ABSTRACT

We consider a problem commonly faced in the nuclear power industry, involving annual selection of plant capital investments under the constraints of a limited and uncertain budget. When the budget is assumed known, a typical approach to such problems is built on a multi-dimensional knapsack model. This model takes as input the available budget in each year, the stream of liabilities induced by selecting each project, and the profit, i.e., net present value (NPV), of each project. The goal is to select the portfolio of projects with the highest total NPV, while observing the budget constraint for each year, as well as any additional constraints. We show that a portfolio selected in this manner can fail to hedge against uncertainties in the budget. While the budget may be known at the beginning of the planning period, external events can cause this to change as time unfolds, and hence the funds that will actually be allocated over time are typically uncertain. So, we propose a model that forms an optimal priority list of projects, incorporating multiple budget scenarios. The model is applied to example projects from the South Texas Project Nuclear Operating Company (STPNOC).

INTRODUCTION

When practitioners plan for capital budgeting they often form a priority list of candidate projects, by scoring the projects individually, using economic measures like net present value (NPV), benefit-to-investment ratio, payback period, internal rate of return, etc. The academic literature frequently points out (e.g., Refs. [1] and [2]) that priority lists built on such simple ranking measures are inferior to allocating funds to capital projects using variants of a multi-dimensional knapsack model (henceforth, called a multi-knapsack model). See Ref. [3] for an overview of both ranking- and knapsack approaches to project selection, and see, e.g., Refs. [4] and [5] for more detailed discussions of the latter. For more on knapsack models and their variants see, e.g., Ref. [6]. The multi-knapsack model takes as input a budget forecast and selects a collection of projects to be carried out, assuming the point forecast for the budget is correct. We will refer to this selected collection of projects as a project portfolio.

If the budgets in coming years are known with certainty, we agree that multi-knapsack models can provide an attractive tool for selection of the portfolio. However, how should we approach capital budgeting when we have uncertain budget forecasts? One approach is to re-solve a multi-knapsack model when

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refined budget forecasts become available. Unfortunately, this is not always viable. Capital projects are typically implemented in phases over time and usually, some irreversible decisions must be made. It is not always practical to fully revise a project portfolio whenever better forecasts become available. Additionally, the process of obtaining and analyzing the necessary data, performing required reviews and obtaining necessary approvals typically is very time consuming and resource intensive. As a result, either simplistic approaches or the intuition and experience of management are used to address the impact of emerging events and conditions.

Many years of successful plant operation indicate that decision-makers often have the right intuition in seeking a priority list that is robust with respect to changes in budget values. We aim to provide a systematic method to producing such priority lists, a method which recognizes that the implemented projects will act as a portfolio. That is, our prioritization scheme captures the types of structural and stochastic dependencies that can arise. Our focus in this paper is on uncertain budgets, but clearly, other parameters such as project costs and profits can also be uncertain. While the general approach we propose can be extended to handle these more general cases, here we focus on a specific model that has computational advantages when only the budget is uncertain. The specific path of investigation described in this paper is as follows:

- We first investigate whether the solution to a multi-knapsack model naturally yields a prioritized list that is robust to the uncertainties described above. We show it does not.
- Next, we heuristically alter the multi-knapsack approach, and force it to produce a prioritized list. We call this the heuristic priority list.
- Finally, we ask whether we can build a priority list that outperforms the heuristic priority list, at least when we assume a probabilistic forecast for the uncertain budget. For the list of candidate projects we consider, this question is answered affirmatively. In particular, we formulate a model that explicitly incorporates multiple budget scenarios and forms an optimal priority list. We then show that the optimal priority list can significantly outperform the heuristic priority list.

In the next two sections, we investigate the three items above. The last section provides a summary and describes future research directions. For earlier variants of the work described here, see Refs. [7,8].

