HEDGING AGAINST UNCERTAINTY IN THE NUCLEAR FUEL CYCLE

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Time-dependent analyses of the nuclear economy, for instance to assess transitions between nuclear fuel cycles, often confront uncertainties by implementing a scenario-based approach in which uncertain variables are parametrically varied. Yet the uncertainties surrounding important state variables – demand growth rates, dates of technology availability, technology costs – will likely remain unresolved for decades. Strong transition strategies should be flexible, enabling reasonable outcomes to be attained once the uncertainty is resolved. This paper demonstrates a decision tree analysis methodology for incorporating uncertainties into the process of developing transition strategies. The method derives hedging strategies, defined as strategies which retain the greatest flexibility for adjustment once uncertainties are resolved. A case study involving transition from a once-through cycle to continuous recycle in fast reactors is presented, in which the future cost of used fuel and high level waste disposal are subject to uncertainty. Transition strategies, consisting of reprocessing facility construction and reactor deployment schedules are simulated using VEGAS, a lightweight fuel cycle mass balance simulation model. From these, a hedging strategy is chosen with the aim of minimizing the integrated cost of electricity (COE) over the remainder of the century in light of disposal cost uncertainties which will not be resolved until 2060. The hedging strategy minimizes the amount by which the strategy's COE exceeds the value that could have been achieved had perfect information about disposal costs been available from the beginning. By explicitly including uncertainties in the decision-making algorithm, the method places high value on strategies whose early steps preserve many courses of action as information becomes available.

I. INTRODUCTION

There are large uncertainties in the cost, performance, and even availability of technologies associated with the back end of advanced nuclear fuel cycles[1]. These uncertainties affect the attractiveness of various fuel cycle options and render the concept of a single optimal strategy for transition from today's nuclear fuel cycle to another invalid. Decision making under uncertainty provides a systematic framework for choosing hedging strategies which retain the flexibility to adjust appropriately once uncertainties are resolved[2].

The work presented here extends the methodology presented in Ref. 3 for handling uncertainty in fuel cycle transition analyses. A case study involving transition from the current U.S. once-through light water reactor (LWR) fuel cycle to one relying on continuous recycle in fast reactors (FRs) is here cast as a no-data decision problem, in which it is impossible to gain information about the future outcome of decision-relevant parameters. Here, the transition is subject to uncertainty in the cost of spent nuclear fuel (SNF) and high-level waste (HLW) disposal in a geologic repository, slated to open some years into the future.

Using this illustrative case, a new methodology for selecting optimal transition and hedging strategies in the nuclear fuel cycle is presented. These hedging strategies allow for flexible decision-making, where agents may alter their decisions once decision-relevant information is available.

II. BACKGROUND

The combination of decision theory and systems analysis has been termed decision analysis[4]. Early 1960s studies that incorporated decision analysis dealt with decision making in oil and gas exploration[5,6]. The work presented here is an application of the no-data decision problem found in decision theory, in which one or more decision-relevant parameters are uncertain and have many possible outcomes. These problems consist of four components:

1. the available *actions* that can be taken,
2. the *states of nature* (or *end-states*) that may occur,
3. the *consequences* of each combination of action and state of nature (known as a *state-act pair*),
4. and a *choice criterion* by which the decision maker solves the final problem of choice.

Several techniques have been proposed to address the no-data problem[7]. Of these techniques, *scenarios analysis* has been the most pervasive for handling uncertainty in the nuclear fuel cycle. The scenarios approach finds an optimal plan for *N* possible scenarios, obtaining a set of *N* solutions. This approach assumes agents have perfect information about the state of nature that will prevail, and no systematic method is available for consolidating the plans to incorporate the uncertainties that are actually present.

The work presented here demonstrates a new methodology for handling uncertainties in the nuclear fuel cycle, derived from concepts utilized in stochastic optimization. Here, uncertainties are explicitly embedded as future bifurcations with assigned probabilities within a single model. Using this model, a single strategy is found whose performance is optimal "on the average" for all scenarios.

Fig. 1 (adapted from Ref. 8) demonstrates the difference between the scenarios approach and the stochastic optimization approach. In Ref. 8, the greenhouse gas (GHG) emissions from an energy system are subject to an upper bound on the cumulative emissions from 2000 to 2030. The value of the upper bound may take on any of four values, but only becomes known in 2010. An *optimal hedging strategy* is found prior to 2010 (see State of nature 1-4 from 2000 to 2010), taking into account that any of the four possible states of nature may occur, and choosing a middle-of-the-road path until the uncertainty is resolved. In contrast, using the scenarios approach, four distinct *optimal transition strategies* exist from 2000 to 2010 (see Scenario 1-4), none of which may match the optimal hedging strategy.

