

Article

Uncertainty Quantification and Sensitivity Analysis of Nuclear Construction Cost Reduction Pathways

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Abstract

High construction costs have plagued recent nuclear projects and they hamper the widespread deployment of nuclear technology. The Nuclear Cost Reduction Tool is a plant economic framework that quantifies the impact that various plant design and construction attributes have on construction costs and cost overruns and shows the positive effects of learning over a series of deployments. However, a downside of the current model is that all model outputs and capabilities are deterministic. To provide a more comprehensive view, this study evaluated the impact of model parameter uncertainty through a sensitivity analysis applied to 18 model parameters. This approach quantified the impact of model uncertainty on the output variables of Net Overnight Capital Cost (Net OCC), Construction Duration (CD), and Levelized Cost of Electricity (LCOE). Monte Carlo analysis revealed uncertainty distributions for these variables, showing that absolute uncertainty decreases over a series of deployments. A local sensitivity analysis showed that even small parameter perturbations (5%) can have a significant impact on project execution, highlighting areas that could reduce costs by billions across an order book of plants. The results of this study have improved the understanding of the model and identified the most impactful model parameters and construction attributes.

Keywords: nuclear; economics; uncertainty quantification; Monte Carlo; sensitivity analysis; construction costs; Levelized Cost of Electricity



Academic Editor: Laura Savoldi

Received: 17 December 2025

Revised: 17 January 2026

Accepted: 27 January 2026

Published: 3 February 2026

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1. Introduction

A key issue impeding the deployment of new advanced reactor designs is cost, specifically the capital costs of first-of-a-kind (FOAK) reactor projects and the potential for cost overruns [1,2]. This is a critical problem given the recent push for the increased deployment of nuclear power and the infrastructure development needed to support it [3].

Understanding what drives these costs is not straightforward—information gaps and inconsistent analysis methods make it difficult to identify which design or construction attributes should be prioritized for investment. As a result, decision-makers often lack clear guidance on where to focus efforts for meaningful cost reductions. Recent studies have attempted to address this by developing plant cost models that predict cost overrun statistics and explore strategies for reducing risk, each using different sets of plant metrics

and assumptions. For example, one model examines the effect of plant capacity and region on cost overrun percentage [4], another evaluates cost overrun reduction strategies based on lessons learned from AP1000 deployments in the US [5], and another estimates financial risk by incorporating a range of design and economic factors [6]. Together, these studies highlight the need for better tools to understand cost drivers and guide strategies for reducing nuclear project costs.

An important study for examining nuclear costs and trends for nuclear cost drivers was the Energy Economics Database, which organized economics data into a code-of-accounts structure to quantify economic correlations in nuclear project economics [7–9]. A code-of-accounts structure groups every cost component into different specific groups, denoted as accounts, which are then added up to obtain larger, top-level account cost values, with the sum of all top-level accounts being the total capital investment for the plant. For example, the “Energy conservation system” and “Electrical equipment” accounts are two component-wise accounts that can be added together with other specific component-wise accounts to obtain the top-level “Capitalized Direct Costs” account. Subsequent studies on nuclear economics and cost drivers used this original data as the basis for their analyses and tools [10–18]. Many cost trend analyses tend to rely on the learning rate equation, which describes how costs decrease due to the improved construction experience and supply chain development that are the result of more plants of the same type being built [19,20]. However, this approach can be an oversimplification of how costs are reduced between deployments and provides little insight into what drives the pathways to cost reduction by only focusing on top-level costs. Improving on this, recent studies have combined the learning rate equation with a bottom-up approach in which costs related to individual components and subsystems of a plant design are calculated and used to derive overall system costs [21–23]. Increasingly, this approach is being used to estimate costs for advanced reactor designs and small modular reactor designs as overall cost data for these yet-to-be deployed designs is nearly non-existent. Consequently, there is a large degree of uncertainty in the estimation of advanced reactor learning rates.

To address these concerns, the Nuclear Cost Reduction Tool was created to provide a framework for estimating the costs over an order book or series of deployments for FOAK advanced reactor designs based on various plant design and construction attributes [24]. The tool uses the generalized nuclear code-of-accounts as a basis for inputting the well-executed FOAK and Nth-of-a-kind (NOAK) cost estimates. Then, it incorporates design attributes, construction attributes, supply chain maturity levels, and other factors to estimate FOAK costs, which include cost and schedule overruns. The tool then projects cost reductions over an order book of the same plants as they approach NOAK costs. This approach allows for the identification of learning and cost savings on a more granular, plant-by-plant level, demonstrating the transition from FOAK to NOAK [19,20]. The hope is that the tool will help catalyze the investment and deployment of FOAK reactor projects by quantifying the size of potential risk associated with early deployments and improving the transparency of risk associated with various design and construction attributes. Additionally, the tool can demonstrate how this risk can be reduced for a specific plant design through the creation of a large order book and the potential cost savings for NOAK plants that result from learning-by-doing [25]. The correlations and calculations in the tool are based on previous studies on nuclear cost drivers [1,10,26] that made progress to untangle the attributes that affect learning rates.

An important aspect of the Nuclear Cost Reduction Tool is that it accounts for the effects of construction attributes (some of which are connected to design) and non-design-related factors on the cost of nuclear projects. The tool uses and follows the findings of several previous reports and studies that attributed reactor project cost increases to

labor and Working Statistics, factory and equipment costs, regulatory interference, design completion, design modularity, and more [27–30]. The tool also integrates indirect costs (related to engineering services, construction management, field supervision, startup, and testing) [31], an important component of project costs that often does not receive robust consideration in cost analyses and is usually attributed to a single static factor of direct costs. The tool leverages these insights and considers the impact of high-level decisions (e.g., government support, contractor proficiency, plant order book size, etc.) to provide FOAK and NOAK cost evolutions.

However, one limitation of the tool is that all model output and capabilities are deterministic; no uncertainty ranges or error bars are used to estimate output variables. This downside has the potential to lead to inaccurate results that do not account for inherent uncertainty in the cost model and therefore lead to lower trust in model outputs. This issue is further exacerbated by the large degree of uncertainty in advanced reactor economic metrics and the wide variety of nuclear economic studies that use different databases and analysis techniques for studying advanced reactor economics and learning rates. For example, a study by Lovering et al. uses an IAEA reactor system database in combination with other sources to examine plant historical cost data over time [2], a different study by Marciulescu et al. uses the EEDB and code-of-accounts structure to estimate NOAK economic metrics and risk mitigation based on industry expert-identified cost drivers [27], and another study by Eash-Gates et al. uses a wide array of academic and industry sources for overnight capital cost estimates that use a gross domestic product price deflator to convert nominal costs to real costs [28]. Because all of these studies began with different databases and considered different factors in their analyses, they can receive a large degree of variation in the economic metrics they obtain.

