COMPARATIVE ANALYSIS BETWEEN PERT AND MONTE CARLO SIMULATION IN MILK PRODUCTION

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***Abstract*:** The manufacturing of milk is a time-sensitive process where even minor delays can have an impact on overall productivity and product quality. Predicting the entire processing time becomes difficult since several processing steps fluctuate in duration due to worker habits, equipment behavior and fluctuating daily volumes. This study helps to compare the Program Evaluation and Review Technique (PERT) and Monte Carlo Simulation (MCS). To manage these uncertainties in a dairy processing setting, PERT determines the steps most likely to cause delays in the process and delivers projected durations based on time estimations collected from the milk processing workflow. Monte Carlo Simulation is then carried out using Excel, where thousands of random scenarios are generated and converted into a Cumulative Distribution Function (CDF) to show the probability of completing the process within specific time limits. The comparison demonstrates that Monte Carlo simulation with offers a more in-depth understanding of risks and variances, whereas PERT provides a clear and organized picture. Dairy managers can plan and oversee the milk production schedule more realistically and confidently when both approaches are combined.

***Keywords* -** PERT, Monte Carlo simulation, Triangular distribution, Cumulative Distribution Function, Critical path, Probability Factor.

1. INTRODUCTION

Dealing with uncertainty is frequently necessary in project planning and process scheduling, particularly when the duration of activities cannot be precisely predicted. Activity times vary in the majority of real-world systems because of changes in operational conditions, human productivity, machinery performance, resource availability and unforeseen disruptions. Activities take longer than anticipated, deadlines change and uncertainty frequently becomes a normal part of the process. In these circumstances, relying on fixed or average values may result in poor planning, erroneous forecasts and a higher chance of delays. In real-world project management is rarely simple. As a result, project managers require tools that can do more than just enumerate tasks; they also require techniques that can comprehend and handle ambiguity. The Program Evaluation and Review Technique (PERT) and Monte Carlo Simulation (MCS) are two such techniques that have influenced contemporary project planning. These are two such techniques that are frequently employed in both industry and research. Therefore, creating accurate and trustworthy forecasts requires analytical techniques that welcome variability rather than ignore it.

1.1 PROGRAM EVALUATION AND REVIEW TECHNIQUE (PERT)

PERT is a probabilistic method that uses a three-point estimation approach to capture uncertainty in activity durations. By defining an Optimistic, Most Likely, and Pessimistic time for each activity. These inputs are used to calculate the expected duration and variance of each task, which helps identify the critical path—the sequence of activities that directly influences the total completion time. As the outcome of PERT not only estimates how long a process might take, but also highlights the activities that carry more uncertainty and may require closer observation. PERT offers a more flexible way to represent real life application.

1.2 MONTE CARLO SIMULATION (MCS)

By using random sampling as input to generate a large number of possible outcomes, Monte Carlo simulation offers a deeper investigation of uncertainty. This method simulates the entire project many times like thousands of times to show the entire range of possible completion times using probability distributions derived from activity duration estimates. The result obtained is a full distribution that illustrates the possibility of various outcomes rather than just a single estimate. This support in analyzing the possibility of meeting particular deadlines, assessing risk, and figuring out confidence levels.

1.3 ROLE OF PERT AND MCS IN MILK PRODUCTION

Milk production is a time-sensitive and quality-critical process where each processing step must be finished within a set amount of time, in order to maintain freshness, safety and consistency. Every stage of the process, from the time raw milk enters the plant until it is processed and stored, is dangerous to unanticipated events. A few of the problems that impact day-to-day operations are variations in the timing of milk supply, variations in the amount of raw milk, equipment failure, uneven heating and cooling, human delays, and unscheduled quality checks. As a result, dairy managers always struggle to predict long the entire production cycle would take under changing conditions. In order to address this difficulty, analytical tools that measure uncertainty and assess time variability are crucial. They provide a plane to improve their productivity for capturing the range of likely durations for each manufacturing activity rather than depending on a single, fixed estimate, these techniques provide a structured way to represent time uncertainty in each step of the production process. By using three time estimates—minimum, most likely, and maximum—for every activity, they reflect real operating conditions more accurately. This helps in understanding how time variations in one stage affect the overall production schedule and how small delays can spread across the entire process.

