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Monte Carlo Methods for Uncertainty and Risk Assessment: A Methodological Review Across Engineering and Applied Statistics

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Abstract
This paper presents a methodological review of the Monte Carlo method as a toolkit for uncertainty analysis in engineering and applied statistical problems and systems. Monte Carlo simulation has become one of the most universal stochastic tools for analyzing systems subject to variability, incomplete information, and complex probabilistic dependencies. Drawing on 24 representative studies published between 1989 and 2025, this review examines the method's fundamental principles, typical implementation workflows, and its broad spectrum of applications from structural reliability to financial evaluation. Particular attention is given to the advantages that explain its widespread adoption—flexibility, interpretability, and robustness under nonlinear and multidimensional settings—as well as to the limitations that constrain its reliability, including slow convergence, dependence on accurate input distributions, and computational costs. The review also highlights recent methodological advances that address these issues, such as hybrid frameworks combining Monte Carlo sampling with machine learning or intelligent variance reduction. Overall, the paper provides a consolidated view of how Monte Carlo methods contribute to engineering decision support and discusses future research directions toward more efficient and integrated stochastic analysis.
Keywords: Monte Carlo simulation. Uncertainty quantification. Risk analysis. Stochastic methods. Applied statistics.

1. Introduction

Uncertainty is an intrinsic characteristic of real-world engineering and statistical systems. Kremljak and Kafol (2007), adopt the definition of risk from the ISO 31000 family of standards, in which risk combines two aspects: the probability of an uncertain event and the consequences if it occurs. When the probability of occurrence is unknown, the risk is undefined, thereby reinforcing the necessity of structured risk management.

The challenge of uncertainty is especially pronounced in the applied sciences, particularly in engineering and applied statistics, where practical problem-solving often depends on incomplete models and imperfect information. Real-world systems—such as civil infrastructure, industrial facilities, and energy networks—must be designed and operated under conditions that constantly vary in material properties, environmental factors, demand, and human performance. As a result, every decision concerning design parameters, safety margins, schedules, budgets, or expected financial returns carries an inherent degree of risk. When this dispersion of possible outcomes is ignored, both structural safety and economic efficiency are compromised (CASAROTTO. KOPITTKE, 2007).

Among stochastic approaches, the Monte Carlo simulation method has become one of the most widely applied frameworks for uncertainty quantification. By propagating probability distributions of input variables through deterministic or empirical models via repeated random sampling, Monte Carlo simulation produces distributions of possible outcomes that describe both expected values and tail events. The approach allows analysts to estimate probabilities of failure,

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exceedance, or economic loss, making it highly versatile in structural engineering, project management, finance, and environmental risk analysis. However, despite its potentials in applications, ubiquity and intuitive appeal, Monte Carlo simulation is not free of methodological challenges.

The purpose of this paper is to synthesize and critically evaluate these methodological aspects. It does not aim to present a specific case study or propose a new algorithm. Instead, it provides a methodological review: a structured, evidence-based assessment of the Monte Carlo method's principles, strengths, limitations, and contemporary developments as reported across literature.

Specifically, this review seeks to:

1. Consolidate theoretical and practical foundations of Monte Carlo simulation as used in engineering and applied statistics;
2. Identify and categorize its main advantages and limitations, particularly in relation to non-linearity, convergence, input modeling, and computational efficiency;
3. Discuss methodological extensions and hybridizations that address current challenges, including machine learning–assisted sampling and variance-reduction techniques; and
4. Offer an integrated perspective on best practices for applying Monte Carlo methods in uncertainty and risk assessment.

The analysis is based on a narrative–methodological review of 24 academic and technical sources published between 1989 and 2025, retrieved from Scopus, Web of Science, and Google Scholar. Studies were included if they presented a methodological contribution or applied Monte Carlo simulation to engineering or applied-statistics contexts. By framing Monte Carlo within this methodological review, the paper aims to provide both practitioners and researchers with a clear understanding of its practical value, theoretical constraints, and evolving role in risk-informed engineering. The discussion emphasizes how methodological awareness, rather than computational sophistication alone, determines the credibility and usefulness of Monte Carlo analysis in decision-making.

2. Monte Carlo in Statistical Simulation

As described by Gujarati (2002, as cited in BARAKAT; BERSSANETI, 2016), the Monte Carlo method is a computerized technique that makes it possible to simulate the execution of a project multiple times, as a means of generating a probabilistic distribution of the possible results that may be achieved. According to Crundwell (2008), the technique is used to solve problems whose complexity makes their resolution through other methods impractical.

