Power of Screening Models for Developing Flexible Design Strategies in Hydropower Projects: Case Study of Ethiopia

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Abstract: Long-term price changes in water resources benefits may greatly affect a project s value, however the traditional approach to river basin planning has not been able to take full account of these uncertainties. Additionally, the relatively recent approach of adaptive management does not provide much systematic guidance for planners. This paper proposes an approach that allows planners of river basins to incorporate flexibility into the design to enable them to increase the expected value of these projects by avoiding untimely elements, taking advantage of favorable opportunities. This paper considers the application of a midfidelity screening model to identify flexible design opportunities and strategies. Such a model is adopted to explore the impacts of future electricity price uncertainty on a proposed system of hydroelectric dams in Ethiopia. Using possible price paths developed from a binomial lattice model calibrated on price variability, the screening model is used to (1) identify the most flexible construction sequence for building the dams and (2) value various options exercised on the most flexible construction sequence. Scenarios are evaluated using the criteria of expected net present value and capital expenditure and assessed using cumulative distribution functions. Results indicate that the best option increases the expected net present value of the most flexible construction sequence by nearly 2%. Furthermore, the cumulative distribution function curve analysis demonstrates how a failure to consider uncertainties such as price may result in a significant underevaluation or overevaluation of the project. Thus, this study highlights the value of a systematic approach using a midfidelity screening model to assess the uncertainties present in water resource infrastructure investments. **DOI: 10.1061/ ASCE)WR.1943-5452.0000417.** *© 2014 American Society of Civil Engineers.*

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Introduction

Historical pproach to Water Resource Design

Traditional river basin planning has historically depended on "most probable" (Peterson 1984) forecasts of critical system variables, including population, water demand, and the use of observed average streamflow. Federal guidelines for water resource development explicitly require planning based on such probable futures (Armah et al. 2009). Long-term planning at the water utility level typically follows a similar approach, developing a deterministic estimate of how future water supply and demands will evolve (Lempert and Groves 2010). For example, the 2009 water planning report of the Southern Nevada Water Authority (SNWA) and 2002 water planning report of the Denver Water utility employ fixed water demand forecasts (Southern Nevada Water Authority 2009; Denver Water 2002).

This is not to suggest that the traditional approach is blind to the presence of economic and resource uncertainties. Approaches to addressing uncertainty include sensitivity analysis [which current federal guidelines require (Armah et al. 2009)], assigning probabilities to uncertain parameters, increasing margins of safety or contingency funds if uncertainties are related to cost, Monte Carlo simulations to provide a distribution of project outputs, and maintaining flexibility in systems (Goodman 1984). The Republic of South Africa, for example, has been doing Monte Carlo analysis risk-based planning of reservoir design for more than 20 years (Basson et al. 1994). In the examples of the SNWA and Denver Water, both agencies acknowledge the need to periodically update their demand forecasts (Southern Nevada Water Authority 2009; Denver Water 2002). Additionally, the SNWA maintains multiple water sources as a hedge against uncertain futures (Southern Nevada Water Authority 2009) and Denver Water adds a contingency factor to its water demand estimate to help account for future uncertainty (Denver Water 2002).

Over the past few decades, properly accounting for uncertainty has garnered increasing attention in water resources planning. Adaptive management is the current U.S. protocol for dealing with uncertainty and variability. Adaptive management is defined as "a systematic learning from the outcomes of implemented management strategies and by taking into account changes in external factors in a proactive manner" (Pahl-Wostle et al. 2011). One of the challenges associated with adaptive management, however, is the difficulty in applying the concept to pragmatic decision making (Pahl-Wostle et al. 2011; de Neufville 2004). For example, although the adaptive management strategy had some higher-level positive results in the Columbia river basin, such as "increased

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appreciation of the complexities of many components of the system," conducting research at the basin level proved to be a difficult task (Dzurik and Theriaque 1996). The benefits of adaptive management have been demonstrated at the conceptual level, but not at the practical level required for design and decision making.

Shortcomings of the Traditional pproach

The traditional design process is grounded in the assumption that the average outcome is equivalent to the outcome of the average input parameters. This motivates the use of deterministic projections that result in a project perfectly planned for a single future that will in all likelihood not occur. It is well known from Jensen s law that the expected value of a nonlinear function is not equal to the value of the function evaluated at the expected value of the function s arguments (Jensen 1906). Because hydropower systems are most certainly nonlinear, the expected outcome of such a project is not the outcome of a project evaluated at the average parameters. For this reason, calculating project performance and values based on average input parameters, known as the "flaw of averages" (Savage 2009), results in the wrong project value and wrong project ranking. The ultimate consequence of the application of the flaw of averages is a project design that fails to capture upside gains or avoid downside losses by inappropriately dealing with, or simply ignoring, uncertain input parameters. Streamflow and precipitation are two relevant uncertainties that should be considered by water management specialists. Especially in light of the potential impacts of climate change on precipitation (Giannini et al. 2008), the use of historical average streamflow or precipitation forecasts potentially misses a wide range of futures. Streamflow and precipitation uncertainty can also have a significant effect on the overall value of the project, as can uncertainties in the price of hydropower and demand for irrigation. These uncertainties furthermore contribute to uncertainty in the value of the product produced by the hydropower project (e.g., electricity, irrigation, and possibly flood control), especially in developing countries.