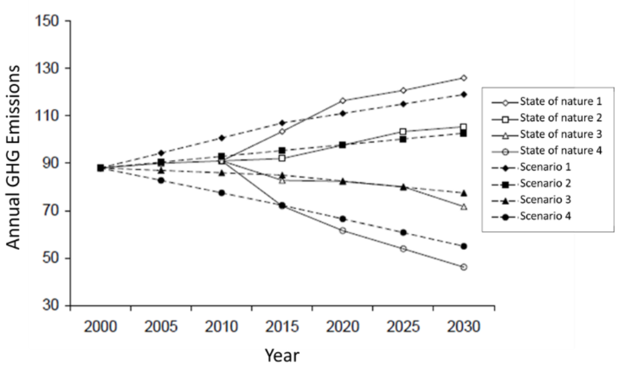

Fig. 1. Optimal GHG trajectories found using scenario analysis (Scenario 1-4) and decision-making under uncertainty (states of nature 1-4); adapted from Ref. 8.

III. METHODOLOGY

A reference transition scenario is described and cast as a no-data decision problem in Section III.A. Strategies for the transition are enumerated and simulated using the VEGAS fuel cycle simulator, described in Section III.B, with the methodology for selecting the optimal transition and hedging strategies presented in Section III.C.

III.A. Reference scenario

The reference transition scenario is modeled after the nominal 1-tier scenario in Ref. 9, from which reactor material balance parameters are obtained. The scenario involves transitioning towards continuous recycle in FRs. LWR SNF from existing LWRs is separated into fission products (FPs) for storage and subsequent disposal, uranium for reuse or storage, and transuranic (TRU) elements. TRU elements are then burned in FRs, producing electricity while achieving partial TRU destruction. FR SNF is subsequently separated into the same three streams: U, FPs, and TRU. Separated TRU is then recycled and again burned in FRs. This closed fuel cycle is aimed at minimizing the existing TRU inventory.

Legacy LWR SNF is assumed to go directly to disposal, and has no bearing on the decision made. This is consistent with current policy following a technical review by Oak Ridge National Laboratory, which found that 98 percent of the total current inventory of commercial SNF may be disposed without the option for retrievability with no shortage of fuel for later reuse or research purposes[10].

Fig. 2 depicts the no-data decision problem examined here. The decision time period is from 2015 to 2100, however, simulations are run until 2160 (an additional lifetime of the longest operating facility) to account for liability costs of materials generated before 2100 but later reprocessed or disposed. In 2015, the current 100 GW_e fleet of LWRs is operating on the traditional once-through fuel cycle, and the annual demand growth rate for nuclear electricity is 1.5 percent per year. First in 2030 and again in 2050, the available *action* is to build a 1,000 MT IHM/yr reprocessing facility, which separates TRU from LWR SNF and thereby enables FR construction. A geologic repository begins accepting spent fuel in 2060, at which time the uncertainty surrounding its cost is resolved, taking on one of the three values given in Table I. Thereafter, one additional action – construction of a final LWR fuel reprocessing facility in 2070 – is available. FR fuel reprocessing capacity is assumed to be co-located with the electricity generating facility.

As mentioned, until 2060 the reference transition scenario is subjected to uncertainty in the cost of SNF and HLW disposal in the geologic repository. The existence of this uncertainty is acknowledged in fuel cycle transition analyses[9], and makes the benefits of the transition unclear. Inexpensive disposal costs favor delaying or even abandoning the transition, and instead using more repository space. Alternatively, higher disposal costs favor an aggressive schedule for closing the fuel cycle in order to minimize reliance on repository space. While the cost per unit mass of disposing HLW is assumed costlier than disposal of SNF, closed fuel cycles benefit in that the volume of waste is greatly reduced. In the presence of this uncertainty, the agent must decide (green squares, Fig. 2) whether to build in LWR reprocessing capacity in 2030 and again in 2050. Only following the repository open date will agents learn the cost of SNF and HLW disposal (the *end-state* which occurred). Prior to this date, the agent *hedges* in order to minimize *regret*. A regret is the difference between the cost paid (*consequences* for the actions taken given a specific end-state occurred) and the cost paid if the agent knew the end-state before taking any actions.