To address this limitation, this study presents an uncertainty quantification of the Nuclear Cost Reduction Tool to determine the effect that uncertainty has on the model outputs of Net Overnight Capital Cost (Net OCC), Construction Duration (CD), and Levelized Cost of Electricity (LCOE). Additionally, a local sensitivity analysis is performed to estimate the relative importance of the model parameters (compared to each other) on output variables and to quantify potential cost savings that arise from perturbing model parameters. Given the large degree of uncertainty in advanced reactor economic data, it is crucial to quantify the uncertainty in the Nuclear Cost Reduction Tool and add uncertainty estimates to it. This will improve the trustworthiness of its results and address the shortcomings in economic data and calculations.

The analysis discussed in this article is broken into three main sections. Section 2 describes the methodology of this work, the underlying model, and the parameters that were analyzed in this study. Section 3 discusses the results and key findings from this study with a discussion of their significance. Lastly, Section 4 summarizes the findings and highlights potential areas of future work.

2. Methodology

The cost reduction framework contains three different types of variables. The first type is input levers, which are values that the user can directly change. Input levers are the independent variables of the model that users can freely modify to assess the impact of different input lever values. The second type is model parameters, which are underlying variables that modify the given input lever values. Model parameters function similarly to coefficients, determining the impact of the input levers on the model outputs. The third and final type is output variables, which are the important variables that users aim to estimate. The output variables are obtained by modifying the given input lever values by the model parameters and are important project statistics, such as costs and construction durations. A

rough overview formula of the relationship between the input levers I, model parameters M(), and output variables O is given in Equation (1):

$$O = M(I) \quad (1)$$

Since the goal of this analysis is to evaluate how uncertainty in the model's underlying assumptions affects its outputs, uncertainty was applied only to the model parameters. These parameters represent the assumptions that govern how input lever values influence output variables. Uncertainty was not applied to the input levers themselves, as users can already explore variability in those values independently. Figure 1 shows the input levels, model parameter groups, and output variables that were important for the analysis (the variables included are not exhaustive).

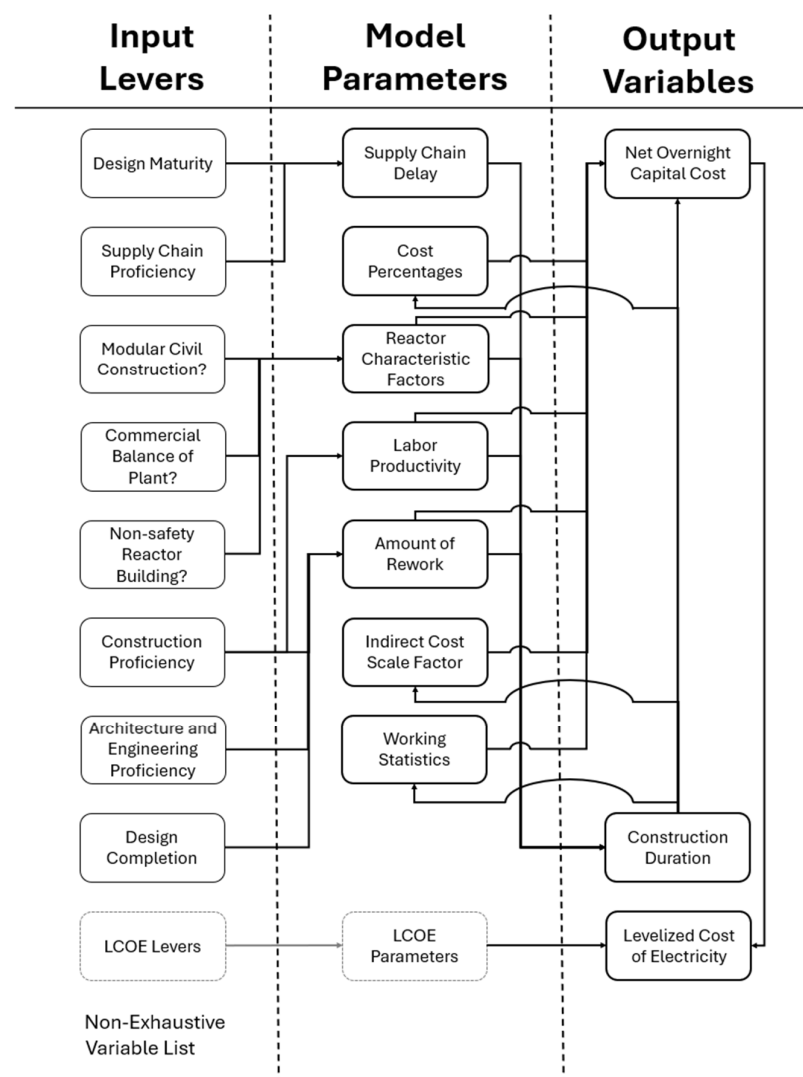


Figure 1. Non-exhaustive chart for the input levers, model parameter groups, and output variables in the cost reduction framework that are important to uncertainty quantification. Arrows from input levers to model parameters indicate that the model parameter modifies the input lever value, while arrows from model parameters to output variables indicate that those modified values are used in the output variable calculation.

2.1. Model Parameters

A total of 18 model parameters, organized into seven groups, were modified for the analysis. The following subsections detail each parameter group and any relation it may

have with the relevant input levers based on the relationship each parameter group has with the input levers. There are three types of parameters discussed below: static parameters that are not affected by inputs, linear parameters that are affected by inputs, and reactor characteristic variables that are affected by design characteristics (also an input).

2.1.1. Static Parameters

These groups of parameters have singular values that do not change as input lever values are changed, nor do they change throughout a plant order book.

Cost Percentages represent the cost amount for specified indirect cost categories as a percentage of the factory and construction supervision indirect costs. The nominal percentage values are taken from a sodium fast reactor study by Prosser [32]. There are three parameters in this group: Startup Cost Percent, Shipping and Transportation Cost Percent, and Engineering Services Cost Percent.

Working Statistics measure statistics related to the size and time commitment of the construction labor force. The nominal statistics are taken from an analysis by Stewart [17]. There are two parameters in this group: Average Number of Workers and Working Hours per Month.

Indirect Cost Scale Factors define the ratio in magnitude between direct costs and indirect costs for different cost categories. The nominal ratios are again taken from an analysis by Stewart [17]. There are three parameters in this group: Indirect Factory Cost Scale Factor, Indirect Materials Cost Scale Factor, and Indirect Labor Cost Scale Factor.

2.1.2. Linear Parameters

This group of parameters contains linear coefficients in linear equations where the independent variable is an input lever variable. Each linear equation has two constraints: a baseline value at the lowest proficiency and an optimal value at maximum proficiency. Because of these constraints, these linear relationships can be controlled just by the baseline value and then by adjusting the linear relationship to meet the constraints. An outline of the linear equation for these parameters is given below by Equation (2):

$$P = P_{\text{base}} + (P_{\text{max}} - P_{\text{base}}) \times (I - I_{\text{min}}) / (I_{\text{max}} - I_{\text{min}}) \quad (2)$$

where P is the final parameter value, P_{base} is the parameter value at minimum proficiency, P_{max} is the parameter value at maximum proficiency, I is the input lever value, and I_{max} and I_{min} are the maximum and minimum possible input lever values, respectively.