One important benefit of these methods is their ability to identify critical stages in the milk production process that have the greatest impact on total processing time. Recognizing these bottlenecks allows managers to focus on improving equipment maintenance, staffing, and workflow efficiency. In addition, analyzing different time scenarios helps estimate the probability of meeting daily production goals. Instead of relying only on fixed schedules or experience, decision-makers can use probability-based results that account for real process uncertainty. When used together, time planning methods and simulation-based risk analysis provide a complete view of the production system and its variability. The insights gained support better scheduling, early detection of possible delays, and preparation for unexpected problems. Applying these tools is essential for milk processing plants to improve reliability, reduce downtime, and ensure consistent production performance. Ultimately, they support smarter, data-driven management of the milk production process.

2. REVIEW OF LITERATURE

A crucial issue in project management is project scheduling under uncertainty, which has prompted the creation of analytical techniques like Monte Carlo simulation and the Program Evaluation and Review Technique. The application of PERT and MCS in project management has been extensively discussed in literature.

According to Tysiak (2011), early criticisms of PERT emphasized that the technique essentially operated as a CPM model with a probabilistic layer added later. This limitation is particularly evident when there is no unique critical path and accuracy may be impacted by critical paths shifting under uncertainty. PERT has been widely used in various industries, including construction, manufacturing and software development, to estimate project duration and identify the critical tasks. Deshmukh and Rajhans (2018) characterized the Monte Carlo simulation as a procedure that converts frequency outcomes into probability measures by varying each activity duration within a predetermined range for hundreds of iterations. According to their research, project activities invariably involve uncertainty and defining a probability distribution—typically normal for simplicity, to improves the completion of likelihood prediction. Hendradewa (2019) elaborates on the significance of precise scheduling by pointing out that projects function in dynamic environments where risk identification, quick decision-making, and time management are crucial. Evaluating schedule alternatives in such complex settings is further aided by Monte Carlo simulation. Bagal and Kulkarni (2019) describe a useful, step-by-step method that involves estimating activity ranges, running simulations to produce minimum and maximum completion dates, and using PERT-based probabilities to evaluate schedules. They concentrate on simulation using Excel.

The statistical distinctions between PERT and MCS are also examined in comparative studies. Doubrave and Doskocil. (2015) discovered that the variations in probability estimates between the two approaches become statistically insignificant as the number of simulation iterations increases. However, by repeatedly generating project durations using randomly selected values from preassigned distributions. Opaleye et al. (2017) point out that while Monte Carlo and PERT follow similar logical steps, MCS's iterative sampling methodology yields richer detail. A number of researchers highlighted the difficulties in parameter estimation with respect to distributional decisions. Although experts find it easier to estimate minimum and most likely values than maximum values because of irregular delays, Mohammadi et al. (2025) observe that triangular distributions are widely used. According to Mirkovic (2021), PERT uses three-point estimation methods derived from the Central Limit Theorem and is based on the beta distribution. Suharni and Lily (2024) also demonstrate how PERT enables the calculation of probability values derived from the normal distribution, target duration and expected time. Karabulut (2017) support the Monte Carlo in project planning by showing how repeated trials of activity durations enable simulation of all potential risk scenarios, hence calculating completion timeframes under various conditions. Accordingly, since specialists can accurately predict boundary values, Koulinas et al. (2020) confirm the benefit of triangular distributions in situations when uncertainty is high but historical data is few. By creating frequency distributions of completion times through thousands of random repeats, Monte Carlo simulation allows managers to measure the probability of achieving deadlines, according to Avlijas (2019).

