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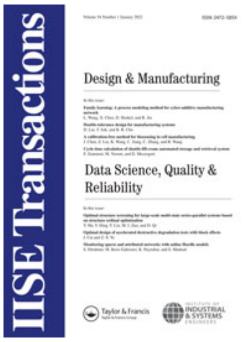

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Flexibility and real options analysis in power system generation expansion planning under uncertainty

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ABSTRACT
Over many years, there has been a drive in the electricity industry towards better integration of environmentally friendly and renewable generation resources for power systems. Such resources show highly variable availability, impacting the design and performance of power systems. In this article, we propose using a stochastic programming approach to optimize Generation Expansion Planning (GEP), with explicit consideration of generator output capacity uncertainty. Flexibility implementation - via real options exercised in response to uncertainty realizations - is considered as an important design approach to the GEP problem. It more effectively captures upside opportunities, while reducing exposure to downside risks. A decision-rule-based approach to real options modeling is used, combining conditional-go and finite adaptability principles. The solutions provide decision makers with easy-to-use guidelines with threshold values from which to exercise the options in operations. To demonstrate application of the proposed methodologies and decision rules, a case study situated in the Midwest United States is used. The case study demonstrates how to quantify the value of flexibility, and showcases the usefulness of the proposed approach.

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Flexibility; real options; stochastic programming; power systems; risk analysis; systems design and analysis; uncertainty

1. Introduction

Making timely investments to expand the generation capacity of a national power system to meet future demand is the focus of long-term Generation Expansion Planning (GEP) problems. Identifying the optimal energy mix that ensures energy security - vital for national security, economic growth, and social welfare - is of utmost importance for planning purposes. Recently, greener renewable energy sources have been actively sought by governments worldwide to address concerns over environmental impact and sustainability of energy sources. For example, a study reported in Global Wind Energy Council (2016) shows that in 2015 alone, annual wind capacity installations reached 60 GW - a record. In 2016, the strong growth of wind energy penetration continued with an additional 50 GW, bringing cumulative wind power capacity to 486.8 GW globally. The PV Market alliance reported that photovoltaic installations for solar power generation hit an annual record-breaking 75 GW capacity in 2016, 50% higher than in 2015 (The PV Market alliance, 2016).

Due to the rising importance of renewable (and variable) energy sources, power systems are now more vulnerable to uncertainties and intermittence in supply. Severe operational malfunctions could arise if such uncertainties are not considered carefully in the design and expansion planning of such systems. To support this view, Sweeney (2013) claims that low rainfall in the year 2000 led to a severe drop in regional hydropower availability in California, which in turn, led to the well-known energy crisis in that important U.S. state. In 2008, Texas experienced an unexpected drop of 1400 MW in wind power generation, coinciding with an unexpected load increase, which forced 1100 MW to be shed over a short time horizon (Ela and Kirby, 2008).

One approach to improve GEP under supply uncertainty is to consider flexibility explicitly in the system design, the system considered here being an expanding portfolio of generator types being setup over time to satisfy demands. Flexibility, as a design concept, can be formally described as aiming to provide "the right, but not the obligation, to change a system easily in the face of uncertainty." Flexibility is typically enabled in early conceptual studies by considering a flexibility strategy, such as designing the system for future capacity expansion and deferring initial investment until market conditions are ripe (Trigeorgis, 1996). The goal of enabling flexibility in the design is to shift the distribution of possible performance outcomes (e.g., net present value, costs) to capture better upside opportunities, while reducing exposure to downside risks. In this work, flexibility is enabled using real options as a value-enhancing strategy. Real options are

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discrete decisions that allow the decision maker to adapt future actions based on altered future market conditions. There are several examples in infrastructure systems whereby the concepts of flexibility through options were successfully exploited, like the construction of the HSCS building in Chicago (Guma *et al.*, 2009) and the design of the de 25 de Abril bridge in Lisbon (Cardin *et al.*, 2015). A lack of flexibility has also proven to be detrimental in some cases, such as the Iridium satellite system, where all 66 satellites were deployed in the initial time period, thus removing any flexibility to adjust capacity with fluctuating demand for cell phone services. The company had to declare bankruptcy in the early 2000s, due to weaker revenues arising from lower-than-expected demands. Other studies in power plant design and deployment have shown the significant economic benefits arising from flexibility (Cardin, Zhang, *et al.*, 2017; Cardin, Xie, *et al.*, 2017; Caunhye and Cardin 2017).

To tackle these issues, we propose an approach to analyze the long-term effects of (i) supply uncertainty and (ii) flexibility in GEP through stochastic optimization modeling. In particular, the methodological contributions of this stud are:

1. We build a novel conditional-go decision rule that guides decision makers on when to exercise generator addition options based on normalized thresholds of output capacity realizations and taking into account the time taken to install generators.
2. We extend the conditional-go rule via the finite adaptability method developed in the robust optimization field (Bertsimas and Caramanis, 2010) to incorporate a greater variety of options portfolios to deploy and provide decision makers with better flexibility on when to deploy options via multiple thresholds.
3. We seek to quantify the value of flexibility recognized by each method and compare the recommended system solutions in each case.

GEP is formulated here as the problem of determining an optimal plan for adding generators over a finite long-term planning horizon, with the goal of meeting increasing future demands for electricity. The model considers supply uncertainty through a scenario-based stochastic programming model, whereby generator output uncertainty is characterized by probabilistically distributed scenarios. Flexibility is embedded into the GEP model by considering the real option of adding generation capacity, which is to be exercised after the supply uncertainty are realized and observed. Such a real option enables timely deferment of generation capacity expansion, thus better capturing the value of flexibility. Conditional-go decision rules are formulated to provide readily usable policies for exercising real options, relying on total output capacities that are leftover from earlier periods. In this article, the rule relies on threshold values of total capacity and optimized generation capacity addition if and when total capacity slips below such thresholds, serving as a demonstration example. One managerial benefit of a decision rule formulation is that many decision-making rules and strategies can be emulated and analyzed, thereby providing decision makers with additional flexibilty to model and analyze rules that may be more intuitive to them, and/or readily applicable in operations.

2. Related work

2.1. Capacity expansion planning in power systems

Many different approaches have been taken to explore GEP problems, typically differentiated based on model types, objectives, constraints, generator types and uncertainty sources considered. A general approach is to formulate the GEP problem using a mixed-integer programming model. The problem can then be modeled using either a deterministic approach (Park *et al.*, 2000; Antunes *et al.*, 2004; Slochanal *et al.*, 2004) or a stochastic approach with two-stage stochastic programming (Kamalinia and Shahidehpur, 2010; Tekiner *et al.*, 2010; Jin *et al.*, 2011; Pereira and Saraiva, 2011; Min and Chung, 2013; Rebennack, 2014; Vithayasrichareon *et al.*, 2015). It is most common in the literature to minimize generation and deployment costs (Slochanal *et al.*, 2004; Kamalinia and Shahidehpour, 2010; Rebennack, 2014), although maximizing profit (Chuang *et al.*, 2001) or minimizing conditional value-at-risk (Jin *et al.*, 2011) have also received some attention. A combination of environmental impact and cost is typically considered in a multi-objective optimization setting (Antunes *et al.*, 2004; Tekiner *et al.*, 2010). Typical constraints include limits on demand–supply balance, new generator emissions and additions, as well as generation capacity, reliability standards, fuel mix diversification. Uncertainty sources often analyzed include demand (Tekiner *et al.*, 2010; Jin *et al.*, 2011; Pereira and Saraiva, 2011; Min and Chung, 2013; Rebennack, 2014; Vithayasrichareon *et al.*, 2015), wind generation intermittence (Kamalinia and Shahidehpour, 2010), fuel prices (Jin *et al.*, 2011; Min and Chung, 2013), pollution limits (Rebennack, 2014), and electricity prices (Pereira and Saraiva, 2011).