Moreover, the sensitivity analyses that are a characteristic part of the traditional design approach are typically of limited value. Many investigate only a finite range of uncertainties for select parameters. The broader analyses performed using Monte Carlo simulations develop a distribution of some outcome metric, for example cost-benefit ratios (Goodman 1984), but do this only for the design based on a single situation, which necessarily has a low probability of occurring. Designers need to know how to create plans that capture upside opportunities and avoid downside losses as new information becomes available. In order to create such flexible designs, planners must consider the full range of uncertainties, not simply the sensitivity of a single design to select input parameters.

Better Way Forward

One facet of adaptive management mentioned by Pahl-Wostle et al. (2011) suggests an attractive departure from the traditional approach. They discuss developing future scenarios to identify key uncertainties and strategies for varying future conditions. "Water management traditionally emphasized the reduction of uncertainties, often by designing systems that can be predicted and controlled" (Pahl-Wostle et al. 2011); adaptive management in contrast suggests developing flexibility into the system. Goodman (1984) and Peterson (1984) also mention the importance of flexible designs. No guidance, however, is given for how to incorporate flexibility into the design process.

The recently developed approach of robust decision making (RDM) promises to provide much needed practical guidance to water management planners. "In brief, a robust decision approach allows analysts to use the computer to lay out a wide range of plausible paths into the long term. They then look for robust near-term policy options—i.e., those that when compared to the alternatives perform reasonably well across a wide range of futures using many different values to assess performance. Often strategies are robust because they are adaptive—that is, they are explicitly designed to evolve in response to new information" (Lempert et al. 2003). This approach has recently been applied to water resource planning in California (Groves and Lempert 2007; Lempert and Groves 2010; Department of Water Resources NR 2012) and Denver Water is currently testing this approach (Means et al. 2010).

Though this paper affirms the necessity of considering a wide range of futures as well as the power of using computers for doing so, the approach it is advocating is distinct from RDM. By seeking near-term policies that perform well no matter the future, RDM follows in the more classical footsteps of robust design, where the focus tends to be on minimizing variance and curtailing losses. This paper s approach, flexibility in design, is agnostic to robustness in this sense. Flexibility in design is an approach that seeks to identify design strategies that minimize downside losses (like classical robust strategies) and capture upside gains (de Neufville and Scholtes 2011). As discussed in more detail in this paper, this is accomplished by exploring many different design strategies in the context of alternative futures. Thus flexibility in design, unlike robust design, does not attempt to minimize variance. A flexible design strategy may even increase a design strategy s variance by skewing the distribution to the right if significant upside gains are made possible by the strategy. In short, robust design identifies passive strategies resistant to change. Flexibility in design is a more proactive approach by being resistant to losses while also capitalizing on good opportunities.

A design strategy is a series of decision rules that guide the actions of system planners and operators as new information becomes available. This paper s design strategy is similar in concept to the adaptive strategies described by Lempert et al. (2003); however, Lempert et al. are primarily concerned with management strategies, while this paper is focused on infrastructure investment strategies.

In addition to design strategies, a second key element of the flexibility in design approach involves exploring many design strategies in detail under various futures. Considering the complete design space, however, may prove to be an intractable task with sophisticated, high-fidelity models of complex engineering systems, even with today s computing power. Screening models are an attractive alternative to using high-fidelity models (Wang 2005; Lin 2008; de Neufville and Scholtes 2011). A screening model of a highly complex engineering system is a simplified, midfidelity representation that enables a rapid investigation of a large number of design strategies. Though too simplified to be used as a predictive tool, a midfidelity screening model preserves the rank order of various strategies that would be predicted by a detailed full fidelity model of the same system (Lin 2008). Once desirable strategies have been identified, the high-fidelity model would again be employed for further analysis.

