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Probability Distribution Selection in Monte Carlo Based Project Schedule Simulation of Highly Parallel Task Structures

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Abstract

Effective project management requires accurate estimation and management of the project timeline and simulation provides a way for project managers to quickly determine the overall critical-path of activities and the earliest completion date. However, many project simulations use arbitrarily chosen probability distributions to model individual task durations. This paper investigates the sensitivity of Monte Carlo simulation outcomes to the selection of task duration distributions. The study compares standard functions such as Triangular Normal, Lognormal, Gamma, and Beta distributions to assess their impact on project completion estimates. Parallel tasks pose a higher risk to project deadlines than more linear task structures. A network of up to twenty tasks with identical precedence and dependency constraints was modeled with task parameters normalized to ensure mean-equivalence across all distributions. Individual task durations were simulated through the use of the output of a random number generator input into the inverse cumulative distribution functions of the aforementioned distributions. Through 10,000 simulation iterations per scenario, the divergences in the mean, median, and standard deviation of the total project duration were analyzed. Histograms of total project durations for each simulation were generated to visualize the completion profile produced by each distribution. These results were verified analytically and presented in an easily repeatable way for project management practitioners for use in projects with simple parallel task structures. The compounding effect created by highly parallel critical-path networks were found to create a strong late-bias in the cumulative final durations of projects with right biased triangular and beta task duration probability distributions. Early task completion times with these distributions in highly parallel task structures were found to result in later than mid-range project completion performance. The long tail distributions of normal, lognormal, and gamma distributed tasks were found to be exaggerated by highly parallel task structures, which amplified variability of completion times with those projects.

Keywords
Project Management, Simulation, Probability Distributions.

1. Introduction

Project management operates in an inherently uncertain environment. Schedules, budgets, and resource allocations are subject to variability arising from technical complexities, human factors, supply chain disruptions, regulatory changes, and unforeseen external events. Traditional deterministic approaches, such as the Critical Path Method (CPM) or Program Evaluation and Review Technique (PERT) with single-point estimates, often fail to capture this uncertainty adequately, leading to overly optimistic projections and frequent project overruns (Malcolm et al. 1959; Flyvbjerg et al. 2002). To address these limitations, simulation techniques, particularly Monte Carlo simulation, have become critical methodologies for quantitative risk analysis and schedule forecasting in project management (Vose 2008; Rubinstein and Kroese 2016). By modeling task durations and costs as random variables drawn from defined probability distributions, these simulations generate thousands of possible project outcomes. These results enable managers to estimate completion probabilities, identify critical risks, and develop more robust contingency plans.

The accuracy and reliability of such simulations depend critically on the selection and parameterization of appropriate probability distributions for individual project activities (Abourizk et al. 1994). Poor choices can distort results, misrepresent risk profiles, and lead to flawed decision-making. This paper examines key challenges and best practices in probability distribution selection for project management scheduling simulations. Specifically, we evaluate the role of common distributions with particular attention to the triangular distribution, analyze systematic biases in duration modeling, and explore the representation of parallel processes as a methodological benchmark for assessing scheduling simulation effectiveness.

Among the probability distributions employed in project risk modeling, the triangular distribution holds a prominent place in project risk modeling due to its simplicity and alignment with practical estimation practices (Johnson 1997). This probability distribution is characterized by only three parameters: minimum (optimistic), mode (most likely), and maximum (pessimistic) values. It is so intuitive that has the advantage of often only requiring expert judgment or limited historical data. Three simple questions can provide a starting point for analysis: "What is quickest, best-case scenario for how long this task might take?", "What is the worst-case for how long it might take?", and "What is the most likely duration"? In practice, these parameters are often simplified by setting the mode equal to the minimum (a left triangular distribution) or to the maximum (a right triangular distribution). In fields such as manufacturing, logistics, construction, software development, engineering, and defense projects, where historical data may be sparse or project-specific, the triangular distribution translates three-point (or two-point, as described above) estimates directly into a probabilistic model. Its linear probability density function creates a straightforward triangular shape, with the peak at the most likely value and tapering to zero at the extremes.