In some cases, decisions related to power dispatch and transmission network expansion are integrated within the GEP problem to form the Generation and Transmission Expansion Planning (GTEP) problem. GTEP considers line addition, line switching, and power dispatch, in addition to GEP decisions. Contingency planning (Samarakoon *et al.*, 2001; Bienstock and Mattia, 2007; Choi *et al.*, 2007; Akbari *et al.*, 2011), network re-design (Moulin *et al.*, 2010), and vulnerability analysis (Pinar *et al.*, 2010) are often discussed in GTEP. Frank and Rebennack (Frank and Rebennack, 2016) provide a thorough introduction to different GTEP optimization models. Many authors have developed approaches to GTEP based on deterministic optimization models (Quelhas *et al.*, 2007; Roh *et al.*, 2007; Motamedi *et al.*, 2010; Pozo *et al.*, 2012; Sharan and Balasubramanian, 2012). Other works incorporate uncertainty using uncertainty sets (Ruiz and Conejo, 2015) and probabilistically distributed scenarios (López *et al.*, 2007; Roh *et al.*, 2009; Alizadeh and Jadid, 2011; Aghaei *et al.*, 2014), where demand, electricity and fuel prices are usually considered as the main uncertainty drivers. Among such studies, only Jin *et al.* (2015) and Caunhye and Cardin (2018) in GTEP incorporate supply uncertainties. Outside the realm of expansion planning, supply uncertainties have been considered in other power system planning problems such as the unit commitment problem (Papavasiliou *et al.*, 2011; Jiang *et al.*, 2016) and energy scheduling in microgrids (Su *et al.*, 2013). In Jin *et al.* (2015), the authors rely on probabilistic constraints (which are difficult to solve), and then on normality methods to improve solvability. In Caunhye and Cardin (2018), an adjustable robust optimization approach is used for transmission expansion planning under supply uncertainties. The current article aims to address an important gap in GEP research, by considering both supply uncertainties and real options in generator capacity expansion, while providing intuitive solution policies based on a conditional-go decision rule approach. To our knowledge, the only applications of real options in power systems expansion planning are in the GTEP problems proposed by van der Weijde and Hobbs (2012), Falugi *et al.* (2017) and Giannelos *et al.* (2018). The problem in van der Weijde and Hobbs (2012) considers the deferment of investment decisions using options and the ones in Falugi *et al.* (2017) and Giannelos *et al.* (2018) deal with real options in storage technologies. However, both studies do not delve into decision rule formulations, which have been shown in many studies to provide significant managerial insights over traditional option methods (Cardin, Zhang, *et al.*, 2017). Such studies show that a decision rule formulation enables more readily considerations of more complex expansion options, as compared with standard investment deferment options.

2.2. Real options analysis

Real Options Analysis (ROA) involves applying concepts of options pricing in finance to the valuation of real assets and investment opportunities under uncertainty (Myers and Turnbull, 1977; Trigeorgis, 1996). Flexibility in engineering design builds upon and expands ROA theory by considering explicitly design and technology as important vectors to enable better adaptability and resilience in the face of uncertainty (de Neufville and Scholtes, 2011). Such an approach to engineering design has shown tremendous performance-enhancing benefits in the early conceptual design of many different systems (Chen and Yuan, 1999; Cardin and Hu, 2016). (Cardin, 2014) provides a general five-phase framework to support the design of flexible engineering systems, along with an overview of relevant design tools to support design work in each phase.

Decision-rule-based ROA aims to provide systematic policies and guidelines to help decision makers exercise flexibility options in a stochastically optimal manner. Formally, a decision rule can be defined as a function mapping observations of uncertainty data to actual decisions in operations (Shapiro *et al.*, 2009). In the stochastic programming literature, four classes of decision rules are typically considered: conditional-go, linear, safety-first and zero-order (Garstka and Wets, 1974). A conditional-go decision rule, as used in this article, can be thought of as an if-then-else statement in programming, whereby a set of criteria must be satisfied by observing uncertainty realizations before the real option can be exercised. If such criteria are not satisfied, the *status quo* is maintained, and the system continues to operate as is, without any changes. In the study by Cardin, Xie, *et al.* (2017), conditional-go decision rules are used in a multistage stochastic programming framework to support design and deployment of a hybrid waste-to-energy system. In another study by Caunhye and Cardin (2017), the idea of conditional-go decision rules is adapted in an approach inspired from robust optimization. Separable models are obtained by relaxing the non-anticipativity constraints typically associated with such problems. In Harper and Thurston (2008), decision rules are employed to address redesign issues in the face of environmental impacts during system operational changes.

3. Methodology

This work illustrates the contributions of real options to a generic GEP problem under uncertainty in supply capacities due to intermittent renewable energy sources. For a comprehensive outlook on the savings brought about by options on generator addition, six model cases are evaluated. Case 1 is a deterministic GEP problem where generator supply capacities are pre-set to their average values. Case 2 introduces uncertainty in the Case 1 model via generator supply capacity scenarios produced by Monte Carlo sampling from assumed probability distributions. It is used as a benchmark to calculate the expected value of flexibility (*EVoF*), following the approach typically used in the literature on flexibility in design and real options (Dixit and Pindyck, 1994; Trigeorgis, 1996; de Neufville and Scholtes, 2011; Cardin, 2014). Quantifying *EVoF* is important, as it enables determining the value added by flexibility for a specific system and strategy. Case 3 applies the concept of real options on generator addition in an idealistic setting. In this setting, the decision maker has perfect foresight on uncertainty realizations and deploys options based on this information. Case 3 is used as a benchmark to calculate the expected value of perfect information (*EVPI*), a traditionally used metric to evaluate the importance of uncertainties in stochastic programming models (Birge, 1982). It represents the maximum one should be willing to pay for complete information about the future. It provides a theoretical upper bound on *EVoF*, which typically cannot be achieved in practice, due to non-anticipative decision-making. Case 4 and Case 5 apply real options on generator addition in a realistic setting using a decision rule-based approach where decision-making is non-anticipative (i.e., meaning that the decision maker only has information about past uncertainty realizations). Case 4 employs a conditional-go decision rule on options deployment. The conditional-go rule, broadly speaking, is an options deployment method where deployment is prescribed only if some conditions on past uncertainty realizations are satisfied. It offers an easily interpretable guideline for decision makers on how and when to deploy options. Given that a conditional-go rule is an approximated decision policy, it sacrifices optimality as compared with decisions made with perfect foresight, but provides a readily applicable guideline for implementation in operations that do not violate non-anticipativity. Case 5 generalizes the conditional-go rule using the concept of finite adaptability to provide even more flexibility. Finite adaptability also follows the if-then-else structure of conditional-go rules, but allows a greater number of conditions on past uncertainty realizations and a catalog of different options on generator deployment, thus reducing the expected value gap as compared with decisions made with perfect foresight. Case 6 is a model for optimal options deployment. This is an optimally flexible model, that is, one that optimizes real options without decision rules. Although decision rules are intuitive and offer interpretable approaches to decision-making, they are approximations and, therefore, generally suboptimal. Case 6 offers a benchmark to evaluate this suboptimality.

