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Uncertainty in Electricity Demand and Public Acceptance

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Abstract

Nuclear power is an important energy source especially in consideration of CO_2 emissions and global warming. Deploying nuclear power plants, however, may be challenging when uncertainty in long-term electricity demand and more importantly public acceptance are considered. This is true especially for emerging economies (e.g., India, China) concerned with reducing their carbon footprint in the context of growing economic development, while accommodating a growing population and significantly changing demographics, as well as recent events that may affect the public's perception of nuclear technology. In the aftermath of the Fukushima Daiichi disaster, public acceptance has come to play a central role in continued operations and deployment of new nuclear power systems worldwide. In countries seeing important long-term demographic changes, it may be difficult to determine the future capacity needed, when and where to deploy it over time, and in the most economic manner. Existing studies on capacity deployment typically do not consider such uncertainty drivers in long-term capacity deployment analyses (e.g., 40+ years). To address these issues, this paper introduces a novel approach to nuclear power systems design and capacity deployment under uncertainty that exploits the idea of strategic flexibility and managerial decision rules. The approach enables dealing more pro-actively with uncertainty and helps identify the most economic deployment paths for new nuclear capacity deployment over multiple sites. One novelty of the study lies in the explicit recognition of public acceptance as an important uncertainty driver affecting economic performance, along with long-term electricity demand. Another novelty is in how the concept of flexibility is exploited to deal with uncertainty and improve expected lifecycle performance (e.g. cost). New design and deployment strategies are developed and analyzed through a multistage stochastic programming framework where decision rules are represented as non-anticipative constraints. This approach provides a new way to devise and analyze adaptation strategies in view of long-term uncertainty fluctuations that is more intuitive and readily usable by system operators than typical solutions obtained from standard real options analysis techniques, which are typically used to analyze flexibility in large-scale, irreversible

investment projects. The study considers three flexibility strategies subject to uncertainty in electricity demand and public acceptance: 1) phasing (or staging) capacity deployment over time and space, 2) on-site capacity expansion, and 3) life extension. Numerical analysis shows that flexible designs perform better than rigid optimal design deployment strategies, and the most flexible design combining the above strategies outperforms both more rigid and less flexible design alternatives. It is also demonstrated that a flexible design benefits from the strategies of phasing and capacity expansion most significantly across all three strategies studied. The results provide useful insights for policy and decision-making in countries that are considering new nuclear facility deployment, in light of ongoing challenges surrounding new nuclear builds worldwide.

1   Introduction

The global electricity demand has rapidly increased in recent decades, from 13,174 TWh in 2000 to 20,301 TWh (54% growth) in 2014 (Enerdata, 2015). Many countries, especially emerging economies like India and China, are facing increasing demand due to rapidly growing populations, while trying to reduce their carbon footprint and greenhouse gas emissions (NDRC, 2015; Plucinska, 2015). A significant proportion of the energy portfolio in those countries still relies on traditional thermal power plants generating electricity from fossil fuels, which contribute significantly to CO_2 emissions (EIA, 2014, 2015).

In the hope of reducing global warming, renewable or green energy sources with little or zero CO_2 emissions like nuclear power technology have received increasing attention in recent years (EIA, 2014, 2015). Compared to expanding renewable energy sources like solar or wind power, nuclear power provides a stable baseload because it does not rely on any given environmental conditions to generate power (i.e., unlike wind farms and PV systems). Furthermore as a generator with high fixed costs and very low marginal costs, baseload generation is typically favored even if the load-following operation is technically possible (Pouret *et al.*, 2009).

In the aftermath of the Fukushima Daiichi disaster, public acceptance has come to play a central role in many countries regarding the continued operations and deployment of new nuclear power systems. Governments, politicians, and the public show a higher degree of concern regarding the safety of nuclear power technology. For example, safety issues concerning the large amounts of energy stored in the nuclear reactor core, or the need to cool it down after shutdown are among chief technical concerns. More importantly for the public are the risks associated with radiation poisoning that may occur after a large-scale nuclear incident.

Noting those ongoing concerns around long-term waste management, nuclear power is still a significant energy source in many developed countries (e.g., the United Kingdom, France the United States, Russia, and South Korea). On the other hand, emerging economies considering nuclear power may face pressure and opposition internally from their own population, from neighboring countries, or even from other national governments, in relation to the safety of their nuclear technology.

There are much uncertainty and risks associated with deploying nuclear power plants from an economic standpoint (Kessides, 2010). This is true, especially when considering upcoming demographic challenges for emerging countries, as well as the new policy-related challenges associated with nuclear power in the public eye. Uncertainty in growing electricity demand, as well as public acceptance of nuclear technology, may affect significantly the economic performance and costs of such systems, and ultimately even the possibility of continuing existing operations, or deploying new capacity. Social factors that may affect the circumstances for making decisions are public acceptance of nuclear technology, which itself influences government support. Public acceptance is "essential for any activity that affects large sectors of a nation" (Golay, 2001).

To deal with uncertainty in demand and public acceptance, this paper introduces the idea of flexibility in engineering system design as a way to deal pro-actively with medium to long-term changes in demand and social acceptance of nuclear power technology. Flexibility is akin to the notion of a real option, which provides system planners and operators "the right, but not the obligation, to change the system deployment and operations as uncertainty unfolds" (Dixit & Pindyck, 1994; Trigeorgis, 1996).

The idea of flexibility stems from the recognition that uncertainty affects significantly the expected lifecycle performance of a system. It focuses on finding systems architecture, design, and capacity deployment strategies that improve the system's expected performance by pro-actively adapting to changing conditions. Flexibility strives, on the one hand, to reduce the impact from downside conditions (e.g., lower demand and/or social acceptance than anticipated), and to provide contingencies to capitalize on upside opportunities (e.g., higher and/or better social acceptance than expected). The net effect is typically to improve the expected economic performance of engineering systems over their life cycle, as demonstrated in many case studies (de Neufville and Scholtes (2011)).

The literature on real options analysis (ROA) (e.g., Cox *et al.* (1979); Dixit and Pindyck (1994); Trigeorgis (1996)) has evolved over recent years to provide better tools to enable system architects, designers, and planners to analyze flexibility in an applied setting (Cardin, 2014). This is because standard ROA techniques focus on quantifying the economic value of flexibility, but many assumptions are not well suited for an engineering driven and applied setting. For example, the path independence assumptions that is crucial to recombining binomial lattices, while realistic for valuing financial options, is not appropriate in an applied setting. An up-down movement in the main stochastic driver (e.g. demand, social acceptance) would not lead to the same decision sequence in terms of deploying power system infrastructures than a down-up sequence, and therefore would not result in the same economic value and performance for the system. In addition, there is no efficient and complete market of tradable assets to replicate the cash flows of such systems, making the risk neutrality and arbitrage-enforced pricing assumptions critical to standard ROA not applicable. Another limitation is that it may be difficult to determine the optimal timing to exercise the flexibility. Decision-makers need to determine their position in the lattice by fitting historical data, projecting the evolution of uncertainty over the next few time periods, and applying a backward induction process to determine the optimal exercise policy (Bellman, 1952). When multiple facilities, flexibility strategies, or uncertainty sources are considered simultaneously, this approach requires the use of multinomial lattices (i.e. using multiple interwoven binomial lattices) (Kamrad & Ritchken, 1991), which make the analysis more difficult from a

computational standpoint, and also even more challenging in terms of determining the position and optimal exercise policy for decision-makers.

To deal with these issues, a novel approach based on decision rules and stochastic programming has been proposed to analyze flexibility in engineering systems design and management (Cardin *et al.*, 2016). The authors show that this approach leads to similar valuation outcomes as standard ROA techniques, but is better suited to the analysis of multiple flexibility strategies and uncertainty sources. The decision rule approach aims to emulate the decision-making process, and therefore it is more intuitive to guide decision-makers and system operators on the optimal timing for exercising the flexibilities (see Section 2 for further details on the approach). On the other hand, this approach has not been extended to the analysis of infrastructure systems, when multiple facilities, flexibility strategies (or real options) and uncertainty sources are considered simultaneously.

To address these issues, the paper introduces a novel approach combining decision rules and stochastic programming to analyze flexibility in nuclear infrastructure systems, and to determine the best capacity deployment strategies accounting for uncertainty in future demand, as well as social acceptance of nuclear power. More specifically, this paper investigates the question of how to exploit the concept of flexibility to design and site nuclear power plants in countries that are considering additional deployment of nuclear power capacity, considering explicitly uncertainty in electricity demand and social acceptance for the technology. Multiple electricity demands are sampled based on historical information using Monte-Carlo simulation. The simulated samples are used both for the optimization analysis, and for an out-of-sample study in the numerical analysis. Social acceptance is defined here as the public's intention to support more/less capacity deployment of new nuclear power facilities. As there is currently no widely accepted approach to measure this socio-technical factor, the cumulative International Nuclear Event Scale (INES) is used as proxy in this paper to analyze and model quantitatively social acceptance. The INES is widely accepted in the nuclear sector as a measurement of the severity of nuclear incidents and accidents. The main contribution is a novel analysis based on decision rules to analyze the strategic power of flexibility in nuclear capacity deployment over multiple sites, while considering explicitly the recent reality of social acceptance, along with the more traditional

considerations of electricity demand associated with demographic growth in developing countries. In doing so, the analysis introduces new design alternatives exploiting strategic-level flexibility, based on multi-stage stochastic programming and the concept of managerial decision rules, and demonstrates how they improve expected lifecycle performance, as compared to more rigid (although stochastically optimal) strategies. These can provide useful insights to decision-makers and system planners concerned with new nuclear capacity deployment.

This paper is organized as follows. Section 2 reviews the related work and provides motivation for the research gaps addressed in this study, as well as potential contributions. Section 3 presents the details of the approach in terms of mathematical formulations. A numerical study is reported in Section 4 in which four design alternatives are analyzed and compared. Concluding remarks, limitations, and possible directions for further research are presented in Section 5.

2   Related work

2.1   Flexibility/Real options analysis

Flexibility in engineering systems design – also referred as real options – provides the "right, but not the obligation, to change a system easily in the face of uncertainty" (Trigeorgis, 1996). Saleh *et al.* (2009) summarized the research efforts on this multi-disciplinary concept of flexibility, while (Cardin, 2014) introduced a five-phase systematic design framework and taxonomy for enabling flexibility in design and management of complex systems (i.e. baseline design, uncertainty recognition, concept generation, design space exploration, process management). In each such phase, procedures exist to help system designers and architects to enable flexibility (or real options) in engineering systems. Specifically, real options "in" projects focus on strategies for changing the physical design of engineering systems, such as expanding/reducing capacity, deploying capacity in phases over time, etc. Real options "on" projects, on the other hand, focus on high-level financial/managerial decisions made about technical issues like deferring investment until favorable market conditions arise and abandoning current projects. Compared to the latter, real options "in" projects require a deep understanding of

technology and systems – or possibly changes – to enable flexibility in the designs (Wang & de Neufville, 2005).

