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Enhancing Economic Resilience in Marginal Oilfields Through Discrete Event Simulation Optimization of Coiled Tubing Reutilization

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ABSTRACT - Coiled Tubing Gas Lift (CTGL) is an artificial lift method contributing the majority of oil production in marginal fields. These fields face a double challenge: reserves continue decreasing while operational costs tend to increase. This research aims to develop optimization models for reutilizing coiled tubing, shifting from current practices where CTGL installations always use new coiled tubing materials. A Discrete Event Simulation (DES) mirrors current operational practices based on empirical historical data (2019-2024) from the mature marginal oilfield Kutai Basin, with a target reservoir interval of 700 to 8000 ft in East Kalimantan, Indonesia. A baseline model (Scenario 0) and four optimization models (Scenarios 1- 4) of DES were developed to evaluate the most optimal strategies incorporating recycling and distinctive cutting policies. Scenario 1 (Dynamic Recycle) emerged as the best-performing model, delivering the highest Net Present Value (NPV) of \$58.53 million with 100% demand fulfillment; Scenario 4 (Hybrid Cut) performed equivalently but generated slightly more scrap, while the fixed-cut policies (Scenarios 2–3) were operationally unviable. Compared to the current practice (Scenario 0), which incurs an average Coiled Tubing (CT) cost of \$69,000 per well, Scenario 1 improves NPV by 7.62% (~\$4.1 million), creating significant value for marginal fields to maintain profitability and continuity. It also drastically reduces CT consumption by 53% and metal scrap by 60% while fulfilling 100% of job demand. The DES approach successfully validated that recycling CT is highly viable without compromising operational continuity. Earlier studies on coiled tubing are related to technical and operational failure factors and quality of service, while this research addresses problems such as the permanent application of CTGL in long-term project economies. Using DES, decision-makers can quantify the economic trade-offs of strategies without risk before implementation in the oil and gas industry.

Keywords: Coiled tubing gas lift, simulation, marginal field, recycle, use and scrap.

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1. Introduction

As reservoir pressure declines naturally in mature oilfields, artificial lift methods such as gas lift are deployed to sustain production (Effa et al., 2019; Khalid et al., 2020; Maurenza et al., 2023). Coiled Tubing Gas Lift (CTGL) serves as a highly effective artificial lift, utilizing continuous tubing as a conduit to inject gas and lift wellbore liquids to the surface (Suharjito & Warno 2025). CTGL has proven an essential artificial lift solution for marginal fields, successfully reviving non-economic wells in Pakistan and doubling production in the Wafa field by countering declining pressures without expensive workovers (Khalid et al., 2020; Kolawole et al., 2020; Sherik et al., 2019).

Despite these operational benefits, CTGL applications face significant technical and economic hurdles. While coiled tubing offers practicality and safety advantages over jointed tubing (Alagoz & Tali 2023; Wiranata et al., 2020), its deployment involves repeated bending that induces plastic-elastic deformation and fatigue failure over time (Shaohu et al., 2019; Tong & Gao 2019). These structural vulnerabilities are further accelerated by high internal pressures, tensile loads, mechanical strain, and corrosion (Hagianu et al., 2020; Shaohu et al., 2020; Yan et al., 2021). Although previous studies have examined these failure mechanisms using inspection methods such as magnetic flux testing (Long et al., 2020; Zhou et al., 2020), rising material costs and the lack of a standardized method to verify the integrity of retrieved coiled tubing for reuse remain critical challenges for sustainable long-term installations. To navigate this complex trade-off between the technical uncertainties of reused tubing and the economic necessity of lowering installation costs, decision-makers require a robust modeling tool capable of simulating dynamic operational variables.

While traditional analytical methods struggle to capture the dynamic complexity of inventory management under stochastic demand, Discrete Event Simulation (DES) offers a robust framework for modelling these uncertainties. Therefore, this study utilizes DES to bridge the gap between technical asset management and long-term economic planning. Simulation models are fundamental decision support tools to design mathematical representations of complex stochastic systems for short- and long-term strategic planning (Marshall et al., 2020; Ordu et al., 2021). DES is widely applied to model, evaluate, and optimize cascading decisions across various sectors by representing operations as sequences of discrete events (Ala & Chen 2020). These models manage uncertainty in dynamic environments, supporting decision-making in logistics (Coelho et al., 2021), complex transportation planning (de la Torre et al., 2021), sustainable space planning (Okeke 2020). Hybrid models integrating DES with forecasting and optimization have become increasingly popular for resource allocation and capacity planning, such as in healthcare systems (Ordu et al., 2021; Teles 2024; Wikman-Jorgensen et al., 2024).

Beyond broad capacity planning, DES is a robust methodology for evaluating specific operational improvements, scheduling, and maintenance scenarios (Golbasi & Turan 2020). For instance, DES has been used to compare stochastic programming for offshore flight scheduling (Bastos et al., 2020), assess lean construction principles (Al-Zqebah et al., 2022; Bajjou & Chafi 2021). Crucially, DES is widely applied to inventory management; tools like Arena simulation can model complex supply chains to reduce shortages (Arani et al., 2020) and determine optimal stock levels (Mitrovi et al., 2021). Simulation-based methods have been shown to significantly lower average inventory costs and volumes, improving overall management efficiency (Chen et al., 2022).

While the Oil and Gas (O&G) industry is increasingly adopting Industry 4.0 technologies and lean management frameworks to navigate market volatility and improve predictive maintenance (Elijah et al., 2021; Shou et al., 2021), DES applications in this sector remain limited. Despite DES's widespread success in modeling complex systems in other industries, existing coiled tubing literature primarily addresses isolated technical issues such as fatigue and corrosion failure mechanisms and fails to integrate these insights with long-term economic sustainability in marginal fields. This fragmented approach creates a critical research gap by overlooking DES's potential as a comprehensive digital twin framework that can optimize the full asset lifecycle, including operational risks, maintenance strategies, and economic trade-offs.

In a marginal oilfield context, the company relies on Coiled Tubing Gas Lift (CTGL) to support its production targets. From 2019 to 2024, CTGL deployment reached 283 installations, while 127 installations

were retrieved due to well depletion or equipment failure. The current operational practice dictates discarding these retrieved Coiled Tubing (CT) materials, generating massive metal scrap and highly inefficient inventory costs. With installation costs between 70 and 100 thousand USD, CT materials account for 30 to 50% of the total. This "use-and-dispose" approach exacerbates the economic challenges of mature fields, creating a critical need for asset reutilization.

To address this operational inefficiency, this research introduces a novel approach by shifting Coiled Tubing Gas Lift management from a linear 'use-and-dispose' model to a circular asset management framework. Unlike previous literature that focuses more on technical failures, this study aims to develop a DES model to optimize the entire lifecycle of CT reutilization. By utilizing Arena simulation software to replicate real-world process flows under stochastic conditions, this research provides a quantifiable, risk-free methodology to evaluate dynamic cutting and inventory replenishment strategies (Lestari et al., 2022), effectively bridging the gap between field operations and long-term economic sustainability.