3.1. Case 1: Deterministic approach

As a base-case, GEP is modeled with a classic deterministic optimization problem where generator output capacities are taken to be their average values. The optimization problem is a mixed-integer programming model with integer decisions on the numbers and types of generators to add in every time period and continuous decisions on the amount of power to produce from these generators so as to meet electricity demands while satisfying output capacity constraints. Mathematically, the model is as follows:

$$\min \sum_{i\in I}\sum_{t\in[T]}\left(\frac{c_{it}^{set}}{(1+r)^t}x_{it}+\frac{c_{it}^{gen}}{(1+r)^t}y_{it}\right) \tag{1}$$

$$s.t. y_{\text{it}} \le \hat{v}_{\text{it}}\sum_{\tau\in[t]}x_{i\tau} \quad \forall i\in I, t\in[T] \tag{2}$$

$$\sum_{i\in I} y_{it} = d_t \quad \forall t\in[T] \tag{3}$$

$$x_{it}\in\mathbb{Z}_+, y_{it}\in\mathbb{R}_+ \quad \forall i\in I, t\in[T]. \tag{4}$$

The objective function (1) minimizes the total discounted cost of generator installation and power generation. Generator capacity constraints are formulated in (2) and demand satisfaction is enforced in constraint (3). Sign and domain constraints on decision variables are ensured in (4). The model presented here, as well as all subsequent models in this article, are cost minimization models. They account for investor incentivization through the positive discount rate used, which captures risk–return tradeoffs typically observed in industry, and reflective of the data used in the Midwest U.S. case study (Jin *et al.*, 2011). Cost minimization is preferred to profit maximization because the latter requires an in-depth analysis of market dynamics to determine the selling price of electricity as more generators are installed. The scope of the current article is limited to the development of novel decision rules for strategic generation expansion planning over time, explicitly accounting for uncertainty and flexibility. Thus, intricate issues related to plant ownership and contractual arrangements are not considered. It is assumed that the sites for deploying the plants are known and set in advance, similar to what is done in Jin *et al.* (2011).

3.2. Case 2: Two-stage stochastic programming approach

Building upon the deterministic model, uncertainty is introduced in the output capacities. A set of scenarios Ω of output capacities is sampled from a pre-set probability distribution (variations to this distribution are explored later in this article) and a two-stage stochastic programming model is proposed whereby generator setup decisions are modeled as *here-and-now* decisions and power generation decisions are construed as *wait-and-see* or *recourse* decisions. This means that setup decisions are made independent of uncertainty realizations, whereas generation decisions are made dependent on uncertainty realizations. The objective function becomes the sum of the total discounted installation cost and the expected total discounted generation cost over all scenarios. The mathematical model is:

$$\min \sum_{i\in I}\sum_{t\in[T]}\frac{c_{it}^{set}}{(1+r)^t}x_{it}+\sum_{\omega\in\Omega}\pi_\omega Q(\boldsymbol{x},\omega) \tag{5}$$

$$\text{s.t. } x_{it}\in\mathbb{Z}_+ \quad \forall i\in I, t\in[T]$$

and where

$$Q(\boldsymbol{x},\omega) = \min \sum_{i\in I}\sum_{t\in[T]}\frac{c_{it}^{gen}}{(1+r)^t}y_{it\omega} \tag{6}$$

$$s.t.\ y_{\text{it}\omega} \le v_{\text{it}\omega}\sum_{\tau\in[t]}x_{i\tau} \quad \forall i\in I, t\in[T] \tag{7}$$

$$\sum_{i\in I} y_{it\omega} = d_t \quad \forall t\in[T] \tag{8}$$

$$y_{it\omega}\in\mathbb{R}_+ \quad \forall i\in I, t\in[T]. \tag{9}$$

The two-stage stochastic programming model has subtle but substantial differences from the deterministic model. The first difference is in the objective function. For the stochastic programming case, the objective (5) is the minimization of the sum of the total discounted setup cost and expectation over realized scenarios of uncertain parameters of a recourse function. The recourse function (also termed the second-stage model) is an optimization model in its own right, where the discounted total power generation cost (6) is minimized. The second difference from the deterministic model is that power generation decisions are dependent on scenario $\omega\in\Omega$. This is because generator output capacity limits are dependent on ω. Capacity and demand satisfaction constraints are formulated in (7) and (8), respectively. The two-stage structure is similar to the one used in Jin *et al.* (2011), with fixed/robust generator addition and scenario-dependent power generation. Generator addition decisions are strategic, whereas power generation decisions are operational. In general, strategic decisions are long-term and cannot be instantly changed or adjusted with scenarios.

3.2.1. Challenges posed by the two-stage stochastic programming approach

A case can be made that fixing generator additions prior to all uncertain generator output capacity realizations is an overly rigid way of planning for the future, and especially the long-term future. The stochastic programming method in Case 2 prescribes those fixed generator addition decisions based on a pre-determined set of scenarios constructed from historical data, when in reality the long-term future can deviate significantly from the past. This reality is especially pronounced in power systems generation expansion planning, where the output capacities of "green" generators rely heavily on weather conditions, for which it is notoriously difficult to provide long-range forecasts because of well-established erratic weather fluctuations due to climate change. One could argue that using a multi-stage stochastic programming approach with a practicable allowance for scenario-dependent generator additions would solve the rigidity of the two-stage approach. Although the multi-stage stochastic programming approach is theoretically sound, it brings important numerical and practical challenges that can make it difficult to implement, particularly for the problem considered in this article. First, a multi-stage stochastic programming approach requires the estimations of conditional scenario probabilities that are hard to obtain and are most of the time assigned arbitrary values, leading to a highly biased perceived value-addition of "optimal" decisions and poor out-of-sample performances, a phenomenon commonly referred to as the *optimizer's curse* (Smith and Winkler, 2006). Second, multi-stage stochastic programming with scenario-dependent generator additions lends itself to black-box implementation, meaning that practitioners using it would have no intuition on the reasoning that lies behind the generator addition decisions, and would therefore, need to accept making hefty investment decisions without understanding the underlying rationale. The next section of this article proposes real options with conditional-go rules as a way to allow flexibility in the generator addition decisions, without the numerical complexity, conditional probability estimations, and black-box disadvantages of classic multi-stage stochastic programming. Moreover, the decision rules approach is intuitive in nature, making it much easier for managers and owners to apply in operations. Moreover, the decision rules approach is intuitive in nature, making it much easier for managers and owners to apply in operations (Cardin, Xie, *et al.*, 2017).

3.3. Real options for flexibility

To incorporate strategic flexibility (discriminating from "operational flexibility", for which recourse decisions are already provided in the stochastic model), options on generator installation deferment are added to the model. For a comprehensive exploration of real options, three variants of the stochastic programming model are provided. The first variant represents an ideal, but unrealistic, case where the decision maker has perfect information about all past and future uncertainty realizations in any time period. The second variant implements a non-anticipative conditional-go decision rule on generator options. The third variant uses a finite adaptability mechanism to generalize the conditional-go rule. These variants are explained below.