A key feature of these parameters is that as the input lever proficiency increases, the range of possible outcomes for the dependent variable becomes smaller when uncertainty is applied to the baseline parameter value (P_{base}). At maximum proficiency, the outcomes converge to a single value with no variation. This is important because the model assumes that proficiency improves with each new plant, which means that the uncertainty in these parameters decreases for subsequent plants.

Labor Productivity measures how efficiently construction converts working hours to project progress. It is linearly dependent on the Construction Proficiency parameter and can be controlled via the Baseline Labor Productivity at minimum Construction Proficiency, which was taken from the average labor productivity of the Vogtle nuclear project [33]. The only parameter in this group is Baseline Labor Productivity.

Rework Factors measure the percentage of the plant construction that must be redone after initial construction is finished. It is controlled via the Baseline Rework Factor at minimum proficiencies that are estimated based on data from two separate studies by Stewart and the U.S. DOE [17,29]. This group contains three parameters: Rework from

Design Completion, Rework from Architecture/Engineering Proficiency, and Rework from Construction Proficiency.

Supply Chain Delay measures the amount of time that construction is delayed due to inefficiencies in the supply chain. The baseline Supply Chain Delay values are from an analysis by Stewart [17]. This group contains two parameters: Delay from Design Maturity and Delay from Supply Chain Proficiency.

2.1.3. Reactor Characteristic Factors

This group of parameters reduces Construction Duration or total cost by a set percentage based on specific reactor design characteristics. These factors are tied to Boolean input levers (denoted by ending with a “?” in Figure 1) and take effect if the input levers have a value of TRUE.

The Modular Civil Construction Characteristic depends on whether or not the reactor parts are designed for modularity. If the characteristic is TRUE, Construction Duration is reduced by a factor taken from an analysis by Stewart [16].

The Commercial Balance of Plant (BOP) Characteristic depends on whether the balance of a plant can be commercially sourced from non-nuclear vendors (and therefore is not subject to nuclear qualifications). If TRUE, the total cost is reduced by a factor derived from a cost data study by Delene [34].

Lastly, the Non-safety Related Reactor Building (RB) Characteristic depends on whether the RB needs safety functionality (if the passive safety features of the reactor are sufficient). If TRUE, the total cost is reduced by a factor derived from a cost data study by Delene [34].

Parameter group behaviors can be used to predict how important each group will be to output variables. We expect the linear parameters to be the most impactful for the earlier plants in the order book because lower lever proficiencies result in greater variation from the different linear parameter baseline values. For later plants in the order book, the higher lever proficiencies will cause less variation in the linear parameters for later plants in the order book. The values of the static parameter and reactor characteristic factors do not change throughout an order book. Because of this consistency in value, the static parameter and reactor characteristic factors should have more impact for later plants in an order book.

2.2. Output Variables

There are three output variables measured by this analysis: Net OCC, CD, and LCOE. Net OCC represents the inherent cost to build the plant itself without the inclusion of harder to control costs such as interest costs and land costs. The Net OCC output is represented by units of dollars or USD/kWe, with the “Net” descriptor being used for the OCC value after investment tax credits are applied. CD measures how long it will take to build the plant and is represented in units of months. The CD value impacts indirect costs, which in turn can affect the Net OCC. LCOE measures the average annual cost of the plant per unit energy of electricity produced. This output is represented in units USD/MWh.

Additionally, each output variable has two variants for FOAK and NOAK. For FOAK, there is no learning-by-doing. Therefore, the Net OCC, CD, and LCOE for the FOAK plant are almost always the highest compared with subsequent plants. For NOAK, the Net OCC, CD, and LCOE represent that maximum learning-by-doing has been achieved. NOAK plants almost always have the lowest Net OCC, CD, and LCOE (compared with previous plants), and their input lever values are at or near their maximum proficiency.

Table 1 summarizes the connections between the model parameters and the different input levers and output variables. The only relevant inputs and outputs listed are the variables that are included in the analysis shown in Figure 1.

Table 1. Summary table of model parameters and relevant inputs and outputs for the analysis.

Model Parameter	Parameter Group, Type	Relevant Inputs (Non-Exhaustive)	Relevant Outputs (Non-Exhaustive)
Startup Cost Percent	Cost Percentages, Static	Construction Duration *	Net OCC, LCOE
Shipping and Transportation Cost Percent	Cost Percentages, Static	Construction Duration *	Net OCC, LCOE
Engineering Services Cost Percent	Cost Percentages, Static	Construction Duration *	Net OCC, LCOE
Average Number of Workers	Working Statistics, Static	Construction Duration *	Net OCC, LCOE
Working Hours per Month	Working Statistics, Static	Construction Duration *	Net OCC, LCOE
Indirect Factory Cost Scale Factor	Indirect Cost Scale Factor, Static	Construction Duration *	Net OCC, LCOE
Indirect Materials Cost Scale Factor	Indirect Cost Scale Factor, Static	Construction Duration *	Net OCC, LCOE
Indirect Labor Cost Scale Factor	Indirect Cost Scale Factor, Static	Construction Duration *	Net OCC, LCOE
Baseline Labor Productivity	Labor Productivity, Linear	Construction Proficiency	Net OCC, Construction Duration, LCOE
Rework from Design Completion	Amount of Rework, Linear	Design Completion	Construction Duration
Rework from Architecture/Engineering Proficiency	Amount of Rework, Linear	Architecture/Engineering Proficiency	Construction Duration
Rework from Construction Proficiency	Amount of Rework, Linear	Construction Proficiency	Construction Duration
Supply Chain Delay Param, Design Maturity	Supply Chain Delay, Linear	Design Maturity	Construction Duration
Supply Chain Delay Param, Supply Chain Proficiency	Supply Chain Delay, Linear	Supply Chain Proficiency	Construction Duration
Modular Construction Factor	Reactor Characteristic Factors	Modular Civil Construction Boolean	Construction Duration
Commercial Balance of Plant Energy Factor	Reactor Characteristic Factors	Commercial Balance of Plant Boolean	Construction Duration
Commercial Balance of Plant Energy Factor	Reactor Characteristic Factors	Commercial Balance of Plant Boolean	Construction Duration
Safe Reactor Building Factor	Reactor Characteristic Factors	Non-safety Reactor Building Boolean	Construction Duration

* The model parameters and input levels that have Construction Duration as an output are transitively used as inputs for any parameter that uses Construction Duration as an input.

2.3. Uncertainty Analyses

Two types of uncertainty analyses are performed on the model parameters: Monte Carlo Sampling and local sensitivity analysis.