The secondary objective is to evaluate the economic impact of these optimization strategies through cost-benefit analysis, specifically using Net Present Value (NPV). Reutilizing coiled tubing offers a significant opportunity to reduce installation costs by approximately \$20,000 to \$30,000 per well. Ultimately, this research provides a sustainable alternative that not only minimizes waste and inventory costs but also ensures long-term operational resilience, thereby improving individual project feasibility and extending the economic life of marginal oilfields.

2. Methodology

The sequence of the research methodology is mapped out in Figure 1, which details the flowchart of the research stages from literature study through problem definition, data collection, and model validation.

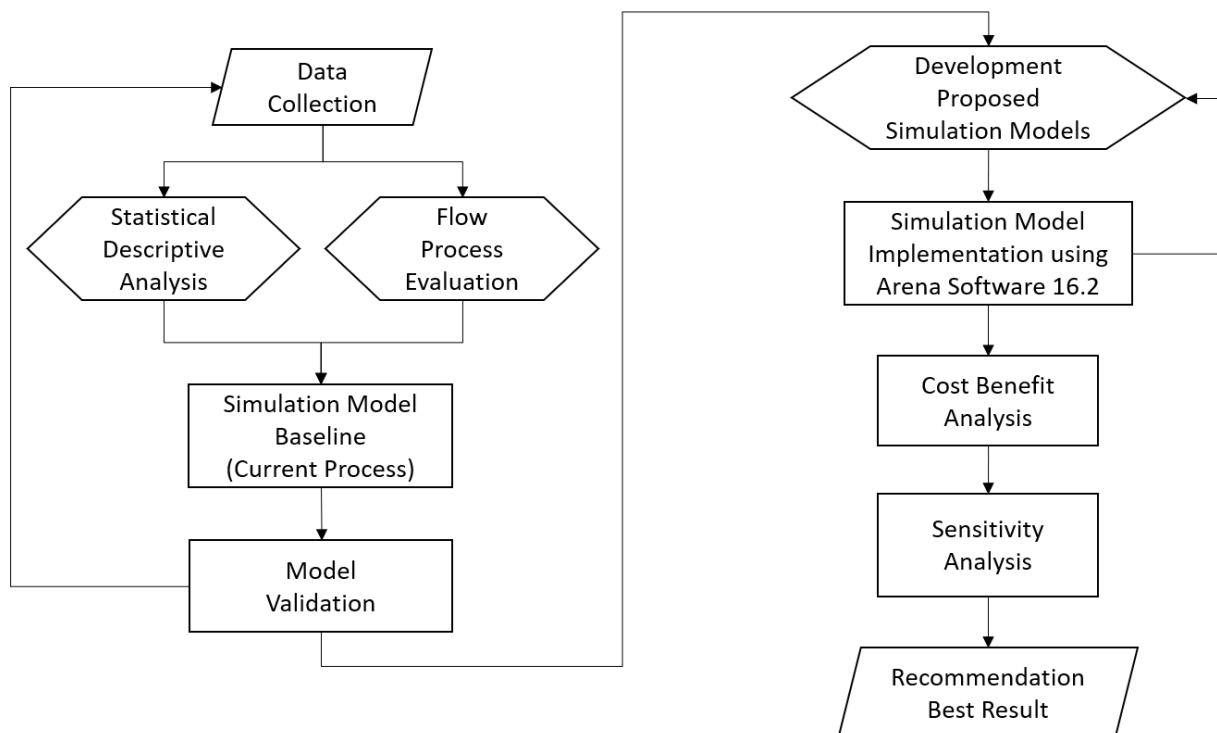


Figure 1.
Research flowchart for DES coiled tubing reutilization.

2.1 Data collection and descriptive characteristics

This study uses a historical dataset from a mature marginal oilfield in the Kutai Basin, with a reservoir depth of 700–8000 ft, operating in East Kalimantan, Indonesia. These historical data cover CTGL installations from 2019 to 2024 and serve as empirical inputs for the simulation. Using these data ensures the model reflects real-world process flows and stochastic conditions, identifying valid optimization opportunities without relying on hypothetical data.

Table 1 Summarized data required for simulation and optimization. Historical data show that installations are evenly distributed, demonstrating that CTGL represents an integral and sustained operational policy. In contrast, the number of retrievals is much lower than installations during the same period, reflecting that they are not integrated into a systematic reuse & cycle strategy, which this research proposes to address.

Furthermore, CTGL installations require coiled tubing lengths ranging from 750 to 8200 ft. Operational reasons suggest leaving around 300 to 1000 ft in the drums to support operational practicability and safety. Based on quartile-based analysis, the majority of CTGL installations require 4000 ft or less (81%), while installations requiring >7000 ft represent only 3% of the population. Therefore, with a requirement of 1000 ft left on the drum, coiled tubing length is segmented into 7 classes ranging from 1000 to 7000 ft, with a 1000 ft increment for each class. For example, class 1 is 1000 ft CT length, class 2 is 2000 ft CT length, and so on until class 7 is CT length > 7000 ft. This segmentation reflects actual field conditions and provides a simplified framework for simulation input, inventory management, and operational decision-making, e.g., for class downgrades when ex-used coiled tubing is included in inventory for the next installation.

2.2 Data preparation and distribution fitting

Distribution analysis of statistical data is essential to understand population behavior based on historical data as input for simulation. The simulation input dataset is stochastic, consisting of installation interval distribution as incoming job orders, retrieval range distribution, and production lifetime distribution. To ensure the data is statistically valid for simulation, we conduct a three-step validation process.

The first step is to check whether the dataset follows a normal distribution (Bayoud 2021). This is done in Minitab using the Anderson-Darling test, with the null hypothesis (H_0) that the data follow a normal distribution. If the resulting p-value is less than a chosen significance level (0.05), reject the H_0 hypothesis and conclude the data is not normal (H_1). Darling-Anderson Equation 1:

$$A^2 = -n - S \quad (1)$$

while,

$$S = \sum_{i=1}^n \frac{2i-1}{n} [\ln F(Y_i) + \ln (1 - F(Y_{n+1-i}))] \quad (2)$$

where n , Y_i and $F(Y_i)$, are the number of observations in the sample, the i^{th} observation, and the cumulative distribution function (CDF) of the normal distribution for the value Y_i , respectively.

If the data does not follow a normal distribution, the second step is to identify the best-fit statistical distribution it does follow. This is accomplished using tools like the Input Analyzer embedded in Arena simulation software. This tool automatically tests the historical data against various theoretical distributions (such as Weibull, Lognormal, or Exponential) and ranks them to suggest the most appropriate model to use as an input parameter for the simulation.