3.3.1. Case 3: Perfect uncertainty realization information

This is a simple baseline model where the decision maker is able to enable real options on generator addition with perfect foresight on future uncertainty realizations. In essence, this model can be viewed as an anticipative stochastic programming model where generator setup decisions are dependent on scenarios. The model is formulated below, with the main purpose of providing a comparison baseline for upcoming decision rule models:

$$\min \sum_{\omega\in\Omega} \pi_\omega \sum_{i\in I} \sum_{t\in[T]} \left(\frac{c_{it}^{set}}{(1+r)^t} x_{it\omega}^o + \frac{c_{it}^{gen}}{(1+r)^t} y_{it\omega} \right) \tag{10}$$

s.t. (8)

and

$$y_{it\omega} \le v_{it\omega} \sum_{\tau\in[t]} x_{i\tau\omega}^o \quad \forall i \in I, t \in [T],\ \omega \in \Omega \tag{11}$$

$$x_{it\omega}^o \in \mathbb{Z}_+, y_{it\omega} \in \mathbb{R}_+ \quad \forall i \in I, t \in [T],\ \omega \in \Omega. \tag{12}$$

This model is a single-stage stochastic programming model where all decision variables are scenario-dependent. The objective function (10) is the minimization of the total expected discounted cost of setup and generation, with π_ω denoting the probability of scenario $\omega \in \Omega$ happening. The constraints (11) and (12) are capacity and sign constraints, respectively, adjusted with scenario-dependent generator setup.

3.3.2. Case 4: Conditional-go decision rule

Case 3 is an idealized situation of perfect foresight. It means that the decision maker knows with certainty the scenario realizations for the whole planning horizon, and is therefore, able to implement the optimal strategic generator addition plan for each of these realizations. Realistically, it is almost impossible for decision makers to perfectly forecast scenario realizations. Furthermore, it takes time to build generators. Decisions at a time period are typically made based on *past* uncertainty realizations, which in stochastic programming literature is called non-anticipativity. Under non-anticipativity and scenario-dependent generator addition, the two-stage model becomes a multi-stage model where decisions in each time period are based on the history of uncertainty realizations. This is due to constraint (11) where the power generated from a generator type in a period t depends on the total number of generators of that type setup from periods 1 to t. The main disadvantage of this approach is that it requires the decision maker to draw up a multi-level scenario tree and optimize decision-making for this particular scenario tree, leaving the possibility of bad out-of-sample performances. Furthermore, the multi-stage scenario tree requires the estimation of conditional probabilities, which may be inaccurate or even impossible in some cases. This work proposes a decision-making paradigm that provides the decision maker with simple guidelines, called decision rules, that are scenario-independent, to simplify and generalize decision-making.

The decision-making paradigm proposed is a conditional-go decision rule. The word "conditional-go" refers to an if-then-else type statement, where options are exercised under some cases of output capacity realizations and not exercised otherwise. The rule in this article is as such: At a time period t, if the Normalized Total Output Capacity Realization (NOCR) of a generator of type i until time period $t-1$ is below an optimized threshold value, then the decision maker exercises expansion options for generator of type i. Else, if that NOCR is greater than or equal to the threshold value, options are not exercised. Mathematically, the NOCR of a generator of type i at time t in scenario ω is defined as

$$R_{it\omega} = \frac{\sum_{\tau\in[t-1]} v_{i\tau\omega} - \min_{\omega\in\Omega}\{\sum_{\tau\in[t-1]} v_{i\tau\omega}\}}{\max_{\omega\in\Omega}\{\sum_{\tau\in[t-1]} v_{i\tau\omega}\} - \min_{\omega\in\Omega}\{\sum_{\tau\in[t-1]} v_{i\tau\omega}\}}.$$

The NOCR is calculated *a priori* from the output capacity realizations and is a unity-based normalization procedure that brings all values in the range $[0, 1]$. This normalization also yields normalized threshold values in the range $[0, 1]$. It has the quality of improving the interpretability of thresholds. For example, a threshold value of zero means that the decision maker should never exercise options and conversely, a threshold value of one indicates to the decision maker that options should always be exercised. The conditional-go decision rule allows the decision maker the flexibility to change generator setup decisions as new data are revealed. Note that the non-anticipativity property that is characteristic of multi-stage stochastic programming models is maintained here, as the NOCR at time t is calculated from the cumulative output capacity realization until time t – 1.

The worst performance of the rule is the optimal solution of Case 2 and this is achieved when all thresholds are zero, effectively eliminating options and fixing generator addition. The main advantage of the decision rule is that it acts as simple guidelines, in the form of optimal threshold values and options deployment, to decision makers. These guidelines are applicable to cases where actual generator capacity realizations are different from every scenario considered in set Ω. The model below optimizes both the threshold values and the number of generators to be deployed as options. Let $[T_a] = [T] \setminus [a]$, where "$\setminus$" is the notation for the relative complement, meaning that $[T] \setminus [a]$ denotes the set of elements that are in $[T]$ but not in $[a]$. The set of time periods for which options on generators of type i are "exerciseable" is denoted by $\Gamma_i = \{t \in [T_1] : t + \lambda_i \le T\}$ and the stochastic programming model with conditional-go decision rules is

$$\min \sum_{i\in I}\sum_{t\in[T]} \frac{c^{set}_{it}}{(1+r)^t} x_{it} + \sum_{\omega\in\Omega}\pi_\omega \left(\sum_{i\in I}\sum_{t\in[T]} \frac{c^{gen}_{it}}{(1+r)^t} y_{it\omega} + \sum_{i\in I}\sum_{t\in[T_{\lambda_i+1}]} \frac{c^{set}_{it}}{(1+r)^t} x^o_{it\omega} \right) \quad (13)$$

s.t. (8)
and

$$y_{it\omega} \le v_{it\omega}\sum_{\tau\in[t]} x_{i\tau} + \sum_{\tau\in[t_{\lambda_i+1}]} x^o_{i\tau\omega} \quad \forall i \in I, t \in [T_{\lambda_i+1}], \omega\in\Omega \quad (14)$$

$$y_{it\omega} \le v_{it\omega}\sum_{\tau\in[t]} x_{i\tau} \quad \forall i \in I, t \in [\lambda_i+1], \omega\in\Omega \quad (15)$$

$$(R_{it\omega} + \epsilon)e_{it\omega} \le \alpha_{it} \quad \forall i \in I, t \in \Gamma_i, \omega\in\Omega \quad (16)$$

$$R_{it\omega}(1 - e_{it\omega}) \ge \alpha_{it} - e_{it\omega} \quad \forall i \in I, t \in \Gamma_i, \omega\in\Omega \quad (17)$$

$$x^o_{i(t+\lambda_i)\omega} \le \beta_{i(t+\lambda_i)} \quad \forall i \in I, t \in \Gamma_i, \omega\in\Omega \quad (18)$$

$$x^o_{i(t+\lambda_i)\omega} \le M e_{it\omega} \quad \forall i \in I, t \in \Gamma_i, \omega\in\Omega \quad (19)$$

$$x^o_{i(t+\lambda_i)\omega} \ge \beta_{i(t+\lambda_i)} - M(1 - e_{it\omega}) \quad \forall i \in I, t \in \Gamma_i, \omega\in\Omega \quad (20)$$

$$\beta_{i(t+\lambda_i)} \ge \frac{1}{|\Omega|}\sum_{\omega\in\Omega} e_{it\omega} \quad \forall i \in I, t \in \Gamma_i \quad (21)$$

$$\beta_{i(t+\lambda_i)} \le M\sum_{\omega\in\Omega} e_{it\omega} \quad \forall i \in I, t \in \Gamma_i \quad (22)$$

$$x_{it} \in \mathbb{Z}_+, y_{it\omega}, \alpha_{i\tau} \in \mathbb{R}_+, e_{i\tau\omega} \in \{0,1\} \quad \forall i \in I, t \in [T], \tau \in \Gamma_i, \omega\in\Omega \quad (23)$$

$$x^o_{it\omega}, \beta_{it} \in \mathbb{Z}_+ \quad \forall i \in I, t \in [T_{\lambda_i+1}], \omega\in\Omega. \quad (24)$$