Studies also address the impact of network topologies and activity dependencies on duration estimation. The sensitivity of project duration to distributional assumptions is highlighted by Hajdu and Bokor (2014), who characterize PERT networks as directed acyclic graphs whose task sequencing is controlled by event-based logic. In their comparison of PERT and triangular distributions, Sobieraj and Metelski (2022) point out that PERT distributions are smoother but may underestimate extreme values when significantly skewed, whereas triangular forms are angular. Wali and Othman (2019) stress that in order to measure schedule risks using both qualitative and quantitative methods, PERT and CPM must be combined. Wyrozębski and Wyrozębska (2013) talked about difficulties in simulation, like figuring out how many repetitions to use, which might vary from a few hundred to several thousand depending on the complexity of the model. In order to simulate real-world randomness in project environments, Naidu and Angadi (2018) reiterate that Monte Carlo simulation uses random number generation to sample from activity distributions. According to Dinelli et al. (2021), PERT facilitates the evaluation of project duration, critical paths and the probability of meeting deadlines by integrating probabilistic among activities. Wolny (2023) goes on to say that, especially in highly interdependent jobs, Monte Carlo analysis can be tailored to entire networks or individual portions. Lastly, research employing discrete-event simulation techniques shows that when minimum, mode and maximum values are available, triangular distributions are frequently utilized to describe activity durations, improving the accuracy of anticipated completion times. The results are transportable and adaptable to real-world project situations since this method enables the model to account for job duration variations. Yudistira et al. (2024) applied PERT analysis in conjunction with discrete event system simulation to forecast project timelines and evaluate related risks, demonstrating a similar methodological approach.

3 RESEARCH METHODOLOGY

3.1 DATA COLLECTION

In this study involved the collection of secondary data from the official website of Amul Dairy, including activity duration, processing stages and past performance records.

3.2 NETWORK STRUCTURE

This study consists of 14 important process and the work processing in Amul dairy and their respective activities are presented in Table 3.1 and Figure 3.1. The Earliest Start (ES) and Earliest Finish (EF) times for each activity during simulation were calculated using these precedence constraints in PERT method. Each activity's expected duration and related uncertainty were estimated using the PERT.

Table 3.1: Work Process in Amul Dairy

Process	Activity	Predecessor
Collection of milk	A	-
Quality check	B	A
Cooling/Chilling	C	B
Rejected	I	B
Pasteurization	D	C
Homogenization	E1	D
Cream separation	E2	D
Flavoring / fortify	E3	D
Standardization / Fortify	F1	E1
Churning/Cream process	F2	E2
Mixing & Quality check	F3	E3
Packaging & sealing	G	F1,F2,F3
Dispatch / distribution	H	G
Coagulate & safe disposal	J	I