The final step is to validate the chosen best-fit distribution normally. This is done using goodness-of-fit tests like the Chi-Square (X^2) or Kolmogorov-Smirnov (K-S) test (Tezel et al., 2021). For these tests, the null hypothesis (H_0) is that the historical data follow the selected theoretical distribution. If the p-value > 0.05, we accept the model, as it indicates there is no statistically significant difference between the historical data and the

theoretical distribution. The Chi-Square test compares observed (O_i) and expected (E_i) data frequencies, while the K-S test finds the maximum difference (D) between the data's cumulative shape and the theoretical distribution's shape. The Chi-Square statistics are calculated as Equation 3:

$$\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i} \quad (3)$$

where: k , O_i , and E_i are the number of categories, The Observed frequency of data in the i^{th} category, and The Expected frequency of data in the i^{th} category, according to the distribution, respectively. The K-S statistic (D) is the maximum vertical distance between the two functions:

$$D = \max_x [F_n(x) - F(x)] \quad (4)$$

where $F_n(x)$ = The Empirical CDF, which is a step function at any value x ; it represents the proportion of data points that are less than or equal to x . $F(x)$ is the theoretical CDF of the distribution being tested (e.g., Weibull, Lognormal).

2.3 Production forecasting methods

Project evaluation tool is NPV of CTGL installation cost against revenue. Revenue is defined as oil production from CTGL installation. The production data in Figure 2 shows two main trends happening at the same time. First, there's an overall declining trend, where the peaks of production are gradually getting lower each year, indicating the overall trend tends to show a gradual decline over the years, reflecting the natural depletion of reservoir pressure. Second, the field exhibits a strong annual seasonal pattern, with predictable drops in production near the start of every year. This pattern is driven by the operational cycle of workover campaigns, where, at the end of the year, there is cumulative installation of CTGL and natural decline phenomena.

In the oil and gas industry, production forecasting is technically challenging because it depends on reservoir properties, tubing performance, surface production facilities performance, and other production methods involving artificial lift. Different approaches had been widely used for production forecasting handling data with trends such as linear regression (Alharbi et al., 2022) and Winter's Holt (Sibuea et al., 2022), decline curve forecasting (Maurenza et al., 2023b; Nguyen & Chan 2005; Tadjer et al., 2021; Thakuria et al., 2019), exponential smoothing, moving average and Arima (Ning et al., 2022; Singh & Pateriya 2019). In this research, three approaches for oil production forecasting are fitted to annual historical data: Moving Average, Holt's (double exponential), and Decline Curve Forecasting (DCF), an industry-standard artificial-lift oil production method.

Forecasting accuracy is defined by the smallest Mean Absolute Percentage Error (MAPE) as the decision metric. Before forecasting, the original data is normalized yearly to avoid bias from monthly noise accumulation. The forecasting methods will follow the formulation of each method.

Table 1.
Historical data CTGL installation.

Data Type	2019	2020	2021	2022	2023	2024
Installation (Job)	44	46	51	50	42	50
CT Length Installed - ft	102,009	104,741	111,478	142,150	115,670	148,600
Retrieval (Job)	34	28	14	28	16	7
CT Length Retrieved - Ft	78,609	55,170	31,245	56,477	42,320	11,450
Production average from CTGL (bbl/day)	2,275	2,034	1,681	1,829	506	1,072
Production/ctgl (bbl/day)	51.7	44.2	33.0	36.7	12.1	21.4

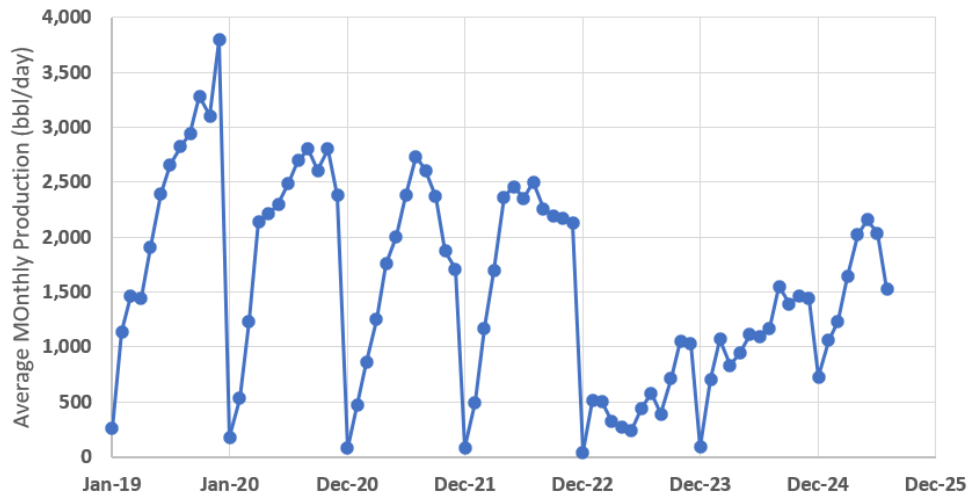


Figure 2.

Depletion trends: CTGL's production contribution based on historical data 2019 to 2024.

- Holt methods (double exponential)

Level (L_t): Estimate value at the current time point:

$$L_t = \alpha A_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \quad (5)$$

Trend (T_t): Estimate the rate of change (slope):

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \quad (6)$$

Forecast (F_{t+m}): Forecast for the following year:

$$F_{t+m} = L_t + mT_t \quad (7)$$

α , β are the smoothing parameters (between 0 and 1) that the model optimizes; A_t is Actual production at time t ; m is the number of periods of forecasting.

- Simple moving average (SMA2)

$$F_{t+1} = \frac{A_t + A_{t-1}}{2} \quad (8)$$

where F_{t+1} , A_t , and A_{t-1} are the forecast for the following year, Actual Production, and Production last year, respectively.

- Decline curve forecasting (DCF)

Exponential as lower case ($b=0$):

$$Q_t = Q_i e^{-D_i t} \quad (9)$$

Hyperbolic as artificial lift forecast ($b = 0.5$):

$$Q_t = Q_i (1 + bD_i t)^{-1/b} \quad (10)$$

Harmonic ($b=1$) as upper case:

$$Q_t = \frac{Q_i}{1 + D_i t} \quad (11)$$

where b , Q_i , D_i , and t , are Arps exponent, Initial production t , Decline rate yearly (%), and corresponding year, respectively.