As indicated, we begin with the recommended approach to capital budgeting when the budget, as well as the cost and profit parameters, are known with certainty, i.e., the multi-knapsack model. In this setting, we have as input the available budget \( b_t \) in each year \( t \in T \), the stream of liabilities \( c_{kt} \) induced in each year \( t \) by selecting project \( k \in K \), and the profit \( a_k \), i.e., NPV, of selecting project \( k \). Further structural dependencies can involve mutually exclusive project selections, precedence relations, and other types of logical constraints between projects. The deterministic capital-budgeting problem is to select the most profitable portfolio of projects in the sense of highest total NPV, while observing the budget constraint for each year in the planning horizon as well as any additional structural dependencies. When the latter constraints are dropped, the model is known as a multi-knapsack problem.

In application to practical budgeting problems, the multi-knapsack approach outlined above can have serious shortcomings because some or all of its parameters, \( b_t \), \( a_k \), and \( c_{kt} \), are typically uncertain. When this is the case, in addition to the structural dependencies among projects mentioned above, stochastic dependencies can arise. To illustrate the flaw of the multi-knapsack approach, suppose we have used it to select a portfolio of projects. Then, over the course of the year, the available budget decreases due to external events. As a practical matter, a low-priority project will now be forced out of the portfolio, i.e., it will not be carried out. Unfortunately, solutions to the multi-knapsack formulation can be fragile to such events. In this paper, we develop an approach that better hedges against these types of future contingencies.

In this paper, we illustrate our approach using data from the South Texas Project Nuclear Operating Company (STPNOC). As the operator of a large commercial nuclear generating station, STPNOC must evaluate investment in numerous projects and choose a portfolio that will achieve the objectives of the organization. As a result, STPNOC annually develops a priority list of projects. This rank-ordered list specifies the highest priority project, the second-highest priority project and so forth. The current budget and project-cost forecasts yield what STPNOC calls a “blue line.” Projects above the blue line are to be funded and those below it are not. Thus, the “blue line” serves as the demarcation cutoff where the available budget is exhausted. Over the course of the year, the blue line can shift for reasons described above. We note that this paradigm is not unique to STPNOC, and it is not unique to the nuclear power industry. Rather, similar capital budgeting practices are employed across a wide range of industries and in government, too. The optimization model we propose recognizes that prioritizing is common practice and aims to build priority lists that are financially robust to budgetary uncertainties.

Our approach to forming an optimal priority list focuses on financial performance measures. However, financial goals alone do not drive capital planning decisions in the nuclear industry. The need to ensure regulatory compliance enters heavily into decision-making at STPNOC, and throughout the nuclear power industry. To address this issue, we emphasize that priority lists should generally include an integration of both financial and non-financial aspects into the decision process. At STPNOC (and many other commercial nuclear plants) this results in application of a multi-attribute utility theoretic approach to performing this integration (see e.g., Refs. [9] and [3]). In the demonstra-
tion of our approach, some projects have negative NPV estimates and hence would be rejected from a purely financial perspective. However, these projects are forced into the project portfolio by managerial dictate for safety and regulatory reasons. We show how this affects our approach and we further discuss how regulatory and safety issues are often well-aligned with financial goals.

We emphasize that our model is appropriate only when irreversible decisions regarding project selection must be made before knowing the budget values. If we can wait until these become known before committing to project selection decisions, we should do so and solve what is then a deterministic multi-knapsack model.