The benefits of incorporating flexibility may help limit system exposure to downside risks, while enabling a system to deal pro-actively with uncertainty to benefit from upside opportunities. For example, a planner may embed flexibility so s/he can decide whether or not to expand easily the capacity of a waste-to-energy (WTE) power plant in the future, depending on prevailing waste generation patterns in a city (Cardin & Hu, 2016; Hu & Cardin, 2015). If a waste generation is stable and can be covered by the current capacity, there is no need to expand the capacity at that time. Once the amount of waste generated in the city is greater than the capacity for several consecutive years, the planner may decide to expand the plant capacity to meet waste generation growth based on a heuristic i.e., a decision rule. This approach to decision-making is in line with the view that decision-makers may prefer to rely on heuristic rules to achieve desired levels of performance when operating under complex and uncertain environments (Simon, 1972). Flexibility is deemed as an emerging concept to improve the expected economic performance of engineering systems, as shown in many studies and industry sectors like aerospace, automotive, manufacturing, real estate, oil and gas, and transportation (Alp & Tan, 2008; Chen & Yuan, 1999; de Weck *et al.*, 2004; Jain *et al.*, 2013a; Jiao, 2012; Koh *et al.*, 2013; Luo, 2015; Nilchiani & Hastings, 2007; Ross *et al.*, 2008; Subrahmanian *et al.*, 2015; Suh *et al.*, 2007).

2.2   Capacity Deployment of Nuclear Facilities

Deploying nuclear power facilities over time and space is a more specific application of the more general capacity deployment problem already addressed in the literature. In such problem, there are typically several uncertainty drivers that may affect the system's key performance indicators (KPIs). Despite some analytical shortcomings, ROA has been considered a valuable approach for economic analysis, and as a way to recognize the additional value that stems from pro-active actions in dealing with uncertainty. Typically, a deferral option can be used to model the capacity deployment of nuclear power plants, aiming to optimize total profits by deferring investments until favorable market conditions arise. For instance, Louberge *et al.* (2002) applied a real options model to study an optimal stopping problem regarding deep geological disposal of nuclear waste. Rothwell (2006) and Abdelhamid *et al.*

(2009) also analyzed this deferral option in the context of nuclear technology. Besides, other studies have focused on valuing alternative reactor technologies that could help improving the economic performance of a nuclear system. Cardin *et al.* (2012) considered a first-of-a-kind commercial thorium-fuelled Accelerator-Driven Subcritical Reactor as a safer alternative for nuclear power generation. Jain *et al.* (2013b) focused on small- and medium-sized reactors (SMRs) and investigated the economic impact of modular construction of such reactors. See, for example, Jain *et al.* (2014); Locatelli *et al.* (2015); Siddiqui and Fleten (2010); Zhu (2012), for other applications.

2.3 Social acceptance of nuclear technology

Grimston *et al.* (2014) introduced six factors that can affect decision-making regarding the siting of nuclear power plants, where the social factors are recognized as public support for the maintenance of existing nuclear power plants and establishing more nuclear power plants nationwide. Abrecht *et al.* (1977) discussed several ethical issues that affect public support. This support, or acceptance, is regional because the factors influencing it are different across the world, such as national economic conditions (e.g., GDP), recognition of current nuclear technology, etc.

Nuclear events, wherever they occur in the world, may significantly reduce public support. The Chernobyl disaster in 1986 in Ukraine was the worst nuclear accident in terms of costs and casualties. This catastrophe ultimately cost 18 billion rubles and affected adversely over 500,000 workers, with 31 people dying during the accident itself. After Chernobyl, the development of nuclear power plants slowed down significantly across the globe until 2005. In 2011, the disaster at the Fukushima-Daiichi plant in Japan due to a tsunami resulted in the nuclear meltdown of three reactors (Wakatsuki, 2014). Estimates of economic losses range from USD $250 billion to $650 billion (Lavelle, 2012). Influenced by the Fukushima accident, developed economies like Germany immediately closed its eight oldest nuclear plants and plans to gradually shut down the remaining ones until 2025, while Switzerland made similar decisions (Joskow & Parsons, 2012). Unlike Germany and Switzerland, some countries were not so constrained by social acceptance issues (Kidd, 2013). One such country is the United Kingdom, where the main policy response was targeted on existing facilities and was actually driven by European Union post-Fukushima requirements, including a set of nuclear "stress tests", which included

considerations of beyond-design-basis accidents. The South Korean government continued to operate its twenty existing nuclear power plants and plans to establish more by 2015 (Song *et al.*, 2013). Developing countries like China and India delayed their projects briefly but restarted then shortly afterward. Although such project delays are not considered as a social acceptance motivated policy response in our study, China is clearly social acceptance sensitive, and so is India. They too faced significant public reluctance, which was a significant issue in the decision-making process (Mishra, 2012).

Following the Chernobyl accident in 1986, the International Atomic Energy Agency (IAEA) was keen to enable prompt communications of safety information to the public, introducing a logarithmic index called the International Nuclear Events Scale (INES) in 1990, similar to the Richter magnitude scale for earthquakes. There are eight levels on the scale, seven of which are non-zero levels. Level 7 is the most severe level (i.e., major accident) and is where the Chernobyl and the Fukushima disasters were categorized. Examples of the other levels include the 1979 Three Mile Island accident near Harrisburg, Pennsylvania, in the United States (level 5: accident with wider consequences), and the 1999 Tokaimura nuclear accident in Japan (level 4: accident with local consequences). INES has been used as a proxy for assessing the perceived risks of nuclear power plants. Taebi and van de Poel (2015) discussed some important considerations, as well as social-technical challenges, regarding nuclear energy in the post-Fukushima era. Huang *et al.* (2013) and He *et al.* (2013) studied the impact of the Fukushima accident on the Chinese public in terms of risk perceptions and trust in government authorities, respectively. This study proposes to use and model the INES scale as a proxy for public acceptance of nuclear technology, as it is an important uncertainty driver potentially impacting future expected economic performance of nuclear capacity deployment.

2.4   Research gaps and contributions

Past studies on nuclear power systems considering the concept of flexibility focused more on real options "on" projects, as opposed to real options "in" projects, and few studies considered the effect of social acceptance in developing a decision support system for deploying nuclear system infrastructure. Among chief concerns, studies relying on standard ROA approaches may cause challenges for planners

and policy-makers trying to determine the optimal exercise policy if multiple flexibility strategies, uncertainty drivers, and flexible infrastructures are analyzed in a combined model.

In light of the above, this article introduces a novel approach based on decision rules and stochastic programming to analyze flexibility in nuclear infrastructure systems. The analysis helps determine the best capacity deployment strategies accounting for uncertainty in future demand, as well as social acceptance of nuclear power. The analysis recognizes the importance of social acceptance as an uncertainty driver, in addition to growing electricity demand, with scenarios developed and modeled under the sample average approximation method based on a realistic scheme already used worldwide for policy-making (i.e., INES). The form of the solutions obtained under the proposed approach can be used easily by decisions-makers, since they depend on the realizations of such uncertainty driver, as well as realized electricity demand, based on the approach for single-site analysis developed by Cardin *et al.* (2016). Building upon that knowledge, the study uncovers new alternative solutions for nuclear capacity planning and operations, incorporating: 1) strategic-level flexibility (e.g., capacity expansion) to deploy and manage the capacity of nuclear power plants over time over multiple sites, and 2) decision rules with optimal parameters (e.g., unit capacity to be expanded if needed) for exercising the relevant flexibility strategies in real-world activities. Such strategies might prove useful for emerging economies that are considering nuclear power as part of their future energy portfolio.

3   The Multi-stage Stochastic Model

In this section, the generic form of the mathematical model is introduced. This generic model is a multi-stage stochastic programming model based on sample average approximation. The more specific and detailed formulation of the optimization problem (i.e. objective function, decision variables, parameters) is provided in the Supplementary Material, and described in Section 4. The model is implemented and solved using a commercial and professional optimization software (i.e., AIMMS). There multiple scenarios considered in the optimization analysis are sampled by Monte-Carlo simulation with a given distribution information for electricity demand derived from historical data, and based on modeling of social acceptance. The optimization results are described in Section 4.1. In section 4.2, more samples

are generated and an out-of-sample analysis is conducted in the numerical experiment, to determine how well the solutions behave under a set of scenarios that were not used for the optimization analysis. A sensitivity analysis follows in Section 4.3 to account for imprecisions in salient parameter assumptions. Section 4.4 discusses the behavior of the alternative solutions obtained.

More specifically, the mathematical model derived from the generic formulation enables the analysis of three strategic-level real options (or flexibility strategies FS) for the design of flexible nuclear power systems. Firstly, the model accounts for flexible capacity expansion at any strategic period (FS-A). Once a plant is deployed, the capacity of this plant can be increased (or uprated) within its useful life (typically 40-60 years) when needed and when external circumstances make it allowable. This flexible expansion benefits from special attention in terms of infrastructure architecture and design (e.g., designing for smaller capacity first, and carefully planning for expansion in the future by installing new nuclear reactor, for instance). The capacity of a nuclear power plant is related to its ability to generate a given amount of electricity. Secondly, flexible phased deployment (FS-B) of plant capacity is analyzed, allowing the deployment of plants over time and space when needed and when external circumstances (e.g., social acceptance) are favorable. Social acceptance is a regional or country-wide factor of recognition that reflects public attitudes towards nuclear technology. Social acceptable can thus influence decision-making regarding capacity deployment of nuclear power plants. The level of acceptance can be diverse for people living in the same country, such as China and India. This study focuses on small- to medium-sized regions or provinces where people may have similar acceptance of nuclear technology. Thus, it is assumed in this study that social acceptance is identical across candidate sites considered in the analysis. Thirdly, the flexible design enables life extension (FS-C) for a plant when it is supposed to be closed (i.e., the useful life time is up), depending on the cumulative INES observed at that moment (i.e. a proxy for social acceptance). This cumulative INES is not a simple accumulation of INES at each period since the beginning of the study life. Instead, it is a rolling cumulative for just a few periods. This is considered because of the limited duration of human memory, and the fact that the effects of past nuclear accidents on the collective memory may not last for an extensive amount of time. It is safe to assume that past accidents may have impacts on decision making

regarding deploying nuclear power plants. This cumulative term, therefore, helps represent better the historical impact of nuclear events in a reasonable timeframe, as compared to using a single INES index.