This distribution's importance stems from several advantages. First, it explicitly incorporates uncertainty by bounding outcomes between realistic minimum and maximum values, preventing unrealistic infinite tails while still allowing variability. Second, it facilitates expert elicitation: team members can readily provide optimistic, most likely, and pessimistic estimates based on experience, fostering buy-in and practical application (Tversky and Kahneman 1974). Third, Monte Carlo implementations using triangular distributions, whether custom programmed in code or spreadsheets or in commercial software packages, are computationally efficient and easy to communicate to stakeholders through visual density plots of their mass probability functions and their cumulative distribution functions (CDFs). Fourth, unlike more complex distributions (e.g., Beta-PERT or lognormal), the triangular distribution requires no advanced fitting and directly reflects elicited parameters (Keefer and Bodily 1983). Additionally, the triangular distribution excels in asymmetric risk modeling. By adjusting the mode closer to the minimum (left triangular distribution) or maximum (right triangular distribution), analysts can introduce skewness, reflecting that many project tasks have a higher likelihood of delays than early finishes. This flexibility has made it a cornerstone in standards and guidelines from organizations like the Project Management Institute, where three-point estimating is encouraged for quantitative analysis (Project Management Institute 2009). Its integration with sensitivity analysis further enhances its utility, allowing identification of critical activities in a project's schedule.

Despite these advantages, triangular and related distributions frequently exhibit a bias toward longer task durations in simulation outputs. This bias arises from multiple sources. First, expert estimates themselves may be prone to optimism bias where the "most likely" value is often unconsciously optimistic, while the pessimistic bound may not fully capture extreme tail delay events (Kahneman and Tversky 1979). When fed into a triangular distribution, this results in means that are pulled upward, especially in right-skewed setups common to projects (where the mode is closer to the minimum than to the maximum). The linear nature of the triangular PDF assumes equal probability density change across the range, which can overemphasize moderate delays compared to distributions with fatter tails (like lognormal). Yet, because the maximum value is hard-stopped, experts tend to provide bounded but still inflated worst-case scenarios, the overall simulated project durations can end up being overestimated. This rightward bias is compounded in networks with multiple tasks. Merge bias (or path convergence effects) amplifies the probability of delays when parallel paths converge, as the latest-finishing predecessor dictates start times (Elmaghraby 2005). Triangular distributions, by truncating extremes, may underestimate true tail risks while still biasing central tendencies upward. Other distributions, such as uniform (flat across the range) or normal (symmetric but unbounded in theory), can introduce different biases, but triangular's popularity makes its tendencies particularly influential. Lognormal or gamma distributions, which naturally model positive skew and long right tails for durations, sometimes reveal even greater potential overruns, highlighting how simpler models like the triangular distribution may understate extreme risks while overemphasizing moderate ones.

A critical yet often underexplored dimension in scheduling simulations is the accurate modeling of parallel processes. In real event networks, many activities occur concurrently rather than sequentially, subject to resource sharing, dependencies, and synchronization points (Herroelen and Leus 2005). For example, in batch manufacturing or when addressing wiring failures in electronic equipment, multiple processes proceed simultaneously. Failing to model parallelism properly, through overly simplistic critical-path assumptions or independent sampling without correlation, can lead to severe underestimation of schedule risk or unrealistic compression opportunities. Parallel processes serve as an important benchmark for simulation efforts because they test the model's ability to handle complexity beyond serial chains. Effective representation requires incorporating resource constraints, stochastic dependencies, and merge events, which Monte Carlo methods can readily address (Kolisch and Hartmann 2006). This modeling reveals hidden bottlenecks, evaluates concurrent engineering benefits, and provides more realistic forecasts for large-scale projects like infrastructure or product development. By using parallel process modeling as a benchmark, researchers and practitioners can better assess the robustness of distribution choices under extreme conditions.

1.1 Objectives

The primary objective of this research is to advance the practice of probability distribution selection in project management scheduling simulations by conducting a focused investigation into the triangular distribution and its variants, with particular emphasis on their application in complex, parallel task environments. This study aims to enhance the accuracy and reliability of Monte Carlo-based schedule risk analysis through rigorous mathematical derivation and empirical evaluation. In so doing, this research will be of use to scheduling practitioners can then more effectively characterize and accurately predict the right bias associated with using the triangular and other related distributions in highly parallel project networks.

Specific objectives include:

1. To model and examine total project durations using a broad parallel task structure as a benchmark. This involves constructing simulation networks with multiple concurrent activities, resource constraints, and merge points to evaluate how different distribution choices affect overall schedule outcomes, critical path behavior, and merge bias.