The use of screening models in water management planning has a history that traces back at least to the Rio Colorado planning process (Major and Lenton 1979). More recent examples include Netto et al. (1996), Sinha et al. (1999), Watkins and McKinney (1999), and Islam et al. (2011). The Rio Colorado planning process evolved in several stages, the first of which employed a screening model that used average streamflow to identify promising plans cite (Peterson 1984). Flow variability was not considered until later in the design process cite (Peterson 1984). However, because optimal projects depend on future conditions, uncertainties should be incorporated into the initial screening phase of the design rather than the later stages, as was done for the Rio Colorado. Using screening models at this early stage in the design process can lead to the discovery of strategies that will increase the likelihood that gains from desirable future conditions can be captured and losses from undesirable future conditions can be avoided, thereby increasing the expected value of the project design. The remaining sections of this paper discuss the development of a midfidelity screening model and illustrate how such a model can be used to identify flexible design strategies for hydropower infrastructure planning in the upper Blue Nile River Basin in Ethiopia.

Investment Model for Planning Ethiopian Nile Development Model

Around the time of the high Aswan Dam construction in Egypt, Ethiopia solicited the assistance of the U.S. Bureau of Reclamation (USBR) to explore the development of Ethiopia s hydropower resource along the Blue Nile. A resulting 1964 USBR study cited four locations along the upper Blue Nile River: Karadobi, Mabil, Mendaia, and Border. With a maximum capacity of 5,570 MW and a total estimated cost between 7 and 9 billion (Block and Strezepek 2010), these four dams still constitute an important part of Ethiopia s current strategic energy design. In fact, the Border Dam, renamed the Grand Renaissance Dam, is currently under construction. A more comprehensive summary of the USBR study is provided in Block (2006).

Brief Model Description

The Investment Model for Planning Ethiopian Nile Development (IMPEND) was designed to estimate the net benefits of the USBR proposed hydropower system (Block 2006; Block and Strezepek 2010). Streamflow, precipitation, and evaporation, dam specifications, dates at which the dams come online, the volume of flow that may be retained by Ethiopia, and the project discount rate serve as input variables to the model. One notable feature of IMPEND is that it stochastically considers the time necessary to fill the reservoir once construction of a dam is complete, appropriately delaying benefits of hydropower generation. IMPEND is a general algebraic modeling system (GAMS) model run on a monthly time step over 30 years.

IMPEND assumes perfect foresight of streamflow conditions over the project time horizon to produce optimal storage and release decisions across all reservoirs in series that maximize hydropower benefits. The system objective function is given by Eq. (1)

$$\text{Objective} = \max\left[\sum_{y}\sum_{s}(E_{y\,s}\quad P^{\mathrm{HP}}\quad D)\right] \tag{1}$$

where the product within the double sum refers to net revenue from hydropower; $P^{\mathrm{HP}} =$. 8/kWh, which is the fixed price for selling hydroelectricity; $E_{y\,s}$ = energy from hydropower from reservoir s in gigawatt hours per year; D = discount rate; y = year; and s refers to the reservoir or dam site—either Karadobi, Mabil, Mendaia, or Border. The price of hydropower, consistent with prior studies [e.g., Whittington et al. (2005)], is appropriately converted to achieve consistent units. The production of energy is given by Eq. (2)

$$E_{m\,s} \le Q^{P}_{m\,s}\quad H_{m\,s}\quad e_{m\,s} \tag{2}$$

where $Q^{P}_{m\,s}$ = flow used for hydropower generation in cubic meters per month; m in the subscript refers to month; $H_{m\,s}$ = monthly head level of each reservoir in meters; $e_{m\,s}$ = turbine efficiency; and = conversion factor. The reservoir storage balance is given by Eq. (3)

$$S_{m+1\,s} = S_{m\,s} + Q^{\mathrm{RO}}_{m\,s} + Q^{\mathrm{US}}_{m\,s}\quad \mathrm{NE}_{m\,s}\quad \mathrm{RA}_{m\,s}\quad \beta_s\quad \mathrm{CE}_{m\,s}\quad Q^{P}_{m\,s}\quad Q^{\mathrm{SP}}_{m\,s} \tag{3}$$

where S = reservoir storage; $Q^{\mathrm{RO}}_{m\,s}$ = runoff into reservoir s from the surrounding basin in cubic meters per month; $Q^{\mathrm{US}}_{m\,s}$ = flow in cubic meters per month from upstream defined as ($Q^{P}_{m\,s}$ $Q^{SP}_{m\,s}$); NE = net reservoir evaporation in cubic meters per month; RA = reservoir surface area in square meters; β = channel properties factor; CE = channel evaporation in cubic meters per month; and $Q^{\mathrm{SP}}_{m\,s}$ = flow passing over the dam spillway in cubic meters per month.

Costs are applied ex post. Each dam is associated with fixed and variable costs (Block 2006). The fixed costs are distributed over the construction period, which is assumed to be 7 years for each dam.