The application of the Monte Carlo Method involves calculations that a human would not be

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able to perform effectively. Since its invention, it has been enhanced by the use of computers, beginning with the development of the first electronic computer, the ENIAC (Electronic Numerical Integrator and Computer), which was originally created to accelerate artillery calculations. Given the speed of computation, and following a suggestion by Ulam, statistical sampling was applied to solve the neutron diffusion problem, which made it possible to estimate neutron multiplication rates to produce nuclear weapons (SOBOL, 1994). From the very beginning, therefore, Monte Carlo was applied to engineering and complex applied statistics-related solutions.

Nasser's (2012) conclusions regarding the Monte Carlo Method were that its very nature makes it unnecessary to describe the detailed behavior of complex systems. He stated the following concerning the information that must be provided for the application of the method:

> The only requirement is that the physical or mathematical system be described (modeled) in terms of probability density functions (PDFs). Once these distributions are known, Monte Carlo Simulation can proceed by drawing random samples from them. This process is repeated countless times, and the desired result is obtained through statistical techniques (mean, standard deviation, etc.) applied to a given number of realizations (samples), which may reach millions (NASSER, 2012, p. 26).

Due to uncertainty and variability, the value of some variables cannot be known until a direct observation is made. Using the example provided by Hayse (2000), when considering a given sample of test animals in a laboratory, it is not possible to know precisely the weight of an animal chosen at random. However, if parameters had been previously collected and statistical information were available, such data could be treated to obtain a more accurate estimate.

The probability density functions (PDFs) described by Nasser (2012) are precisely intended to represent the variability of parameters, as exemplified by Hayse (2000). As emphasized by Hayse (2000), PDFs are the foundation of Monte Carlo analysis and therefore modeling them accurately is fundamental. These functions may follow a variety of shapes or behaviors, with some common examples being the normal, exponential, uniform, Poisson, and binomial distributions. Even so, it may happen that a predefined distribution does not adequately represent the variable under study. In those cases, an appropriate solution is described:

> In addition, custom probability functions that do not fit any of the theoretical distributions can be derived for a particular parameter by using the
> frequencies at which particular values for the parameter are observed. (HAYSE, 2000, p. 5).

The contribution is particularly significant, since as the method begins to be applied in different contexts, the variables of each situation do not necessarily fit into established distributions. In any case, once the distributions have been defined, it becomes necessary to understand the sequence that enables the method. Its process can be described in simple terms, "In a deterministic model, a single value for each of the model's input parameters is used to calculate a single output parameter" (HAYSE, 2000). The author described the sequence of the method through the following

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steps, also represented in Fig. 1.

a) Each of the input parameters is assigned a probability density function (PDF);

b) The model output is calculated multiple times, each time randomly selecting a new value from the probability distributions for each input parameter;

c) The outputs from each execution of the model are recorded, and a probability distribution of the output values is generated; and

d) Finally, the probability of occurrence of any specific value or interval of values for the output is calculated.