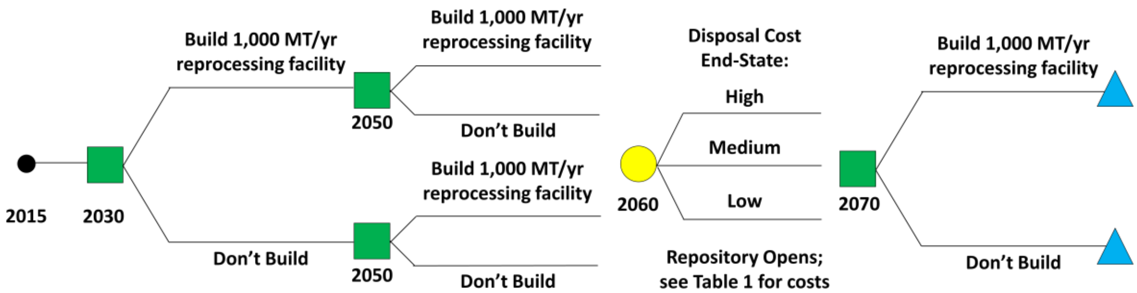

Fig. 2. Reference transition scenario decision tree

TABLE I. Disposal costs for end-states i.

	SNF Disposal ($/kg IHM)	**HLW Disposal** ($/kg IHM in HLW)
Low (i = 1)	650	3,575
Medium (i = 2)	1,950	10,725
High (i = 3)	6,500	35,750

III.B. Analysis Platform

VEGAS, a systems tool for simulating the nuclear economy[11], is chosen as the analysis platform here as it offers an economic model of the nuclear fuel cycle and a reduced runtime over more detailed fuel cycle systems tools. In addition, the VEGAS code offers the unique roll-back feature for calculating constrained annual material balances for the reactor fleet. In the simulation, VEGAS is instructed to build FRs to accommodate demand growth and replace retiring facilities. Given charge and discharge fuel compositions by reactor type at the U/TRU/FP level, if material is unavailable to fulfill FR fuel requirements at any point in the simulation, the simulation is reverted to the year that the most recent FR was built and instead adds equivalent generating capacity from an LWR. Through this functionality, VEGAS is capable of maximizing the usage of deployed reprocessing capacity, thereby building the largest number of FRs that the installed capacity could support.

Each VEGAS simulation calculates the annual levelized cost of electricity (LCOE) in cents per kWh of electricity produced, whose calculation is summarized here. The LCOE is the price at which electricity must be generated in order to break even over the lifetime of the simulation and consists of two components: fuel cycle charges and reactor charges. Default unit costs are assigned to each distinct fuel cycle process in VEGAS. Unit costs are expressed in dollars per unit of mass throughput, typically kg U, IHM, or SWU. Reactor costs are broken into capital costs (dollars) and annual operations and maintenance (OM) costs (dollars per year).

Mass flows through front-end and back-end technologies are used to calculate the total fuel cycle cost (C_{FC}) by Eq. (1):

$$C_{FC} = \sum_{l=1}^{L} M_l \cdot UC_l \cdot PVF_l \qquad (1)$$

where $l = 1, 2\ldots L$ indexes over fuel cycle technologies, M_l is the mass throughput of the l^{th} technology, UC_l is the unit cost of the l^{th} technology, and PVF_l is the present value function (PVF) of the l^{th} technology. The PVF discounts the charge to the year the technology was employed through lead and lag times input to the VEGAS simulation. Back end costs are assumed to be covered by a sinking fund from revenues generated while the fuel is in reactors producing electricity, however, the risk-free rate of return is set to zero percent to avoid results that are driven by discounting-driven benefits associated with deferring a future liability.

The second component of the LCOE consists of reactor costs ($C_{reactor}$) are the sum of their annual capital cost repayment (ACC) and OM costs. The ACC is calculated using Eq. (2):

$$ACC = (TOC + IDC) \cdot AF \qquad (2)$$

where the total overnight capital cost (TOC) is given in dollars and the interest during construction (IDC) is given by Eq. (3):

$$IDC = \sum_{m=0}^{T_c-1} TOC \cdot f_m[(1+r)^{T_c-m} - 1] \qquad (3)$$

and the amortization factor (AF) is given by Eq. (4):

$$AF = \frac{r}{1-(1+r)^{-T_O}} \tag{4}$$

where T_C and T_O are the reactor construction and operation times in years, respectively, r is the real discount rate in $1/_{yr}$, and f_m is the fraction of TOC expended in year m of construction (summing f_m over all m = 1, 2… T_C equals 1).

Given C_{FC} and $C_{reactor}$ specified in cents, the annual LCOE is then given by Eq. (5):

$$LCOE = \frac{C_{FC} + C_{reactor}}{E} \tag{5}$$

where E is the total amount of electricity produced in kWh for that year.