Motivating a Fast nalysis Framework

Most analyses of the USBR hydropower system prior to Block (2006) assumed that all dams were constructed simultaneously and that upon completion of construction, hydropower is immediately produced. Block developed IMPEND to test the impact of these assumptions, showing that significantly lower net benefits and cost-benefit ratios result when a more realistic staggered construction schedule and the time necessary to fill the reservoirs are incorporated. IMPEND has been further employed to assess the impacts of climate variability, climate change, and various discount rates.

Block only considered one staggered construction schedule: Karadobi, Border, Mabil, and Mendaia. This is only one of 24 possible staggered construction schedules. Furthermore, Block conducted his analysis with an assumed fixed price of hydropower. Given uncertainties in future prices, it is not obvious that constructing the dams in the sequence mentioned previously would produce the greatest benefits; however, exploring each construction schedule under various future price paths would be a computationally intensive task for IMPEND. A single 30-year optimization takes approximately 20 min. With the consideration of 24 construction schedules, computation time climbs to 8 h. Adding in the effects of uncertainty (e.g., price, streamflow) can easily push the computation time into days or even weeks. Thus, the use of a screening model version of IMPEND could greatly facilitate analysis of many sources of uncertainties to help identify design strategies that maximize the expected net benefits of the project by reducing downside risks and capturing upside gains.

Development of a Midfidelity Screening Model Version of IMPEND

The objective in developing a midfidelity screening model for the Ethiopian hydropower system is to remove sufficient complexity from IMPEND to reduce computation time while maintaining the system s essential features to preserve the rank order of various design strategies. To accomplish this, three primary modifications to IMPEND were undertaken.

The first modification relaxes the constraint that all dams are constructed in the 30-year optimization window. The screening model instead allows for any subset of the four dams to be constructed. As part of this modification, decision rules that control whether a dam should be built are incorporated into the modeling framework. These decision rules are dependent on various future electricity price paths (which will be discussed in more detail subsequently). The second modification is the incorporation of construction costs into the modeling framework. Costs are based on the project initiation month and a set construction schedule. The third modification to IMPEND is a change from a monthly to a 6-month time step. Each 6-month time step roughly corresponds to the Ethiopian wet (April to September) and dry (October to March) seasons. This modification required aggregating the monthly input data to the 6-month seasons noted previously by summing each month s data for every 6-month season. The time-step modification reduces computation time to 1 to 2 min. It is likely that removing various nonlinearities in the model would further reduce run time however, 1 to 2 min is sufficiently fast for the purposes of this analysis.

Exploring Flexible Design Strategies: Application of the Screening Model

This section introduces the value of the screening model for developing flexible design strategies. "Hydropower Price Uncertainty Model" develops a description of the uncertainty in future electricity price paths using a binomial lattice model. Then it is shown how the screening model can be used to identify flexible design strategies given the various future electricity price paths. Finally, it is shown how the screening model can be used to value various options exercised on the most flexible design strategies.

Hydropower Price Uncertainty Model

The high-fidelity IMPEND model produces a range of cost-benefit ratios from a low of 1.07 to a high of 1.91 depending on flow policy and historic or climate change streamflow scenarios (Block and Strezepek 2010). Block and Strzepek assume that the price of hydropower is fixed at . 8/kWh. Here, a binomial lattice model is developed to explore the impact of price uncertainty. A binomial lattice model is a standard approach to showing possible future price paths and is widely used in investment analyses. In each period, there is a fixed probability that the price will increase by a constant factor or decrease by a (not necessarily equal) constant factor. Because the respective factors of increase and decrease are constant, binomial lattice models are recombinant. Thus, as the number of periods in the model becomes large, the distribution of outcome probabilities generated by the binomial lattice model approaches the normal distribution. More detail regarding binomial lattice models can be found in Luenberger (1998). This six period (one period is 5 years) lattice model produces 32 future price paths. Table 1 shows the prices generated by the lattice model in each period, along with that price s probability of occurrence. Derivation of the binomial lattice model is included in the Appendix.

Table 1 Energy Price Lattice Showing Possible Prices in Dollars per Kilowatt Hour and Their Probability of Occurrence in Percent for Each Period (Shown in Parentheses)

Period (Year A–Year B)					
1–5	6–10	11–15	16–20	21–25	26–30
0.08	0.086	0.092	0.099	0.106	0.113
(100)	(54.71)	(29.93)	(16.38)	(8.96)	(4.90)
—	0.075	0.08	0.086	0.092	0.099
—	(45.29)	(49.56)	(40.67)	(29.67)	(20.29)
—	—	0.07	0.075	0.08	0.086
—	—	(20.51)	(33.66)	(36.84)	(33.59)
—	—	—	0.065	0.07	0.075
—	—	—	(9.29)	(20.33)	(27.80)
—	—	—	—	0.061	0.065
—	—	—	—	(4.21)	(11.51)
—	—	—	—	—	0.056
—	—	—	—	—	(1.90)

Identifying Flexible Strategies

As mentioned previously, the 1964 USBR study considers only one construction sequence; however, it is not clear that this sequence is optimal, especially given uncertainties in influential parameters, such as electricity prices. The screening model developed previously provides us with a method to very quickly screen all possible construction sequences and identify those that appear most flexible under various uncertainties.

