices	Year-2005	\$2/MMBTU
Coal	123301	73573
Natural Gas	152692	200941
Total	380688	379269

6 Conclusions

Recent developments, including low natural-gas prices, are changing the short-run operation and long-term planning of power systems. Among others, a question that is raised by these developments is how industry practice should change to maintain levels of power-system reliability to which consumers are accustomed. Much of the existing literature [4–6] examines this question through the lens of long-term planning. This is a vitally important approach to answering the question, because planning decisions can take years or decades to come to fruition. Without looking through a long-term lens, a power system may encounter reliability issues that may take years or longer to address.

However, a gap in the extant literature is understanding how fuel prices impact power-system operations and reliability in the short run. We demonstrate the importance of considering the operational impacts of fuel prices through an illustrative case study. Our methodology employs a three-step approach that consists of operational modeling, determining the maximum potential output of each resource, and reliability modeling. Our case study demonstrates that shifting (for economic reasons) the mix of generators that is committed and dispatched away from coal- to natural-gas-fired units can impact power-system reliability in two ways. First, natural-gas-fired units are less reliable overall than their coal-fired counterparts. Second, natural-gas-fired units tend to be more flexible than coal-fired generators. When natural-gas-fired generators are costly and not committed, their idle capacity can help mitigate reliability events. Coal-fired generators do not have the same capabilities, thus their idle capacity does not help in the same way when natural-gas-fired units are relatively inexpensive.

The differences in power-system reliability that we observe stem entirely from how the system is operated with different fuel prices. Indeed, the results that are reported in Tables 2–4 correspond to cases with the exact same installed capacity mix (the same can be said for Tables 5–7). Thus, our case study illustrates the importance of considering power-system operations in conducting reliability analyses. Many analyses neglect operational decisions, assuming that capacity is available fully, so long as it does not experience a forced or maintenance outage. The modeling framework that we develop is flexible and could be applied in other settings, *e.g.*, for system operators to adjust their operational practices to ensure reliability with fuel-price or other power-system changes.

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