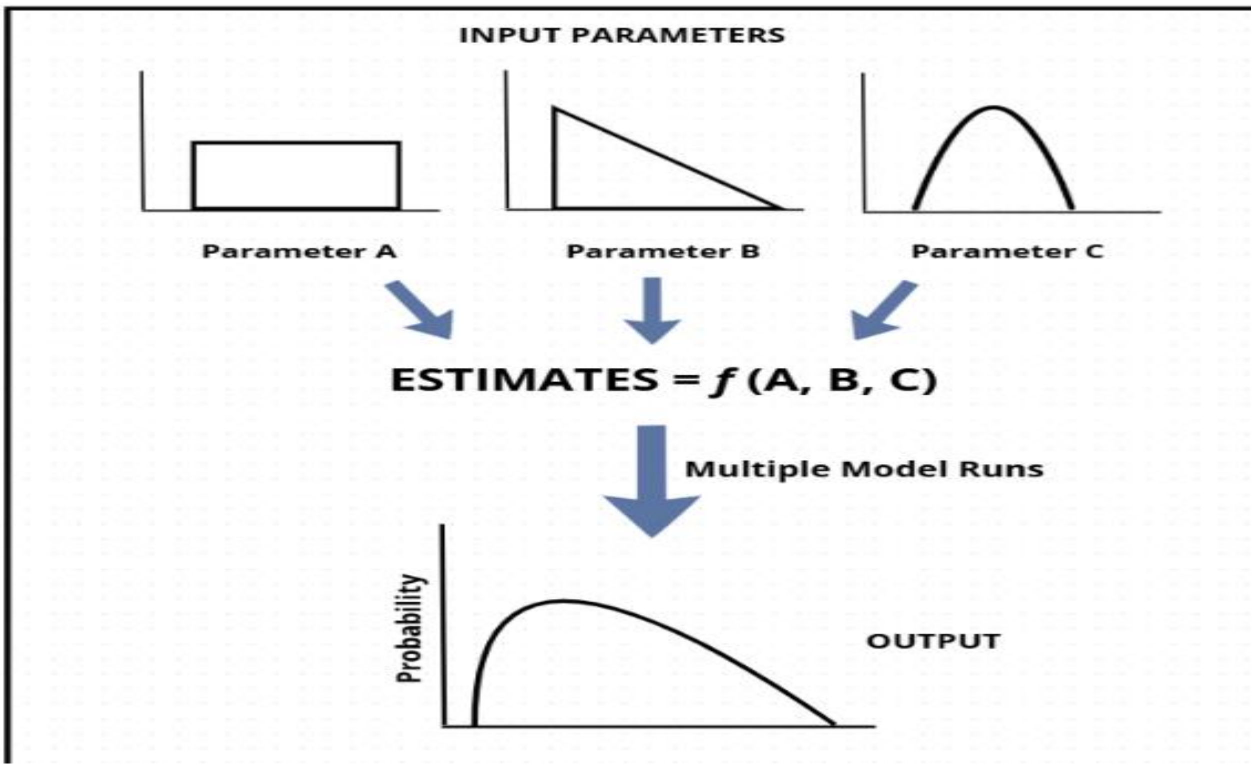

Fig. 1. Diagrammatic representation of the application of Monte Carlo analysis to a model. (Adapted from Hayse, 2000, p. 05)

Once all Monte Carlo simulations have been completed, it is possible to interpret the results by analyzing the frequency with which certain output values were obtained. The set of output values can be evaluated to determine descriptive statistics such as mean, range, standard deviation, and others. Additionally, it is possible to assess the probability that the result exceeds a specific value or falls within a given interval by using the distribution of output values to obtain a cumulative probability graph (HAYSE, 2000). By reading Fig. 2 (in which dnorm(x) and pnorm(x) correspond, respectively, to the normalized distribution of x and the cumulative probability associated with the normalized distribution of x), one can infer, for example, that the probability of observing a value of x greater than 0 is 50%.

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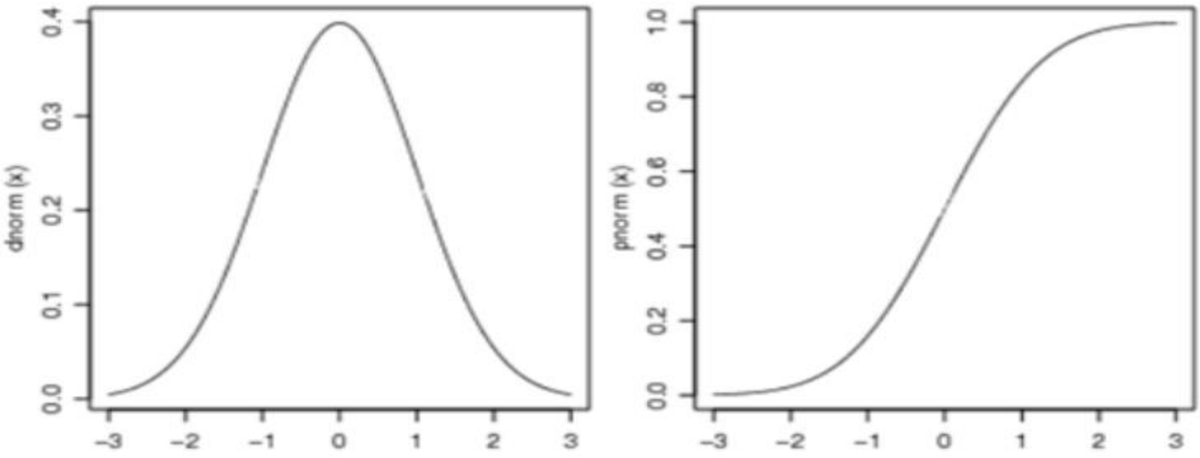

Fig. 2. Transformation of an output probability distribution into probability of cumulative distribution. (Laboratório de Estatística e Geoinformação UFPR 2023).