2. To compare simulation results obtained from triangular distributions against other commonly used distributions, such as uniform, normal, lognormal, beta, and gamma distributions. The comparison will assess metrics including mean project duration and variance.

3. To demonstrate analytically the exponentially compounded effect that right-biased distributions have when arranged in highly parallel process networks.

Additional objectives are to quantify the inherent bias toward longer task durations exhibited by triangular and related distributions, to identify conditions under which specific distributions perform best, and to develop practical guidelines for analysts and project managers. Ultimately, this research seeks to bridge theoretical distribution properties with real-world project simulation needs, improving decision-making under uncertainty.

2. Literature Review

The selection of appropriate probability distributions for Monte Carlo simulation (MCS) in project scheduling is a foundational element of quantitative risk analysis (Visser, 2016). Triangular distributions remain among the most widely used due to their simplicity and direct compatibility with three-point estimating practices (optimistic, most likely, pessimistic) commonly applied in project management (Danielson and Khan, 2015).

Researchers frequently endorse the triangular distribution for modeling activity durations, particularly when historical data is scarce (Purnus and Bodea, 2013). This distribution is intuitive for subject matter experts and readily captures asymmetry in estimates. Comparative studies indicate that it produces results comparable to alternatives such as beta-PERT when mean and variance parameters are aligned, with relatively minor differences in overall project duration forecasts across serial and parallel network structures (Visser, 2016). However, the triangular distribution's sharper peak and linear slopes can sometimes lead to different tail behaviors compared to smoother distributions like beta-PERT, affecting extreme risk estimates.

Optimism bias represents a persistent challenge in constructing reliable input distributions (Flyvbjerg, 2006). Project planners systematically underestimate durations and costs due to cognitive tendencies associated with the planning fallacy. This bias typically compresses the range of three-point estimates, resulting in overly narrow triangular or PERT distributions and optimistic MCS outputs. Mitigation approaches include reference class forecasting, explicit bias uplifts, and structured calibration of expert judgments (Flyvbjerg, 2006; UK Department for Transport, 2021).

In project networks, merge bias (also known as path convergence bias) further complicates distribution choices (Klingel, 1966). When multiple paths converge on a single milestone or activity, the project completion time is governed by the longest path in each simulation iteration. Traditional deterministic methods and analytical approximations such as classic PERT significantly underestimate this effect, while MCS naturally accounts for it by sampling the full network (MacCrimmon and Ryavec, 1964).

Early studies identified the optimistic tendencies of PERT due to merge bias, a limitation that persists in modern analyses unless full stochastic simulation is employed (Klingel, 1966; MacCrimmon and Ryavec, 1964). Recent work confirms that convergence points amplify schedule uncertainty, underscoring the need for robust distribution modeling and correlation between activities.

Literature in this area consistently shows that while the precise shape of the input distribution (triangular versus beta-PERT or others) exerts limited influence on central tendency measures when parameters are consistent, it has greater impact on tail probabilities and high-confidence forecasts critical for decision-making (Visser, 2016; Purnus and Bodea, 2013). Effective practice therefore combines expert elicitation with historical data, explicit adjustment for optimism bias, and comprehensive MCS that captures network convergence effects (Love et al., 2015; Danielson and Khan, 2015).

3. Methods

This study incorporates a structured methodology for project management scheduling simulation using defined probability distributions. Several Monte Carlo simulations of project management schedule test cases were constructed and tested under a variety of conditions in this analysis. All procedures were implemented in Excel or Python and validated for reproducibility. The results were compiled and tested for their respective outcomes.

3.1 Assumptions

Projects were simulated using a Program Evaluation and Review Technique activity structure with predecessor and dependent activities in a network structure. The duration of each task was generated using that distribution's inverse cumulative distribution function and a random number between zero and one. The structure and number of tasks for each model were defined for each test instance.

3.2 Model

A Monte Carlo simulation was conducted to analyze the distribution of critical durations in a project network consisting of 20 parallel tasks. Each task duration was modeled using triangular distribution with parameters (a=0, b=10, c=10), where a represents the minimum duration, b represents the maximum duration, and c represents the mode. This right-triangular distribution (mode at maximum) was selected to represent tasks where completion times are more likely to approach the maximum duration.