The objective function (13) is the minimization of the sum of the total discounted cost of fixed generator setup and the expected total discounted cost of power generation and options deployment. Constraints (14) and (15) are capacity constraints, taking into consideration, the time to build generators when they are exercised as options. Since decisions on options exercising are updated in every time period, the time taken for a generator option to become fully operational is an important consideration. Constraint (14) provides capacity bounds for time periods $[T_{\lambda_i+1}] = \{\lambda_i + 1, \ldots, T\}$, which are the time periods where it is possible for deployed options for generator type i to start operation. Constraint (15) provides capacity bounds for time period $[\lambda_i + 1] = \{1, \ldots, \lambda_i + 1\}$, which are the time periods where it is not possible for generator options of type i to start operation, given a time-to-build of λ_i. These capacity bounds therefore depend only on fixed generator deployments. Constraints (16)–(20) model the conditional-go rule. Constraints (16) and (17) ensure that for a generator of type i at time t in scenario ω, the NOCR is below the threshold value α_{it} if and only if the binary variable $e_{it\omega} = 1$. When $e_{it\omega} = 1$, constraint (16) becomes $R_{it\omega} \le \alpha_{it} - \epsilon$ and when $e_{it\omega} = 0$, constraint (17) is $R_{it\omega} \ge \alpha_{it}$. Constraints (18) to (20) ensure that if expansion options are exercised for a generator of type i at time t, a quantity of $\beta_{i(t+\lambda_i)}$ generators become operational $t + \lambda_i$ time periods later and that if expansion options are not exercised, no generators are added. When $e_{it\omega} = 1$, constraints (18) and (20) yield $x^o_{i(t+\lambda_i)\omega} = \beta_{i(t+\lambda_i)}$ and when $e_{it\omega} = 0$, constraint (19) guarantees that $x^o_{i(t+\lambda_i)\omega} = 0$. Constraint (21) enforces the condition that if an option exercising decision is made, the number of generators deployed must be at least one. This prevents the model from considering zero deployment as a possible real options decision. Constraint (22), conversely, guarantees that if a decision is made to not exercise options, no generators are deployed. Constraints (23) and (24) specify the decision variables of the model.

Note on NOCR: In this work, output capacities are the only uncertain parameters and as such, the conditional-go rule is based on NOCR, a function of output capacities. However, the conditional-go rule is not restrictive, in the sense that different metrics can be used to adapt it if more parameters such as costs and demands are uncertain. For example, reserve margins such as those described in Hemmati *et al.* (2013), which are functions of demands and output capacities, can replace NOCR to tailor the decision rule for cases when both demands and capacities are uncertain.

Illustration of the decision-making paradigm. To fully grasp the decision-making paradigm under the conditional-go rule, it is essential to understand the chronology of decision-making in stochastic programming. Prior to any uncertainty realization, the decision maker solves the model for Case 4, with all possible scenarios of uncertain parameters as input. The model outputs an optimal decision vector $(\boldsymbol{x}^*, \boldsymbol{y}^*, \boldsymbol{\alpha}^*, \boldsymbol{e}^*, \boldsymbol{x}^{\boldsymbol{o}*}, \boldsymbol{\beta}^*)$. Consider a simple situation with one generator type, two scenarios, and a 3-year planning horizon. Suppose that the model for Case 4 gives optimal decisions (we only illustrate those decision variables that showcase the conditional-go rule here) $\boldsymbol{x}^* = (1, 1, 2)$, $\boldsymbol{\alpha}^* = (0, 0.2, 0.5)$ and $\boldsymbol{\beta}^* = (0, 2, 3)$, where $\boldsymbol{\alpha}^*$ is in MW. The decision vector $\boldsymbol{x}^*$ is a fixed deployment plan for generators and indicates that one generator should be deployed at time $t=1$ and at time $t=2$ and two generators should be deployed at time $t=3$. Suppose that the output capacity realizations at times 1, 2, and 3 are (2, 3), (2, 5), (3, 8), respectively, for the two scenarios. This means that in the first time period, the generator can produce a maximum of 2 MW of power in the first scenario and 3 MW in the second scenario, in the second time period, it can produce a maximum of 2 MW of power in the first scenario and 5 MW in the second scenario, and in the third time period, it can produce a maximum of 3 MW of power in the first scenario and 8 MW in the second scenario. Let us illustrate how decision-making is conducted as data is revealed. Suppose that at time $t=1$, scenario 2 happens. The decision maker has one generator available from the fixed deployment and generates power from it to satisfy demands. At time $t=2$, the decision maker possesses historical data on the output capacity at time $t=1$ and can calculate the NOCR as (3–2)/(3–2)=1. Since this is greater than the threshold value $\alpha_2^* = 0.2$, no option is exercised. Now, at time $t=2$, scenario 1 happens. The decision maker has two generators from fixed deployments and therefore, $2 \times 2 = 4$ MW of power available to satisfy demands. At time $t=3$, the decision maker has historical data on scenario realizations for times 1 and 2. The NOCR is $((3+2)–(2+2))/((3+5)–(2+2))=0.25$. Since this is smaller than the threshold value $\alpha_3^* = 0.5$, options are exercised and therefore, $\beta_3^* = 3$ generators are deployed (assuming a time-to-build of zero), in addition to the two generators already planned for in the fixed deployment plan. Note that if scenario 2 had happened at time $t=2$, the NOCR for time $t=3$ would be 0.75, instead of 0.25, and options would not have been deployed. This illustrates the concept of flexibility through the delaying of strategic decisions until further information is revealed. It also shows the power of flexibility in protecting against downside risks by avoiding generator deployment when unnecessary. In contrast, the model for Case 2 would have fixed all generator deployments, irrespective of the evolution of available information. This provides a useful benchmark (or baseline) from which one can measure the improvement brought about by flexibility, and quantified as the *EVoF*. Case 3 is a situation of complete flexibility that can only be implemented when perfect information is considered. This means that at time $t=1$, the decision maker knows exactly what scenarios will happen in every time period and implements the generator deployment plan for that specific set of scenario realizations. Case 3 effectively gives a theoretical upper bound on *EVoF*, which we term the *EVPI* to conform to conventional stochastic programming literature (Birge, 1982). This case is unrealizable in practice, although it is instructive in terms of evaluating the decision maker's willingness to pay to embed flexibility in a power system.