3. Methodological Strenghts

Monte Carlo is prized for its universality because it requires only that a model—no matter how nonlinear or context-specific—can be evaluated at specified inputs. As Veen and Cox (2021) note, "All that is needed is a measurement model, which can be in the form of an algorithm, and a specification of the probability distributions for the input quantities." Monte Carlo naturally captures such effects because it evaluates the full nonlinear mapping from inputs to outputs trial by trial. Nonlinear problems arise when the relationship between inputs and outputs deviates from linearity—due to various effects, that depend on the nature of the problem at hand: some examples could be plastic deformation, structural behavior, inter-variable interactions in economic forecasts. These systems often cannot be addressed with analytical or closed-form methods, especially in high-dimensional settings typical of engineering dynamics. Monte Carlo is particularly well-suited for such tasks because it requires only that the model be evaluable at sampled input points. Recent research demonstrates this potential through practical problem-solving approaches:

- Bamer et al. (2021) applied Monte Carlo to nonlinear structural dynamics, noting that "failure usually occurs in the non-linear range of structural behavior… Monte Carlo… provides an unbiased estimate of the response statistics". The authors, satisfied with the results, state that it was useful for the analysis of structural serviceability and prediction of the probability of failure.
- Cvetanoska and Stojanovski (2012) applied Monte Carlo to valuing American options and was able to give the upper bound on the value for the selected options. The authors not only felt satisfied with the results, but also laid out extensions and future directions for more research.
- Wagener and Kollat (2006) applied Monte Carlo to modeling environmental systems. In this case, they used tools for hypothesis testing, sensitivity and evaluation of performance.

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So as demonstrated, the method brings a universality decisive in engineering, where models often combine empirical rules, physical formulas, and business constraints, since the primary deliveries of Monte Carlo are distributions of outputs. For engineering economics, this includes classic financial indicators such as net present value (NPV), internal rate of return (IRR), modified internal rate of return (MIRR), and variants of payback that incorporate discounting; in project controls, schedule risk measures and cost deviations distributions are also core outputs. for reliability analysis, probabilities of failure or safety margins under uncertain loads are of interest (BAMER et. al, 2021). On top of that, for each output, Monte Carlo supplies not only central tendencies but also quantiles—for instance, the 5th, 50th, and 95th percentiles—and exceedance probabilities relative to decision thresholds. This is particularly advantageous for estimating tail probabilities, which are often the quantities of greatest concern in engineering, general risk management and safeguards.

On top of that, a notable part of this kind of results is that they are interpretable to both technical and non-technical audiences. Histograms, Probability Distribution Functions (PDFs), and Cumulative Distribution Functions (CDFs) communicate intuitively. Tabulated quantiles (e.g., p5, p50, p95) can be the foundations of decision templates and investment memoranda, these examples are particularly effective for communicating probabilities of being above or below a target, as many deterministic stakeholders reason naturally about “chances of hitting” or “risks of breaching” important levels. Monte Carlo supports this decision language directly through exceedance probabilities and percentile bands organizing a risk profile from where decisions and contingencies can be made. This facilitates adoption in governance processes where decisions must be explained and defended and move organizations toward risk-aware decisions.

On a different note, Monte Carlo models can also be used as a means of studying the sensitivity of a model to changes in specific parameters. As Hayse (2000) explains, one straightforward approach is to hold all input parameters fixed except one and then vary that parameter through random sampling. By observing how the output changes, analysts can assess the effect of that single input on the results. Glasserman (2004) on the other hand, introduces more advanced techniques—such as the path wise derivative and likelihood ratio methods—that allow sensitivities to be estimated directly as derivatives within Monte Carlo simulations. These approaches are particularly important in financial engineering, where they are applied to efficiently compute a set of sensitivity measures used in finance for option pricing and other risk measures.

The broader point is that sensitivity analysis, whether simple or advanced, is not only a diagnostic tool but also a way to improve the model itself. By identifying which inputs exert the greatest influence on outputs, analysts can prioritize their efforts on refining the distributions of those key drivers. In this sense, sensitivity analysis directs attention to where accuracy in assumptions matters most, thereby increasing both the credibility and efficiency of Monte Carlo applications.