As in the full version of IMPEND, it is assumed that new dam construction begins immediately following the completion of the previous dam. Given that Border Dam is currently under construction and holding to the 7-year construction period criteria, there are six possible construction sequences, listed in Table 2. In principle, there are of course an infinite number of construction sequences and timings that could be analyzed; however, because the primary purpose of this study is to illustrate the power of screening models for developing flexible strategies, exploring additional permutations is deferred to future work.

The screening model is used to calculate the net present value (NPV) of each construction sequence given each particular price path, assuming that all dams are constructed in the 30-year simulation (this assumption is relaxed in the next section). The screening model, therefore, returns 32 NPVs for each sequence in Table 2. Because each price path has an associated probability of occurrence, expected NPV (ENPV) is calculated for each sequence. The discounted capital expenditures (CAPEX) is also calculated for each sequence. CAPEX is considered along with ENPV because many countries are capital constrained, motivating decision makers to pay special attention to the capital requirements of (especially large infrastructure) projects. Table 3 presents ENPV and CAPEX values for each construction sequence. Although all four dams are assumed to come on line regardless of sequence, CAPEX values differ due to discounting and differential dam costs. Considering ENPV, Sequence 1 is optimal, while for CAPEX, Sequence 4 is optimal.

Table 2 Possible Construction Sequences

	Dam construction start date			
Order	Year 1	Year 8	Year 15	Year 22
Sequence 1	Border	Karadobi	Mabil	Mendaia
Sequence 2	Border	Karadobi	Mendaia	Mabil
Sequence 3	Border	Mabil	Karadobi	Mendaia
Sequence 4	Border	Mabil	Mendaia	Karadobi
Sequence 5	Border	Mendaia	Karadobi	Mabil
Sequence 6	Border	Mendaia	Mabil	Karadobi

Table 3 ENPV and CAPEX Criteria

Order	ENPV	CAPEX
Sequence 1	**1,824**	2,870
Sequence 2	1,758	2,902
Sequence 3	1,676	2,792
Sequence 4	1,731	**2,784**
Sequence 5	1,506	2,887
Sequence 6	1,678	2,847

Note: Values are given in millions of U.S. dollars; The most desirable values for ENPV and CAPEX are highlighted in bold.

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While informative, ENPV or CAPEX tells us little about the flexibility associated with each construction sequence, that is, which sequences minimize downside risks and capture upside gains. To identify the flexibility of each construction sequence, the distribution of design strategy outcomes is considered. Thus cumulative distribution functions are employed, also called value at risk and gain or target curves (de Neufville and Scholtes 2011).

Fig. 1 illustrates the target curves for each construction sequence. The target curves are constructed using the NPV and probability of occurrence associated with each price path generated by the binomial lattice model. In evaluating design alternatives, target curves completely to the right and not overlapping other curves are said to be stochastically dominant. That is, for any given outcome, the likelihood of a higher outcome is always greater for a stochastically dominant strategy. Furthermore, a stochastically dominant strategy will have the smallest probability of bad outcomes (and by implication has the best worst outcome) and the highest probability of good outcomes (and by implication has the maximum best outcome). Thus, of all the design strategies considered, a stochastically dominant design strategy is also the most flexible design strategy; downside risks are minimized and upside gains are maximized. Fig. 1 shows that Sequence 1 stochastically dominates the alternatives and is therefore the preferred construction sequence from the standpoint of flexibility in design. The preference for Sequence 1, however, should not be interpreted to mean that Sequence 1 will always yield the best result for any given future. It does, however, indicate that Sequence 1 has the best chance of the highest return across all futures considered in the analysis. In other words, flexible design strategies have better outcomes on average compared with an inflexible, or less flexible, design strategy. For a given particular future, however, it is certainly possible that a less flexible design strategy may perform better than the most flexible design strategy. For example, a design strategy may perform poorly if a very low streamflow year is realized, whereas another strategy may perform particularly well under the same conditions, but less well for all other futures, such that the first strategy s target curve is everywhere to the right of the second.