For parallel task configurations, the critical path duration is determined by the maximum duration among all concurrent tasks. Mathematically, if $X_1, X_2, \ldots, X_{20}$, represent the duration of 20 parallel tasks, the critical path duration M is defined as:

$$M = \max(X_1, X_2, \ldots, X_n)$$

The simulation was implemented using Excel and/or Python. For each iteration, 20 independent random samples were drawn from triangular (0,10,10) distribution. The maximum value among the 20 samples was recorded as the critical path duration. The process was repeated for 10,000 iterations to generate a robust empirical distribution. The histogram and cumulative distribution function were generated.

This was compared with other probability distributions including the normal, lognormal, gamma, and beta distributions.

4. Data Collection

Monte Carlo simulation was used to generate synthetic data for the analysis. All observations across the 20 tasks were drawn independently from the same distributions with identical parameter settings. Then the maximum value among the observations was recorded. This was repeated for a total of 10,000 iterations to ensure statistical stability and reliable estimation of distribution properties. Python Numpy and/or Excel were used to generate the data. This process was repeated for each distribution (and parameter) listed below for comparison. The following distributions and parameters were used:

- Triangular distribution with parameters (min=0, mode=10, max=10)
- Triangular distribution with parameters (min=0, mode=0, max=10)
- Normal distribution with parameters (mean= 6.667, std=2.357)
- Lognormal distribution with parameters (mean= 1.838, std=0.343)
- Gamma distribution with parameters (shape=8, scale=0.833)
- Gamma distribution with parameters (alpha=2, beta=1)

The summary statistics of each of these distributions were compiled along across all trials. A histogram of calculated total duration of each simulated project was made along with a graph of the cumulative distribution function of each distribution's output.

5. Results and Discussion

5.1 Numerical Results

The summary statistics of 10,0000 simulations of 20 parallel tasks which are characterized as extreme, right biased triangular distribution are presented in Table 1. These triangular distributions have test parameters of a minimum value of zero with their mode and maximum both being ten. What appears to be a roughly exponential right leaning bias is apparent in the percentile results. This compounding of the lateness of each task duration in the critical path of the overall project is clearly apparent.

Table 1. Descriptive statistics of critical path duration of 20 parallel triangular (0,10,10)

Statistic	**Value**
Mean	9.7554
Median	9.8279
Standard Deviation	0.2389
Minimum	7.6631
Maximum	10.000
25^{th} Percentile	9.6603
75^{th} Percentile	9.9271

90th Percentile	9.9748
95th Percentile	9.9880
99th Percentile	9.9975

The second set of results in Table 2 describes the same network situation with the opposite triangular distribution. This uses an extreme right biased distribution with minimum and mode both being zero and the maximum being ten. This distribution is far more balanced than the previous, as the early bias of each task is tempered by the longest time requirement of the critical path of the project.

Table 2. Descriptive statistics of critical path duration of 20 parallel triangular (0,0,10)

Statistic	**Value**
Mean	8.0502
Median	8.1531
Standard Deviation	0.9947
Minimum	2.943
Maximum	9.9687
25th Percentile	7.3812
75th Percentile	8.813
90th Percentile	9.2808
95th Percentile	9.4995
99th Percentile	9.7873

The next set, Table 3, describes the result of 20 parallel tasks, with each task being a normal distribution. The mean was set at two-thirds the distance to the right, and the standard deviation to 2.357, which are the same values as the right biased triangular distribution. Both the mean and the right tail of this set are beyond what would be possible with parallel triangular distributions, due to the infinite possibilities of normal distributions.

Table 3. Descriptive statistics of critical path duration of 20 parallel normal (mean = 6.667, std =2.357)

Statistic	**Value**
Mean	11.0742
Median	10.9565
Standard Deviation	1.238
Minimum	7.1902
Maximum	16.7674
25th Percentile	10.2005
75th Percentile	11.8319
90th Percentile	12.7258
95th Percentile	13.2908
99th Percentile	14.3847

In Table 4, we output the results of 20 parallel lognormal distributions with parameters mean 1.838 and sigmas of 0.343. These results are more variable than the previous normally distributed tasks of the previous results in Table 3.