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Another important aspect of these problems is that real-world systems are inherently multivariate. When dependence among variables is ignored, simulations can produce deceptively narrow risk profiles. Monte Carlo methods address this by allowing input distributions to incorporate correlation and dependence structures—provided that the model is appropriately programmed to enforce them.

Loase and Sheenan (1989) illustrated this concept through a simplified real-world scenario, where they created not only one method, but by enforcing multiple types of dependance by itself. In their example they created a Monte Carlo model to run simulations on two groups of 30 students taking a test, with the first group performing independent scores (as appropriate) and the second group performing dependent scores because of cheating. The correlation arose from the fact that the performance of a student was not a direct result of an isolated event but relied on the performance of other students. That dependance was addressed by introducing a “cheating factor” (CF).

In their first example, every below average student was allowed to cheat if the preceding student was above average. Dependance was implemented by increasing the cheating student’s grade by the multiplication of their score by the variable CF. In the second example, the model was modified so that the score of the cheating student is made equal to the preceding above average score. In the third case, the rule defining which students could cheat was changed: instead of being simply below average, they were defined as those in the bottom 10th percentile of the entire class. Finally, the authors analyzed the resulting data to examine the relationship between the set dependance/correlation and mean scores. As they concluded, “Most importantly, we may be able to adjust hypothesis testing to more accurately model real-world phenomena, which are typically dependent”, they expressed satisfaction with the results and encouraged the use of this type of application in other contexts that could benefit from such problem-solving approaches.

In this case, the analysis was conducted dealing with over 10000 results per experiment in a complexity of variables that demanded computational analysis. It is relevant to address that in this context (High Performance Computing) Monte Carlo is also a very time efficient method. This can be explained by Cvetanoska and Stojanovski (2012).

> “Using Monte Carlo is very convenient because the computational time of Monte-Carlo simulation increases approximately linearly with the number of variables, while in most other methods, the computational time increases exponentially with the number of variables.”

Finally, of course, this kind of application utilizes a developed model, but this is not necessarily a requirement for most cases. Sobol (1994) describes Monte Carlo as a method with a simple computational structure. Analysts ranging from engineers in small organizations to statisticians in research groups can run simulations in spreadsheets, scientific computing environments, or dedicated risk software. Spreadsheets are often appropriate for first models of small experiments because they lower barriers to participation, maintain a structure that can be monitored,

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maintained and checked through cell formulas, and facilitate reviews. However, it is important to highlight that good simulation practice in Monte Carlo analysis goes beyond running many trials. As recommended by Wilson et al. (2014), scientific computing workflows should follow a structured, reproducible design—this includes documenting the code and workflow clearly, using version control, and preserving the full analytic context. Specifically in Monte Carlo, cautions necessary would be to record the random number seeds—allowing for exact replication of results—and verify output stability by repeating simulations using non-overlapping subsequences (EPA, 2002). These practices ensure transparency and allow future analysts to fully reconstruct and validate assumptions and computational logic.

4. Methodological Limitations and Challenges

Firstly, every method has a guiding principle, in the case of Monte Carlo it is the relationship between probability and volume. What makes the method distinctive is that this relationship is applied in reverse. Normally, mathematics defines the probability of an event associating such event with a set of outcomes and measuring how large the set of events that fit x description is compared to the universe of all possible outcomes. Monte Carlo reverses the classical definition of probability: rather than starting from a known volume to calculate probability, it estimates the probability of an event by sampling random inputs from their distributions and checking whether the corresponding outputs fall inside the set of interest (e.g., cost below budget, stress below capacity). The fraction of draws inside provides the estimate, which converges to the correct value as the number of samples increases, because of the law of large numbers (GLASSERMAN, 2004).

However, when working with a finite number of draws, this method will always have some level of magnitude of mathematical error. The central limit theorem provides information about the likely magnitude of such error. Glasserman (2004) worked around the mathematical foundation of such sets and concluded that the error of the estimator decreases proportionally to n^(-1/2), where n is the number of simulations. In straightforward terms, this means that the precision of the estimate improves very slowly: to cut the error in half, one must quadruple the number of samples, and adding a decimal place of precision requires 100 times as many runs. In practical terms, this means histograms at modest sample sizes can be misleading, even with apparent stability, especially in tails where uncertainty matters most.