FORMING AN OPTIMAL PORTFOLIO: DETERMINISTIC CAPITAL BUDGETING

In this section, we first describe a multi-knapsack formulation for the deterministic capital-budgeting problem, and then discuss the implications of instead having stochastic budget levels. For simplicity, we will only consider stochastic budget levels, but our approach easily extends to handle uncertain project costs and profits. The notation and formulation of the multi-knapsack model are as follows:

Indices and sets:
\( k \in K \) candidate projects
\( t \in T \) time periods (years)

Data:
\( a_k \) net present value of project \( k \)
\( c_{kt} \) cost of project \( k \) in year \( t \)
\( b_t \) available budget in year \( t \)

Decision variables:
\( x_k \) 1 if project \( k \) is selected; 0 otherwise

Formulation:

\[
\begin{align*}
\text{max } & \sum_{k \in K} a_k x_k \\
\text{s.t. } & \sum_{k \in K} c_{kt} x_k \leq b_t, \quad t \in T \\
& x_k \in \{0, 1\}, \quad k \in K.
\end{align*}
\]

Constraint (1b) ensures the total cost of all investments in each year is within the budget for that year, \( b_t \). Yes-no restrictions on selecting alternatives are enforced by (1c). The objective function (1a) sums the NPV contributions of all the projects that are selected. The optimal solution to model (1) gives the portfolio of projects to select, which stays within the budget and maximizes the total NPV. This multi-knapsack model has been available for decades (Ref. [5]) as an approach to capital budgeting.

To demonstrate the application of the approach, we consider a numerical example with 16 projects each having liabilities in some or all of the next 5 years. Table 1 shows the \( c_{kt} \) and \( a_k \) values for each of the projects. Note projects 10-16 have negative NPVs, i.e., \( a_k < 0 \). Our optimization model (1) is driven by a purely financial goal, and hence would not choose any of these projects. However, projects 10-16 have been managerially mandated, i.e., they have been selected for reasons beyond the scope of our analysis. Regulatory and safety goals are of foremost concern in the nuclear power industry, and in fact, many regulations are legally required. Furthermore, unlike other industries where the result of inaction on regulatory or safety requirements may be an “acceptable” fine (i.e., one that could be accepted as a profitable business decision), failure to meet regulatory and safety goals in commercial nuclear power can very easily result in significant revenue loss. A yearlong shutdown could lead to revenue losses in the range of hundreds of millions of dollars in some cases, and more than a billion dollars at a multi-plant site. Restated, a more detailed financial analysis of projects 10-16 would likely lead to their NPVs being positive.

<table>
<thead>
<tr>
<th>Proj. ( k )</th>
<th>( c_{kt}/\text{year} )</th>
<th>NPV ( (a_k) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.740 6.134 10.442</td>
<td>60.589</td>
</tr>
<tr>
<td>2</td>
<td>0.425</td>
<td>0.667</td>
</tr>
<tr>
<td>3</td>
<td>0.030 0.030 0.688</td>
<td>0.122</td>
</tr>
<tr>
<td>4</td>
<td>0.122 0.103 0.013</td>
<td>0.824</td>
</tr>
<tr>
<td>5</td>
<td>0.950</td>
<td>0.582</td>
</tr>
<tr>
<td>6</td>
<td>0.219 0.257 0.085</td>
<td>2.315</td>
</tr>
<tr>
<td>7</td>
<td>2.125 2.122</td>
<td>5.173</td>
</tr>
<tr>
<td>8</td>
<td>2.387 0.190 0.012 2.383 0.192</td>
<td>4.003</td>
</tr>
<tr>
<td>9</td>
<td>5.044 1.839</td>
<td>22.459</td>
</tr>
<tr>
<td>10</td>
<td>4.025 0.297</td>
<td>-3.996</td>
</tr>
<tr>
<td>11</td>
<td>0.2 0.763 0.739 0.688 2.315</td>
<td>-2.870</td>
</tr>
<tr>
<td>12</td>
<td>0.095 0.095 0.095</td>
<td>-0.246</td>
</tr>
<tr>
<td>13</td>
<td>0.347</td>
<td>-0.322</td>
</tr>
<tr>
<td>14</td>
<td>0.300</td>
<td>-0.278</td>
</tr>
<tr>
<td>15</td>
<td>5.484 5.664 0.500 6.803 6.778</td>
<td>-20.155</td>
</tr>
<tr>
<td>16</td>
<td>0.081 0.032</td>
<td>-0.102</td>
</tr>
</tbody>
</table>

Table 1. PROJECT DATA (ALL VALUES IN $M).
but since they are managerially mandated there is little reason to justify them financially. In our work, projects 10-16 are not included when solving model (1), except that they do reduce the budget available for choosing among projects 1-9, and they do decrease overall NPV by almost $28M.