Table 4. Descriptive statistics of critical path duration of 20 parallel lognormal (mean = 1.838, std =0.343)

Statistic	**Value**
Mean	12.1348
Median	11.7308
Standard Deviation	2.3073
Minimum	6.7811
Maximum	27.3264
25th Percentile	10.5087

75th Percentile	13.3247
90th Percentile	15.1759
95th Percentile	16.4763
99th Percentile	19.3194

A network comprised of 20 parallel gamma distributions of shape factor 8 and scale of 0.833 was used to generate the summary results presented in Table 5. These results are similar but more compact than the normal and log-normal task durations presented in Tables 3 and 4.

Table 5. Descriptive statistics of critical path duration of 20 parallel gamma (shape = 8, scale = 0.833)

Statistic	**Value**
Mean	11.7755
Median	11.5182
Standard Deviation	1.853
Minimum	6.8946
Maximum	22.1282
25th Percentile	10.4764
75th Percentile	12.8102
90th Percentile	14.2264
95th Percentile	15.1563
99th Percentile	17.3489

Table 6 shows the results of a similar network of 20 parallel tasks with durations described according to a beta distribution with parameters alpha equal to 2 and beta equal to 1. Although structurally limited to a range of zero to one, the shape of the distribution is almost identical to that of the left biased triangular distributions in Table 1.

Table 6. Descriptive statistics of critical path duration of 20 parallel beta (alpha = 2, beta = 1)

Statistic	**Value**
Mean	0.9758
Median	0.9831
Standard Deviation	0.0239
Minimum	0.7939
Maximum	1
25th Percentile	0.9657
75th Percentile	0.9929
90th Percentile	0.9976
95th Percentile	0.9989
99th Percentile	0.9998

All of the results tabulated above correspond to the behavior we would expect from each respective distribution. The compounding effect of taking the critical path of parallel activities creates new distributions which are more applicable to real project management completion durations.

5.2 Graphical Results

In Figure 1 we can see visually how the parallel execution of right triangular tasks with a minimum of zero and a mode and a maximum of ten. This compounding effect creates an almost exponential like bias in the cumulative final durations of these simulated projects. This result is meaningful for project managers in that parallel right biased tasks of similar duration will almost certainly result in the worst-case project completion time.

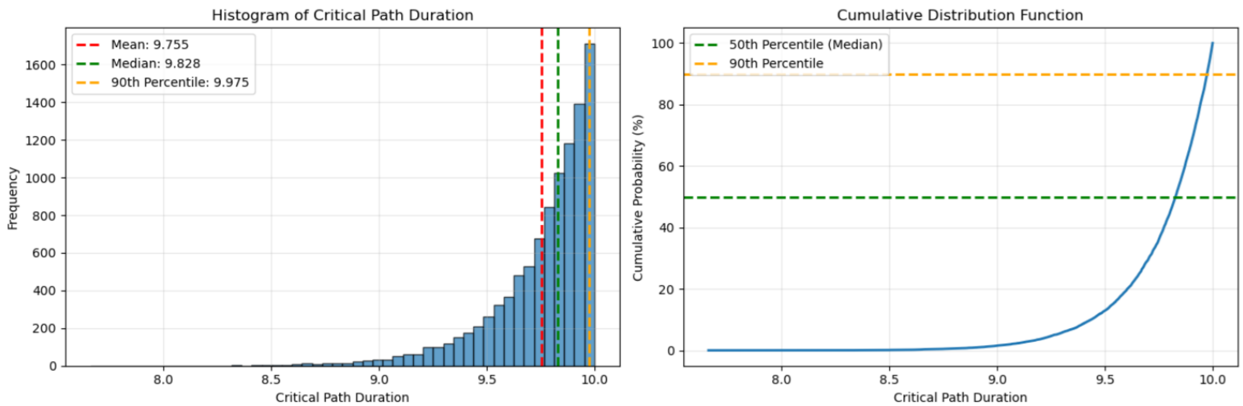

Figure 1. Critical path analysis of 20 parallel triangular (0,10,10) tasks

The Figure 2 shows the effect of individual task durations which are triangularly distributed with minimum and mode durations of zero with a maximum duration of ten. Despite these durations being forward biased toward earlier completion, the overall effect on project completion is still biased strongly toward later than mid-length completion. This provides an important insight for project managers that, at least with high levels of parallel tasks, early individual task completion should not be expected to result in projection completion times much better than worst-case scenario for any given project.