In addition to identifying the most flexible design strategies, target curves provide decision makers guidance regarding which strategies may benefit from further refinement. Consider two design strategies, A and B, where ENPV   > ENPV_B because of relatively large potential gains of design strategy A. However, without these gains, assume that B would stochastically dominate A. Simply analyzing ENPV would hide this fact. The entire range of outcomes must be explored to highlight that B is nearly stochastically dominant. Such an analysis motivates developing ways that allow design strategy B to capture higher gains. As B is modified to capture higher gains, it approaches stochastic dominance and thus becomes increasingly flexible. This example highlights the importance of exploring the entire range of values when developing flexible design strategies and how an analysis of the entire range of values helps identify regions that would benefit from further refinement for the purpose of increasing the flexibility of the strategy.

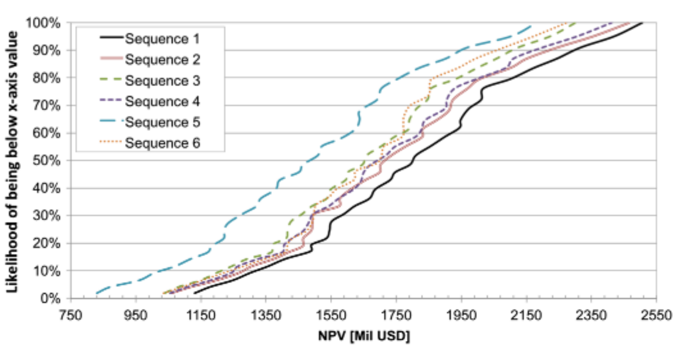

Fig 1 Target curves illustrating project NPV for flexibility in construction ordering

Improving the Flexibility of   ttractive Strategies

This section illustrates the power of screening models for investigating ways to increase the flexibility of attractive design strategies. In the previous section, Sequence 1 is determined to be the most flexible option of the six sequences considered. But as is demonstrated subsequently, Sequence 1 could be made even more flexible by developing decision rules that enable the design strategy to adapt to future contingencies. For example, if a planner is faced with falling electricity prices (or if any other change takes place that renders building dams unattractive), the planner would want to exercise the option of refraining from constructing future dams. The screening model provides the planner with a method of valuing different options, and in so doing enables the planner to chose a set of decision rules that provide the design strategy with the most increase in flexibility.

This concept is illustrated by analyzing Sequence 1 and three following associated options (which in this case correspond to simple decision rules; the combination of multiple options exercised at different time periods could lead to more complex decision rules) for refraining from building dams in particular future price paths:

1. Refrain from building Mendaia if the electricity price falls in every period.
2. Refrain from building Mendaia and Mabil if the electricity price falls in every period.
3. Refrain from building Mendaia and Mabil if the electricity price falls in every period and refrain from building Mendaia for any electricity price path that results in a price of . 65/kWh (Table 1, see also Table 7).

Sequence 1 will also be evaluated with no options—that is, all dams are built as prescribed.

These alternatives are run through the screening model for each of the 32 price paths prescribed. Table 4 shows ENPV and weighted CAPEX, where the weights are the probabilities of each price path. Option 3 adds the most value (approximately 2%) to the design strategy, and is therefore the superior option. Fig. 2 illustrates the target curves for the three options compared with the no options case, illustrating the increasing value of Sequence 1 by reducing downside losses. Option 3, therefore, is analogous to purchasing insurance, which reduces downside risk in undesirable states of the world, e.g., low electricity price paths. To summarize, the exercise of options increases the flexibility of Sequence 1 and Option 3 is the option that provides the greatest degree of increased flexibility.

Fig. 2 also illustrates the project value when no uncertainty in the price path is considered (solid black vertical line). By failing to consider uncertainty in the price path, the valuation of the project is severely distorted. Neither downside losses (which may be crucial

Table 4 ENPV and CAPEX Criteria

Strategy	ENPV	CAPEX
Number of options	1,824	2,870
Option 1	1,828	2,866
Option 2	1,833	2,859
Option 3	**1,857**	**2,836**

Note: Values are given in millions of U.S. dollars; The most desirable values for ENPV and CAPEX are highlighted in bold.

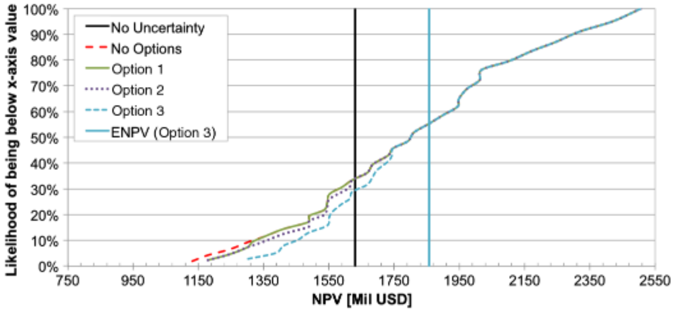

Fig 2 Target curves illustrating project NPV for flexibility in construction scheduling

to risk-averse decision makers) nor upside gains are realistically represented. Failure to include uncertainty can also lead to significantly misrepresenting the project s expected value (recall the flaw of averages). For example, as illustrated in Fig. 2, the expected value of the project considering uncertainty in electricity prices, ENPV (Option 3) in Fig. 2, is greater than the value of the project considering no uncertainty. While it will not always be the case that the expected value considering uncertainty is greater than expected value not considering uncertainty, the failure to include uncertainties will virtually guarantee misevaluation of the project.