We solve 10 instances of model (1) with $b_t = 11, \ldots, 20$ for each of the five years in these respective instances, and display the solutions in Table 2. For each budget level, the 1s and 0s indicate whether the corresponding project was selected (1) or not (0), and the final column gives the optimal NPV. For example, when $b_t = 14M$ we select projects 2,3,\ldots,7 and do not select projects 1, 8 and 9. The corresponding NPV for this budget level is -$18.29M.

Our motivation for solving model (1) for a range of budget values is that as the year unfolds, adjustments to the budget must be made. These adjustments occur due to myriad reasons such as response to unplanned events (either internal or external) or deviations in expenditures from those assumed during the planning stage. As a result, from the perspective of choosing an optimal portfolio of investment projects, the budget can be viewed as possessing some uncertainty. Thus, we seek a solution that will perform well across multiple budget scenarios. As we notice from Table 2, for the subset of projects evaluated, some of them are part of the portfolio for a particular budget level but are absent from the portfolio at larger budget levels. For instance, as we increase the budget level from $11M to $20M, projects 2, 6, 7, 8 and 9 are alternatively in and out of the portfolio. This is a typical situation in capital budgeting problems, and more generally, in resource-constrained combinatorial optimization problems. That is, when the problem data are slightly perturbed, the new solution can be far from the previous solution. We note that this phenomenon represents a significant issue to decision-makers because it can result in decreased confidence in the investment decisions that are made.

To illustrate why the solutions behave in this manner, it is instructive to compare projects 1 and 8. Project 1 has a high profit-to-investment ratio as compared to project 8. However, as can be seen in Table 1, it also has a very large implementation cost ($23M over three years). Hence, one would like to include project 1 in the portfolio if it can fit within the available budget. This is exactly what happens for budget levels of $18M and up. On the other hand, project 8 is not that profitable (NPV of $4M compared to $60M for project 1). Effectively, it is selected only when its relatively low cost allows it to “just fit” within the residual budget when other more profitable projects are too costly to do so, and this is what occurs at the $15M budget level. Notice that at larger budget levels, other more profitable projects enter the portfolio and “kick out” project 8. Thus, one can view project 8 as a “filler” project that only would be funded if its costs just fit into the residual planned budget.

As mentioned above, STPNOCC’s solution to the capital budgeting problem is in the form of a priority list. The “volatility” of the optimal portfolios as the budget changes complicates our ability to derive a priority list from the solutions in Table 2, and more generally, this volatility may be disconcerting to decision makers. To address this volatility, we investigate an alternative solution approach that better lends itself to building a more robust priority list: As an initial simplistic approach (but one that is often used in practice), we begin by solving model (1) with $b_t = 11M$. Then, we solve model (1) for increasing levels of available budget (i.e., with $b_t = 12M$) under the additional requirement that all projects selected at the $11M$-budget level remain in the portfolio. We continue in this way to larger budget levels. The results of this approach for the set of candidate projects listed in Table 1 are shown in Table 3. We call this approach to solving the restricted capital budgeting problem a heuristic priority list.

We have now put restrictions on the optimization model, which were not present in the solutions in Table 2. Thus it is natural that the NPV figures are worse. Note the magnitude of the difference between the NPVs can be significant, particularly at the larger budget values. The intuition behind this result should be clear: As we incrementally raise the budget level we continue to add projects which fit within the new budget increment. While these projects increase NPV, this incremental strategy never allows us to select the higher-cost project 1. In practice, project 1 would likely be funded by management because its benefits are so clear. However, less extreme instances of this issue often arise for projects, and collections of projects, that fall near the cutoff point, i.e., the blue line. Without the type of analytical tool developed in this paper, the benefits of such projects are easily
Table 3. THE HEURISTIC PRIORITY LIST.