The generic form of the optimization model is described as follows, with further details available in the Supplementary Material. Considering a life cycle planning horizon of T periods over which electricity demand and social acceptance are random. Index i denotes a candidate site for deploying a new power plant, and θ_{it}^s denotes the capacity deployed at site i at period t under uncertainty scenario s. To simplify the model, it is assumed that geographical locations of candidate sites are given information, and that all candidates are suitable for deploying nuclear power plants. Therefore, the number of candidate sites is limited because the location requirements are extremely strict. Let cost functions $C_t^s(\theta_t^s, \xi_t^s)$ and $\mathcal{H}_t^s(\theta_t^s, \theta_{t-1}^s)$ represent the basic costs (e.g., fixed costs, reactor costs) and costs associated with flexibility strategies (e.g., flexible phased deployment, capacity expansion), respectively. Note that θ_t^s is the total capacity deployed over the system scale. It also should be noted that $\xi_t^s \in \mathbb{R}, t = 1, \dots, T$, is the uncertainty (i.e., electricity demand and social acceptance) considered in the design and treated as stochastic process. x_t^s is the vector of decision variables chosen at period t based on information observed up to now (i.e., $\xi_{[t]}^s$). Equation (1) is the general form of objective function that aims at minimizing the expected total costs over the life cycle. $f_t(.)$ are continuous functions of interests, and consist of $C_t^s(\theta_t^s, \xi_t^s)$ and $\mathcal{H}_t^s(\theta_t^s, \theta_{t-1}^s)$.

$$Min \quad f_1(x_1) + E\left[Q_2\left(x_1, \xi_{[2]}\right)\right] \tag{1}$$

$$s.t. \quad Q_t\left(x_{t-1}, \xi_{[t]}\right) = f_t\left(x_t, \xi_{[t]}\right) + \sum_{s=1}^{S} p_s Q_{t+1}^s\left(x_t, \xi_{[t+1]}\right), \ t \in \{2, \dots, T\}; \tag{2}$$

$$x_1^k = x_1^l, \ \forall k, l \in \{1, \dots, S\}; \tag{3}$$

$$\mathcal{F}_t^s\left(\theta_{t-1}^s, \xi_{[t]}\right) = \theta_t^s, \ s \in S, \ t \in \{2, \dots, T\}; \tag{4}$$

The optimal solution of a t-stage problem is denoted as $Q_t(x_{t-1}, \xi_{[t]})$, and it is equal to the sum of costs function and the expectation of $Q_{t+1}(x_{t-1}, \xi_{[t]})$. Equation (2) holds because of the assumption with

regards to the sample average approximation, where Ξ is a finite set of $\{\xi^1, ..., \xi^S\}$ with corresponding probability $\sum_{s=1}^{S} p_s = 1$, $p_s \geq 0$. Equation (3) ensures that initial decision making should be consistent under different scenarios (i.e., non-anticipative constraints). In Equation (4), $\mathcal{F}_t^s$ denote the abstract form of decision rules that map from each scenario to a solution at period t.

Other modeling assumptions include the fact that a plant will not be used again if it is closed, and this closure is effective immediately. The possible value of the cumulative INES is partitioned into three areas – safe, warning, and dead. If the cumulative INES falls into the safe area, the system will be operated as usual and all types of decisions will be available. If the cumulative INES falls into the warning area, however, the system can still be operated, but no flexibility strategies can be exercised until the cumulative INES falls into the safe area again. When the cumulative INES falls into the dead area, the whole project will be terminated immediately, and it will not be opened again for the remainder of the study life. To simplify the model and analysis, it is assumed that a nuclear power plant will not continue to generate electricity after a decision is made to close the plant. Yet to fulfill the contract the system will purchase electricity from the market, which imposes as a penalty. The threshold values for partitioning these areas are predetermined by experienced professionals, and they may not necessarily be the same in different countries.

4   Numerical Analysis

The case study focuses on how to site and manage the nuclear power system capacity over the next 40 years (which is the study life) in a hypothetical region or province of a developing country like China or India, considering uncertainty in long-term electricity demand and social acceptance. The purpose of the study is to determine: 1) the usefulness of the concept of flexibility in deploying and managing new nuclear power capacity and 2) evaluating the value of flexibility based on uncertainty realization. The analysis focuses on how to flexibly site nuclear power plants in such developing economy, assuming there is a clear governmental wish to further develop and expand nuclear power capacity – as motivated in Section 1. The number of candidate sites for the plants is assumed to be six due to the availability in

the hypothetical region. Most parameters are chosen for demonstration purposes and need to be adapted to the realities of a given country and context.

Four alternative design solutions are analyzed and compared subject to both long-term electricity demand and social acceptance uncertainty (see Fig. 1). The first design is termed the "rigid design" or deterministic design, and it deploys all resources at once at the beginning of the study life. The rigid design deploys capacity in a stochastically optimal manner in light of anticipated scenarios (i.e., considering multiple forecasting scenarios in the modeling session). This design captures a robust approach to capacity deployment under uncertainty and aims to maximize cost effectiveness considering a wide range of uncertainty scenarios. The other three design alternatives are proposed based on the concept of flexibility, in which three flexibility strategies are considered. The first strategy is flexible capacity expansion (i.e., FS-A), which allows an existing nuclear power plant to install additional nuclear reactors *if and when needed*. More specifically, the expansion strategy will be exercised when 1) the demand is not fulfilled for $t_d = 3$ consecutive years, 2) social acceptance falls into the safe area (i.e., $I_{ts} \leq q_1$), and 3) there is(are) plants that do not reach their upper bound in terms of capacity. The second strategy is flexible capacity deployment (i.e., FS-B). It allows the system to deploy flexibly new nuclear power plants over time (not necessarily at period $t = 0$), and over space (multiple candidate sites). It is akin to a deferral real option whereby new plants will only be deployed *if* market conditions are favorable. The conditions for exercising the deployment strategy are similar to those of the capacity expansion strategy, except that it requires empty sites to install new plants. The third strategy is called life extension (i.e., FS-C). This alternative allows an aged power plant to extend its lifetime by an additional period, if certain conditions are met. In this study, enabling FS-A may require a structural feature regarding the power plant and it thus introduces a cost premium to enable the flexibility. For FS-B and FS-C, there is no cost premium for the flexibilities. FS-A and FS-B are considered in Flex A design, while FS-C is considered in the Flex B design. As a combination, Flex C design takes into account all three flexibility strategies. The rigid and Flex A designs do not incur any life extension, while the Flex B-C designs incur a life extension governed by decision rules, and subject to social acceptance. All designs have an early shutdown capability if social acceptance is not favorable.

To have a clear idea of flexible designs, the reader is referred to a table containing all flexibility strategies (see Table 5), and the full mathematical model in the Supplementary Material.

Electricity demand (i.e., d_{ts}) is simulated via a Geometric Brownian Motion (GBM) process with a particular expected growth rate ($\mu = 10.11\%$) and volatility ($\sigma = 3.59\%$) as shown in Equation (5), with values extracted from historical data. W_t is a Wiener process or so-called Brownian motion.

$$dS_t = \mu S_t dt + \sigma S_t dW_t; \tag{5}$$

The values for the GBM parameters are obtained from the statistical analysis using real data from electricity production in China from 2000 to 2014 (Enerdata, 2015), as can be found in Fig. 2. It provides historical information on electricity production in different countries, including China, the United States and India. Specifically, the same approach as presented in Jin *et al.* (2011) is used here, calculating the logarithm of the percentage changes for every year (i.e., $Y(t) = \log(X(t)/X(t-1))$), where $X(t)$ is the electricity production in year t. Since variables $X(t)$ are independent and identical distributed, $Y(t)$ is suitably normalized and $\{Y(t)\}$ thus should be approximately behaving as a GBM process (Ross, 1995). The value of the initial point (i.e., S_0) is 5.583 TWh (equivalent to 0.005583 billion MWh), which is 0.1% of the total electricity production in China in 2014. This assumption is realistic because this province may be underdeveloped and only 10% of local electricity demand in the country is currently supplied by nuclear power. Refer to public sources (e.g., IAEA (2016)), nuclear power accounted for only 3.03% of the total electricity production in China up to 2015. It is therefore safe to assume a goal of 10% of total electricity production from nuclear power plants in the case study, according to reports published on the World Nuclear Assocation (2016). Fig. 3 illustrates some outcomes of the GBM process generated for the out-of-sample analysis. The costs and generation assumptions are adapted from the paper by Steer *et al.* (2012) and Jin *et al.* (2011), and are detailed in the supplementary material. Several figures are valid as of 2006, and are converted from British pounds to US dollars. The variable cost (e.g., operation and maintenance costs, fuel costs) is assumed to increase gradually by a given annual growth rate (i.e., 3% for O&M costs and 2% for fuel costs). To simplify the assumptions, costs associated with shutting down a unit or plant is not considered in the case study.

We do not explicitly include this cost because of the modeling complexities involved, such as waste management and disposal, which is beyond the scope of the study.
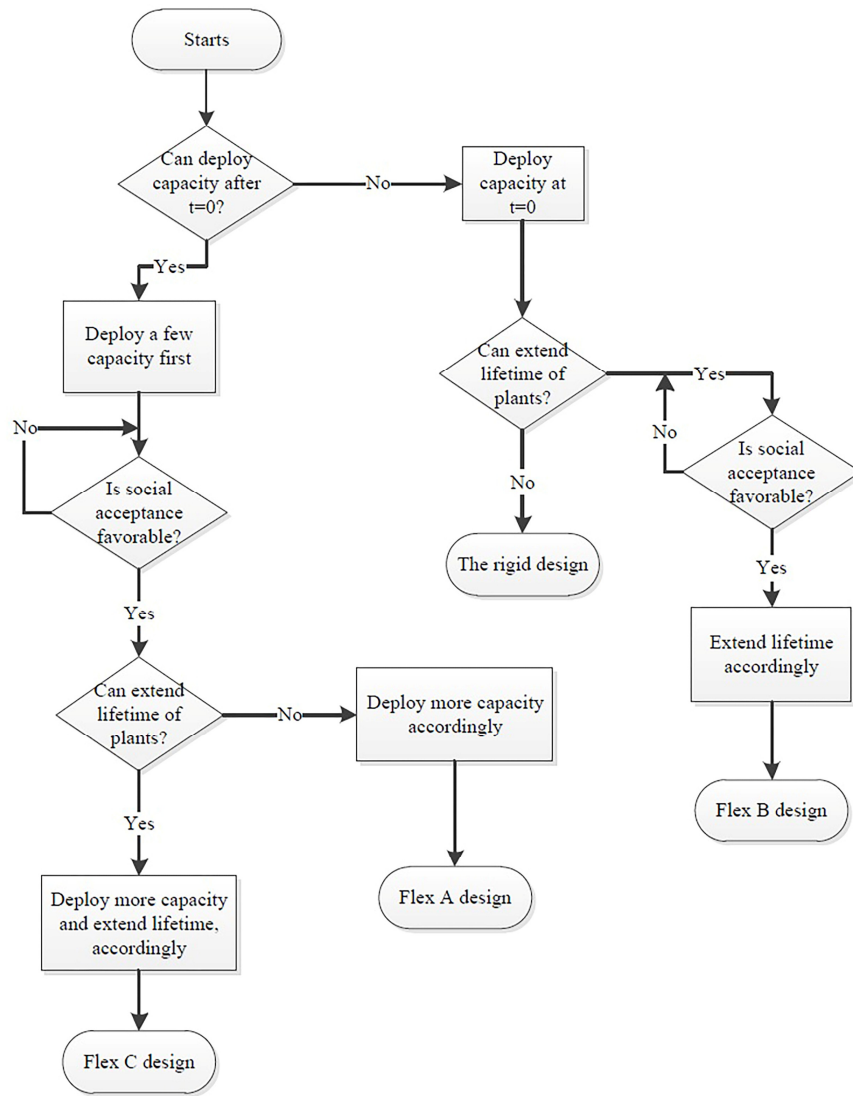

Fig. 1. A flow chart illustrating the decision-making dynamics for all four design alternatives.