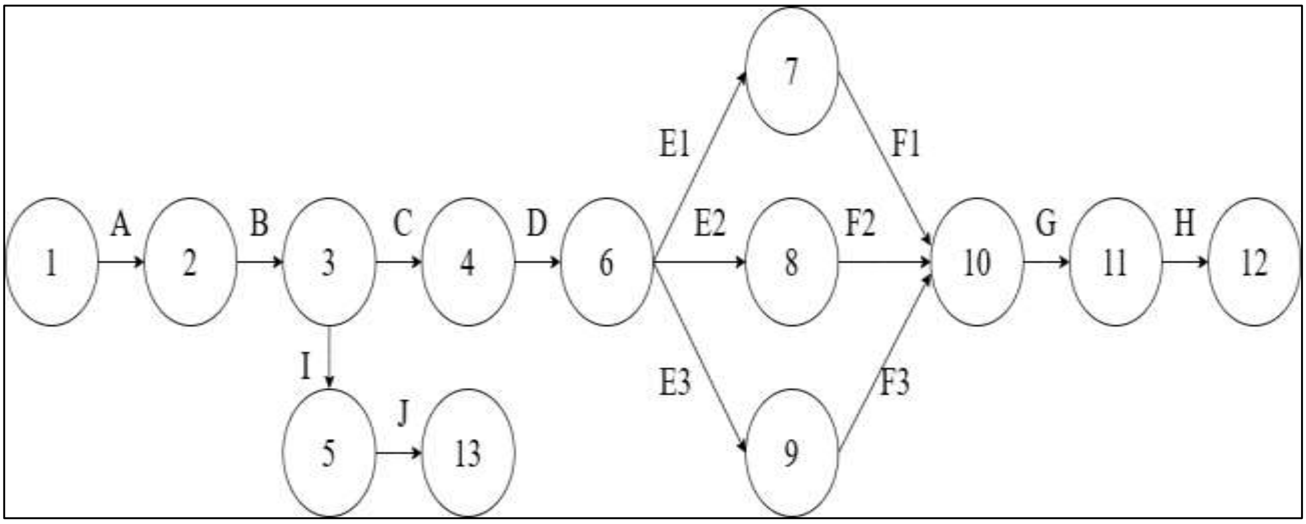

Figure 3.1: Network Diagram for Work Process in Amul Diary

3.3 PERT FORMULAS

Expected Activity Duration

Expected time for each activity is given by

$$t_e = \frac{(a+4m+b)}{6} \qquad (3.1)$$

variance for each activity is calculated as

$$\sigma^2 = \frac{(b-a)^2}{36} \qquad (3.2)$$

the completion of the project will be calculated as

$$z = \frac{t_s - t_e}{\sigma} \qquad (3.3)$$

3.4 MONTE CARLO SIMULATION

Monte Carlo simulation allows us to comprehend a wide range of potential outcomes, whereas PERT only provides one expected value. It generates thousands of potential project durations and displays the frequency of each.

Applying the Triangle Distribution

To create a triangular distribution, we employed the same three PERT estimates (a, m and b). Monte Carlo Simulation using the Inverse Transform Sampling Method for triangular distribution. The distribution's turning point from rising to falling is determined by:

$$f = \frac{m-a}{b-a} \qquad (3.4)$$

Simulating Activity Durations

Tysiak (2011) states that each random number was used to calculate a simulated activity duration using:

$$t = \begin{cases} a + \sqrt{r.(b-a)(m-a)} & if \quad r < f \\ b - \sqrt{(1-r)(b-a)(b-m)} & if \quad r \geq f \end{cases} \qquad (3.5)$$

$$P(T \leq t) = \frac{\text{Number of simulated project durations } \leq t}{\text{Total number of simulations}} \qquad (3.6)$$

Let us consider, *r* be a random number between 0 to 1. The random numbers were generated in Excel using the RAND( ) function, with this converted into a time durations of each activity. In Excel which is used to create the cumulative distribution function (CDF) by sorting the simulated project times and assigning cumulative probabilities.

4. CASE STUDY

In the present study, the proposed approach to analyse the activity in Amul dairy. Milk collection took anywhere from 60 minutes to an average of 120 minutes and in high-load or delayed situations, it could take up to 240 minutes. At its fastest, the quality check at reception took 10 minutes; during regular operations, it took 20 minutes; and when further examination was needed, it took 40 minutes. The holding or rejection stage took at least 10 minutes, 20 minutes under typical circumstances, and up to 60 minutes under extreme circumstances when milk did not meet quality standards. It took 30 minutes at its fastest to cool or chill the milk to ≤5°C, 60 minutes when the plant was operating normally, and up to 180 minutes when there were operational delays. It was found that the HTST pasteurization process could take as little as 5 minutes, typically 15 minutes, and up to 60 minutes when equipment slowed down. Similar trends were seen in homogenization, which took at least 10 minutes, 20 minutes under normal circumstances, and up to 40 minutes. Standardization or fortification took five minutes at the very least, ten minutes on average, and up to twenty minutes during prolonged processing.

Cream separation took anywhere from 15 minutes to an average of 30 minutes for cream-based operations, and up to 60 minutes when there were delays. In the fastest cases, churning or cream processing took 30 minutes; on average, it took 60 minutes; and when the process took longer, it could take up to 120 minutes. The duration of certain stages, like flavoring or fortification, varied from a minimum of 10 minutes to an average of 20 minutes and a maximum of 40 minutes. For flavored milk, the mixing and quality check process took at least ten minutes, twenty minutes during regular plant operations, and up to thirty minutes when further validation was required. Repeated observations showed that packaging and sealing processes took at least 15 minutes, up to 30 minutes, and up to 60 minutes when operating at maximum capacity. Lastly, rejected milk should be dispatch and distribution required as little as 60 minutes, about 120 minutes under normal working conditions, and up to 240 minutes during peak or constrained operations, exhibiting one of the largest time variations. When taken as a whole, these measured durations provide a solid data base for further analytical modelling and represent the actual operational variability found throughout every stage of dairy processing. These time estimations are listed in Table 4.1.