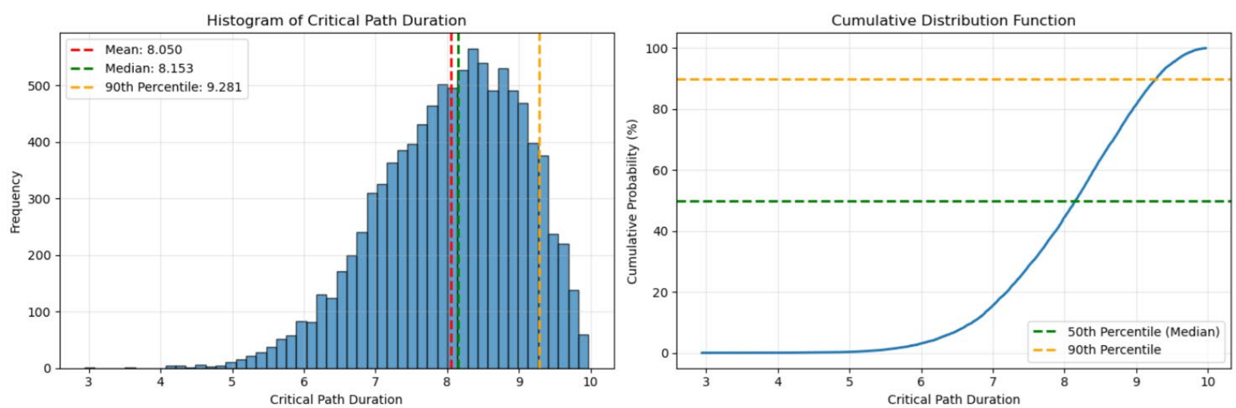

Figure 2. Critical path analysis of 20 parallel triangular (0,0,10) tasks

The outcome is more complex for the normally distributed task durations in Figure 3. In projects with these kinds of tasks, large numbers of parallel tasks are likely to be highly biased toward late project completions. The graph of cumulative distributions on the right side of the figure shows the long tail behavior of the overall distribution. Project managers would be wise to try and limit how many tasks occur in parallel if task durations are normally distributed.

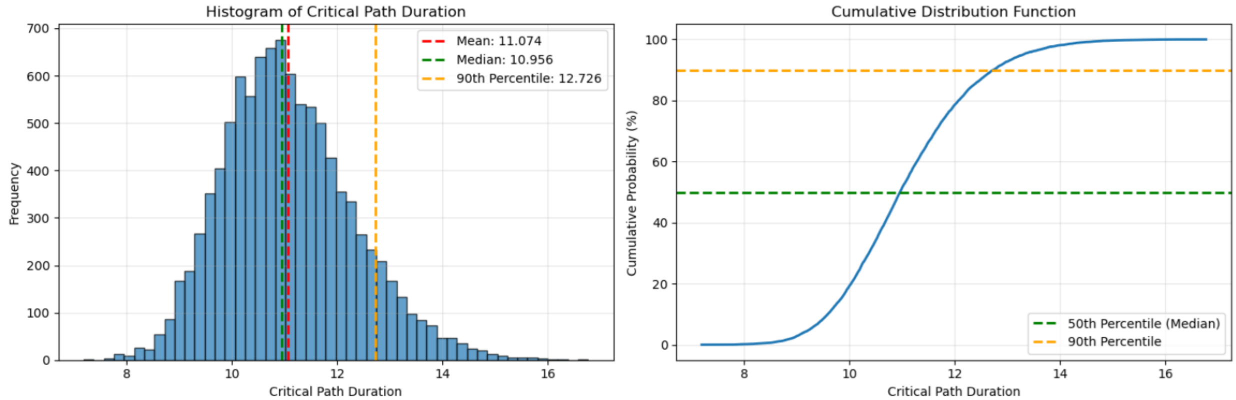

Figure 3. Critical path analysis of 20 parallel normal (6.667, 2.3578) tasks

The long right tail apparent in the distribution in Figure 4 reflects the danger that lognormal project durations pose to the completion times of highly parallel projects. Although these lognormal distribution with means of 1.838 and sigmas of 0.343 somewhat resemble normal distributions, their longer tails have a deleterious effect for meeting project deadlines.