As a significant input parameter, it is assumed that social acceptance is a major concern for the decision-making authorities, which either reflects the concerns of the population within the country or at an international level (e.g. from neighboring countries). For demonstration purposes, the lower bounds for the warning and dead areas are assumed to be fairly low at 5 and 7, respectively, meaning that the country is relatively conservative in terms of social acceptance. Social acceptance (i.e., I_{ts}) is modeled using the cumulative INES, as introduced in Sections 2-3. Since this INES factor is intended to be

logarithmic according to its definition, it is assumed that this factor is generated through formulas (6) and (7). Parameter i denotes the level of this INES factor, and $p(i)$ is the corresponding probability. More specifically, the approach firstly samples a value between 0 and 1 based on a uniform distribution. This value is then categorized into one of these levels accordingly. For instance, if $\beta = 2$ and the sample is 0.85, then it implies that the INES factor of this year is level 2.

$$p(i) = p(0)\beta^{-i}, \ i = \{1,\dots 7\};\tag{6}$$

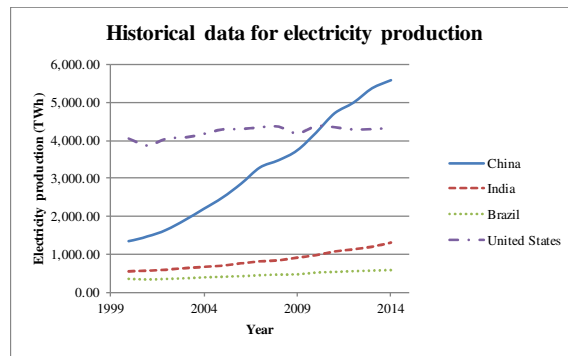$$\sum_i p(i) = 1, \ i = \{0,\dots 7\};\tag{7}$$

Fig. 2: Historical electricity production from the year 2000 to 2014.
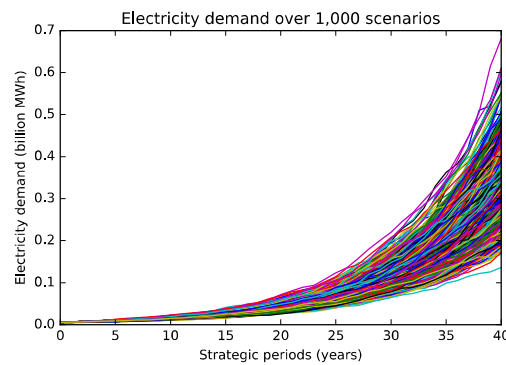

Fig. 3. Demand for electricity throughout plant lifetime over 1,000 scenarios

The probability of one level is approximately $1/\beta$ that of the previous level, i.e., $p(i) = \frac{1}{\beta} p(i-1), i = 1, \ldots, 7$. Parameter β is referred as a magnification factor on the logarithmic INES scale, which is nominally assumed as $\beta = 3.5$ in this case study, based on expert discussions. Note that there is no confirmed approach to assign a value to this magnification factor. A better and more realistic value of β may requires more sophisticated research of the historical data and social impacts, which is out of the scope of this study. Different β values are considered in the sensitivity analysis Section 4.3 to determine the impact on the value of flexibility.

The value of flexibility is assumed to be the difference between the expected total costs of any flexible design and the rigid design used as a benchmark, as shown in Equation (8). The expected value of total costs can be obtained through the out-of-sample analysis, which will be introduced later.

$$E\big[Value(\text{Flex})\big] = \max\big(0, E\big[Total(\text{Rigid})\big] - E\big[Total(\text{Flex})\big]\big); \qquad (8)$$

Typically, there is a cost premium for enabling flexibility. It is, however, not included in the construction costs. The difference in Equation (8) thus indicates the upper bound on the cost premium that the decision-makers should be willing to pay to embed flexibility in the nuclear power system. This cost may vary depending on the system; location, technology, the need for shared infrastructure to plan for capacity expansion, purchase additional land, and other socio-economic conditions that are difficult to detail here, and are out of scope. The max condition captures the fact that if flexibility does not create positive value (e.g., cost savings), it will not be embedded in the system design – and therefore, the lower bound is 0.

Firstly, all design alternatives were solved to optimality in the optimization procedure. The optimal solution(s) then went through an out-of-sample test to verify the robustness of the solution in the face of unseen scenarios. After that, a sensitivity analysis was conducted to show how objective values evolve when input parameters changed. The computational analysis was run on a desktop PC machine with a 3.30 GHz CPU and 8.0 GB of random access memory (RAM). All design alternatives were coded in AIMMS 4.2 (AIMMS, 2014) and CPLEX 12.6 was used as the MIP solver. Since the model is

formulated as a mixed-integer program based on the sample average approximation, the default algorithm is used for solving it. This default algorithm for MIP is the standard Branch and Bound (B&B) method, which terminates when the relative gap is smaller than or equal to 0.01, or the number of iterations reaches an upper bound (e.g., 20 million), or the computation time reaches an upper bound (e.g., 10,000 seconds).

4.1 Uncertainty and flexibility analysis

Table 1 lists the characteristics of the four design alternatives in terms of the problem size and optimization results, while Fig. 4 and Table 2 illustrate the solutions obtained for the four designs. The solutions were obtained via a standard Branch and Bound algorithm with given stopping criteria. Note that some solutions (e.g., Flex A and C designs) are not the true optimal solutions because the algorithm terminated before converging. However, they are good enough in terms of the quality of the solution, and enable a fair comparison between one another (e.g., solution of Flex A is even smaller than that of Flex B, while the gap of Flex A is larger). The expected total cost for the Flex C design is 23.42% less than for rigid design, considering the best solutions. More specifically, Fig. 4 compares the capacity evolution at site 1 (i.e., variable x_{jvts} as defined in the mathematical model in the Supplementary Material, where $j = 1$) under two sample scenarios, out of the ten scenarios used for optimization. It shows, for instance, that the plant at site 1 is closed at period 18 (which is earlier than its lifetime) because social acceptance is not favorable in sample scenario 2, as the cumulative INES falls into the dead zone at that time. The second column of Table 2 displays the initial deployment plans (i.e., variable o_{jv}^1) for the flexible design alternatives. For Flex A design, 1 unit of capacity (i.e. 600 MWe, see Table 6 in the Supplementary Material) is equally deployed at sites 3 (i.e., $o_{jv}^1 = 1$ where $j = 3$ and $v = 1$) and 6 since the beginning, respectively. For Flex B design, 3 units of capacity are equally deployed at each site 1, 2, and 3, while 3 units of capacity are equally deployed at sites 2, 4, and 6 for Flex C design. Column 3 shows the threshold (i.e., x_d) to determine whether the demand satisfaction is fulfilled or not, while columns 4-7 represents the values for decision rule parameters. For Flex A (C) design, if the system loses more than $x_d = 3.3434\%$ (0.0001%) of electricity demand for 3 consecutive years, the planner may expand capacity by $m_e = 1$ (1) unit of capacity at $n_e = 2$ (3) non-empty sites, or deploy

$m_c = 3$ (3) units of capacity at $n_c = 4$ (3) empty sites, depending on the feasibility of the expansion.

Columns 8 and 9 list the threshold values for partitioning the cumulative INES into safe-unsafe areas.

If the cumulative INES is greater than or equal to the threshold $q_1 = 5$ but less than the threshold $q_2 = 6$ (i.e., the cumulative INES falls into the warning area), the system can still be operated but no strategic-level decisions can be implemented.

Table 1. Characteristics and results for design alternatives

Alternatives	No. of constraints	No. of integer variables	Best LP bound ($billion)	Best solution ($billion)	Gap (%)	CPLEX time (sec)
Rigid	35,465	16,076	158	158	0.00	2.5
Flex A	89,685	27,510	99	133	25.48	9531.07
Flex B	35,865	16,226	138	138	0.00	3.24
Flex C	91,485	27,510	94.47	121	21.81	6277.08
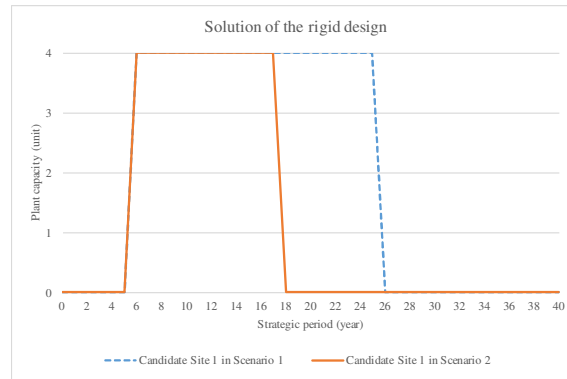
Fig. 4. Illustration of the solution obtained for the rigid system ($r = 10\%$).

Table 2. Tabular illustration of solutions obtained by the flexible designs

Alternatives	o_{jv}^1	x_d	m_e	m_c	n_e	n_c	q_1	q_2
Flex A	1 ($j = 3, 6$)	0.033434	1	3	2	4	5	7
Flex B	3 ($j = 1, 2, 3$)	N.A.	N.A.	N.A.	N.A.	N.A.	5	7
Flex C	3 ($j = 2, 4, 6$)	0.000001	1	3	3	3	5	7

4.2   Out-of-sample analysis

Table 3 shows the values of the significant performance measures, based on 1,000 out-of-sample scenarios generated through the same GBM process used to produce the ten samples for optimization purposes. The purpose of this out-of-sample analysis is to estimate the performance of the solution based on forecasts calibrated using historical data, albeit using scenarios that were not used during the optimization process. It helps to evaluate how well the solutions perform on scenarios that were not seen and deal with the issue of over fitting. It is a complementary analysis of the in-sample test because modelling that relies only on in-sample tests is likely to understate the error and overfit the features (Tashman, 2000). The possibility of overfitting exists because the criterion used for optimizing (or training) the model is not the same as the criterion used for judging the efficacy of the model. The optimal solution of a stochastic model is obtained by optimizing the model based on seen or given data, but the efficacy is determined by the ability to perform well on unseen data. This unseen data is not necessarily based on the same distribution as the given data. Therefore, the efficacy of the solution of a model could be much lower than expectations if the model is developed, solved, and tested under the same group of data.