4.1 PERT Evaluation

Table 4.1: Activities with Durations of the Amul dairy

Activity	Optimistic Time (a)	Most Likely Time (m)	Pessimistic Time (b)	t_e	σ^2
A	60	120	240	130	900
B	10	20	40	21.66667	25
I	10	20	60	25	69.44444
C	30	60	180	75	625
D	5	15	60	20.83333	84.02778
E1	10	20	40	21.66667	25
E2	15	30	60	32.5	56.25
E3	10	20	40	21.66667	25
F1	5	10	20	10.83333	6.25
F2	30	60	120	65	225
F3	10	20	30	20	11.11111
G	15	30	60	32.5	56.25
H	60	120	240	130	900
J	60	120	240	130	900

From the Figure 3.1 and Table 4.1, calculating critical path

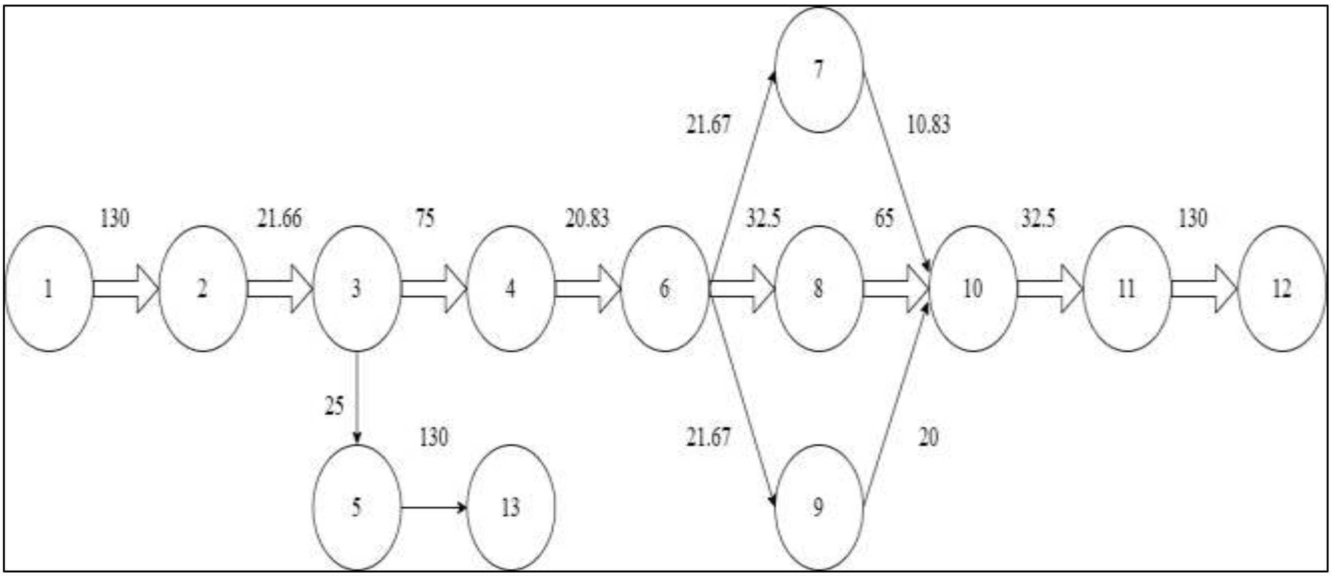

Figure 4.1: Critical path

Critical path: A – B – C – D – E2 – F2 – G – H

From Table 3, the expected time and variance of project length are t_e = 507.5 & σ^2 = 2871.53

σ = 53.59

Let us assume that the target time (t_s) = 550 minutes and then the probability of completion time is, z = 0.793. From Normal distribution, there is a 78.52% probability of achieving 550 or less.