2.4 Discrete event simulation (DES) model development

Arena simulation is utilized to develop a Discrete Event Simulation (DES) model for CTGL installation and replenishment. The primary goal is to evaluate alternative scenarios against current practices to optimize coiled tubing reutilization, maximize cost-benefits, and minimize material waste. The proposed models optimize CT reutilization by inspecting retrieved materials to determine usability, as illustrated in the framework in Figure 3, as follows:

- Scenario 0 (Baseline): Represents the current "as-is" practice where all retrieved CT is scrapped, and job demand is met entirely by dynamically cutting new 20,000 ft rolls. Inventory replenishment is only from new CT material purchased to meet job demand. This system operates with a "take and cut" procedure, where resources (new rolls) are considered unlimited, and remaining material is considered unrecoverable.
- Scenario 1 (Dynamic Recycle): The primary optimization strategy where successfully inspected CT is downgraded by one class to serve as prioritized inventory for incoming jobs.
- Scenario 2 (Fixed Cut 4k): Tests a rigid inventory policy by pre-cutting each new roll into five fixed 4,000 ft lengths
- Scenario 3 (Fixed Cut 4k and 8k): Modifies the fixed-cut strategy by pre-cutting new rolls into three 4,000 ft pieces and one 8,000 ft piece.
- Scenario 4 (Hybrid Cut): Refines the dynamic approach by using standardized 4,000 ft cuts for smaller jobs while cutting larger jobs dynamically.

2.5 Cost-benefit and sensitivity analysis

Profitability of this project will be evaluated using NPV as the financial metric for cost-benefit analysis. NPV is used to assess potential return by comparing current model (scenario 0) against proposed model (Scenario 1-4). NPV is described in Equation 12. In this simulation, cash flow is oil production revenue, while investment cost is derived from material and operational costs under different scenarios. The NPV evaluation input is obtained from production forecasting and simulation results during the years of the project.

$$NPV = \sum_{t=1}^T \frac{Revenue_t}{(1 + Discount Rate)^t} - Investment Cost \quad (12)$$

Some conditions for this simulation are assumptions due to limitations and simplifications. This simulation is based on assumptions such as a coiled tubing inspection pass threshold of 90% based on field best practice, a Hurdle NPV of 46.04 MUSD over six years, an oil price of 60 USD/bbl, a discount rate of 10.22%, and t years. This assumption is made based on company policy to project investment evaluation. Material cost for recycled coiled tubing is zero because holding inventory cost assumes no additional resources are required, no space limitations, and No Scrap handling is considered in this research, as shown in Table 2. The financial figures in this analysis are based on a standard industry cost structure and normalized historical data to reflect the economic trade-offs of the scenarios.

The cost differential between the two columns follows the procurement basis of each line item rather than a uniform discount. Coiled Tubing Material is booked at zero for reused CT because the string is already owned; its handling is absorbed within the Service Charge, which is why that line is unchanged. Surface Equipment falls from \$11,182 to \$1,326 because a reused installation requires only re-dressing and recertification of components

already held in inventory, whereas a new installation is charged the full procurement value of those components. Bottom Hole Assembly falls by a smaller margin, from \$5,940 to \$3,100, because only part of the assembly is recovered intact; consumable and sealing elements are replaced at every installation regardless of the string's origin, which sets a floor on the achievable reduction. Personnel Cost is identical because the same crew and duration apply in both cases.

Because cost-benefit analysis comes with inherent uncertainties, sensitivity analysis is used to evaluate and determine the impact of results and understand variation due to uncertainty. Purpose of sensitivity is to evaluate the responds of models against parameters change, identify the weakness and benefit of the model, and provide more realistic decision making in optimization model (Menberg et al., 2016; Usher et al., 2023). Three main parameters measure the sensitivity of simulation results to real-world uncertainty relevant to this project: oil price, production forecast, and material cost increments to anticipate market volatility. A Monte Carlo simulation of 10,000 iterations was constructed to evaluate the financial robustness of the models. Each of the three parameters was varied around its base case using an independent triangular distribution, whose bounds were derived from a distinct source. The production forecast band was set based on the accuracy of the selected forecasting method. The oil price band was derived from the historical volatility of the realized selling price over the 2019 to 2024 dataset period, around the base case of \$60/bbl. The CT material cost band reflects anticipated supply-chain inflation, tested up to a 20% increment applied from the fifth project year. The bounds applied were therefore -50% to +200% on the production forecast, \$45 to \$100 per barrel on the oil price, and 0 to +20% on the CT material cost.

Table 2.
Cost structure with new and reused CT.

Cost component	Installation with new CT	Installation with reused CT
Surface Equipment	\$ 11,182	\$ 1,326
Bottom Hole Assembly (BHA)	\$ 5,940	\$ 3,100
CT Material (3000 ft)	\$ 26,370	-
Personnel Cost	\$ 4,025	\$ 4,025
Service Charge	\$ 21,450	\$ 21,450
Total Cost	\$ 68,967	\$ 29,901

Table 3.
Normality testing and distribution fitting results.

Process Step	Installation	Time to failure (production life)	Retrieval
Data Characteristics	N :282, μ : 7.75, Median: 6.00, σ : 7.08	N :318, μ :591.1, Median:335.0, σ : 653	N :126, μ :16.57, Median:8.50, σ : 2.88
Normality Test (Poisson Fit)	Chi-Square p: 0.000 Anderson-Darling p< 0.05 Skew:1.54	Chi-Square p:0.000 Anderson-Darling p < 0.05 Skew:1.64	Chi-Square p 0.000 Anderson-Darling p < 0.05 Skew:2.88
Best-Fit Distribution with input analyzer	-0.5 + GAMM (5.98, 1.38) Sq.Error: 0.0046	-0.001 + LOGN (821, 2.11e+03) Sq.Error: 0.00245	-0.001 + WEIB (14.9, 0.817) Sq.Error: 0.00145
Conclusion (Chi-Square p > 0.05)	Chi-Square p-value: 0.0625.	Chi-Square p-value: 0.1500	Chi-Square p-value: 0.1690