3.3.3. Case 5: Finite adaptability

The conditional-go principle is that of deciding on a single threshold value per generator type in every time period. This means that a single condition is used per generator type in every time period. This section proposes a further enhancement of the conditional-go principle through a generalization with multiple thresholds per time period per generator. The generalization is analogous to the concept of finite adaptability used in robust optimization (Bertsimas and Caramanis, 2010). Under a vector $(\alpha_{it1}, ..., \alpha_{itP})$ of P threshold values and a set $(\beta_{it2}, ..., \beta_{itP})$ forming a catalogue of $P - 1$ options for every generator type i in time period t, the generalized finite adaptability decision rule, formally defined, becomes: if $\alpha_{itp-1} \le R_{it\omega} < \alpha_{itp}$, exercise β_{itp}, $\forall p \in [P_1]$, where $\alpha_{it1} = 0$ and $\alpha_{itP} = 1 + \epsilon$. Note that when $P=3$, this reduces to an enhanced version of the conditional-go rule, in the sense that if $R_{it\omega} < \alpha_{it2}$, an option quantity of β_{it2} is deployed, else an option of β_{it3} is deployed where, unlike the conditional-go decision rule, β_{it3} is not necessarily zero. The model under finite adaptability decision rules is:

$$\min \sum_{i \in I} \sum_{t \in [T]} \frac{c_{it}^{set}}{(1+r)^t} x_{it} + \sum_{\omega \in \Omega} \pi_\omega \left(\sum_{i \in I} \sum_{t \in [T]} \frac{c_{it}^{gen}}{(1+r)^t} y_{it\omega} + \sum_{i \in I} \sum_{t \in [T_{\lambda_i+1}]} \frac{c_{it}^{set}}{(1+r)^t} x_{it\omega}^o \right) \tag{25}$$

$$\text{s.t. } (8), (14), (15), (23)$$

and

$$R_{it\omega} \leq \alpha_{itp} + 1 - e_{it\omega p} - \epsilon e_{it\omega p} \quad \forall i \in I, t \in \Gamma_i, \omega \in \Omega, p \in [P_1] \tag{26}$$

$$R_{it\omega} \geq \alpha_{it(p-1)} + e_{it\omega p} - 1 \quad \forall i \in I, t \in \Gamma_i, \omega \in \Omega, p \in [P_1] \tag{27}$$

$$x^o_{i(t+\lambda_i)\omega} \leq \beta_{i(t+\lambda_i)p} + M(1 - e_{it\omega p}) \quad \forall i \in I, t \in \Gamma_i, \omega \in \Omega, p \in [P_1] \tag{28}$$

$$x^o_{i(t+\lambda_i)\omega} \geq \beta_{i(t+\lambda_i)p} - M(1 - e_{it\omega p}) \quad \forall i \in I, t \in \Gamma_i, \omega \in \Omega, p \in [P_1] \tag{29}$$

$$\beta_{i(t+\lambda_i)p} \leq M \sum_{\omega \in \Omega} e_{it\omega p} \quad \forall i \in I, t \in \Gamma_i, p \in [P_1] \tag{30}$$

$$\alpha_{itp} \geq \alpha_{it(p-1)} + \delta \quad \forall i \in I, t \in \Gamma_i, p \in [P_1] \tag{31}$$

$$\alpha_{it1} = 0 \quad \forall i \in I, t \in \Gamma_i \tag{32}$$

$$\alpha_{itP} = 1 + \epsilon \quad \forall i \in I, t \in \Gamma_i \tag{33}$$

$$\alpha_{itp} \in \mathbb{R}_+, e_{it\omega p'} \in \{0,1\} \quad \forall i \in I, t \in \Gamma_i, \omega \in \Omega, p \in [P], p' \in [P_1] \tag{34}$$

$$x^o_{it\omega}, \beta_{itp} \in \mathbb{Z}_+ \quad \forall i \in I, t \in [T_{\lambda_i+1}], \omega \in \Omega, p \in [P_1]. \tag{35}$$

The objective function is the same as for Case 4. Constraints (26) and (27) make sure that if $\alpha_{itp-1} \leq R_{it\omega} < \alpha_{itp}$, options for partition p are exercised. Constraints (28) and (29) stipulate that if option exercising is carried out on generators of type i in time t for partition p, a number $\beta_{i(t+\lambda_i)p}$ options become available λ_i time periods later. Constraint (30) ensures that if options are not exercised, zero generators are deployed. Constraints (31) to (33) formalize bounds on threshold values. The term δ is a minimum threshold value change that the decision maker needs to observe before changing options decisions. Constraints (34) and (35) specify the decision variables of the model.

In the finite adaptability model, there is a clear trade-off between complexity and optimality. If an infinite number of partitions is chosen, the model becomes akin to a perfect-information case. In less extreme cases, as the number of partitions is increased, the model gives better solutions. However, the number of constraints increases, sacrificing model tractability.

3.3.4. Case 6: Two-stage stochastic programming with generator installation recourse

In order to provide a legitimate benchmark to evaluate the sub-optimality of both the conditional-go rule and the finite adaptability rule, the following model is proposed wherein recourse decisions are allowed on generator installations, without decision rules. This is different from the model with perfect information (Case 3) in that both first- and second-stage generator additions are allowed, non-anticipativity is maintained, and the time taken to build generators are also considered:

$$\min \sum_{i\in I} \sum_{t\in[T]} \frac{c^{set}_{it}}{(1+r)^t} x_{it} + \sum_{\omega\in\Omega} \pi_\omega \left(\sum_{i\in I} \sum_{t\in[T]} \frac{c^{gen}_{it}}{(1+r)^t} y_{it\omega} + \sum_{i\in I} \sum_{t\in[T_{\lambda_i+1}]} \frac{c^{set}_{it}}{(1+r)^t} x^o_{it\omega} \right) \tag{36}$$

$$\text{s.t.}(8)$$

and

$$y_{it\omega} \leq v_{it\omega} \sum_{\tau\in[t]} x_{i\tau} + \sum_{\tau\in[t_{\lambda_i+1}]} x^o_{i\tau\omega} \quad \forall i \in I, t \in [T_{\lambda_i+1}], \omega \in \Omega \tag{37}$$

$$y_{it\omega} \leq v_{it\omega} \sum_{\tau\in[t]} x_{i\tau} \quad \forall i \in I, t \in [\lambda_i + 1], \omega \in \Omega \tag{38}$$

$$x_{it} \in \mathbb{Z}_+, y_{it\omega} \in \mathbb{R}_+ \quad \forall i \in I, t \in [T], \omega \in \Omega \tag{39}$$

$$x^o_{it\omega} \in \mathbb{Z}_+ \quad \forall i \in I, t \in [T_{\lambda_i+1}], \omega \in \Omega. \tag{40}$$

This model is used to evaluate optimality losses when implementing decision rules. The conditional-go and finite adaptability decision rules, although providing decision structures that are easy to understand and interpret, do lead to optimality losses. Decision rules are, in essence, approximations of optimal decisions that offer more interpretable rules of thumb for decision makers in order to make implementations less black-box, at the expense of optimality losses. Modeling-wise, the difference between Case 6 and the models with decision rules (Case 4 and Case 5) is that there are no additional constraints imposed on recourse installation decisions. The constraints imposed in Case 4 and Case 5 are to structure real options deployment in such a way that it follows the if–else rules. With respect to the decision structure, whereas Case 4 and Case 5 output optimal thresholds and options portfolios, Case 6 only outputs the scenario-dependent generator installation plan.

3.4. Summary of trade-offs

Cases 1 to 6 trade off flexibility, implementability, and numerical complexity to various degrees. In order to guide practitioners on how to compare these models and apply them appropriately, we summarize the trade-offs that exist among the models and discuss the contexts in which each model is best applied. As a reminder, Case 1 is the deterministic model, Case 2 is the two-stage stochastic programming model with fixed generator addition decisions, Case 3 is a theoretical model for planning under perfect information, Case 4 is the stochastic programming model with real options and the conditional-go decision rule, Case 5 is the stochastic programming model with real options and the finite adaptability decision rule, and Case 6 is the stochastic programming model with real options and no decision rule. Evidently, Case 3 is a purely theoretical model used to calculate the expected value of perfect information, a common metric used to evaluate stochastic programming models. We therefore omit it from the following discussions.