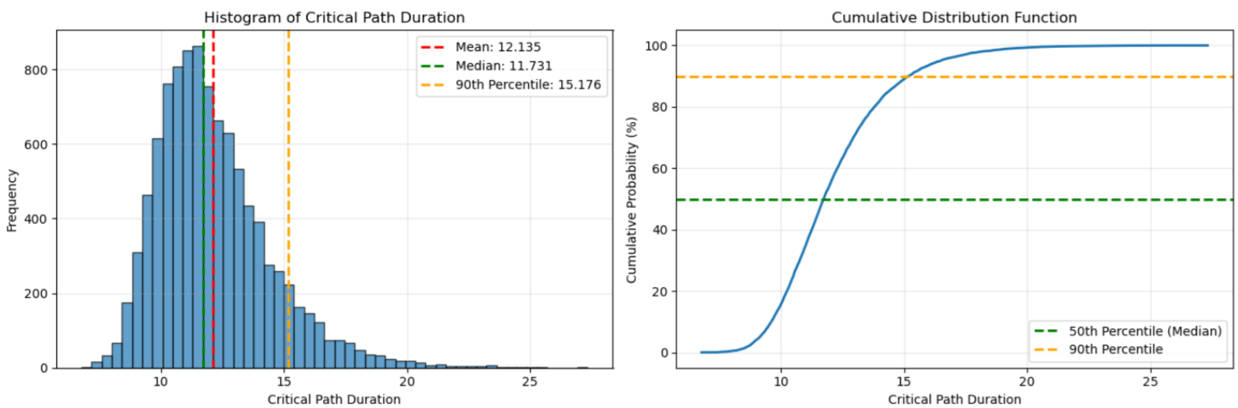

Figure 4. Critical path analysis of 20 parallel lognormal (mean = 1.838, sigma = 0.343) tasks

The output of the gamma distributed task durations in Figure 5 show similarly long late tails to those with the normal and log-normal based simulations shown in Figures 3 and 4. Project managers need to carefully set their project deadlines with these types of projects.

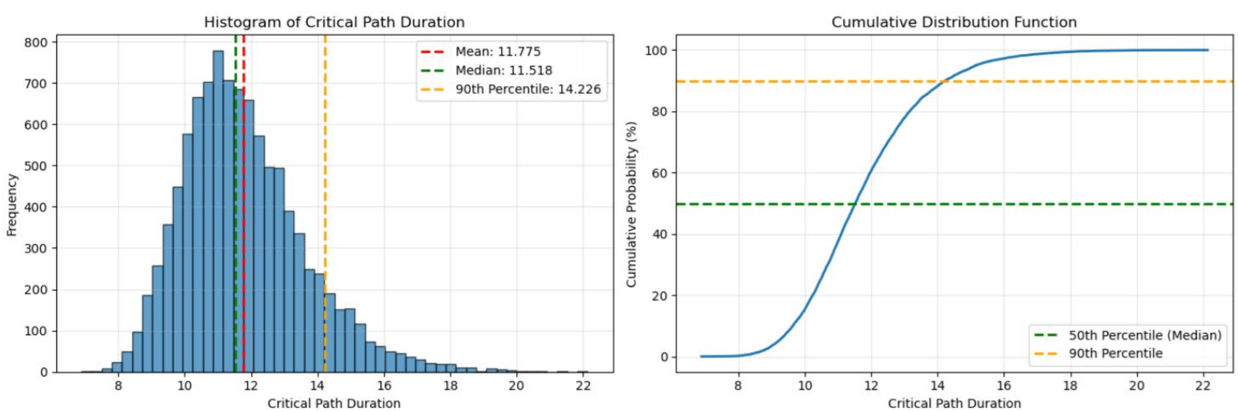

Figure 5. Critical path analysis of 20 parallel gamma (shape = 8, scale = 0.833) tasks

The output of the simulations of projects with tasks which are beta distributed shows a nearly identical outcome as those with the left biased triangular distribution. As with those, highly parallel projects with beta distributed tasks durations are almost doomed to latest possible completion times.