Summary and Discussion

The purpose of this paper is to show how to use screening models to identify flexible design strategies that add value. The preceding analysis illustrates this point using a screening model based on the sophisticated IMPEND framework applied to the case of Ethiopian hydropower development. A set of future hydropower price paths is developed using a binomial lattice model and six construction sequences are analyzed for each price path using the screening model.

The results highlight how a screening model can be used to quickly identify attractive design strategies by highlighting those strategies that are most flexible. The screening model enabled analysis of 192 total scenarios (six design strategies, i.e., construction sequences, each for 32 electricity price paths) in a reasonable time frame. By relating each uncertain future to its probability of occurrence, the output of the screening model allows development of target curves for each of the six design strategies. The target curves allow identification of the most flexible strategy. Furthermore, target curves highlight where a particular design strategy may benefit from increased flexibility.

The example regarding optimal strategy identification (Fig. 1) focused on identifying stochastically dominant strategies. Certainly planners should aim for developing stochastically dominant design strategies, but it is not always possible to do so. In such cases, target curves serve to identify that subset of design strategies, as opposed to just one strategy, that are most flexible compared with other strategies being considered. The strategy ultimately selected may depend on the extent to which the design can be modified (for example, with options) or the decision maker s preferences and constraints. If the decision maker is particularly capital constrained, the option with the lowest CAPEX rather than maximum ENPV may be preferred. For this reason, it is important to present project outcomes using multiple criteria, as has been demonstrated in the analysis.

In addition to identifying flexible strategies, this analysis demonstrates that target curves are useful for developing and valuing options that when applied to design strategies increase their flexibility. Through the use of target curves, it is shown that in very low price path states of the world, Option 3 provides more flexibility than either Option 1 or Option 2 by reducing downside losses. An options analysis also helps planners decide what to do and when, or in other words, guides planners in formulating decision rules contingent upon given realizations of uncertain futures. For example, this analysis suggests the following decision rule: apply Option 3 in very low price path states of the world. Valuing additional options will enable planners to develop more specific decision rules (e.g., if the prices ever reaches X/kWh in year Y, the most flexible course of action is to build/not build the next dam). This paper does not intend to develop the analysis to this extent, but rather to illustrate how it can be done. As options or future uncertainties become increasingly complex, being able to develop decision rules is of high value to planners.

While this example only valued the flexibility to avoid bad situations due to low prices (by deferring projects), planners may similarly want to value the flexibility to take advantage of good opportunities due to high prices (e.g., by accelerating construction). This would provide a series of strategies extending the upper right-hand side of the target curves in Fig. 2, indicating the benefits of this complementary flexibility. In short, the flexibility in design approach potentially delivers a win-win: it reduces downside losses and increases upside gains.

Ultimately, uncertainties other than price that should factor into the design of water resources systems. A further analysis might therefore consider price, cost, streamflow, and demand uncertainty, with construction sequences incorporating the added option of variability in reservoir design volume. Given the linkage between energy prices and climate, another analysis could consider nonstationary future streamflow conditions for each price path. The flexibility in design approach presented in this paper provides a powerful method for conducting these increasingly complex analyses.

Appendix Details of the Binomial Lattice Model

A binomial lattice model is characterized by the initial value, a factor of increase, u, factor of decrease, d, probability of increase, p, and the number of periods. The first three parameters are calculated via

$$u = e^{\sigma\sqrt{\Delta t}} \tag{4}$$

$$d = e^{-\sigma\sqrt{\Delta t}} \tag{5}$$

$$p = .5 + .5\left(\frac{v}{\sigma}\sqrt{\Delta t}\right) \tag{6}$$

where σ defines the standard deviation of a forecast of the value of interest (in this case, electricity price) and v defines the growth rate of the value of interest for the given Δt. In this model, $\Delta t = 1$. The values of σ and v are calculated using an African wide relative electricity price forecast generated from the Massachusetts Institute of Technology (MIT) Emissions Prediction and Policy Analysis (EPPA) model reference case that projects electricity prices from 1997 to 2100 in 5-year time steps beginning in 2000 (Gurgel et al. 2007). The relative price forecast is shown in Table 5. Prices in EPPA are relative prices, plus an additional tax rate; thus the price in the base year, 1997, is not exactly 1.