Flexibility. The flexibility of a system is its ability to react to uncertainty. Case 1 yields the least flexible system since it does not consider uncertainty at all and provides both a fixed generator addition plan and a fixed power generation plan. Case 2 offers operational flexibility by allowing power generation to be uncertainty-dependent. Case 4 adds strategic flexibility via a single set of real options on generator additions and if–else conditions on the deployment of these options. Case 5 further improves the flexibility by nesting more if–else conditions, thereby allowing choices among multiple real option sets. Case 6 yields the most flexible system, being optimally flexible, in the sense that it is constructed without restrictions on the set(s) of real options to be deployed and without any if–else conditions. It finds the best option deployment strategy without rule-of-thumb assumptions.

Implementability. The implementability of a model is the ease with which the model can be put in practice, especially with respect to future uncertainty realizations. Case 1 is the least implementable model, since its reliance on fixed decisions for nominal parameter values means that it is likely to severely under-perform when these parameters vary. Although Case 2 and Case 6 address parameter uncertainties, they do so by relying solely on historical data. Without decision rules, these two models offer no insights to practitioners on the rationale behind the optimal decisions, and therefore provide no common understanding on how best to react to future data. Case 4 and Case 5 provide rules of thumb to practitioners, via decision rules, to establish a common and interpretable decision-making rationale for reacting to uncertainties.

Numerical complexity. The numerical complexity is the ease with which a model can be solved. Case 1 is the easiest to solve, with no constraints for flexibility implementation and no attachment of decision variables or constraints to uncertainty realizations. Case 2 increases in numerical complexity, as power generation decisions are made for every uncertainty realization and generator output capacities and demand satisfaction have to be met for every uncertainty realization as well. In addition to those, Case 6 contains real options decisions for every uncertainty realization. Case 4 further increases in numerical complexity by necessitating additional uncertainty-dependent constraints and variables to represent the conditional-go rule. Notably, binary decision variables are needed to represent the if–else aspect of the rule. Case 5 is the one with the highest numerical complexity, containing further decision variables and constraints to represent the nested if–else conditions of the finite adaptability decision rule. Table A in the Online Supplemental Materials summarizes those insights, ranking the models from 1 (best) to 5 (worst) in each category.

4. Case study

The various models developed are implemented in a demonstration GEP problem for Midwest U.S. with a planning horizon of 10 years. In terms of wider applicability, these models can be used in joint coordinated system planning, such as that initiated in 2007 by Regional Transmission Organizations and Independent System Operators in Midwest and Northeast U.S. which conducted economic studies with prescribed renewable penetration mandates (Jin *et al.*, 2011) and in the expansion of microgrids (Khodaei *et al.*, 2014). In addition, these models can be integrated in GTEP problems to allow strategic flexibility. In GTEP problems, investments in generation expansion are conducted jointly with grid/transmission expansion and the real options and decision rule concepts provided in this work can be incorporated in the generation phase of GTEP problems.

Five candidate generators are available for deployment, namely pulverized coal (PC), combined cycle (CC), combustion turbine (CT), wind, and finallly integrated gasification combined cycle (IGCC). The construction of this case study is based on demand, setup cost, generation cost, output capacity, and discount rate data provided in Jin *et al.* (2011). To keep this article self-contained, the data is also described here. The discount rate is a constant 8% over the whole planning horizon. The forecast of the incremental peak electricity demand is shown in Table B of the Online Supplemental Materials. Following the approach in Jin *et al.* (2011), incremental demand data are used, the goal of the GEP problem being to build an entirely new power system to satisfy these incremental electricity demands over a 10-year planning horizon. Table C of the Online Supplemental Materials shows the setup and generation costs for each generator type. The setup/installation cost comprises the initial capital investment to purchase the generator, as well as the fixed operations and maintenance expenditure over the generators lifespan in the planning horizon. The generation cost consists mostly of fuel cost and variable infrastructure deterioration cost with usage. The nameplate generator capacities are 650 MW, 400 MW, 210 MW, 400 MW, and 600 MW for PC, CC, CT, Wind, and IGCC, respectively. The time to build PC, CC, CT, Wind, and IGCC generators are, in years, 6, 3, 2, 2, and 5, respectively. To characterize output capacity losses, availability factors (which can be viewed as percentages of up-times) are used, with averages of 0.90, 0.90, 0.90, 0.35, and 0.90 for PC, CC, CT, Wind, and IGCC, respectively. The uncertainty in generator capacities is characterised through uncertainty in availability factors. Probabilistically-distributed scenarios are generated through Monte Carlo simulation from the distributions shown in Table D of the Online Supplemental Materials. The models in this article are solved using IBM-ILOG CPLEX 12.6.

4.1. Results for baseline cases: Case 1, case 2, case 3, and case 6

The optimal objective values of Case 1, Case 2, Case 3, and Case 6 are (in $billion) 28.5, 87.5, 41.9, and 45.7 respectively and the solution times are (in seconds) 0.22, 30.7, 174.6, and 55.8 for Case 1, Case 2, Case 3, and Case 6, respectively. Case 2 and Case 6 are solved over 1000 scenarios generated via Monte Carlo simulation. These results show that the presence of uncertainty greatly increases the optimal cost, due to the additional generators needed

Table 1. Generator setup results from SAA for Case 4.

Year	*1*	*2*	*3*	*4*	*5*
Fixed	14 Wind, 1 IGCC	25 Wind	3 Wind	33 Wind	1 IGCC
Threshold	–	0.13 for IGCC	0.84 for Wind	1.00 for Wind	–
Options	–	–	–	–	3 Wind
Year	*6*	*7*	*8*	*9*	*10*
Fixed	2 Wind, 1 IGCC	1 IGCC	–	–	–
Threshold	–	–	0.77 for Wind	–	–
Options	11 Wind	1 IGCC	146 Wind	1 Wind	–

to hedge against uncertainty. Table E of the Online Supplemental Materials compares the optimal setup decisions in the deterministic model (Case 1) against those of the stochastic programming model (Case 2) and the stochastic programming model with real options and no decision rule (Case 6).

4.2. Results for case 4

Case 2 is the traditionally used method in the literature to tackle GEP. The main issue with this methodology is that generator setup decisions are fixed and cannot be changed as new uncertainty realizations are revealed. Over the long term, circumstantial changes risk making the proposed generator setup plan difficult, or even impractical, to implement. Case 4 addresses the rigidity of the setup plan by adding flexibility to the system design through real options on generator setup. With the conditional-go decision rules implemented in Case 4, an optimal solution is obtained through Sample Average Approximation (SAA). In the SAA procedure, the model is first solved for a set of 50 scenarios to obtain optimal threshold value results that are then entered as input parameters in the model before solving over the 1000 scenarios that were generated for Case 2. The normalization used for total output capacity realizations is essential to keep threshold values sample-independent and, thus, valid for the 1000-scenario model. The optimal objective value for Case 4 is $87.2 billion. The SAA results for Case 4 are shown in Table 1. Only the threshold values greater than zero are shown for clarity.

The interpretation of Table 1 is as follows: Suppose the decision maker is in year 3. She calculates the NOCR until year 2 from past uncertainty realizations in every scenario and for every generator. If, for a scenario, that value is less than 0.84 for wind generators, an option to add three wind generators is exercised. Since the time to build wind generators is 2 years, these three wind generators become fully deployed and functional in year 5. An analysis of the results of Case 5 can be found in the Online Supplemental Materials.