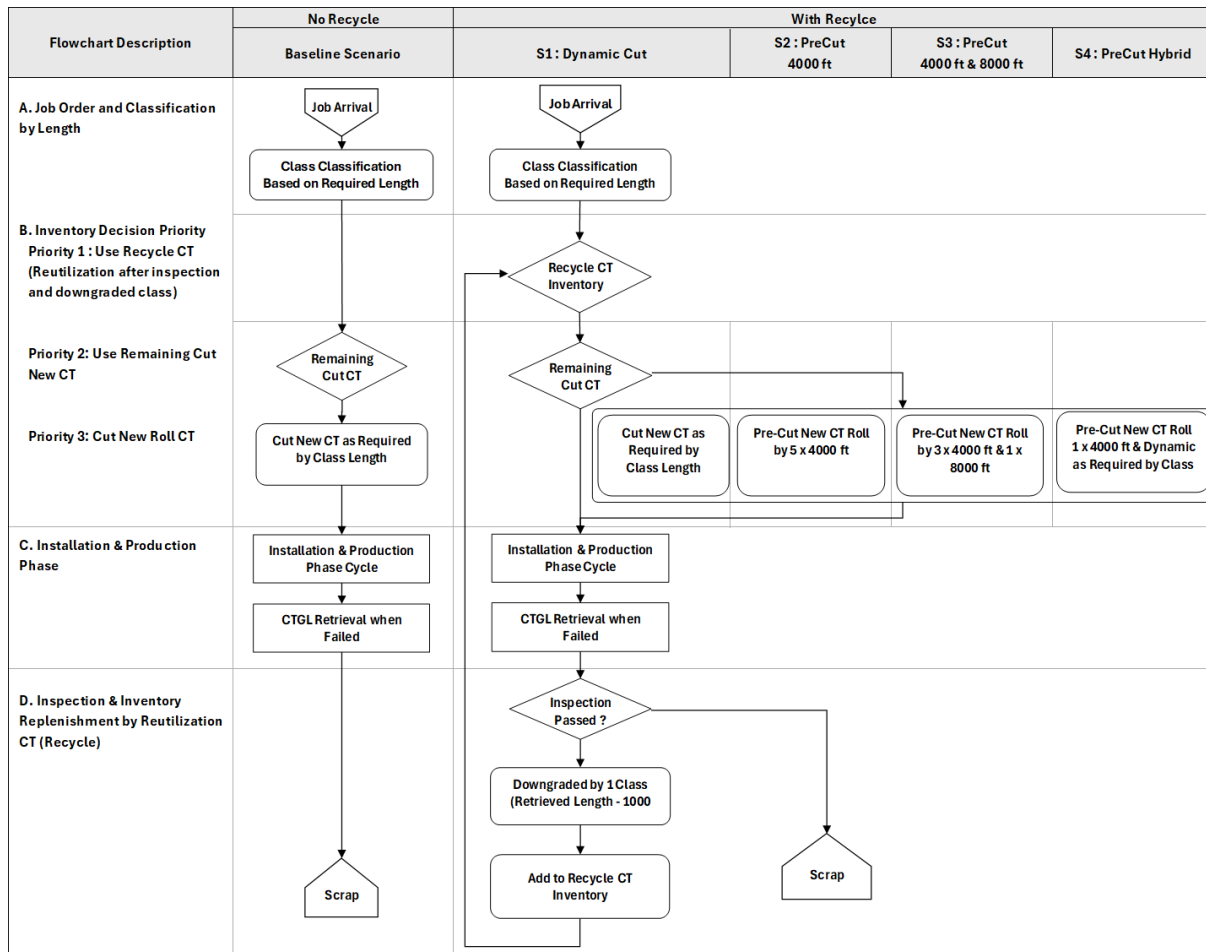


Figure 3.

DES framework for Current Practice (Scenario 0) compared to Proposed Optimization Scenario (Scenario 1–4).

3. Result and analysis

3.1 Data distribution and production forecast

To construct a reliable simulation, the historical operational datasets required statistical distribution fitting. The normality tests showed that all three historical datasets were not normally distributed, as evidenced by an Anderson-Darling test $p < 0.05$. Therefore, Arena's Input Analyzer was utilized to find the best fit based on minimum square error criteria. The installation data best fit a Gamma distribution, the time-to-failure data best fit a Lognormal distribution, and the retrieval data best fit a Weibull distribution. These goodness-of-fit results, summarized in Table 3, provide valid stochastic inputs for the simulation models.

Evaluating the cost-benefit analysis requires an accurate projection of the production contribution from Coiled Tubing Gas Lift (CTGL). The normalized historical dataset displayed a downward trend, which aligns with marginal field behavior where the reservoir is naturally depleted, and artificial lift is utilized for recovery. Figure 4 illustrates the forecasting results comparing Moving Average, Holt's double exponential, and Decline Curve Forecasting (DCF). DCF outperformed the other methods with the lowest Mean Absolute Percentage Error (MAPE) of 6.1; therefore, its results are used as the revenue reference for the Net Present Value calculations.

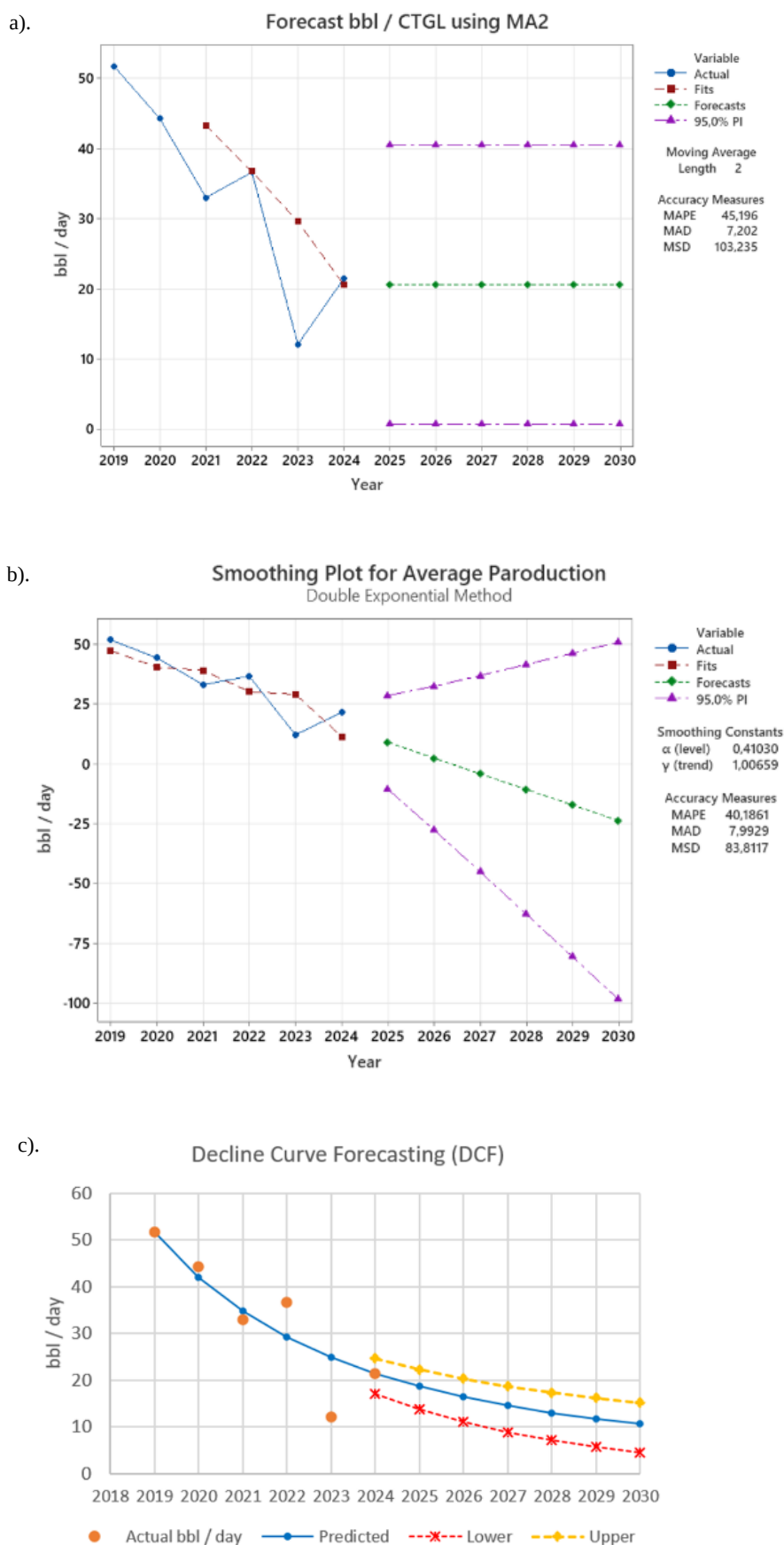


Figure 4.
 Comparison of Production Forecasting Methods using:
 (a) Moving average; (b) Holt's double exponential; (c) Decline curve forecasting (DCF).