Secondly, since Monte Carlo's principle is based on sampling random inputs, different data sources can legitimately produce different distributions and therefore different conclusions. Put simply: if the inputs are flawed, the outputs will inevitably inherit, and may even amplify, those flaws. This vulnerability shifts the burden of credibility to the analyst: it is the analyst's responsibility to

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make a careful judgment about whether to rely on a data-driven distribution, a parametric form, or the judgment of an expert.

In many engineering projects, historical data is abundant enough to allow purely statistical modeling without relying heavily on expert judgment (for example, in cost databases, structural resistance test results, or equipment reliability records). However, sometimes conditions change over time and certain important factors cannot be measured directly. In these situations, expert judgment becomes essential. Specialists are consulted to provide estimates, such as percentiles or the most likely ranges for key variables, and probability distributions are then modeled to fit those values. While this approach is valid, and sometimes required, it introduces a dangerous degree of subjectivity. If not carefully examined and validated, expert-based distributions can distort the results of the entire analysis, mask real risks or produce unjustified confidence. Hayse (2000) noted that empirical or custom distributions may sometimes better reflect observed frequencies than purely theoretical forms. However, it is crucial that they are grounded in sufficient data or theory; otherwise, analysts are left with assumptions that may be fragile and untestable. In such cases, Monte Carlo simulations risk becoming a tool that merely formalizes uncertain guesses rather than providing reliable insight.

Thirdly, it is important to emphasize that Monte Carlo is a toolkit for evaluating outputs, but it does not transform weak decision metrics into strong ones. It remains the analyst's responsibility to understand the problem and identify which outputs are meaningful for decision-making. In financial engineering, for example, payback and ROI remain limited statistics whether it is computed deterministically or stochastically. For example, if an organizational stakeholder relies on payback as a headline figure, it would be valid to affirm the risk assessment was flawed or at least incomplete. In this situation, the Monte Carlo simulation should be accompanied by clear communication about what payback omits, as well as by presenting complementary indicators such as NPV and IRR distributions. The point is not to elevate weak metrics through simulation, but to place them in context and complement them with stronger, risk-sensitive indicators that give a fuller picture for decision-making.

Another critical element is dependence. What was previously mentioned as a potential strength of Monte Carlo, must now be addressed as a limitation. As explained earlier, variables in real systems often co-vary, and simulations must reflect correlation rather than assume independence. The limitation is that the method can only enforce dependence if it is explicitly modeled, leaving open the possibility that analysts ignore correlation among inputs, which then becomes source of error often minimized.

In engineering, many risks arise precisely because multiple drivers shift together. For example, the relationship between material properties, workforce productivity, and the quality of the final product in construction; the link between productivity, production costs and retail prices in a

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financial study; or the co-movement of load and resistance factors in structural analysis. Modeling these interactions is essential: analysts should estimate correlation structures when data are available or gather correlated input from experts.

Finally, while in most cases Monte Carlo models can be executed on conventional computing equipment, serious difficulties arise when dealing with highly complex models. Because the method's error decreases only at the rate of n^(-1/2), complex problems that require convergence demand a very large number of simulations to achieve the desired confidence. This means if complex enough, this can generate significant computational costs which can overwhelm modest computing budgets.

Analysts therefore face a budgeting dilemma: choosing a sample size that balances the need for reliable estimates against the limits of available computing power and project timelines. In this context, it is valid to consider the Law of Diminishing Marginal Returns. As explained by Khan et al. (2012), this law establishes that the gains in output obtained from adding variable inputs are essentially limited. In the beginning, output (or quality) may increase in relatively larger proportion to the additional input, but beyond a certain point the increases become progressively smaller.

Practical illustrations of this principle mentioned by the authors can be seen in machines such as electric motors or production lines: once they reach optimal efficiency, additional investment in input factors yields only marginal improvements. As Khan et al. (2012) emphasize in their book Principles of Engineering Economics with Applications, "In view of the fact that capital and markets are also limited input factors because of the increasing cost of procuring them, the law of diminishing return occupies an important place in making many investment-related decisions".

5. Discussions and Conclusions

As analyzed, Monte Carlo is a very powerful instrument, and remains one of the most powerful tools available in engineering and applied statistics. Its advantages are evident: universality, interpretability, and compatibility with existing workflows. The method is flexible enough to handle nonlinear, multidimensional problems, can used for sensitivity analysis and allows the possibility to enforce covariance when needed. This strenght explains the continued use in risk analysis, and real world applications.