4.3. Summary of results

The results obtained in the previous sub-sections can be used to quantify, on the one hand, the *EVoF*, and on the other hand, the *EVPI* for different systems. The former is a measure of how much economic value is added by explicit consideration of uncertainty and flexibility, as compared with a rigid or inflexible system. The latter is a measure of the upper bound on *EVoF* specific to a given system, and is obtained by comparing the expected performance of a flexible system with the expected performance of a system that is optimized using perfect foresight (i.e., adapting perfectly and flexibly to each scenario). *EVoF* is important to quantify the added value from flexibility for a specific system and strategy, considering decisions that are non-anticipative and imperfect. Such analysis is widely performed and accepted in the literature on real options analysis and flexibility in design see Dixit and Pindyck (1994); Trigeorgis (1996); de Neufville and Scholtes (2011); and Cardin (2014). Here, Case 2 is used as a benchmark inflexible system, since investment decisions (i.e., setup costs) are the same across all output capacity scenarios. *EVPI* is a theoretical measure (i.e., unrealizable) that violates non-anticipativity, a fundamental constraint in stochastic programming. Quantifying *EVPI* is also important, nonetheless, as it places an upper bound on *EVoF*, and therefore may affect the willingness to pay by a decision maker to embed flexibility in the design of a power system.

The following relationships can be derived, using the expected value (*EV*) of cost for different systems:

$$EVoF = EV_{Inflexible} - EV_{Flexible} \tag{41}$$

$$EVPI = EV_{Flexible\ or\ Inflexible} - EV_{Perfect\ Information} \tag{42}$$

$$0 \leq EVoF \leq EVPI_{Max} \tag{43}$$

In (41), the inflexible system is always Case 2, as it is the benchmark rigid system, and the flexible systems are Cases 3-6. For Case 2, $EVoF = 0$ since the system is inflexible, and for Case 3, $EVoF = 87.5 - 41.9 = 45.6$ billions, the theoretical upper bound on the value added by flexibility. By similar principles, $EVoF = 0.3$ billions for Case 4, for Case 5 $EVoF = 1.3$ billions, and for Case 6 $EVoF = 41.8$ billions. The values for Case 4 and 5 are significantly lower than the upper bound, due to non-anticipativity and the sub-optimalities incurred by using decision rule approximations. The value for Case 6 is close to the theoretical upper bound, as Case 6 does not have any optimality loss due to decision rules. The lesson here is that there is a significant price to pay for interpretability. Although Case 6 yields significantly higher *EVoF*, its solutions do not provide any rule of thumb that will facilitate implementation, which means that practitioners have to take its solution at face value and implement it blindly. In (42), *EVPI* is measured by subtracting the expected value for Case 3 (i.e., the system with perfect foresight) from the expected value for Cases 2, 4, 5, and 6. For Case 2, this leads to $EVPI = 87.5 - 41.9 = 45.6$ billions, which is the same *EVoF* for Case 3. It is the highest *EVPI* across all cases (referred as $EVPI_{Max}$), since the potential for flexibility is untapped. For Case 3, $EVPI = 0$ since there is no further value improvement possible from flexibility under perfect foresight. For Case 4 $EVPI = 45.3$ billions, for Case

Table 2 Summary of results for *EVoF* and *EVPI*.

Case	Description	EVoF ($, billions)	EVPI ($, billions)
1	Deterministic	N/A	N/A
2	Benchmark Inflexible	0.0	45.6
3	FlexiblePerfect Information	45.6	0.0
4	Flexible, Conditional-go	0.3	45.3
5	Flexible, Finite Adaptability	1.3	44.3
6	Flexible, No Decision Rule	41.8	3.8

5 $EVPI = 44.3$ billions, and for Case 6 $EVPI = 3.8$ billions. *EVPI* for Case 5 is lower than *EVPI* for Case 4, as finite adaptability provides greater flexibility than conditional-go decision rules, thereby lowering the value discrepancy measured under perfect foresight. Case 6 has even lower *EVPI*, as it provides an optimally flexible system, without perfect foresight (non-anticipativity is maintained). Equation (43) captures the relationship between *EVoF* and *EVPI*. It represents the fact that *EVoF* for flexible non-anticipative systems (i.e., Cases 4 and 5) is bounded from below at zero (i.e., Case 2) and from above by *EVoF* of a flexible system with perfect foresight (i.e., Case 3), which corresponds to $EVPI_{Max}$ from Case 2. This relationship is confirmed by the results summarized in Table 2.

5. Concluding remarks

This article addresses two important questions in GEP research. First, it addresses the question of how to best incorporate uncertainty in generator output capacities into a GEP model. Second, it explores how to add strategic decision-making flexibility through real options into a GEP model formulation, with the goal of improving expected system performance. To tackle these issues, six models are proposed, each analyzing different aspects of GEP. The first model is a deterministic model and the second is a stochastic programming model with fixed generator setup plans. The second model is used to analyze the effect of uncertainty and the expected value of flexibility (*EVoF*). The third model assumes that the decision maker has perfect foresight into uncertainty realizations and reacts according to these realizations to formulate different generator setup plans. This model is an idealized fully flexible model and is used to gauge the expected value of perfect information (*EVPI*), which provides an upper bound on *EVoF*. The fourth and fifth models implement flexibility through real options on generator setup and non-anticipative decision rules. The fourth model implements a conditional-go principle where thresholds are evaluated below which options are exercised. The fifth model implements finite adaptability decision rules whereby a metric of past uncertainty realizations (in this article, a normalized total output capacity realization metric is used) is partitioned, with different options decisions made in each partition. The sixth model is a two-stage stochastic model with generator installation recourse. The six models are used in a demonstration GEP case study in Midwest U.S., showing significant savings when flexibility is implemented with the conditional-go principle and with finite adaptability.

Nomenclature

Sets

I	Set of generator types
$[T]$	Set of running indices from 1 to T
Ω	Set of scenarios

Parameters

$v_{it\omega}$	Output capacity of generator type i in period t in scenario ω
λ_i	Number of time periods taken to install a generator of type i
δ	Minimum threshold value change necessary to change options decisions
T	Planning horizon
c_{it}^{set}	Setup cost for a generator of type i in period t
c_{it}^{gen}	Unit power generation cost of generator type i in period t
r	Discount rate
d_t	Electricity demand in period t
$\hat{v}_{it}$	Average output capacity of generator type i in period t
π_ω	Probability of occurrence of scenario ω
M	A big number
ϵ	A small number
$\lvert\Omega\rvert$	Cardinality of set Ω

Decision Variables

x_{it}	Number of generators of type i installed in period t
y_{it}	Power generated from generator type i in period t
$x_{it\omega}^o$	Number of generators of type i installed in period t in scenario ω
$y_{it\omega}$	Power generated from generator type i in period t in scenario ω
$e_{it\omega}$	Binary variable for if options for generator type i are exercised in period t in scenario ω
α_{it}	Conditional-go threshold value for generator type i in period t
β_{it}	Number of generators of type i installed as options in period t under the conditional-go rule
α_{itp}	The pth threshold value for generator type i in period t under the finite adaptability rule
$e_{it\omega\rho}$	Binary variable for if options for partition ρ of the finite adaptability rule are exercised for generator type i in period t in scenario ω
$\beta_{it\rho}$	Number of generators of type i installed as options for partition ρ in period t under the finite adaptability rule

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