III.C. Hedging Strategy Selection

The annual LCOE in cents per kWh of electricity produced is calculated using the VEGAS code for each action shown in Fig. 2 (2^3 = 8 unique actions corresponding to the 3 reprocessing facility build decision nodes) and each end-state (3 unique disposal cost end-states: low, medium and high). Actions are indexed over j while end-states are indexed over i.

For each end-state, an optimal action j_i^* is found from among the possibilities j = 1, 2… 8. The optimal action is the one that has the lowest integrated LCOE:

$$j_i^* = \underset{j}{\operatorname{argmin}} \sum_{k=1}^{T} c_k^j E_k, \tag{6}$$

where T is the number of years in the simulation, E_k is the electricity produced in year k, and c_k^j is the annual LCOE for year k for action j. These optimal transition strategies $j_{i=1,2,3}^*$ correspond to the optimal actions that would be followed if an agent had perfect information about which disposal cost end-state would prevail.

Given the optimal transition strategies found under perfect information, it is possible to identify the best hedging strategy under the limits of imperfect information. This is done using the expected regret decision criterion:

$$g = \underset{j}{\operatorname{argmin}} \frac{1}{I} \sum_{i=1}^{I} \left(\sum_{k=1}^{T} c_k^j E_k - c_k^{j_i^*} E_k \right). \tag{7}$$

Here, the coefficient $1/_I$ implies that each end-state occurs with equal probability.

The regret for taking action j instead of the optimal action j_i^* is the difference between the integrated costs for j and j_i^*. The expected regret for each action j is then computed as the increase in cost from following the j^{th} action instead of the optimal action identified under perfect information for each end-state, weighted by the probability of realizing each end-state. In the case of hedging and optimal strategies, the regret for following a hedging strategy instead of the optimal strategy given perfect information on future outcomes represents foregone savings, and provides an upper bound on the value of that information.

IV. RESULTS

Table II defines each action (j = 1, 2… 8) by listing the build decisions for each decision node in Fig. 2. Fig. 3 gives the LCOE for each action and end-state (i = 1, 2, 3). For the j = 1 case, no LWR reprocessing capacity is ever built, and the transition does not occur. For all others except the j = 8 case, installed LWR reprocessing capacity is insufficient to sustain a complete transition to the synergistic LWR-FR fuel cycle. Instead, for j = 2, 3… 7, only the older discharged spent fuel is reprocessed. Under the LCOE methodology, back end (reprocessing or disposal) costs are paid via a sinking fund from revenues generated while the nuclear fuel is in reactors producing electricity. Hence a jump in the LCOE is seen in the j = 2, 3… 7 cases at the transition time past which LWR SNF is no longer reprocessed.

TABLE II. Build decisions (x = don't build, ✓ = build reprocessing facility) for actions j.

Actions (j)	Decision year 2030	2050	2070
8	✓	✓	✓
7	✓	✓	x
6	✓	x	✓
5	✓	x	x
4	x	✓	✓
3	x	✓	x
2	x	x	✓
1	x	x	x

The electricity-generated weighted average LCOE for each state-act pair is given in Table III, with the corresponding regrets in Table IV. In Table III, the weighted average LCOE associated with the optimal action is displayed in bold, and in Table IV the expected regret for the optimal hedging strategy (as defined by Eq. 7) is displayed in bold. The optimal action displayed in Table III represents the action that would be taken if agents had perfect information available of which end-state would occur, similar to the scenarios approach. If this were the case, for the low and medium end-states, there would be no transition (j = 1), and for the high end-state, the most aggressive transition would be pursued (j = 8).

The optimal hedging strategy suggests only a partial transition to a closed fuel cycle (action j = 3 or 4) with a 1,000 MT IHM/yr reprocessing facility built in 2050 but not earlier in 2030. Actions j = 3 and 4 are the same prior to the resolution date, and likewise for actions j = 1 and 2; 5 and 6; and 7 and 8. Then, selecting a hedging strategy is choosing between these 4 sets of actions.

Following the 2060 resolution date, agents may alter their transition strategy using information about the prevailing end-state disposal costs. Table V lists the regrets accrued over the simulation for each end-state if an agent were to follow the j = 3 or 4 hedging strategy before 2060, and then alter their strategy accordingly with information made available. For both the low and medium end-states, agents would choose to abandon the transition by not constructing a third reprocessing facility in 2070, whereas for the high end-state, agents would build the facility and continue to pursue their transition.

TABLE III. Electricity-generated weighted average LCOE (cents/kWh$_e$) for each action j and end-state i.