3.2 Baseline simulation model and validation

The baseline DES model (Scenario 0) is developed as a digital twin of the current process, where coiled tubing installation and retrieval are conducted without considering coiled tubing reutilization of CT retrieved from the well. Figure 5 shows the developed model using Arena 16.2 without recycling loops for CT material, to measure the extent of cost and waste before any process improvements are made. Simulation inputs are taken from data distributions fitted as stochastic conditions, coiled tubing class segments, and simulation parameters to mirror real-world flow processes. The simulation flow chart and logic are described as follows:

- Part A (Job Order & Classification): Acts as the system generator. Job arrivals are generated stochastically based on the fitted Gamma distribution, and each job is assigned a required CT length class (Class 1 to 7).
- Part B (Installation Decision Flow): In the baseline model, job installation uses only new coiled tubing.
- Part C (Retrieval of Installation): Simulates the CT lifecycle. In the baseline model, the system follows a linear "take and cut" procedure: retrieved CT is immediately scrapped, and new jobs are fulfilled only by cutting from new CT rolls.
- Part D (Retrieval of Existing Backlog): Models the depletion of the initial 207 historical installations, feeding them into the inspection module (Part C) to simulate real-world starting conditions. Several essential stochastic parameters derived from historical data control the system's behavior, including the job arrival rate (λ_{job}), the time a Coiled Tubing unit remains in a well before failure ($T_{\text{in_well}}$), and the frequency of retrieval operations (Tretreival). The simulation evaluates discrete strategic alternatives (Scenarios 0 to 4) by measuring the impact on key performance indicators (KPIs) such as New Coiled Tubing Rolls and Scrap generated. Table 4. Illustrates the simulation parameters used in this research.

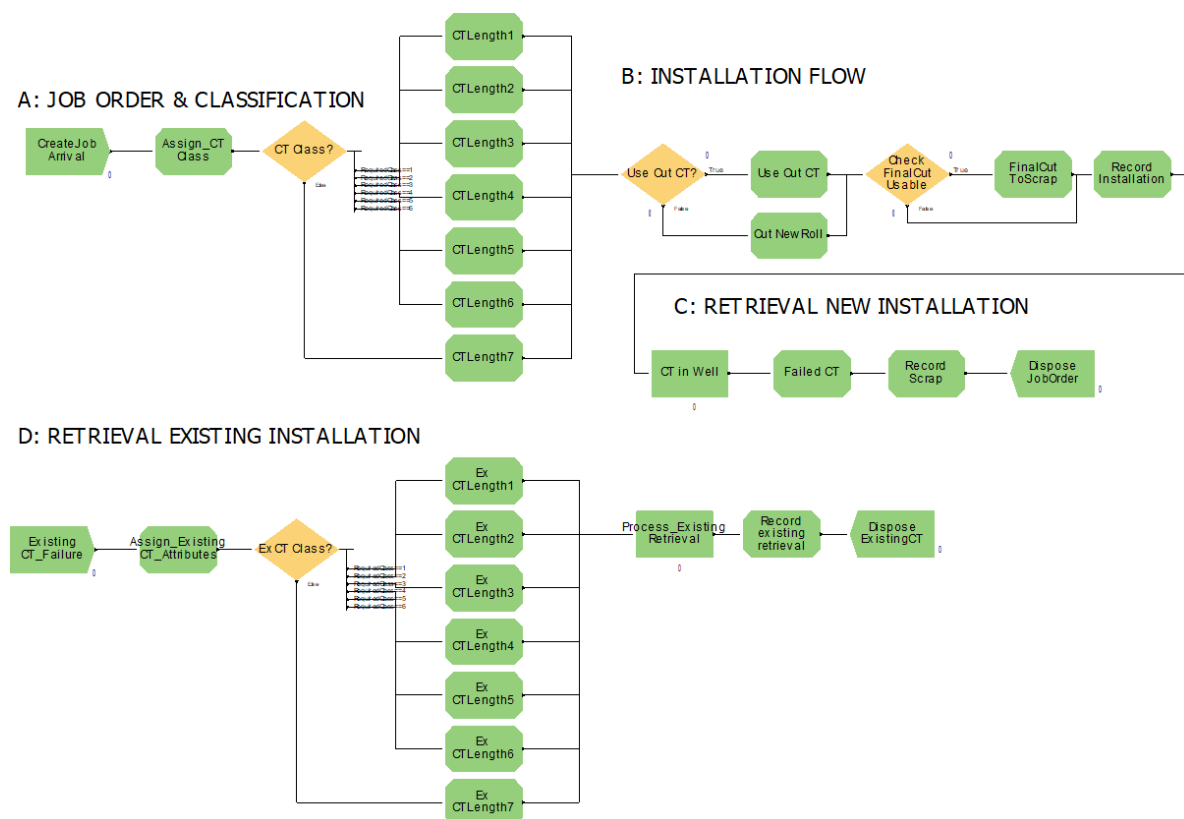


Figure 5.
Baseline DES model in arena software representing the current linear 'Use-and-Dispose' practice (Scenario 0).

Table 4.
Simulation parameters.

Element	Name	Description
Entity	JobOrder	Represents a new installation request.
	ExistingCT	Represents a retrieved unit from the initial 207 CTGL backlog.
Attribute	RequiredClass	The length class (1-7) needed for a job.
	RequiredLength	The specific length in feet for a job.
	OriginType	A tag (1=New Installation, 2=Existing CT) to distinguish the source of a retrieved CTGL
Variables	isRecycled	A flag (1 or 0) to track if a recycled CT was used for an installation (Applied to Scenarios 1-4).
	JobsCount	Counter for total installations completed.
	RetrievalsCount	Counter for total retrieval operations performed.
	ExistingRetrievedCount	Counter for retrievals from the initial backlog only (Max 207 CTGL Installations)
	NewRollsUsed	Counter for new 20,000 ft rolls consumed.
	UsedLengthTotal	Sum of all installed CT lengths.
	ScrapFromNewRoll	Sum of scrap generated from new material.
	ScrapFromRecycle	Sum of scrap generated from retrieved/recycled material.
	InspectionPassCount	Counter for CTs that pass inspection (Applied to Scenario 1-4).