On the other hand, relevant limitations must be addressed. Standard Monte Carlo converges slowly. It has critical dependence on input modeling, which means flawed or oversimplified distributions inevitably result into flawed outputs, sometimes amplifying the very uncertainties analysts seek to control. Computational costs are not a barrier in most practical applications, but in complex simulations or rare-event estimation, they can become an obstacle. These weaknesses do not discredit the method, but they highlight the conditions under which it must be applied with care.

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A caution that carries over from most applied solutions is the necessity of knowing the problem thoroughly in order to model it correctly and reach the right conclusions. Monte Carlo itself does not guarantee meaningful insights; what makes it valuable is how it is applied. The expertise of the group responsible for setting up the simulation is what ultimately determines how helpful the method can be.

A team with a deep understanding of the engineering or financial context will be able to frame the simulation around the right questions and select assumptions that reflect reality. By contrast, a less prepared team may generate distributions that look rigorous but lack the accuracy needed to add real value. The key to doing a good job is combining technical skill with contextual awareness: this is the bridge between complex models and actionable insights.

What distinguishes competent applications is not just running the simulations, but ensuring credible input distributions, a faithful treatment of dependence, transparent reporting of assumptions, and the pairing of output distributions with sensitivity and robustness checks. These are the steps that make sure it is not a blind application of large numbers and assumptions. So when adopting Monte Carlo, a complete, through and methodological approach should follow the sequence listed bellow:

1. Understand the problem, identify variables, and define outputs of interest anchored in clear questions and decision metrics;
2. Treat input modeling as a main idea: collecting data, selecting appropriate distributions and justifying the assumptions;
3. Verify and enforce dependence where applicable, rather than assume independence by default;
4. Determine the number of iterations needed to achieve the desired precision;
5. Run the simulation and conduct a sensitivity analysis to understand how the variables affect outputs;
6. Refine the input distributions of the most influential variables to get more accurate results;
7. Report distributions of decision metrics with quantiles and probabilities of threshold exceedance;
8. Contextualize outputs for stakeholders, interpreting the results and practical relevance;
9. Document sources, seeds, and logic for reproducibility; and finally
10. Continually make adjustments to improve results. "No plan is set-it-and-forget-it, and frequent revisits to any plan are desirable" (BLANCHETT; PFAU, 2016).

As a final note that can be addressed, the limitations identified in the previous section (particularly those concerning convergence efficiency, computational cost, and dependence on input distributions) have motivated the development of several methodological refinements within both engineering and statistical domains.

Variance reduction techniques such as importance sampling, stratified sampling, and control variates have been developed to decrease estimator variance without increasing the number of

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simulations, thus improving accuracy under limited computational resources. In parallel, extensions like Markov Chain Monte Carlo (MCMC) and Quasi–Monte Carlo (QMC) have expanded the method's reach to high-dimensional and complex probability spaces, enabling applications in Bayesian inference, stochastic optimization, and reliability analysis.

For example, Wang and Julier (2013) presented two alternatives in the context of robot path planning under uncertainty: Sampling in Planning Process (SiPP): a method that performs lazy sampling within the planning algorithm itself; Hierarchical PD Planner: an approach that performs dimensionality reduction by decomposing the environment into homogeneous regions. Both applications were able to reduce computational cost by more than a factor of two, with minimal loss of performance.

More recently, Guo et al. (2025) introduced a machine learning–based enhanced Monte Carlo method for structural reliability analysis under low failure probabilities. In their work, a Kriging surrogate model directs the sampling toward the most relevant input regions, making the simulation far more efficient.

Such developments demonstrate the continuity of Monte Carlo as both a classical and modern statistical instrument. They also strengthen the view that Monte Carlo is steadily overcoming many of its traditional limitations and remains a method of constant refinement, now evolving toward hybrid approaches that combine its generality with intelligent variance reduction, efficient input sampling, and machine learning integration.

In conclusion, classical Monte Carlo as presented here, remains highly relevant. Practitioners can preserve simplicity where possible, but can also add sophistication when the decision context requires extra effort—or simply as a process of continuous improvement. Even without extensions, methodologically mindful Monte Carlo delivers value: it replaces the simple knowledge of a scenario that can happen with explicit risk profiles, frames situations in the language of probabilities, and supports decisions in engineering and risk management. Looking ahead, while its scope will likely remain centered on uncertainty analysis, its ongoing adaptability ensures that it will continue to improve as computational techniques evolve.

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