Because growth rates are compounded, one cannot simply divide the 33-year growth rate shown in Table 5 by 33 years. Rather, the 33rd root of the 33-year growth rate must be taken, shown in Eq. (7). This is a valid approach if a constant yearly growth rate is assumed

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Table 5 EPPA Price Forecast

Year	Relative price
1997	1.0002
2000	0.9332
2005	0.9803
2010	1.0621
2015	1.1195
2020	1.1701
2025	1.2178
2030	1.241

Table 6 Binomial Lattice Model Parameters

Parameter	Value
V	0.006563
Σ	0.069631
u	1.07
d	0.93
p	0.55

$$v_{\text{yearly}} = \sqrt[33]{v_{33\ \text{years}}} \quad 1 \tag{7}$$

To calculate σ, 40% variability about the final price forecast in Table 5 is assumed. Forty percent therefore represents the 33-year standard deviation, or $\sigma_{33\ \text{years}}$. If a process with no memory is assumed, then the variance for 33 years can be related to the 1-year variance by $\text{variances}_{33} = 33 \quad \text{variance}_1$. Therefore, the yearly standard deviation can be calculated as follows:

$$\sigma_{\text{yearly}} = \frac{\sigma_{33\ \text{years}}}{33} \tag{8}$$

Solving Eqs. (7) and (8) and plugging in the values to Eqs. (4)–(6) with $\Delta t = 1$ result in the binomial lattice parameters given in Table 6. Table 7 presents the 32 price paths generated by the lattice model; the probability column in Table 7 sums to 100.

Table 7 Binomial Lattice Model Price Paths

Price path	1–5	6–10	11–15	16–20	21–25	26–30	Probability (%)
Price path 1	0.080	0.086	0.092	0.099	0.106	0.113	4.9
Price path 2	0.080	0.086	0.092	0.099	0.106	0.099	4.1
Price path 3	0.080	0.086	0.092	0.099	0.092	0.099	4.1
Price path 4	0.080	0.086	0.092	0.086	0.092	0.099	4.1
Price path 5	0.080	0.086	0.080	0.086	0.092	0.099	4.1
Price path 6	0.080	0.075	0.080	0.086	0.092	0.099	4.1
Price path 7	0.080	0.086	0.092	0.099	0.092	0.086	3.4
Price path 8	0.080	0.086	0.092	0.086	0.092	0.086	3.4
Price path 9	0.080	0.086	0.092	0.086	0.080	0.086	3.4
Price path 10	0.080	0.086	0.080	0.086	0.092	0.086	3.4
Price path 11	0.080	0.086	0.080	0.086	0.080	0.086	3.4
Price path 12	0.080	0.086	0.080	0.075	0.080	0.086	3.4
Price path 13	0.080	0.075	0.080	0.086	0.092	0.086	3.4
Price path 14	0.080	0.075	0.080	0.086	0.080	0.086	3.4
Price path 15	0.080	0.075	0.080	0.075	0.080	0.086	3.4
Price path 16	0.080	0.075	0.070	0.075	0.080	0.086	3.4
Price path 17	0.080	0.086	0.092	0.086	0.080	0.075	2.8
Price path 18	0.080	0.086	0.080	0.086	0.080	0.075	2.8
Price path 19	0.080	0.086	0.080	0.075	0.080	0.075	2.8
Price path 20	0.080	0.086	0.080	0.075	0.070	0.075	2.8
Price path 21	0.080	0.075	0.080	0.086	0.080	0.075	2.8
Price path 22	0.080	0.075	0.080	0.075	0.080	0.075	2.8
Price path 23	0.080	0.075	0.080	0.075	0.070	0.075	2.8
Price path 24	0.080	0.075	0.070	0.075	0.080	0.075	2.8
Price path 25	0.080	0.075	0.070	0.075	0.070	0.075	2.8
Price path 26	0.080	0.075	0.070	0.065	0.070	0.075	2.8
Price path 27	0.080	0.086	0.080	0.075	0.070	0.065	2.3
Price path 28	0.080	0.075	0.080	0.075	0.070	0.065	2.3
Price path 29	0.080	0.075	0.070	0.075	0.070	0.065	2.3
Price path 30	0.080	0.075	0.070	0.065	0.070	0.065	2.3
Price path 31	0.080	0.075	0.070	0.065	0.061	0.065	2.3
Price path 32	0.080	0.075	0.070	0.065	0.061	0.056	1.9

Note: Values are given in dollars per kilowatt hour.

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