As can be seen, the Flex C solution has the lowest expected total costs across all designs, which are 24.48% less than the highest cost. It is also the best of the four designs in terms of all performance measures except STD and Standard error. The value of flexibility for Flex A, $VoF(A)$ = \$23 billion, as compared to the rigid design. This value is mainly attributed to both capacity expansion (FS-A) and phasing deployment (FS-B). Given that Flex B only contains life extension flexibility (FS-C), its value of flexibility $VoF(B)$ = \$20 billion indicates that life extension alone has such value, as compared to the rigid design. Flex C, on the other hand, contains all three flexibility strategies (FS-A, -B and -C), its value of flexibility $VoF(C)$ = \$35 billion is attributed to a combination (or interaction) of all three flexibility sources, which makes it less than the linear sum of the VoFs above. Therefore, life extension is slightly less valuable as compared to capacity expansion plus phasing deployment, based on the information given above. It is also possible that life extension is slightly more valuable than capacity expansion or phasing deployment, as the sum of these two strategies is just slightly greater than the

value of life extension alone (e.g. Flex A design may be lagging or deploying capacity not fast enough under some scenarios, and therefore life extension may not be as valuable in some cases).

Table 3. Results for the out-of-sample analysis ($billion)

Alternatives	Mean	STD	P5	P95	Standard error	VoF
Rigid	143	28	104	194	0.168	-
Flex A	120	30	79	175	0.175	23
Flex B	123	31	83	184	0.179	20
Flex C	108	32	67	171	0.182	35
Best?	Flex C	Rigid	Flex C	Flex C	Rigid	Flex C

Fig. 5 illustrates the out-of-sample analysis in terms of cumulative density functions. Expected costs for Flex C design are clearly lower than those for other designs, while expected costs for Flex A design are close to those of the Flex B design. Also, the expected costs for flexible designs are much lower than the rigid design. This shows that more typical flexible strategies of phased deployment and capacity expansion, and novel flexibility strategy of life extension, do add as much value to the system even when the discount rate is fairly large (i.e., 10%) and when public acceptance is taken into consideration. This makes sense because the implemented flexibility may result in enough financial return (i.e. cost savings) from the investment if the project ends earlier.
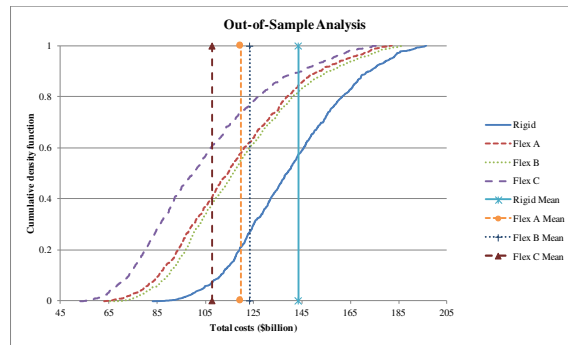
Fig. 5. Cumulative density functions for the out-of-sample analysis ($r = 10$%).

4.3 Sensitivity analysis

The sensitivity analysis shows how uncertainty in the output is affected by variability in the input parameter assumptions. A one-factor-at-a-time (OFAT) approach is applied to identify how the significant parameters (e.g., expected growth rate, discount rate) influence the expected value of

flexibility. The corresponding results are shown in Tornado diagrams in Fig. 6. The terms "base", "low", and "high" represent different values for the significant parameters, which are listed in Table 4. In the flexibility analysis above, the parameters used are based on the base case values listed in Table 4, except for mean growth rate and volatility (which are based on the upper cases). The low and base values for mean growth rate and volatility are calculated from actual electricity production data in the United States and India. This examines how the value of flexibility evolves if the flexibility strategies are applied to a developing economy with slower growth than China (e.g., India), or like a developed economy (e.g., the United States), instead of simply focusing on an optimistic demand growth scenario (i.e., China). The low value for magnification is $\beta = 3$ because too small magnification makes little sense in reality (i.e., the probability of occurrence of the high-level events is considerably large). The cost associated with a penalty is also known as the Value of Lost Load (VOLL). The Levelized Cost of Electricity (LCOE) for nuclear power was around 80 to 105 British pounds in 2010 (Department of Energy and Climate Change (2011)). A medium penalty cost is thus assumed to be around twice the highest value of the real LCOE, which is £200/MWh, or the equivalent of $364.33/MWh when converting from British pounds to US dollars using the exchange rate from 2006.

Table 4. Values for the significant parameters in the sensitivity analysis

Parameters	Low	Base	Upper
Mean growth rate (μ)	0.0047	0.0587	0.1011
Volatility (σ)	0.0197	0.0273	0.0359
Discount rate (r)	7.5%	10%	12.5%
Magnification (β)	3	3.5	4
Penalty costs ($/MWh)	273.25	364.33	455.42

Fig. 6 shows the results of the sensitivity analysis focusing on the value of flexibility when each parameter is varied independently, while keeping other parameters at their constant base value. As can be seen, this value is most affected by the discount rate, then by expected growth rate and the penalty costs. The lower (higher) the discount rate, the more (less) valuable flexibility is. Therefore, the ability to avoid unnecessary cost deployment as enabled by the flexible alternatives should have a bigger (lower) impact in terms of expected discounted cost savings when the discount rate is lower (higher).
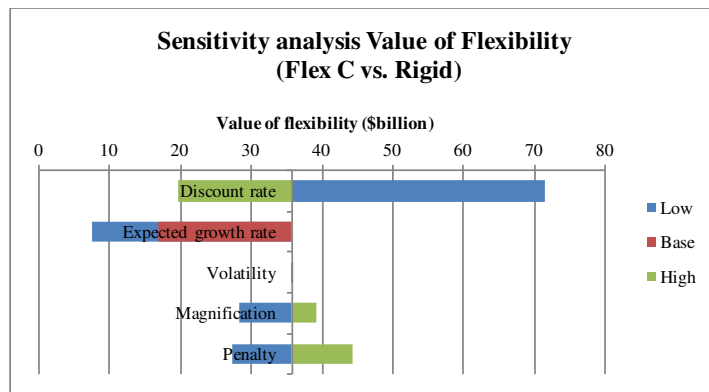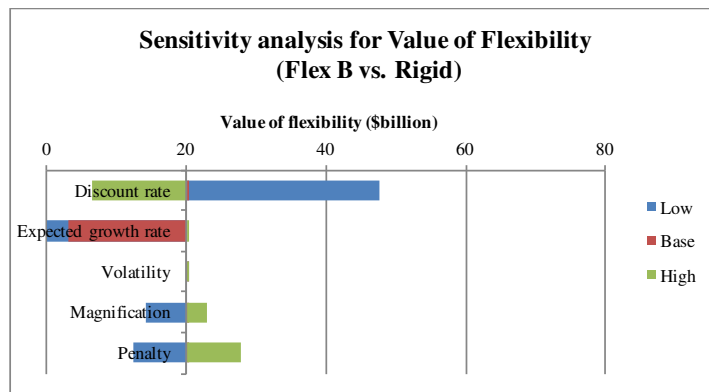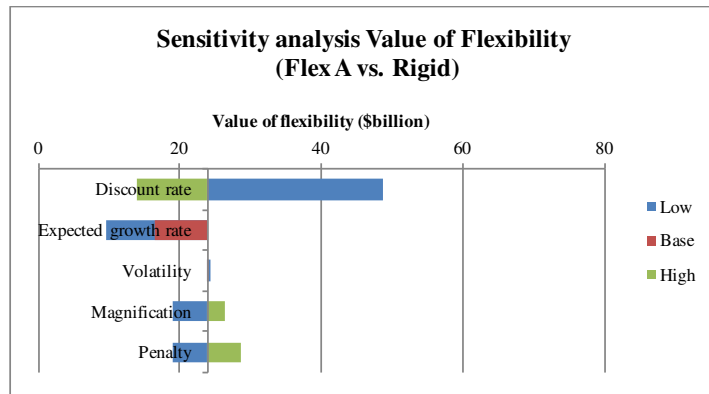
Fig. 6. Tornado charts for the value of flexibility.

As the expected growth rate decreases, flexibility also becomes less worthwhile, as there may not be as much need for change over a longer term horizon. The value of flexibility also decreases (increases) when the penalty cost decreases (increases). This is because the planner can consider losing some demand instead of deploying new capacity to satisfy the demand. As magnification decreases (increases), the probability of accidents (level 4 and above) decreases (increases), and the value of

flexibility, therefore, decreases (increases). One interesting observation is that volatility has very little impacts on the value of flexibility. One may expect higher volatility to increase the expected value of flexibility. This may be because the value of volatility considered in the analysis is too small to enable the system to deal better or worse when uncertainty is more (less) significant.

4.4 Rigid design vs. Flex C design

This subsection revisits the rigid and Flex C designs in order to illustrate the benefits of the Flex C design over a more rigid solution. These two design alternatives are analyzed in the same exogenous scenarios, which are selective samples from the 1,000 out-of-sample scenarios in the previous subsection. It also aims to show some extremely rare cases where the rigid design performs best. Fig. 7 details the two sample scenarios used to analyze the performance of these two designs when the discount rate is 10%. As can be seen in the second graph of Fig. 7, the cumulative INES never goes up to 5 in Scenario 1, which implies that the flexibility strategies will always be exercised if and when needed. On the other hand, in Scenario 2, the cumulative INES goes up to 7 in periods 22 and 40, and up to 6 in several other periods. This indicates that the system will be closed after period 22, and flexibility strategies may not be implemented for this reason.
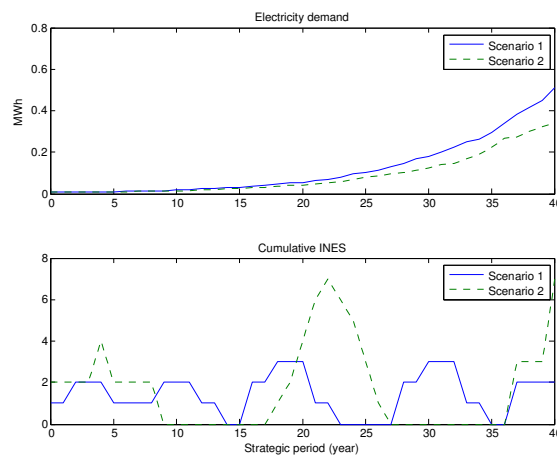