		End-states (i)	
Actions (j)	**1**	**2**	**3**
8	7.78	7.87	***8.19***
7	7.69	7.84	8.34
6	7.65	7.81	8.38
5	7.54	7.77	8.57
4	7.61	7.79	8.42
3	7.50	7.75	8.61
2	7.46	7.73	8.64
1	***7.37***	***7.69***	8.80

TABLE IV. Regrets [$B, billion USD] for each action j and end-state i, and expected regret for each action j.

		End-states (i)		
Actions (j)	**1**	**2**	**3**	Expected Regret
8	638	288	0	309
7	498	229	222	316
6	435	194	285	305
5	266	127	575	322
4	371	158	347	***292***
3	201	88	629	306
2	151	63	689	301
1	0	0	935	312

TABLE V. Final regrets for each end-state. For decision year, x = don't build, ✓ = build reprocessing facility.

	Decision Year			
	2030	**2050**	**2070**	**Regrets [$B]**
Low	x	✓	x	201
Medium	x	✓	x	88
High	x	✓	✓	347

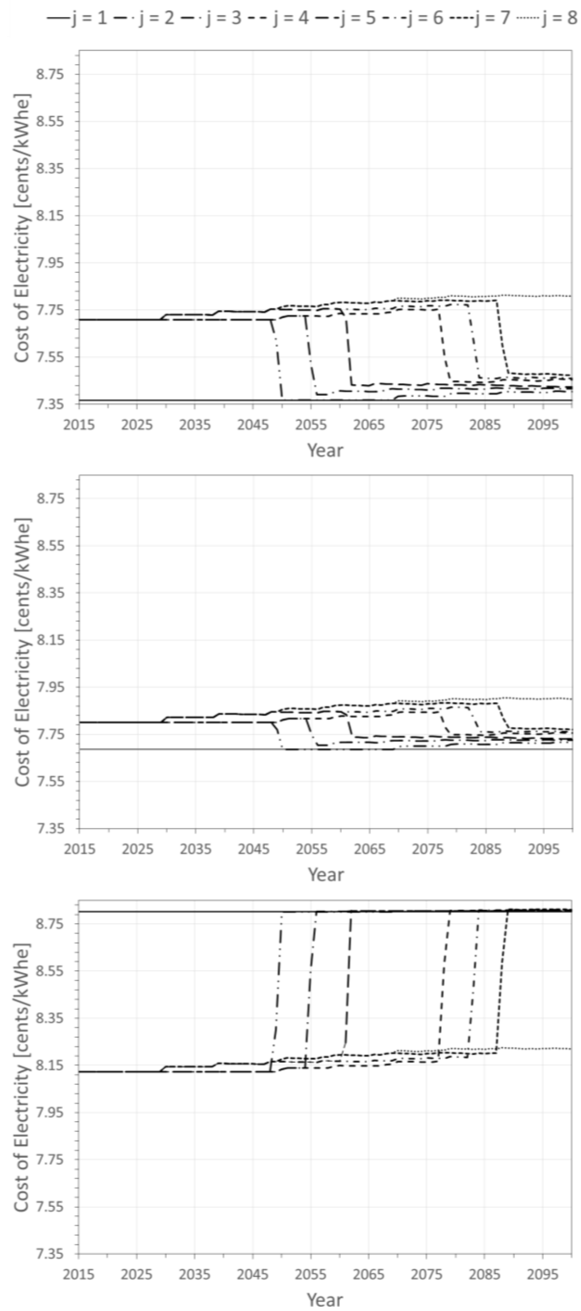

Fig. 3. Annual LCOE for actions j and end-states i: (a) low, (b) medium, and (c) high.

V. CONCLUSIONS

This work demonstrates a new methodology for handling uncertainty in fuel cycle transition analyses. Previous approaches in fuel cycle transition analyses have focused on equilibrium studies or take the scenarios approach. The scenarios approach assumes that decision-makers would be able to correctly guess the state of nature that will ultimately prevail. In contrast, the methodology here recognizes that uncertainties render the concept of a unique, optimal action invalid. Borrowing from decision-making under uncertainty, this methodology provides a systematic approach to devising hedging strategies for fuel cycle transition analysis.

A case study involving transition to a closed fuel cycle where the final cost of SNF and HLW disposal was subject to uncertainty is presented. The optimal hedging strategy found through this method suggests that only a partial transition to a closed fuel cycle be made prior to 2060 when uncertainties surrounding disposal costs were assumed to be resolved. Following the optimal hedging strategy represents a "middle-of-the-road" approach to closing the fuel cycle, and is beneficial if outcomes are different than an agent anticipated.

After the resolution date when uncertainties are resolved, agents are allowed to alter their strategy. This is similar to the real options analysis approach, as it allows agents to adopt a "wait-and-see" strategy until the uncertainty is lessened or resolved.

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