For the Monte Carlo Sampling, all model parameter values are sampled from normal distributions where their mean value is their respective nominal value, and their standard deviation is 5% of their respective nominal value. A normal distribution was chosen as a generic distribution due to the lack of information about the uncertainty behavior of the

parameters and because the underlying formulation for top-level economic metrics in the code-of-accounts structure used by the tool is based on the linear additions of component-wise cost accounts [24]. Meanwhile, the perturbation percentage was chosen because it is a good representative value that can capture the effect of uncertainty on the output variables without being too large. This is completed for a set number of samples, and the output variable values are recorded for each sample. This list of output values can then be analyzed using distribution plotting and uncertainty measurements for different plants in an order book. The varied model parameter values were randomly sampled independently of other model parameters in the same sample, as well as independently of model parameter values in different samples.

For the local sensitivity analysis, all model parameters are individually perturbed by a set amount of their nominal value ($\pm 5\%$ in this study) and the change to the output variable values is recorded. This change can be used to estimate the impact that each parameter has on the output variables and the potential cost savings, or Construction Duration decreases that can be achieved by perturbing the parameter values.

2.4. Input Lever Values

The same input lever values were used for all analyses and are shown in Table 2. The plant design used for all analyses is the dual-unit, 2234 MWe Large Passive Safety Reactor (LPSR) [17]. A few input lever values were changed from their original values to improve the quality of the uncertainty analyses. Firstly, all the reactor characteristic Boolean levers were set to TRUE so the effect of changing the reactor characteristic factors could be measured. If the Boolean levers were set to FALSE, then changing the factor values would have had no effect. Next, all input lever FOAK proficiencies were set to a value of 1 because it was the middle value in the proficiency range of values (ranging from 0 to 2). Lastly, a feature of the tool is that the proficiency lever values increase toward the maximum proficiency values for each subsequent plant. Since the learning effects and NOAK performance of advanced reactors are not well understood, the number of plants to achieve best proficiency was set to 9 so that all proficiencies would reach their maximum value at the final 10th plant instead of the optimistic scenario where maximum proficiency is reached before the final plant.

Table 2. The important input lever values used for all uncertainty analyses.

Input Lever Label	Input Lever Value
Number of Firm Orders (N)	10
Number of Plants to Reach NOAK	8
FOAK Design Completion	70%
FOAK Supply Chain Proficiency	1
FOAK Architecture/Engineering Proficiency	1
FOAK Construction Proficiency	1
Cross Site Standardization	80%
Cross Site Transfer Efficiencies	80%
Modular Civil Construction? (All plants)	TRUE
Commercial BOP? (All plants)	TRUE
Non-Safety-Related RB (All plants)	TRUE
Number of plants to achieve best proficiency (All)	9

3. Results and Discussion

3.1. Omitted Parameters

Some parameters that were originally included in the uncertainty quantification were removed for the final analysis:

Land cost measures the dollars per acre needed to acquire the land needed for a nuclear construction project. Applying uncertainty to this parameter had no impact on Net OCC, CD, or LCOE because this cost is not included in the Net OCC or LCOE calculations. For the sake of brevity, it was omitted.

The Indirect Labor Hours Scale Factor measures the ratio between labor hours needed for indirect cost-related tasks and the labor hours needed for direct cost-related tasks. Applying uncertainty to this parameter had no impact on Net OCC, CD, or LCOE. At the time of this analysis, it was unclear whether this was an actual result or a mistake in the code. Once this has been determined, this parameter will be included in future analyses.

The Baseline Cross Site Standardization measures the percentage of the FOAK plant design that can be standardized for different sites. Applying uncertainty to this parameter did have an impact on the output variables, but the results were unexpected, with a higher Baseline Cross Site Standardization resulting in worse output variable metrics. This may be due to an issue with the model or how the uncertainty quantification was applied to this parameter. Therefore, this variable was omitted and remained at its nominal value for this analysis so as not to alter the results of the other parameters.

3.2. Monte Carlo Sampling: Output Variable Distributions

Figure 2 shows the resulting distributions for FOAK Net OCC (top), CD (middle), and LCOE (bottom) when all model parameters are sampled from normal distributions with a 5% standard deviation compared with their nominal values. All output distributions appear to be normally distributed, but the FOAK Net OCC distribution has a slight rightward tail which is more apparent in the Cumulative Distribution Function (CDF) plot, where the difference in the last two percentile points is larger than the difference in the first two percentile points. The nonlinear relationships of the sampled model parameters with the output variables are seen with rightward tails on the distributions of the FOAK Net OCC and FOAK LCOE variables; the parameter perturbations that increase costs are more impactful than parameter perturbations that decrease costs. These nonlinear relationships might be a contributing factor to the difficulty in lowering the costs of nuclear construction projects; the relevant parameters are more sensitive to increasing costs than to decreasing costs. The relative uncertainties for FOAK Net OCC (3.24%) and FOAK LCOE (2.40%) are larger than the relative uncertainty for CD (0.87%), which indicates that uncertainty in the model parameters has a greater impact on FOAK Net OCC and FOAK LCOE than on FOAK CD. This indicates that uncertainty in model parameters affects cost-related outputs more significantly than CD, underscoring the need to focus on cost-controlling strategies in FOAK nuclear projects.

Figure 3 shows the resulting distributions for NOAK Net OCC (top), CD (middle), and LCOE (bottom) when all model parameters are sampled from normal distributions with a 5% standard deviation compared with their nominal values. All three output distributions are mostly normally distributed, with the slight rightward tail for FOAK Net OCC and FOAK LCOE still present for NOAK Net OCC and NOAK LCOE. While the relative uncertainties for NOAK Net OCC (2.49%) and NOAK LCOE (1.36%) are larger than the relative uncertainty for CD (0.97%), the gap in relative uncertainty for the NOAK outputs is smaller than it is for the FOAK outputs. Similarly to before, costs appear more sensitive to uncertainty than Construction Duration, likely due to a compounding effect where construction issues drive both schedule delays and cost increases, while schedule delays independently contribute to additional costs.