Fig. 7. Projections of an uncertainty scenario. (Above) electricity demand; (Below) cumulative INES. Fig. 8 shows clearly how these two designs perform under the same assumptions and the same exogenous scenarios depicted in Fig. 7. The negative value indicates that electricity production (i.e.,

supply) is less than customers' needs (i.e., demand), and vice versa. In Scenario 1 the rigid design deployed 4 units of capacity at both sites 1 and 2 (8 units of capacity in total) at the beginning of the study life, while Flex C design only deployed 1 unit of capacity at sites 2, 4 and 6 (3 units of capacity in total), respectively. The rigid system then stopped operations after year 26 (i.e., capacity becomes zero) due to the limited lifetime of the plants. In contrast, the Flex C design gradually deployed capacity based on the decision rules and kept operating until the end of the life cycle of the system. The phased deployment and capacity expansion strategies allow the system to deploy capacity over time and space, while the life extension strategy extends the lifetime of a plant to 30 years (the original useful life is 20 years). These flexibility strategies enabled the system to generate more electricity, and thus reduced the total expected costs because the system needed to buy less electricity from the market over its lifecycle. Although the Flex C design dominates stochastically the rigid design, there are few scenarios where the rigid design performs best, namely Scenario 2 in Fig. 7. This is because the initial capacity deployed for the rigid design is higher than the Flex C design (i.e., 8 units vs. 6 units), while the flexibility strategies could not be fully exercised due to the realization of the scenario (e.g., unfavorable market conditions and social environment). The two graphs in Fig. 8 show how the Flex C design differs from the rigid design, and how much system operators could benefit from enabling flexibility under certain conditions. One should note that this example capacity deployment applies only to the scenarios shown in Fig. 7. Every new combination of scenario would lead to a different capacity deployment path, based on the stochastically optimal decision rules found by solving the mathematical model (see Supplementary Material). This dynamic property of the flexible solutions is an important benefit of the approach used for real option and flexibility analysis.
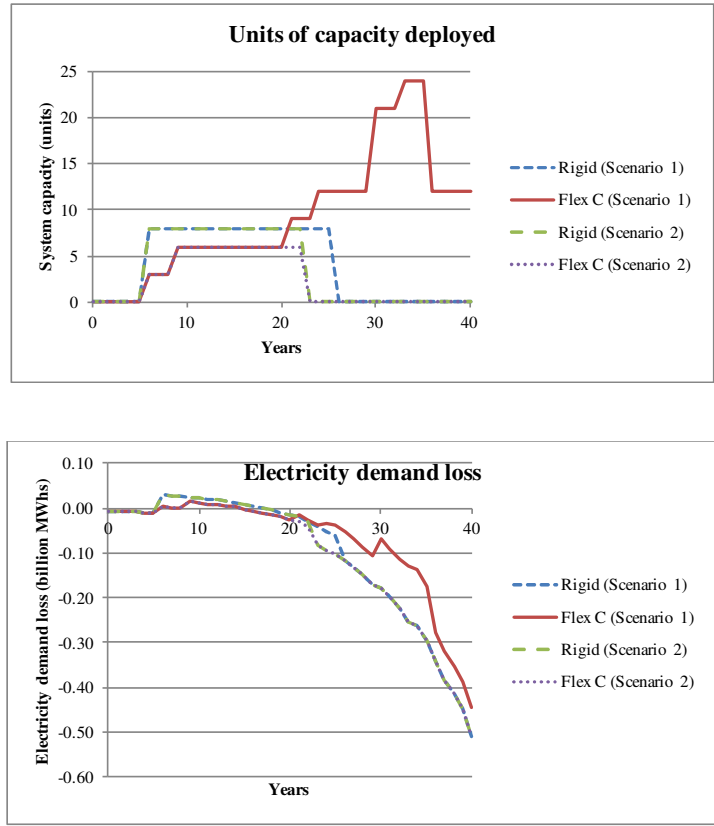
Fig. 8. Performance comparison between Rigid and Flex B designs.

5   Conclusions

Growing electricity demand will inevitably lead energy planners to face the issue of public acceptance of nuclear technology in the near future. The main contribution of this paper is a novel approach combining decision rule and stochastic programming for determining the optimal technology, design and deploying policies for nuclear power infrastructure systems. The approach exploits the idea of strategic-level flexibility to improve the expected life cycle performance of the system under long-term uncertainty in electricity demand and social acceptance. It shows how a decision rule based approach can be further extended to consider simultaneously multiple flexibility strategies, uncertainty sources, and sites for capacity deployment, which as not yet been done (Cardin *et al.*, 2016). The case study results focusing on nuclear capacity deployment in a province of a developing economy like China from showed that a flexible system combining capacity deployment, expansion, and life extension (i.e. the Flex C design) could significantly reduce the expected total cost and outperformed the three other

designs, including a rigid design that determines the stochastically optimal deployment plan over the system lifecycle. In addition, the sensitivity analysis showed that all flexible systems provided better adaptability and higher value than a stochastically optimal but rigid design strategy when assumptions about input parameters change. This analysis also demonstrated that the flexible designs are better at taking advantage of upside opportunities and reducing downside risks in demand and social acceptance, thus improving overall the expected economic performance and costs.

Another contribution of this study was the demonstration of a feasible optimal deployment plan for deploying nuclear power systems, which may provide useful insights to policy and decision-makers. A planner could deploy an amount of capacity firstly at the beginning of the lifecycle, following the recommended initial configuration, and deploy additional capacity following the decision rule guidelines. After initial capacity deployment is complete, the decision-maker monitors the demand satisfaction for the past several periods (e.g., three years in this study) to decide whether or not to add more capacity, and monitors as well social acceptance levels for nuclear technology – which can be assessed via polls, complemented by a proxy such as the INES system. S/he may decide whether or not to exercise flexibility strategies or keep operating the system at specific times, and revisit such decisions on a regular basis.

There are, however, several shortcomings in this study that fuel opportunities for future work and improvement. First, the model inherits weaknesses from the stochastic programming and the sample average approximation method, i.e., the observed performance difference between optimization and when the out-of-sample analysis is performed. If the distribution of the future demand is not perfectly fitted with the distribution considered in the model, the result may not be as good as expected. Second, the flexibility strategies considered in this study may not be the only ones feasible. It is possible to find other practical flexibility strategies and/or decision rules to improve the expected system performance. Furthermore, the assumptions of the method for generating INES are made based on the authors' understanding of the scale system. There is no unique and ultimately accepted approach for generating such data at present times in simulations. The demonstration is intended to be used as guidelines, and can be modified in the model. Moreover, some assumptions may be revisited, since some

simplifications have been made to suit the purpose of the study. For instance, demolishing a unit or plant would result in issues regarding waste management and disposal, as well as corresponding costs. Considering post-closure issues and costs could make the analysis more realistic and reliable. Also, the study life of nuclear power plants can be longer (e.g., 60 years) and close to the real useful life of nuclear power plants.

To further improve this work, the generation of INES indices could be modeled more closely through detailed data analytics and calibration. This may require a more in depth study of the INES factor, and the treatment of ethics as far as nuclear power is concerned – see studies by Taebi and van de Poel (2015). Relaxing some of the assumptions (e.g., a power plant can operate for a few years after a decision is made to close the plant) or modifying important parameter inputs (e.g., study life) may be an opportunity for future work. The consideration of uncertainty in construction costs could also make the study more realistic. In addition, the proposed model could be modified to analyze other strategic-level flexibility (e.g., switching between technologies, safety upgrades), objective functions (e.g., net present value), and/or to test various decision rules. The proposed model could be generalized accordingly as a framework to the analysis of facility location problems, considering flexibility in infrastructure systems. To improve the attributes of the solution, such as the Quality of the Solution (QoS) and the Time to Best Solution (TBS), more advanced algorithms could be developed to accelerate the solving (e.g., based on Bender's decomposition). Last but not least, the proposed design alternatives could be of interest for facility location problems in the energy sector as a whole, considering uncertainty. The analysis of the capacity deployment problem of nuclear power plants illustrates the potential of the proposed framework for flexibility and real options analysis.

Acknowledgements

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Supplementary Material

Data Replication

Data and programs used in this paper are available to any researchers for purposes of replication. All materials can be provided on request by contacting the corresponding author.

The International Nuclear Event Scale (INES)

The International Nuclear (and Radiological) Event Scale (INES) was introduced in 1990 by the International Atomic Energy Agency (IAEA) to serve as "a tool for promptly and consistently communicating to the public the safety significance of events associated with sources of ionizing radiation" (International Atomic Energy Agency, 2015). The scale is intended to be logarithmic, and each increasing level represents an accident approximately ten times more severe than the previous level. The following figure shows the severity structure of the INES factors. Level 1 to level 3 are defined as incidents, while level 4 to level 7 are referred to as accidents. Level 0 is deviation, which has no safety significance (e.g., a fire in the Nuclear Waste Volume Reduction Facilities of the Japanese Atomic Energy Agency in Tokaimura). To help understand the INES and its level, a few examples are listed below.
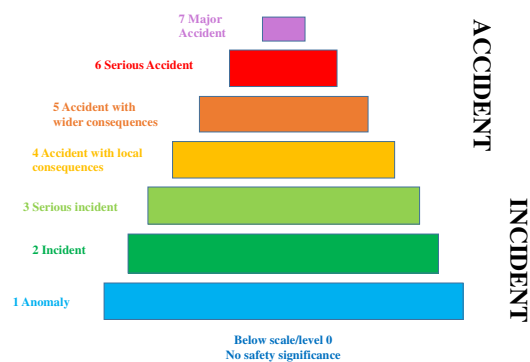

Fig. 9. Visualization of the structure of the INES (International Atomic Energy Agency, 2015).

Level 7 is also called major accidents, and corresponding examples are the Chernobyl disaster in Ukraine and the Fukushima disaster in Japan. Level 6 is serious accidents, such as the Kyshtym disaster

in the USSR in 1957. Level 5 and level 4 are accidents with wider (local) consequences. For example, the Three Mile Island accident in the United States in 1979 (level 5), and the Buenos Aires criticality accident on a research reactor in Argentina in 1983. Other examples are the THORP plant incident in the UK in 2005 (level 3), and the TNPC incident in France in 2008 (level 1).