<table>
<thead>
<tr>
<th>Budget Level ($M)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>NPV ($M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-23.58</td>
</tr>
<tr>
<td>12</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-23.46</td>
</tr>
<tr>
<td>13</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-23.46</td>
</tr>
<tr>
<td>14</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-18.29</td>
</tr>
<tr>
<td>15</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-18.29</td>
</tr>
<tr>
<td>16</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-14.28</td>
</tr>
<tr>
<td>17</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-14.28</td>
</tr>
<tr>
<td>18</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-14.28</td>
</tr>
<tr>
<td>19</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-14.28</td>
</tr>
<tr>
<td>20</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-14.28</td>
</tr>
</tbody>
</table>

From the solutions in Table 3 we infer the following priority list: Projects \{2, 4, 5, 6\} all receive top priority because they are funded for all budget levels we consider. Projects 3, 7 and 8 follow, prioritized in that order. Finally, projects \{1, 9\} receive lowest priority because they are not funded even with the largest budget level.

Thus, in our view, the initial solution when selecting a portfolio from these projects under budget uncertainty is a priority list of the projects. Then, given the budget realization, we implement that list by always selecting projects \{2, 4, 5, 6\} (since they can be implemented under any budget scenario that is evaluated).

Next, project 3 is added if the budget is $12M or above, project 7 if the budget is $14M or above, and project 8 if the budget is $16M or above.

To proceed with further analysis, we require more information be assumed on the budget forecast. In particular, we will assume that the most likely budget value (in each year) is $17M. There is some chance that the budget will be larger and we assume the associated probabilities drop off linearly for budget values of $18M, $19M and $20M. Similarly the budget can drop below $17M, and we allow for a substantial drop, all the way to $11M, but the associated probability masses drop quickly, exponentially, from $17M to $11M. The resulting budget probability distribution we assume on the budget values is given in Table 4.

Under this probability distribution we obtain an expected NPV of -$15.42M by implementing this priority list. At the other extreme, we can compute the expected NPV under perfect information by weighting the NPVs in Table 2 using the weights given in Table 4 to obtain $11.90M. Of course, this latter value is obtainable only if we can know the budget value when we select our portfolio of projects. These figures indicate that the “value of information” is significant in this problem. If we could improve the budget forecast, e.g., by further data collection and performing a more detailed forecasting analysis then it could improve our ability to prioritize projects at the beginning of the year.

Assuming that the budget forecast cannot be further improved, we ask the following fundamental question: Without knowing the future, can we form a priority list that outperforms the heuristic list’s expected NPV of -$15.42M? The next section develops an optimal prioritization model that allows us to answer this question affirmatively.

**FORMING AN OPTIMAL PRIORITIZATION: STOCHASTIC CAPITAL BUDGETING**

The deterministic capital budgeting model of the previous section assumes that we know the budgets over the planning period (say, five years) in advance. As we have shown, the model does not naturally produce a priority list. In the analysis of previous section, we used the deterministic model to deal with uncertain budgets, but that analysis was admittedly ad hoc and that is why we referred to the result as a heuristic priority list. In this section we build a model that explicitly incorporates multiple budget scenarios. While the previous section’s multiknapsack model was an example of an integer program, this section’s model is an example of a two-stage stochastic integer program. Stochastic programs extend linear and integer programs to deal with uncertain data (e.g., Refs. [10–12]). The notation and formulation of the optimal prioritization model are as follows:
Indices and sets:
k, k' ∈ K candidate projects
p ∈ P priorities; P = {1, 2, . . . , |P|} 
t ∈ T time periods (years)
ω ∈ Ω budget scenarios