Table 5.
Validation of Baseline Model (Scenario-0).

Key performance index (KPI)	Simulation (Average)	Actual data	T-Test
Installation	284.3	283	p:0.992
Retrieval	132.9	127	p:0.935

Before proceeding to the next step of the simulation, validate the model to evaluate whether it represents the real-world system. Validating a simulation model is essential to ensure outputs are reliable and to avoid ineffective decisions. Model validation is achieved by comparing simulation results with historical data to confirm the model's accuracy. The significant difference between the two is evaluated using a t-test. This significance test is essential to proceed to the next step: an alternative simulation model for optimization.

Table 5 shows the simulation result against six years of historical data. The simulation, acting as a virtual timeline, projected an average of 284.3 installations and 132.9 retrievals, closely mirroring the actual historical counts. A two-sample T-test confirmed the accuracy, with p-values of 0.992 for installations and 0.935 for retrievals, both well above the p-value 0.05 threshold. This statistical alignment confirms the simulation model is valid and its outputs are reliable for strategic decision-making.

3.3 DES optimization scenarios

The simulation evaluates Scenario 0 against four alternative models (Scenarios 1–4) designed to introduce a CT reutilization process, which differ primarily in their cutting strategies as optimization models. The fundamental logic behind these optimization scenarios is to transform retrieved CT from recycle into a high-priority inventory source. Figure 6 illustrates the process flow modeled in Arena software Figure 6 illustrates the process flow

modeled in Arena software, using Scenario 1 as the representative simulation. Job arrivals (Part A) and existing retrievals (Part D) function identically to the baseline model. The critical optimization occurs in Part C, where retrieved CT undergo an inspection process. Passing CT are downgraded by one class and routed into the system as recycled inventory. For example, CT class 3 with length 3000 ft becomes class 2 when introduced to inventory. Part B (Installation Decision Flow): The core optimization that dictates the inventory routing logic. For Scenarios 1-4, it applies a strict priority rule: the system first searches for available downgraded CT in the recycle inventory. If unavailable, it pulls from pre-cut inventory and only cuts a new 20,000 ft roll as a last resort, which diverge according to the specific scenario: executing fully flexible dynamic cutting from new rolls (Scenario 1), utilizing pre-cut fixed lengths (Scenarios 2 and 3), or applying a hybrid approach (Scenario 4).

3.4 Discrete event simulation results

Figure 7 shows the simulation results. The simulation compared the highly inefficient current practice (Scenario 0), which consumes 47 new rolls and generates over one million feet of scrap, against four alternative recycling strategies (Scenarios 1–4). While all proposed scenarios significantly reduced new roll consumption (down to 19–26 rolls) and minimized overall waste, the rigid fixed-cutting policies of Scenarios 2 and 3 proved operationally unviable, failing to complete 46 and 26 jobs, respectively, due to inflexible inventory policies. Because fulfilling full customer demand is a critical operational metric, this failure disqualifies them from serious consideration. Consequently, Scenario 1 (Dynamic Recycle) and Scenario 4 (Hybrid Cut) emerged as the optimal and most robust strategies; both successfully maintained the highest production output by completing the full demand of approximately 284 installation jobs with zero rejections, all while maximizing the utilization of recycled materials.

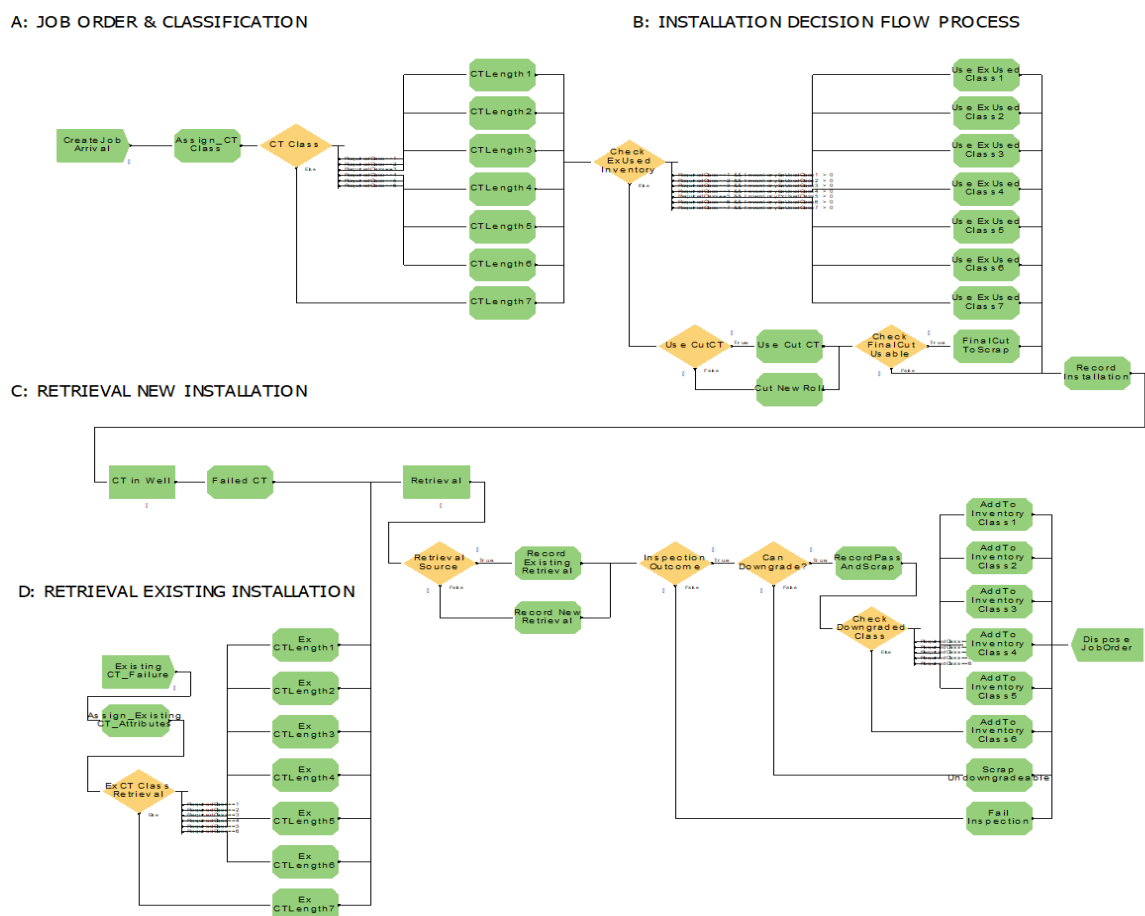


Figure 6.
Example of DES Arena Simulation for optimization Scenario 1,
demonstrating Dynamic Cutting and Recycled Coiled Tubing.