Attributes of all flexibility strategies and flexible designs

Table 5. A simple outline of flexible designs and flexibility strategies

			Flex A	Flex B	Flex C
Flexibility strategies	FS-A: Flexible capacity expansion	A nuclear power plant could be uprated if needed.	√		√
	FS-B: Flexible phased deployment	Nuclear power plants could be deployed over time and space.	√		√
	FS-C: Life extension	The useful life of a nuclear power plant could be extended if need.		√	√

Mathematical Model

The following summarizes the modeling notation. For simplicity, the values of the parameters considered in the numerical study are also shown here:

T = the set of strategic periods in a complete life cycle ($t \in T, |T| = 40$), which is the study life;

T_1 = the set of strategic periods excluding $t = 0$;

J = the set of candidate sites for the nuclear power plants ($j \in J, |J| = 6$);

S = the set of uncertainty scenarios ($s \in S, |S| = 10$);

V = the set of plant phases ($v \in V, |V| = 4$);

d_{ts} = the demand for electricity within strategic period t under scenario s;

I_{ts} = the cumulative INES factor in strategic period t under scenario s;

r = discount rate per strategic period (e.g., 10%);

p_s = the corresponding probability of scenario s (e.g., 10%);

v^*, v^{**} = the smallest and biggest phases of a plant, respectively;

U', U^* = the smallest and biggest capacity of a plant, respectively;

$C_{fix}, C_{rac}, C_{var}, C_{fuel}$ = the fixed costs ($954.55 million), unit cost of a nuclear reactor ($1.776 billion), unit variable cost ($7.01/MWh), and unit cost for fuel ($2.00/MWh), respectively;

C_p = the unit cost of losing electricity demand ($364.33/MWh). This penalty or contractual cost would occur when power plants cannot generate enough electricity to meet the electricity demand;

t_c, t_e, t_l = the delay periods for new plant construction (6 years) and capacity expansion (3 years), and the additional period for life extension (10 years), respectively. For instance, a plant is decided to be deployed at $t = 0$, and this plant will be available for use starting from $t = t_c$;

t_d = the review period for the decision rules regarding phased deployment and capacity expansion;

t_{LE} = the first period when life extension is available;

θ_j = transmission loss factor of electricity for a plant at site j. The corresponding transmission loss factor is simply assumed to be inversely proportional to the distance between electricity generators (i.e., nuclear reactors) and electricity consumers linked by the power grid network, which are 1 (θ_1), 0.98 (θ_2), 0.96 (θ_3), 0.94(θ_4), 0.92(θ_5), and 0.9(θ_6), respectively;

ε, M = a small tolerance (e.g., 10^{-3}) and an arbitrary large integer (e.g., 10^{6}), used to ensure a given constraint is always or never satisfied.

The specific decision variables are introduced as follows.

$o_{jv}^1 = 1$ if a phase v plant is deployed at site j in strategic period $t = 0$;

$o_{jts}^2 = 1$ if a plant is deployed at site j in strategic period $t \geq 1$ under scenario s;

$u_{jts} = 1$ if the capacity of a plant is expanded at site j in strategic period $t \geq 1$ under scenario s;

$l_{jts} = 1$ if the life cycle of a plant is extended at site j in strategic period $t \geq 1$ under scenario s;

$x_{jvts} = 1$ if a phase v plant is open at site j in strategic period t under scenario s;

$x_d \in (0,1)$, the threshold for triggering decision rules regarding phased deployment and capacity expansion;

q_1, q_2 = integers, the thresholds for partitioning the cumulative INES index into three zones, e.g., if this index is greater than or equal to q_2, it indicates that the cumulative index in t has fallen into the dead zone;

n_c, n_e = integers, the number of plants to be deployed or expanded if the decision rule is triggered, respectively;

m_c, m_e = integers, the capacity of a plant that should be deployed or expanded if the decision rule is triggered, respectively;

CO_{jts}, CE_{jts} = integers, the capacity of a plant to be deployed or expanded at site j in strategic period t under scenario s;

$y_{ts}^1, y_{ts}^2 = 1$ if the cumulative INES factor falls into the warning or dead areas in strategic period t under scenario s, respectively;

DR = binary, decision rules related variables;

ω_{ts}, ξ_{ts} = non-negative, used to express the difference between the demand for electricity and the electricity generated by plants;

δ = binary, indicator variable.

The objective of the model is to minimize the expected total costs over the life cycle of the system. This is analogous to the wide use of levelized cost of electricity, which can be compared directly to the price of electricity to determine whether a system is profitable. The total discounted costs comprise fixed, variable operation and maintenance, variable fuel, and penalty costs. The costs spent since period 1 are discounted back to period 0. The equation numbers follow from the sequence in the paper.

$$\min \quad \sum_j (C_{fix} o^1_{jv^*} + \sum_v C_{rac} o^1_{jv}) + \sum_s p_s \sum_t r_t$$
$$(\sum_j [C_{fix} o^2_{jts} + C_{rac}(CO_{jts} + CE_{jts}) + \sum_v (C_{var} + C_{fuel}) x_{jvts}] + C_p \omega_{ts}) \tag{9}$$

Formulations (10) –(12) are normal logic constraints that make the model realistic. For instance, inequality (11) indicates that any candidate site has one and only one chance to deploy a new plant over the life cycle. According to the definitions of variables o^1_{jv} and x_{jvts}, inequalities (10) and (12) ensure that a non-zero value associated with a larger phase (i.e., v) of such a variable will force the value associated with a smaller phase to be equal to one.

$$s.t. \quad o^1_{j,v+1} \le o^1_{jv}, \; j \in J, \; v \in V; \tag{10}$$

$$o^1_{jv^*} + \sum_t o^2_{jts} \le 1, \; j \in J, \; s \in S; \tag{11}$$

$$x_{j,v+1,ts} \le x_{jvts}, \; j \in J, \; v \in V, \; t \in T, \; s \in S; \tag{12}$$

The following inequalities ensure that variables o^2_{jts} and CO_{jts} get the right values. Formulations (13) – (14) indicate that the capacity to be initially deployed at a candidate site (if needed) from period 1 is a constant, and so is the capacity of expansion. The number of plants to be deployed or expanded at different times should also be consistent, as shown in (15) – (16).

$$U'o_{jts}^2 \leq U'CO_{jts} \leq U^*o_{jts}^2, \; j \in J, \; t \in T_1, \; s \in S; \tag{13}$$

$$U'\left(1-o_{jts}^2\right) \leq U'\left(m_c - CO_{jts}\right) \leq U^*\left(1-o_{jts}^2\right), \; j \in J, \; t \in T_1, \; s \in S; \tag{14}$$

$$DR_{ts}^c \leq \sum_j o_{jts}^2 \leq |J| DR_{ts}^c, \; t \in T_1, \; s \in S; \tag{15}$$

$$1 - DR_{ts}^c \leq n_c - \sum_j o_{jts}^2 \leq |J|\left(1-DR_{ts}^c\right), \; t \in T_1, \; s \in S; \tag{16}$$

Constraints (17) – (22) represent the relationship between the thresholds (i.e., q) and the cumulative INES indicators (i.e., y_{ts}). More specifically, inequalities (17) - (20) determine which area the cumulative INES falls into at period t, while inequalities (21) and (22) represent the logical relationship among areas. That is, decisions restricted in the warning area should also be restricted in the dead area. Once the cumulative INES falls into the dead area, no matter when, the status of indicator y_{ts}^2 will not change for the rest of the life cycle.

$$I_{ts} \leq q_1 - \varepsilon + My_{ts}^1 + My_{ts}^2, \; t \in T, \; s \in S; \tag{17}$$

$$I_{ts} \geq q_1 - M\left(1 - y_{ts}^1\right) - My_{ts}^2, \; t \in T, \; s \in S; \tag{18}$$

$$I_{ts} \leq q_2 - \varepsilon + My_{ts}^2 + My_{t-1,s}^2, \; t \in T, \; s \in S; \tag{19}$$

$$I_{ts} \geq q_2 - M\left(1 - y_{ts}^2\right) - My_{t-1,s}^2, \; t \in T, \; s \in S; \tag{20}$$

$$y_{ts}^2 \leq y_{ts}^1, \; t \in T, \; s \in S; \tag{21}$$

$$y_{t-1,s}^2 \leq y_{ts}^2, \; t \in T, \; s \in S; \tag{22}$$

The following inequalities ((23) - (25)) indicate the possible cases when flexibility strategies could not be exercised, such as when the cumulative INES falls into the warning area (i.e., $y_{ts}^1 = 1$) or a plant is under expansion (i.e., $\delta_{ts}^{DR1} = 1$).

$$DR_{ts}^A \leq 1 - y_{t-1,s}^1, \ t \in T_1, \ s \in S; \tag{23}$$

$$DR_{ts}^A \leq 1 - \delta_{ts}^{DRk_1}, \ t \in T_1, \ k_1 = \{1,\ldots,4\}, \ s \in S; \tag{24}$$

$$DR_{ts}^A \geq 1 - y_{t-1,s}^1 - \delta_{ts}^{DR1} - \delta_{ts}^{DR2} - \delta_{ts}^{DR3} - \delta_{ts}^{DR4}, \ t \in T_1, \ s \in S; \tag{25}$$

The following formulations explicitly describe the conditions when the indicator variables, with respect to decision rule availability, can be non-zero value (i.e., logically true). For instance, inequalities (26) and (27) represent the case when indicator variable δ_{ts}^{DR1} must be equal to one if the target plant is still under expansion, and zero otherwise. Similarly, the indicator variable δ_{ts}^{DR2} will be one if an initial installation or phased deployment was exercised within previous t_c periods, see (28) – (31). Formulations (32) and (33) indicate that no more deployment can be exercised if all candidate sites are full.

$$\sum_{t-t_e+1}^{t-1} \sum_j u_{jts} \leq M \delta_{ts}^{DR1}, \ t \in T_1, \ s \in S; \tag{26}$$

$$\sum_{t-t_e+1}^{t-1} \sum_j u_{jts} \geq \varepsilon - M\left(1 - \delta_{ts}^{DR1}\right), \ t \in T_1, \ s \in S; \tag{27}$$

$$\sum_{t-t_c+1}^{t-1} \sum_j (o_{jts}^2 + o_{jv^*}^1) \leq M \delta_{ts}^{DR2}, \ t = \{0,\ldots t_c\}, \ s \in S; \tag{28}$$

$$\sum_{t-t_c+1}^{t-1} \sum_j (o_{jts}^2 + o_{jv^*}^1) \geq \varepsilon - M\left(1 - \delta_{ts}^{DR2}\right), \ t = \{0,\ldots t_c\}, \ s \in S; \tag{29}$$

$$\sum_{t-t_c+1}^{t-1} \sum_j o_{jts}^2 \leq M \delta_{ts}^{DR2}, \ t = \{t_c+1,\ldots T\}, \ s \in S; \tag{30}$$

$$\sum_{t-t_c+1}^{t-1} \sum_j o_{jts}^2 \geq \varepsilon - M\left(1 - \delta_{ts}^{DR2}\right), \ t = \{t_c+1,\ldots T\}, \ s \in S; \tag{31}$$

$$\sum_j x_{jv^{**}ts} \leq |J| - \varepsilon + M \delta_{ts}^{DR3}, \ t \in T, \ s \in S; \tag{32}$$

$$\sum_j x_{jv^{**}ts} \geq |J| - M\left(1 - \delta_{ts}^{DR3}\right), \ t \in T, \ s \in S; \tag{33}$$

$$\sum_j \delta_{jts}^{LE3} \le |J| - \varepsilon + M \delta_{ts}^{DR4}, \ t = \{t_{LE}, \dots T\}, \ s \in S; \tag{34}$$

$$\sum_j \delta_{jts}^{LE3} \ge |J| - M\left(1 - \delta_{ts}^{DR4}\right), \ t = \{t_{LE}, \dots T\}, \ s \in S; \tag{35}$$