Data:

ak net present value of project k
c_kt cost of project k in year t
b^o_t available budget in year t under budget scenario ω
q^o_ω probability of budget scenario ω

Decision variables:
x^o_k ∈ {0, 1}; 1 if project k is selected under scenario ω; 0 otherwise
y_kk' ∈ {0, 1}; 1 if project k has higher priority than k'; 0 otherwise
zkp ∈ {0, 1}; 1 if project k is assigned priority level p; 0 otherwise

Formulation:

\[ \text{max}_{x^o_k \forall k \in K} \sum_{k \in K} \sum_{\omega \in \Omega} q^o_\omega a_k x^o_k \text{ (2a)} \]

s.t. \[ \sum_{k \in K} c_k x^o_k \leq b^o_t, \quad t \in T, \quad \omega \in \Omega \text{ (2b)} \]
\[ \sum_{k \in K} z_k p = 1, \quad p \in P \text{ (2c)} \]
\[ \sum_{p \in P} z_k p \leq 1, \quad k \in K \text{ (2d)} \]
\[ |P| y_{kk'} \geq \sum_{p \in P} (|P| - p)(z_k p - z_{k'} p), \quad k \neq k', k, k' \in K \text{ (2e)} \]
\[ y_{kk'} + y_{k'k} = 1, \quad k < k', k, k' \in K \text{ (2f)} \]
\[ x^o_k \geq x^o_{k'} + y_{kk'} - 1, \quad \omega \in \Omega, k \neq k', k, k' \in K \text{ (2g)} \]
\[ x^o_k \in \{0, 1\}, \quad k \in K, \omega \in \Omega \text{ (2h)} \]
\[ y_{kk'} \in \{0, 1\}, \quad k \neq k', k, k' \in K \text{ (2i)} \]
\[ z_k p \in \{0, 1\}, \quad k \in K, p \in P. \text{ (2j)} \]

The timing of the decisions in model (2) is as follows: First, the priority list is formed. Then, the budget is realized. We then effectively work down the priority list performing the projects one at a time until the budget is exhausted. These dynamics are illustrated in Figure 1.

Model (2) is a two-stage stochastic integer program. The first stage variables, z and y, form the priority list and establish the precedence between projects based on their ranking in the list, respectively. The second stage variable, x^o_k, selects the portfolio of projects to implement under each budget scenario. Objective (2a) denotes the expected NPV over all scenarios. Constraint (2b) ensures the implemented projects stay within budget under each scenario, for each year. Constraint (2c) assigns exactly one project to each priority level. Constraint (2d) assigns at most one priority level to each project. Given z, constraints (2e) and (2f) define y, ensuring each pair of projects is properly ordered. Constraint (2g) requires the projects implemented by x^o_k, under each scenario, are consistent with the priority list’s ordering. The last three sets of constraints are binary restrictions.

We solve an instance of model (2), using the values for a_k and c_kt given in Table 1, and the values for the budget scenarios b^o_t and associated probabilities q^o_ω as given in Table 4. (All of the problem instances in this paper have been solved with ILOG’s commercially-available optimization software CPLEX, version 10.1.) These values match those used in computing the expected NPV under perfect information and under the heuristically-obtained priority list discussed in the previous section. The solution to this instance of model (2) is a priority list and that list is given in Table 5. The heuristically-obtained priority list associated with Table 3 is also given for reference. The performance of the optimal priority list under each scenario is given in Table 6. When comparing this with Table 3 we see that the optimal priority list underperforms the greedy heuristic (but only by a relatively small amount) for budget values of $14M-17M. However, for larger amounts of available budget, the stochastic approach significantly outperforms the heuristic priority list (as seen by the resultant portfolio NPVs obtained for the budget values between $18M-20M). Weighting across all budget scenarios leads to the optimal expected NPV from the prioritization problem of $2.60M. This value is (necessarily) larger than that of the heuristic (-$15.42M) and, of course, smaller than that under perfect information ($11.90M). Figure 2 compares the NPVs for each budget scenario under each method. The values obtained under the heuristic (-$15.42M), the optimal prioritization ($2.60M) and perfect information ($11.90M) can be obtained from Figure 2 by weighting the respective points for each budget realization by the probabilities from Table 4 and summing. Again, as the figure shows the heuristic priority list outperforms the optimal list.
under some budget scenarios ($14M-17M), but not in the overall expected value of the NPV due to the performance under budget values $18M-20M.