4.2 MONTE CARLO SIMULATION

Random input values (0–1) generated for Case 1 to Case 10 for each activity. These values serve as the stochastic drivers of the Monte Carlo Simulation and remain unchanged throughout the duration calculations by using Triangular distribution

Table 4.2: Simulation of Random Numbers

Activity	a	m	b	f	Random Numbers (r)									
					Case 1	Case 2	Case3	Case4	Case5	Case6	Case7	Case8	Case9	Case 10
A	60	120	240	0.33	0.67	0.61	0.94	0.76	0.19	0.86	0.93	0.03	0.45	0.04
B	10	20	40	0.33	0.87	0.95	0.07	0.98	0.24	0.14	0.95	0.04	0.45	0.03
I	10	20	60	0.2	0.17	0.01	0.88	0.95	0.41	0.43	0.38	0.78	0.94	0.04
C	30	60	180	0.2	0.39	0.77	0.22	0.28	0.67	0.46	0.2	0.53	0.23	0.78
D	5	15	60	0.18	0.05	0.6	0.1	0.31	0.38	0.79	0.95	0.01	0.18	0.53
E1	10	20	40	0.33	0.97	0.6	0.87	0.66	0.58	0.51	0.55	0.24	0.62	0.01
E2	15	30	60	0.33	0.45	0.68	0.85	0.52	0.34	0.8	0.94	0.15	0.61	0.24
E3	10	20	40	0.33	0.54	0.6	0.51	0.92	0.69	0.42	0.52	0.68	0.58	0.15
F1	5	10	20	0.33	0.65	0.35	0.2	0.42	0.24	0.73	0.27	0.48	0.17	0.68
F2	30	60	120	0.33	0.34	0.8	0.2	0.62	0.38	0.21	0.08	0.52	0.89	0.48
F3	10	20	30	0.5	0.68	0.06	0.34	0.54	0.95	0.16	0.36	0.47	0.34	0.52
G	15	30	60	0.33	0.73	0.66	0.64	0.49	0.33	0.67	0.61	0.89	0.5	0.47
H	60	120	240	0.33	0.8	0.65	0.27	0.13	0.46	0.36	0.39	0.29	0.17	0.89
J	60	120	240	0.33	0.7	0.64	0.68	0.09	0.28	0.1	0.18	0.92	0.14	0.29

Activity duration outcomes for each simulation case, calculated by transforming the random inputs from above table using the triangular/PERT distribution. The final column shows the total path duration for each case.

Table 4.3: Results of Monto Carlo Simulation by using Random Numbers

Case	A	B	I	C	D	E1	E2	E3	F1	F2	F3	G	H	J	Total path
1	155.57	31.17	19.22	75.21	10.24	35.76	32.75	23.39	12.75	60.3	22	40.91	174.27	159.5	580.42
2	148.22	34.52	12.24	115.66	28.54	24.51	39.22	24.51	10.13	87.14	13.46	38.58	153.05	151.82	644.93
3	204	14.58	44.51	61.51	12.42	31.17	45.77	22.85	8.87	53.24	18.25	37.95	114	156.86	543.47
4	168	36.54	50	66.16	18.68	25.72	34.54	33.07	10.67	74.7	20.41	33.76	97.47	91.18	529.85
5	105.3	18.49	25.65	102.93	20.83	24.13	30.15	26.36	9.24	62.14	26.84	29.93	132	114.99	501.77
6	185.01	16.48	26.24	81.41	37.2	22.85	43.57	21.35	13.64	53.81	15.66	38.89	122.42	92.86	578.79
7	201.12	34.52	24.79	60	48.88	23.57	51	23.03	9.5	44.7	18.49	37.05	125.21	104.09	602.48
8	78	13.46	39.02	88.02	7.35	18.49	25.06	26.14	11.17	69.09	19.7	47.81	115.96	198.43	444.75
9	131	21.83	49.05	62.27	14.95	24.9	37.05	24.13	8.57	95.63	18.25	34.02	102.85	98.88	499.6
10	80.78	13	14.47	117.07	25.89	11.73	27.73	16.71	13.07	67.01	20.2	33.25	191.26	115.96	555.99

To find Probability factor, we check Table 5 where only 5 simulations out of 10 simulations are reaching the target time. There is a 50% probability of achieving 550 or less.