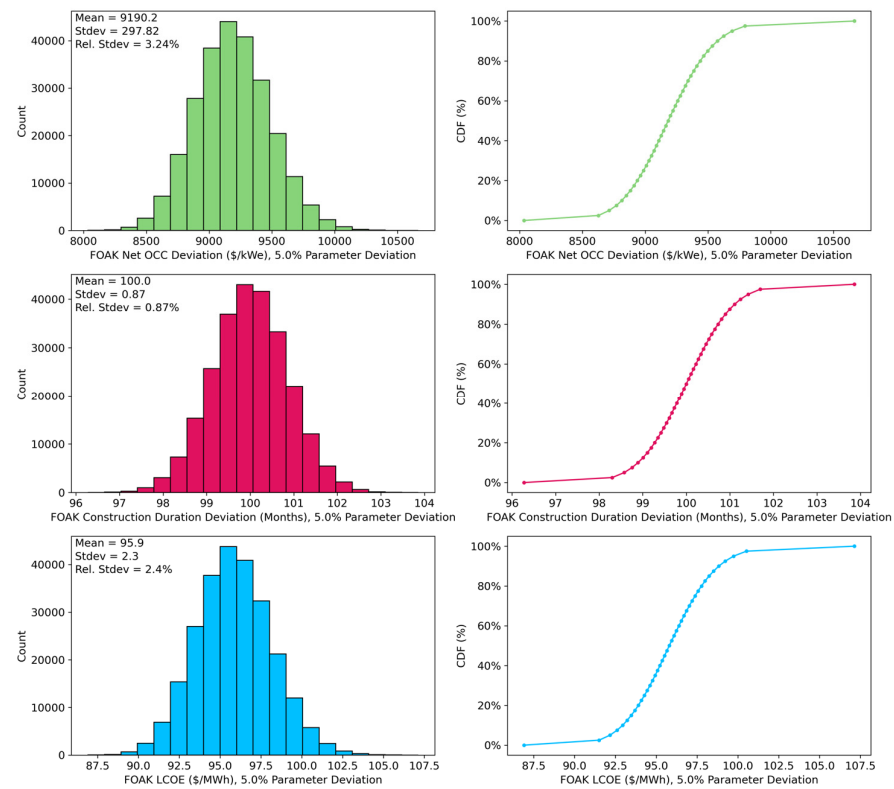


Figure 2. Histogram distribution (left) and CDF plots (right) for FOAK Net OCC (top), CD (middle), and LCOE (bottom) for 250,000 samples.

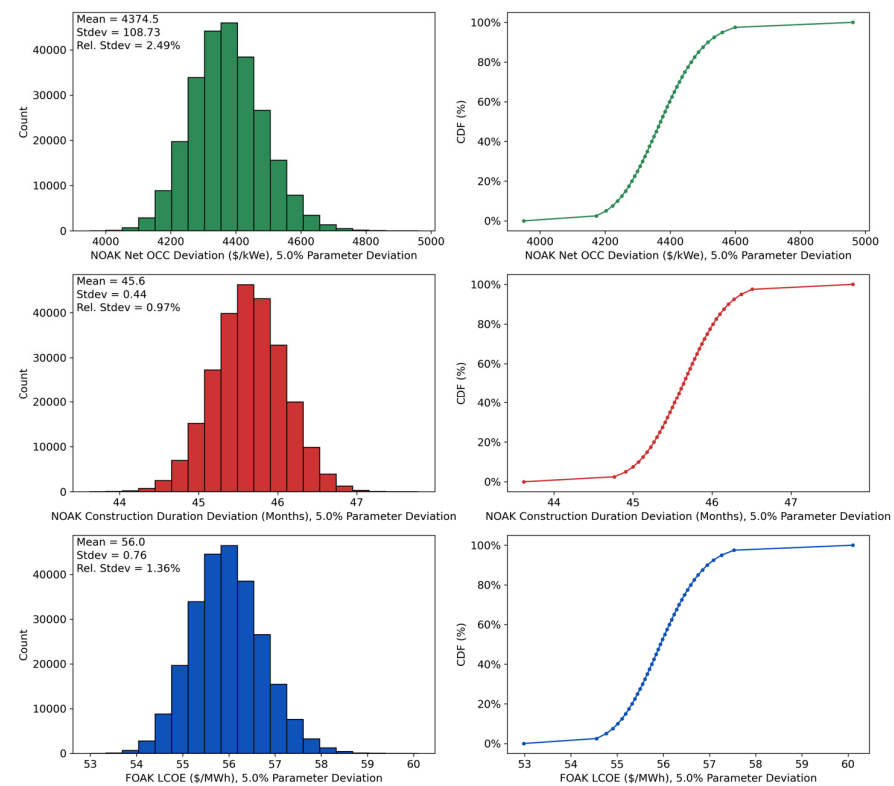


Figure 3. Histogram distribution (left) and CDF plots (right) for NOAK Net OCC (top), CD (middle), and LCOE (bottom) for 250,000 samples.

3.3. Monte Carlo Sampling: Uncertainty Trends

Because tracking the values of output variables over a plant order book is an important capability of the tool, an analysis of how uncertainty in output variables changes over a plant order book was performed. Figure 4 shows the trend in standard deviation for Net OCC, CD, and LCOE from the first plant built to the tenth. The absolute uncertainty trend figures for all three output variables show the same thing: the absolute uncertainty in the output variables is highest for the FOAK plant before decreasing with diminishing returns for subsequent plants. This trend matches the trend in the output variable values themselves, of starting at the highest value for the FOAK plant and decreasing with diminishing returns for subsequent plants [24]. This result meets expectations where uncertainty reduces as learning increases.

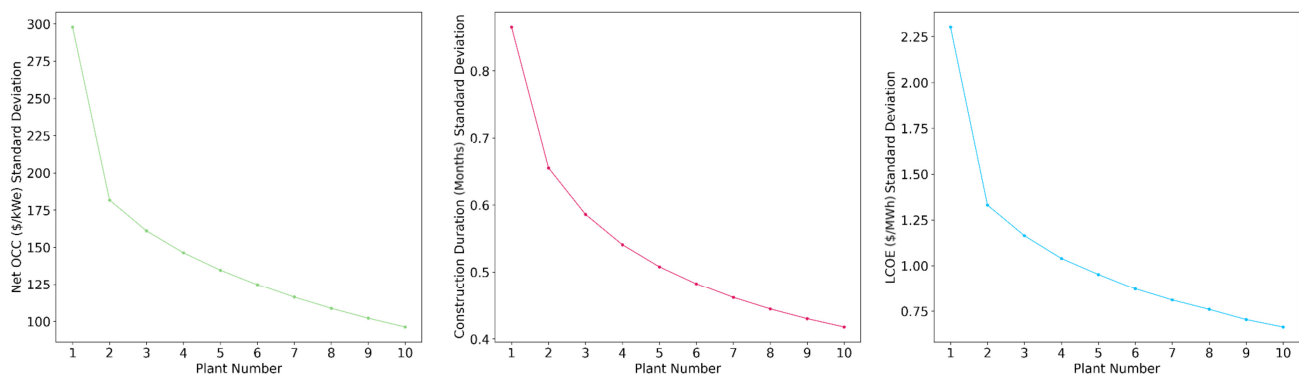


Figure 4. Trend in absolute uncertainty versus plant number for Net OCC (left), CD (middle), and LCOE (right).

3.4. Local Sensitivity Analysis: Cost and Time Savings

This section contains sensitivity analysis results from perturbing the model parameters one at a time by a set 5% perturbation amount (shown in Figure 5). For a better understanding of some of the underlying formulas that connect some of the model parameters to the output variables, potential information is provided in the original Nuclear Cost Reduction framework report [24]. However, the complexity of the Nuclear Cost Reduction tool makes exact formulas between many of the model parameters and output variables difficult to determine, which is one of the justifications for this analysis.