From Table 5 we can see that the difference between the heuristic and optimal priority list is that the latter moves project 1 up in the prioritization. This change leads to a significant improvement in expected NPV and demonstrates the potential value of the prioritization model. Of course, with the small number of projects in this example, we could have obtained this improvement by trial-and-error. However, the prioritization model can produce similar results when the number of projects is larger and it is impossible to exhaustively examine all such alternatives.

To illustrate this, we carried out the same type of analysis we have just described on a larger problem instance with a separate set of 48 projects from STPNOCS, and we obtained qualitatively similar results. We will not describe these projects in detail, but the following gives a rough idea about the problem data: All projects now have positive NPV, ranging from $8k up to $38M, and these values are “smoother” than those in our first example that had the dominating project 1. The budget distribution again has 10 possible realizations however over a different range ($2.5M up to $7M, in increments of $0.5M); in our analysis the same probability distribution as given in Table 4 was applied over this range. Figure 3 plots the NPV of the projects implemented as a function of the budget for this larger problem instance for the prioritization model, the heuristic procedure and the problem under perfect information, and the figure looks roughly similar to that of Figure 2. The expected NPV of the prioritization model exceeds that of the heuristic by 12.5% and falls short of that under perfect information by 10.4%.

The goal of the prioritization model we have developed here is to give decision makers a tool that provides insight as to the relative merit of the candidate projects, given plausible budget scenarios. Such insight can be difficult to obtain when using current practice, whether by scoring projects individually (e.g., using a measure like benefit-to-investment ratio), by solving a deterministic multi-knapsack problem as in the previous section, or by heuristically devoting a portion of the budget to a contingency fund.
SUMMARY AND FUTURE WORK

In practice, it is common to use performance measures like payback period, internal rate of return, benefit-to-investment ratio and net present value for individual capital projects to form a priority list of candidate projects. Such an approach fails to recognize that the selected projects will act as a portfolio, and ignoring this fact can lead to sub-optimal priority lists. It is recommended in the literature that capital budgeting be done using variants of a multi-knapsack problem formulation. In this paper we have demonstrated through an example that such solutions can be volatile with respect to changes in budget values. This can be disconcerting to decision makers, especially since it is almost certain that budget allocations will need to respond to emerging events. In this setting, a properly formed priority list can provide a valuable approach to hedging against such uncertainties, at least when irreversible decisions must be made prior to knowing the budget realizations. We have discussed an optimal prioritization model that explicitly incorporates multiple budget (and/or cost and profit) scenarios to develop an optimal priority list that is robust to external events that impact plant budgets. We showed that this priority list can significantly outperform priority lists formed through heuristic means. This concept was illustrated on two separate sets of projects from STPNOC.

There are multiple important directions to be pursued as future work associated with the model and analysis presented here. At this stage, we have demonstrated our approach using budget data provided from a commercial nuclear power plant. However, before the approach can be used more broadly, additional research is necessary. First, the computation in this paper focused solely on treating the budgets as random variables. We aim to extend this to also treat project profits and costs as random variables. Second, many projects are implemented in phases with the potential for delaying implementation of one or more of those phases. We aim to capture this within the prioritization framework. These first two issues all present significant computational challenges that need to be addressed. Third, we will further investigate the issue of structural dependencies among projects in the prioritization model, e.g., the piggybacking effect.

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