Since the system capacity and actual electricity demand are not always equal, it is necessary to know the difference between these values, which is described in (36) – (38). Auxiliary variables ω_{ts} and ξ_{ts} are the positive and negative part of this difference, respectively. According to the definition, only one of these values can be greater than zero at a time. Constraints (39) – (42)show the condition of demand satisfaction when phased deployment and/or capacity expansion could be triggered, and (43) – (45) indicate that flexibility strategies are available only if the conditions of demand satisfaction and social acceptance are favorable.

$$d_{ts} - \sum_j \theta_j U' \sum_v x_{jvts} = \omega_{ts} - \xi_{ts}, \ t \in T, \ s \in S; \tag{36}$$

$$\omega_{ts} \le M \delta_{ts}^D, \ t \in T, \ s \in S; \tag{37}$$

$$\xi_{ts} \le M\left(1 - \delta_{ts}^D\right), \ t \in T, \ s \in S; \tag{38}$$

$$\omega_{ts} \le d_{ts} x_d - \varepsilon + M \delta_{ts}^{DM}, \ t \in T, \ s \in S; \tag{39}$$

$$\omega_{ts} \ge d_{ts} x_d - M\left(1 - \delta_{ts}^{DM}\right), \ t \in T, \ s \in S; \tag{40}$$

$$\sum_{t-t_d}^{t-1} \delta_{ts}^{DM} \le t_d - \varepsilon + M DR_{ts}^T, \ t \in T, \ s \in S; \tag{41}$$

$$\sum_{t-t_d}^{t-1} \delta_{ts}^{DM} \ge t_d - M\left(1 - DR_{ts}^T\right), \ t \in T, \ s \in S; \tag{42}$$

$$DR_{ts}^{Tr} \le DR_{ts}^T, \ t \in T, \ s \in S; \tag{43}$$

$$DR_{ts}^{Tr} \le DR_{ts}^A, \ t \in T, \ s \in S; \tag{44}$$

$$DR_{ts}^{Tr} \ge DR_{ts}^T + DR_{ts}^A - 1, \ t \in T, \ s \in S; \tag{45}$$

If there is no plant in the system, capacity expansion is of course unavailable. Similarly, if all sites are occupied, phased deployment also becomes unavailable. These are represented in (46) – (47) and (51) – (52), respectively. The priority of exercising capacity expansion is higher than that of phased deployment when conditions are favorable. This can be found in formulations (48) - (50) and (53) -(56).

$$\sum_j (x_{jv^*ts} - x_{jv^{**}ts}) \geq \varepsilon - M\left(1 - \delta_{ts}^E\right), \ t \in T, \ s \in S; \tag{46}$$

$$\sum_j (x_{jv^*ts} - x_{jv^{**}ts}) \leq M\delta_{ts}^E, \ t \in T, \ s \in S; \tag{47}$$

$$DR_{ts}^e \leq \delta_{ts}^E, \ t \in T, \ s \in S; \tag{48}$$

$$DR_{ts}^e \leq DR_{ts}^{Tr}, \ t \in T, \ s \in S; \tag{49}$$

$$DR_{ts}^e \geq \delta_{ts}^E + DR_{ts}^{Tr} - 1, \ t \in T, \ s \in S; \tag{50}$$

$$\sum_j (x_{jv^*ts} + \delta_{jts}^{LE3}) \leq |J| - \varepsilon + M\delta_{ts}^C + M\delta_{ts}^E, \ t \in T, \ s \in S; \tag{51}$$

$$\sum_j (x_{jv^*ts} + \delta_{jts}^{LE3}) \geq |J| - M\left(1 - \delta_{ts}^C\right) - M\delta_{ts}^E, \ t \in T, \ s \in S; \tag{52}$$

$$\delta_{ts}^C \leq 1 - \delta_{ts}^E, \ t \in T, \ s \in S; \tag{53}$$

$$DR_{ts}^c \leq \delta_{ts}^C, \ t \in T, \ s \in S; \tag{54}$$

$$DR_{ts}^c \leq DR_{ts}^{Tr}, \ t \in T, \ s \in S; \tag{55}$$

$$DR_{ts}^c \geq \delta_{ts}^C + DR_{ts}^{Tr} - 1, \ t \in T, \ s \in S; \tag{56}$$

Formulations (57) – (61) represent situations when life extension could be exercised. That is, situations when there is already a plant deployed at the target site t_{LE} periods before and social acceptance is favorable. Constraints (62) – (71) specifically show how a life extension strategy is exercised at a candidate site.

$$l_{jts} \leq 1 - y^1_{t-1,s}, \ j \in J, \ t = \{t_{LE}, \dots T\}, \ s \in S; \tag{57}$$

$$l_{jts} \leq o^1_{jv^*} + My^1_{t-1,s}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{58}$$

$$l_{jts} \geq o^1_{jv^*} - My^1_{t-1,s}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{59}$$

$$l_{jts} \leq o^2_{j,t-t_{LE}+1,s} + My^1_{t-1,s}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{60}$$

$$l_{jts} \geq o^2_{j,t-t_{LE}+1,s} - My^1_{t-1,s}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{61}$$

$$\delta^{LE2}_{jts} \leq o^1_{jv^*} + l_{jts}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{62}$$

$$\delta^{LE2}_{jts} \geq o^1_{jv^*} - l_{jts}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{63}$$

$$\delta^{LE2}_{jts} \geq l_{jts} - o^1_{jv^*}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{64}$$

$$\delta^{LE2}_{jts} \leq 2 - o^1_{jv^*} - l_{jts}, \ j \in J, \ t = t_{LE}, \ s \in S; \tag{65}$$

$$\delta^{LE2}_{jts} \leq o^2_{j,t-t_{LE}+1,s} + l_{jts}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{66}$$

$$\delta^{LE2}_{jts} \geq o^2_{j,t-t_{LE}+1,s} - l_{jts}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{67}$$

$$\delta^{LE2}_{jts} \geq l_{jts} - o^2_{j,t-t_{LE}+1,s}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{68}$$

$$\delta^{LE2}_{jts} \leq 2 - o^2_{j,t-t_{LE}+1,s} - l_{jts}, \ j \in J, \ t = \{t_{LE}+1, \dots T\}, \ s \in S; \tag{69}$$

$$\delta^{LE1}_{jts} \leq \delta^{LE1}_{jt-1,s} + l_{j,t-t_l,s}, \ j \in J, \ t = \{t_{LE}+t_l, \dots T\}, \ s \in S; \tag{70}$$

$$\delta^{LE1}_{jts} \geq \frac{1}{2}\left(\delta^{LE1}_{jt-1,s} + l_{j,t-t_l,s}\right), \ j \in J, \ t = \{t_{LE}+t_l, \dots T\}, \ s \in S; \tag{71}$$

Constraints (72) – (74) show when regular operation (including life extension) is done at a site. Formulations (75) – (79) show the correlation between different decisions. For example, capacity

expansion cannot occur if there is no existing plant (see (75)), or if the existing plant reaches its upper bound (see (76)).

$$\delta_{jts}^{LE3} \leq \delta_{jts}^{LE1} + \delta_{jts}^{LE2} + \delta_{jt-1,s}^{LE3}, \ j \in J, \ t \in T, \ s \in S; \tag{72}$$

$$\delta_{jts}^{LE3} \geq \delta_{jts}^{LE1}, \ j \in J, \ t \in T, \ s \in S; \tag{73}$$

$$\delta_{jts}^{LE3} \geq \delta_{jt-1,s}^{LE3}, \ j \in J, \ t \in T, \ s \in S; \tag{74}$$

$$u_{jts} \leq x_{jv^*ts}, \ j \in J, \ t \in T_1, \ s \in S; \tag{75}$$

$$u_{jts} \leq 1 - x_{jv^{**}ts}, \ j \in J, \ t \in T_1, \ s \in S; \tag{76}$$

$$o_{jts}^2 \leq 1 - x_{jv^*ts}, \ j \in J, \ t \in T_1, \ s \in S; \tag{77}$$

$$u_{jts} \leq 1 - \delta_{jts}^{LE3}, \ j \in J, \ t \in T_1, \ s \in S; \tag{78}$$

$$o_{jts}^2 \leq 1 - \delta_{jts}^{LE3}, \ j \in J, \ t \in T_1, \ s \in S; \tag{79}$$

The remaining inequalities explicitly show dynamics of the capacity of a nuclear power plant. The capacity in period t will be equal to the capacity in the last period plus the expected capacity by deployment and/or expansion, when public acceptance is favorable and the plant (system) is still in operation.

$$\sum_v x_{jvts} \leq \sum_v x_{jv,t-1,s} + CO_{j,t-t_c,s} + CE_{j,t-t_e,s} + My_{t-1,s}^2$$
$$+ M\delta_{jts}^{LE1} + M\delta_{jts}^{LE2}, \ j \in J, \ t \in T, \ s \in S; \tag{80}$$

$$\sum_v x_{jvts} \leq \sum_v x_{jv,t-1,s} + CO_{j,t-t_c,s} + CE_{j,t-t_e,s} - My_{t-1,s}^2$$
$$- M\delta_{jts}^{LE1} - M\delta_{jts}^{LE2}, \ j \in J, \ t \in T, \ s \in S; \tag{81}$$

$$\sum_v x_{jvts} \leq M\left(1 - y_{t-1,s}^2\right), \ j \in J, \ t = \{t_{LE},\dots,T\}, \ s \in S; \tag{82}$$

$$\sum_v x_{jvts} \leq M\left(1 - \delta_{jts}^{LEk_2}\right), \ j \in J, \ k_2 = \{1, 2\}, \ t = \{t_{LE}, \dots, T\}, \ s \in S; \qquad (83)$$

Values of Parameters

Table 6. List of assumptions for the numerical analysis.

Parameters	Assumption
Declared net capacity (DNC) of a nuclear reactor (i.e. 1 unit of capacity)	600 MWe per reactor
Pre-development costs (PD)	$455.41 million in 2006 money
Construction costs of a nuclear power plant (w/o reactor) (C_{fix})	$954.55 million
Costs of a reactor (C_{rac})	$1.776 billion
Operation and maintenance (O&M) costs of a nuclear power plant (C_{var})	$7.01/MWh per plant, followed by a $7.01/MWh per reactor
Fuel supply costs for thorium (C_{fuel})	$2.00/MWh
Contractual (penalty) costs for losing demand (C_p)	$364.33/MWh
Costs of capital (discount rate) (r)	Nominally 10%
Annual growth rate	Nominally 3% for O&M costs and contractual costs, 2% for fuel costs
The study life of the system	40 years
The useful life of nuclear power plants	Nominally 20 years
Construction period of initial deployment (t_c)	6 years
Construction period of capacity expansion (t_e)	3 years
Additional period of life extension (t_l)	10 years
Observation period for flexible phased deployment and capacity expansion (t_d)	3 years
Observation period for life extension	6 years
Small tolerance (ε)	Nominally 10^{-3}
Large integer (M)	Nominally 10^6