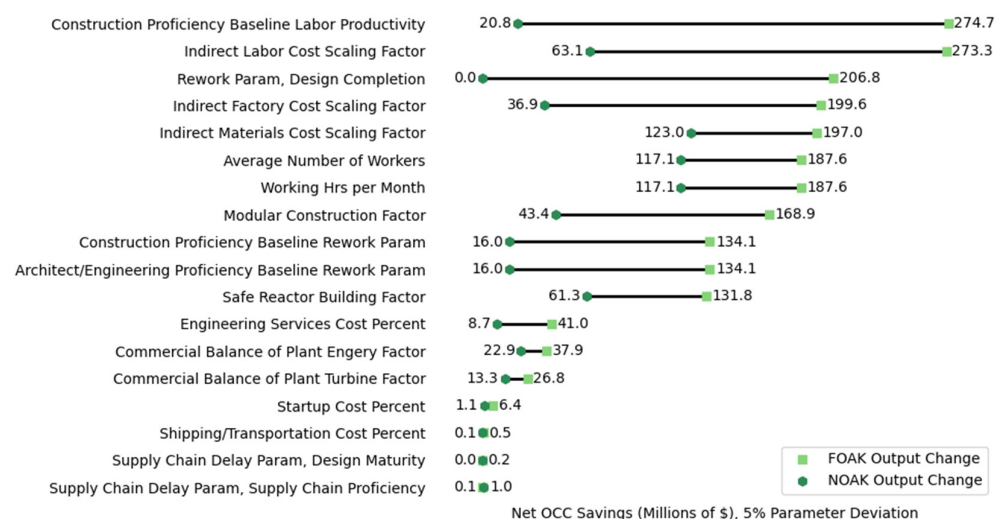


Figure 5. Potential cost savings (in millions of dollars) comparison for FOAK and NOAK Net OCC from parameter perturbations of 5% for a 2234 MWe plant design.

The most impactful variables for FOAK Net OCC changes are related to Labor Productivity, Rework from Design Completion, Indirect Cost Scale Factors, and Working Statistic parameters. The Labor Productivity parameter is the most impactful with a potential Net OCC change of roughly USD 270 million from just a 5% parameter perturbation, and the savings from the other parameter perturbations are still in the range of hundreds of millions of dollars. The Average Number of Workers and Working Hours per Month parameters correspond to assumptions for a baseline PWR-BE and not for the plant for which costs are being estimated. These model parameters only impact the indirect cost.

For NOAK Net OCC, only the Working Statistics and Indirect Cost Scale Factors parameters have high importance, having a change of approximately USD 100 million in Net OCC from 5% parameter perturbations, while the impact of the Rework and Labor Productivity parameters drops dramatically. This is expected due to the behavior of linear parameters (Labor Productivity, Rework, and Supply Chain Delay parameters) at near-maximum-input-level proficiencies for NOAK plants (see Section 2.1.2. for more details). While the Net OCC changes for the NOAK plants are smaller than the changes in the FOAK plants for all parameters, potential cost savings of USD 100 million are still a significant change from 5% individual parameter perturbations.

Figure 6 shows the changes in FOAK and NOAK CD from 5% individual parameter perturbations in the 18 input variables for a 2234 MWe dual reactor plant design. One interesting observation is that many parameters do not affect CD (compared with Net OCC, for which nearly all parameters have some impact). This difference in the number of impactful variables may explain why the relative uncertainty in CD is lower than it is for Net OCC because there are fewer sources of uncertainty.

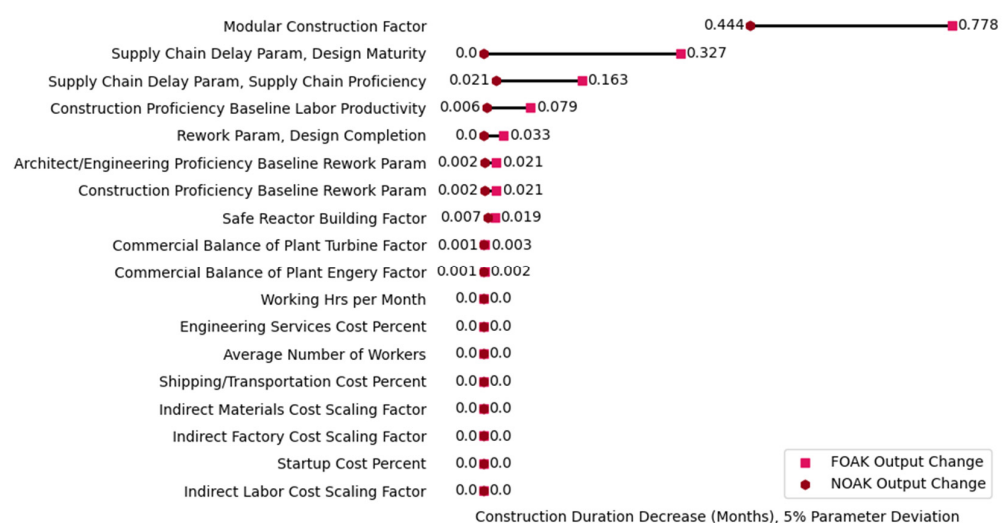


Figure 6. Potential time savings (in months) comparison for FOAK and NOAK CD from parameter perturbations of 5% for a 2234 MWe plant design.

The most impactful parameters for FOAK CD changes are related to Modular Civil Construction and Supply Chain Delays. This makes sense given that the Modular Civil Construction Factor and Supply Chain Delay parameters have a direct impact on CD with the Modular Civil Construction Factor directly reducing the CD by a specified factor and Supply Chain Delay being a duration term directly included in the CD formula.

For NOAK CD, only the Modular Civil Construction Factor appears to have any impact. This is because the other variables with significant impacts on FOAK CD are all linear parameters (Supply Chain Delay, Labor Productivity, Rework), and their uncertainty decreases significantly when input-level proficiencies are nearly maximized for the NOAK

plants (see Section 2.1.2. for more details). The results suggest that making effective changes to Modular Civil Construction is one of the more meaningful ways to impact NOAK CD.

Figure 7 shows the changes in FOAK and NOAK LCOE from 5% individual parameter perturbations in the 18 input variables for a 2234 MWe dual reactor plant design. The trends for the most impactful parameters for FOAK and NOAK LCOE are nearly identical to those of the most impactful parameters for FOAK and NOAK Net OCC. They even have the same relative magnitudes in change from parameter perturbations, though slight differences do exist for the less impactful parameters. This matches expectations because Net OCC is the largest driver of LCOE, and as such, the results for both output variables should look very similar.