4.3 COMPARATIVE STUDY OF PERT & MONTE CARLO SIMULATION

4.3.1 Cumulative Distribution Function

The PERT approach generates a theoretical estimate of project completion time based on the expected time and variation derived from activity-level optimistic, most-likely, and pessimistic values. It assumes independence among activities and approximates the project duration using a Normal distribution throughout the critical path. Conversely, the Monte-Carlo simulation provides an empirical distribution of project durations by periodically selecting activity times from their defined probability distributions and reconstructing the network, thereby replicating the genuine stochastic behaviour of the system.

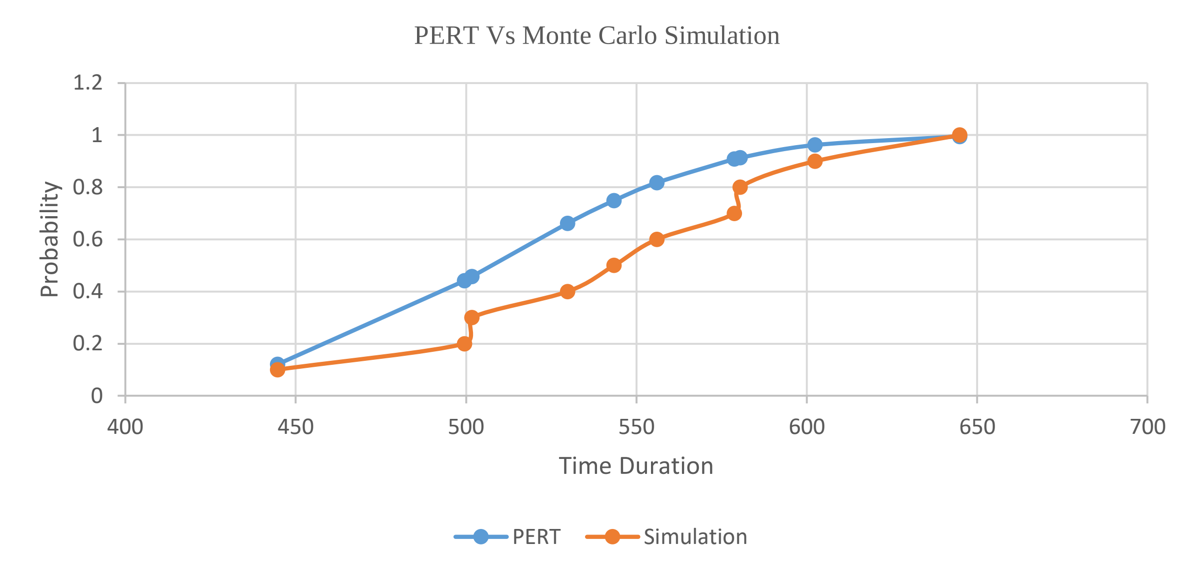

Figure 4.2: PERT Vs Monte Carlo Simulation

In Figure 4.2, CDF comparison of milk production time duration between Monte Carlo simulation (ECDF) and the PERT method (CDF) within the time interval of 400–700 minutes. The Monte-Carlo illustrates the true probability distribution derived from simulated completion times, reflecting all variations in the procedure. The PERT created using the Normal approximation, yields a more fluid theoretical curve derived from the anticipated duration and standard deviation of the critical path. The variations observed in this particular range highlighted how Monte-Carlo simulation demonstrates greater uncertainty and more extreme outcomes, whereas PERT typically offers a tighter and more favorable probability estimation.

5. CONCLUSION

This study demonstrates that utilizing a PERT–Monte Carlo method on Amul Dairy's activity-duration information offers a more transparent and accurate perspective on the variability of processing times. The findings pointed the stages, like milk reception and pasteurization, that contribute significantly to schedule unpredictability and affect the critical path. This integrated model improves Amul Dairy's capacity to schedule operations, manage risks and allocate resources more efficiently by quantifying the likelihood of achieving target processing times. In general, the PERT–Monte Carlo framework provides a dependable and data-oriented instrument for enhancing efficiency in dairy processing operations. In this study, Monte Carlo provides more reliable, data-driven insights for risk analysis and scheduling decisions, While PERT is useful for initial estimation. Monte Carlo simulation proved more effective than PERT in capturing the full range of uncertainty in activity durations, offering a complete probability distribution rather than a single expected value. Therefore, Monte Carlo simulation is the stronger method for modeling variability in real-world processing systems.

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