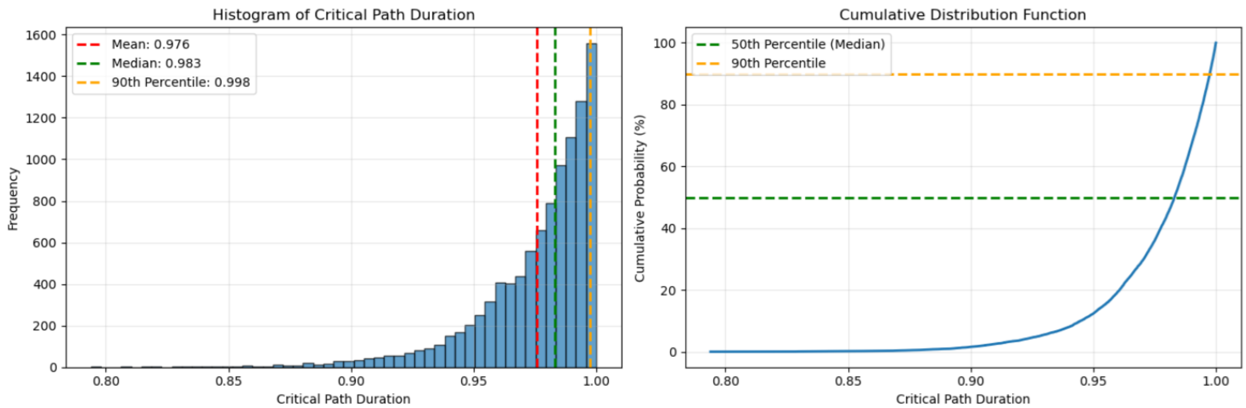

Figure 6. Critical path analysis of 20 parallel beta (alpha = 2, beta = 1) tasks

The Figure 6 above clearly illustrate the often-complex interactions of highly parallel network structures. The seemingly exponentially late outcomes of the right biased triangular and beta task distributions shown in Figures 1 and 6 are not nearly as much of a threat to on-time project management performance and the exaggerated late tails of the normal, lognormal, and gamma distributed tasks of Figures 3, 4, and 5.

5.4 Validation

The simulation results can be validated theoretically. For a triangular distribution with parameters (a=0, b=10, c=10). The individual task distribution has:

$$PDF: f_X(x) = \frac{x}{50}$$
$$CDF: F_X(x) = \int \frac{x}{50}\, dx = \frac{x^2}{100}$$

For n independent parallel tasks, the critical path duration is the maximum task duration, M. The CDF of M is obtained by: $(\frac{x^2}{100})^n = (\frac{x}{10})^{2n}$

PDF of maximum of n parallel tasks is $F_M(x) = \frac{d}{dx}\left(\frac{x}{10}\right)^{2n}$

$$= 2n\left(\frac{x}{10}\right)^{2n-1} * \frac{1}{10}$$
$$= \frac{2n}{10}\,(\frac{x}{10})^{2n-1}$$

This is a power function with exponent (2n-1) which exhibit left skewed behavior. For n=20 parallel tasks, this yields:

$$F_M(x) = 4(\frac{x}{10})^{39}$$

The inverse cdf for n triangular (0,10,10) tasks is $10 * p^{1/2n}$. This is obtained from solving for x in $F_X(x) = p = \left(\frac{x}{10}\right)^{2n}$

$$x = 10 * p^{1/2n}$$
$$F^{-1}(p) = 10 * p^{1/2n}$$

This inverse cumulative distribution function of n parallel triangular (0,10,10) tasks, $F^{-1}(p)$, is thus equal to $10 * p^{1/2n}$. We also observed that the PDF of the maximum of 20 parallel triangular (0,10,10) tasks is left-skewed with an exponential like growth pattern. We verified the PDF by analytically differentiating the CDF and identified it as a power function, $\frac{2n}{10}\left(\frac{x}{10}\right)^{2n-1}$. Furthermore, this analytical approach enables direct percentile calculations without simulation for certain simple situations.

6. Conclusion

In conclusion, we examined the expected completion times of several task completion probability distributions used in project duration simulation of highly parallel project activity networks. We observed how the different distribution choice affects the mean project duration and other metrics. The compounding effect created by highly parallel critical-path networks can create an almost exponential bias in the cumulative final durations of projects. Project managers should be aware that late completion of tasks in these structures will almost certainly result in worst-case project completion times. However, even early task completion times in highly parallel task structures will still likely result in later than mid-range project completion performance. Worst of all, the long right tails of normal, lognormal, and gamma distributed tasks are exaggerated by highly parallel task structures, and can cause extremely late completion times. These results were verified analytically and presented in an easily repeatable way for project management practitioners for use in projects with simple parallel task structures.

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Biographies

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