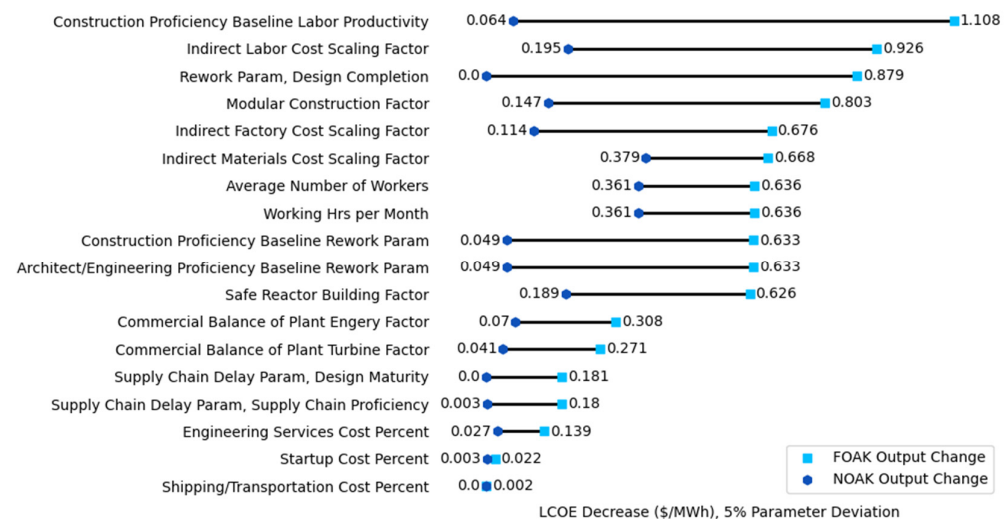


Figure 7. Potential cost savings (in USD/MWh) comparison for FOAK and NOAK LCOE from parameter perturbations of 5% for a 2234 MWe plant design.

Because tracking the values of output variables over a plant order book is an important capability of the tool, the total summed cost and time savings from parameter perturbations over a ten-plant extended deployment were estimated for Net OCC, CD, and LCOE. Figure 8 shows the total summed savings in Net OCC from 5% parameter perturbations for a ten-plant extended deployment of a 2234 MWe dual reactor plant design. The potential cost savings for a ten-plant order book are in billions of dollars, and the most impactful variables overall are related to Working Statistics and indirect cost scaling factors. Keep in mind that these large savings occur from a singular 5% perturbation from one parameter. The Labor Productivity parameter still has a large impact on potential cost savings, but its perturbation impact shrinks significantly for the building of subsequent plants due to it being a linear parameter (see Section 2.1.2. for more details).

Figure 9 shows the total summed time savings in Construction Duration from 5% parameter perturbations for a ten-plant extended deployment of a 2234 MWe dual reactor plant design. The Modular Civil Construction Factor is the only parameter that significantly reduces CD, likely because the other parameters with notable impacts are linear parameters whose effects decrease dramatically after FOAK deployment (see Section 2.1.2 for more details).

Figure 10 shows the total summed savings in LCOE from 5% parameter perturbations for a ten-plant extended deployment of a 2234 MWe dual reactor plant design. Once again, the trends for LCOE are similar to the trends seen in Figure 8 for Net OCC, which is expected because Net OCC is the largest driver for LCOE.

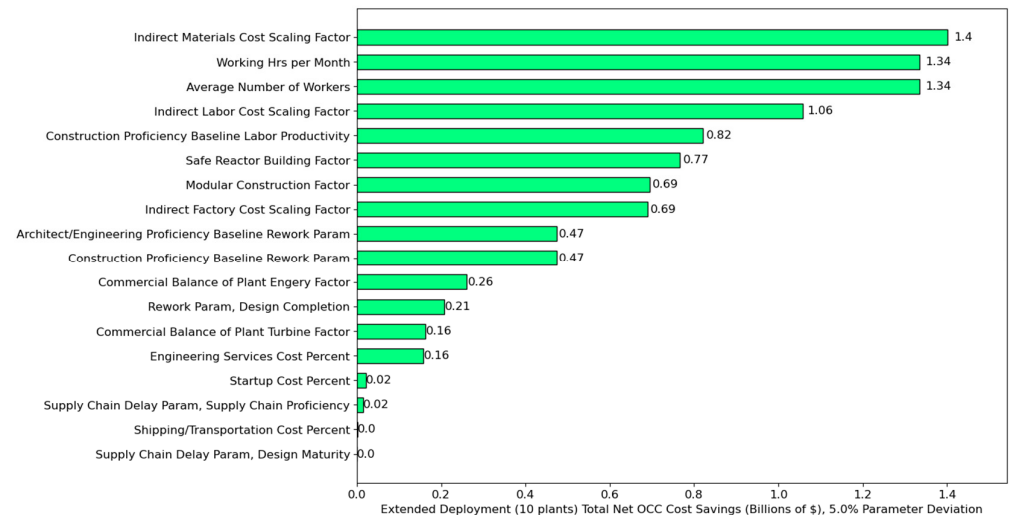


Figure 8. Total potential cost savings (in billions of dollars) for Net OCC from parameter perturbations of 5% for a ten-plant order book of a 2234 MWe plant design.

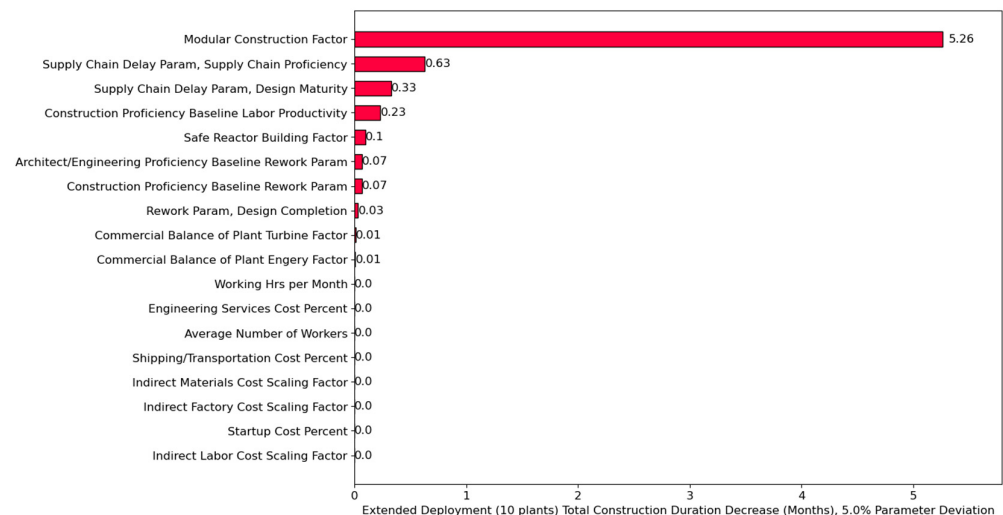


Figure 9. Total potential time savings (in months) for CD from parameter perturbations of 5% for a ten-plant order book of a 2234 MWe plant design.

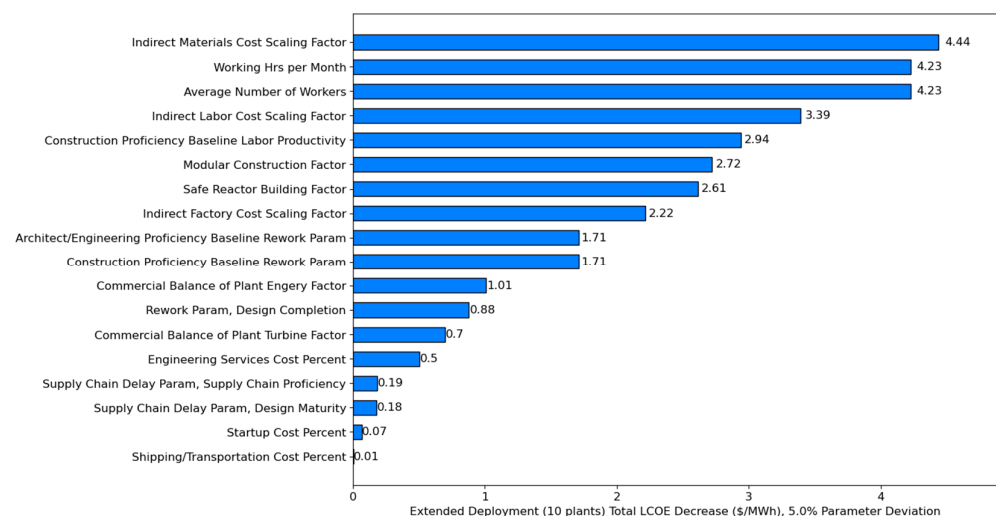


Figure 10. Total potential cost savings (in USD/MWh) for LCOE from parameter perturbations of 5% for a ten-plant order book of a 2234 MWe plant design.

3.5. Significance of Results

The results obtained from the uncertainty quantification provide valuable insights into how variation in model parameters translates to uncertainty in the nuclear project costs and Construction Duration to provide a more holistic estimation of these important model outputs. Additionally, the results provide data on how impactful the plant design and construction attributes represented by the model parameters are in estimating project costs and Construction Duration. Even small differences and perturbations in model parameters have the potential to change project costs by hundreds of millions of dollars for a single plant and billions of dollars for an order book of plants, as shown in Figure 8.

The results can also be used to verify that the model is functioning correctly by identifying if trends in parameter uncertainty and perturbations match intuition on how the parameters impact model outputs. For example, earlier iterations of the uncertainty quantification showed that the Rework from Design Completion was not as impactful in modifying project cost variables as it should have been. This discovery led to a closer examination of how Design Completion was used in the model which allowed for improved model accuracy and development.

4. Conclusions

This work showed that applying uncertainty and perturbations to model parameters can improve the functionality of the Nuclear Cost Reduction tool and provide valuable insight into the tool itself and the quantification of possible cost savings related to improving plant design and construction attributes. The Monte Carlo analysis of the model parameters we performed provided information on the distributions of the output variables of Net OCC, CD, and LCOE. These variables can be applied as uncertainty bounds for the output variables, making future applications of the tool more accurate. This analysis also showed how the uncertainty in the output variables decreases with diminishing returns as subsequent plants are built, which matches the trend of the output variable nominal values from the FOAK to NOAK plants indicated by the tool [24]. Researchers can use the distributions and trends from this study to estimate a realistic range of possible cost values (and the likelihood of each possible cost value), and to estimate how the possible range of cost values will change as more plants of the same design are built, thus improving future cost estimations for nuclear projects.

The local sensitivity analysis of the model parameters we performed showed the relative importance of different model parameters and quantified the impacts of model parameter perturbations. This information can be used for cost–benefit analyses to determine, for example, if the cost of improving a particular construction parameter will lead to net cost savings. Small perturbations of important model parameters such as Baseline Labor Productivity, Indirect Cost Scale Factors, Baseline Rework Factors, and Working Statistics can potentially lead to hundreds of millions of dollars in savings for a single large plant and billions of dollars for an entire order book of large plants. The results of this work also provide insight into which plant design and construction attributes, connected to the various model parameters, should be a focus for developers based on their impact on the economic performance of reactor deployment. Table 3 below lists specific recommendations for parameters that are the most important to keep in mind for specific project types and goals.

Future work will involve further analysis of other model parameters and general sensitivity analyses. Further examination of the omitted parameters listed in Section 3.1 could allow for them to be included in future analyses along with more possible parameters that were not identified in this study. Also, sensitivity analyses could be performed with specific perturbation percentages from a literature review of past nuclear studies. This

could give a better understanding of how impactful each parameter value is in affecting nuclear construction costs. Lastly, the uncertainty results from this study and the Nuclear Cost Reduction tool could be used to estimate costs of possible cost ranges for recent and upcoming plant design projects to validate if the cost and uncertainty estimates give accurate values.

Table 3. Recommendations for important parameters to modify based on project type and goal.

Project Type and Goal	Important Parameter Recommendations
FOAK Plant, Reducing Cost Metrics	(1) Improving Labor Productivity; (2) Reducing Indirect Costs; (3) Reducing amount of Rework
Order book of Plants, Reducing Cost Metrics	(1) Reducing Indirect Costs; (2) Increasing Number of Workers; (3) Improving Labor Productivity
FOAK Plant, Reducing Construction Time	(1) Improving effectiveness of Modular Civil Construction; (2) Reducing Supply Chain Delays
Order book of Plants, Reducing Construction Time	(1) Improving the effectiveness of Modular Civil Construction

Author Contributions: Conceptualization, R.M.S., L.M.L., C.B., B.H., J.Z. and A.A.-J.; methodology, R.M. and R.M.S.; formal analysis, R.M.; investigation, R.M., R.M.S. and L.M.L.; resources, R.M.S. and A.A.-J.; data curation, R.M.; writing—original draft preparation, R.M.; writing—review and editing, R.M., R.M.S., L.M.L., J.Z., B.H. and C.B.; visualization, R.M.; supervision, R.M.S., L.M.L. and A.A.-J.; project administration, R.M.S. and A.A.-J.; funding acquisition, R.M.S. and A.A.-J. All authors have read and agreed to the published version of the manuscript.

Funding: Funding was provided by the U.S. Department of Energy (DOE) through the Systems Analysis & Integration (SA&I) Campaign and a University Nuclear Leadership Program (UNLP) Graduate Fellowship from the Nuclear Energy University Program (NEUP).

Data Availability Statement: The authors do not have permission to share the data.

Acknowledgments: This report was authored at Idaho National Laboratory (INL) by Battelle Energy Alliance, LLC, with the U.S. DOE.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Net OCC	Net Overnight Capital Cost
CD	Construction Duration
LCOE	Levelized Cost of Electricity
FOAK	First of a kind
NOAK	Nth of a kind
RB	Reactor building

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