The primary requirement of any operational strategy is meeting customer demand. Figure 8 demonstrates that while Scenarios 0, 1, and 4 serviced the full job demand of 283 to 284 installations, the fixed-cutting strategies (Scenarios 2 and 3) were operationally unviable. Scenario 2 failed to complete 46 jobs, and Scenario 3 rejected 26 jobs because their inflexible inventory policies could not service the full range of required CT lengths.

The operational success of the dynamic recycling strategies is rooted in establishing a circular supply chain. Figure 9 (a) shows that in Scenarios 1 and 4, nearly 60% of all work (168 jobs) was fulfilled using recovered ex-used CT. This heavy reliance on recycled inventory led to a dramatic 53% reduction in new material consumption, requiring only 22 new 20,000 ft rolls compared to the 47 rolls consumed in Scenario 0, as detailed in Figure 9 (b).

A detailed analysis of waste generation further highlights the inefficiency of current practices. As illustrated in Figure 10 (a), Scenario 0 generates a significant 1,002,270 ft of scrap entirely from disposing of retrieved installations. By successfully re-using fit materials (Figure 10 (b)), Scenario 1 minimizes total scrap by 60% to 404,860 ft. Table 6 summarizes the performance of all strategies and shows that Scenario 1 (Dynamic Recycle) offers the optimal balance of operational flexibility and material efficiency.

The simulation results support implementing Scenario 1 (Dynamic Recycle). While the fixed-cutting strategies (Scenarios 2 and 3) are operationally inefficient due to unmet customer demand, and the hybrid approach (Scenario 4) offers no significant benefit over the simpler dynamic model while creating slightly more scrap, Scenario 1 delivers optimal performance. It provides a massive reduction in new material costs, generates the least scrap, and maintains operational flexibility to service 100% of installation jobs.

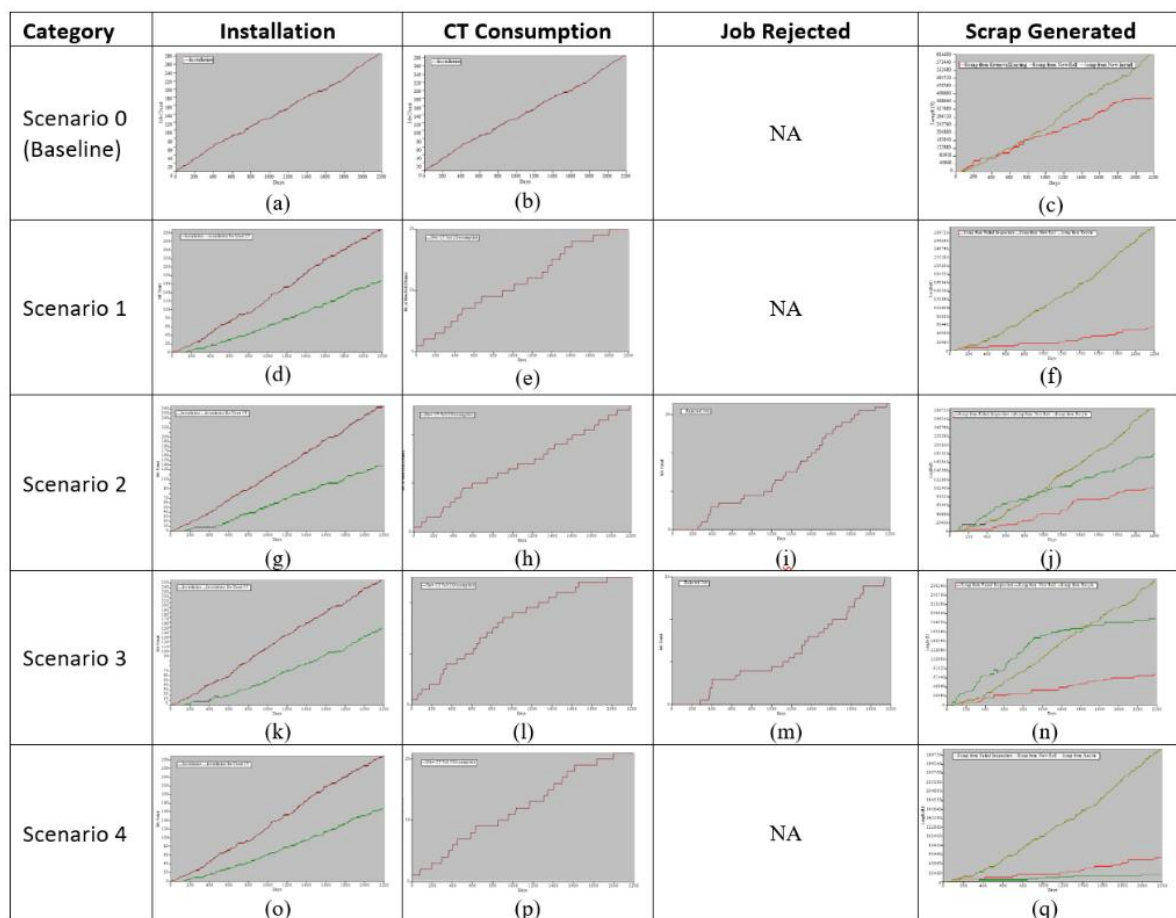


Figure 7.
Simulation outputs comparing Key Operational Metrics across all scenarios (Using Arena Software 16.2).

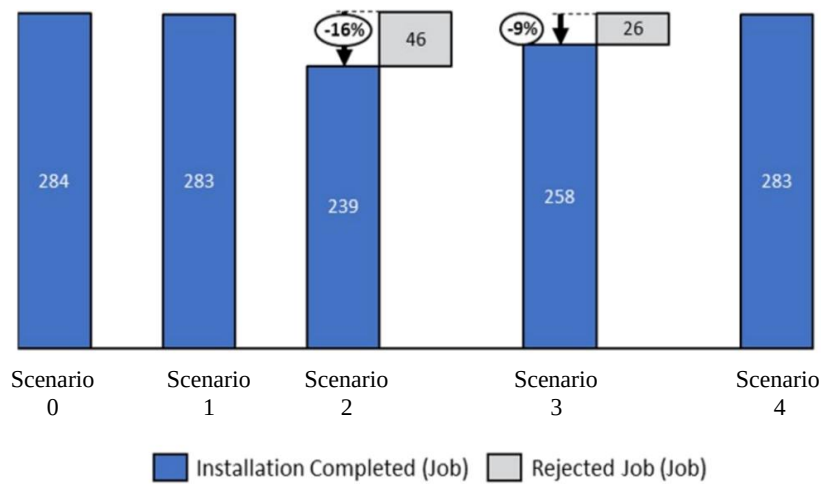


Figure 8.

Successful versus Rejected Installation Jobs, highlighting the limitations of fixed-cut strategies (Scenarios 2 and 3).

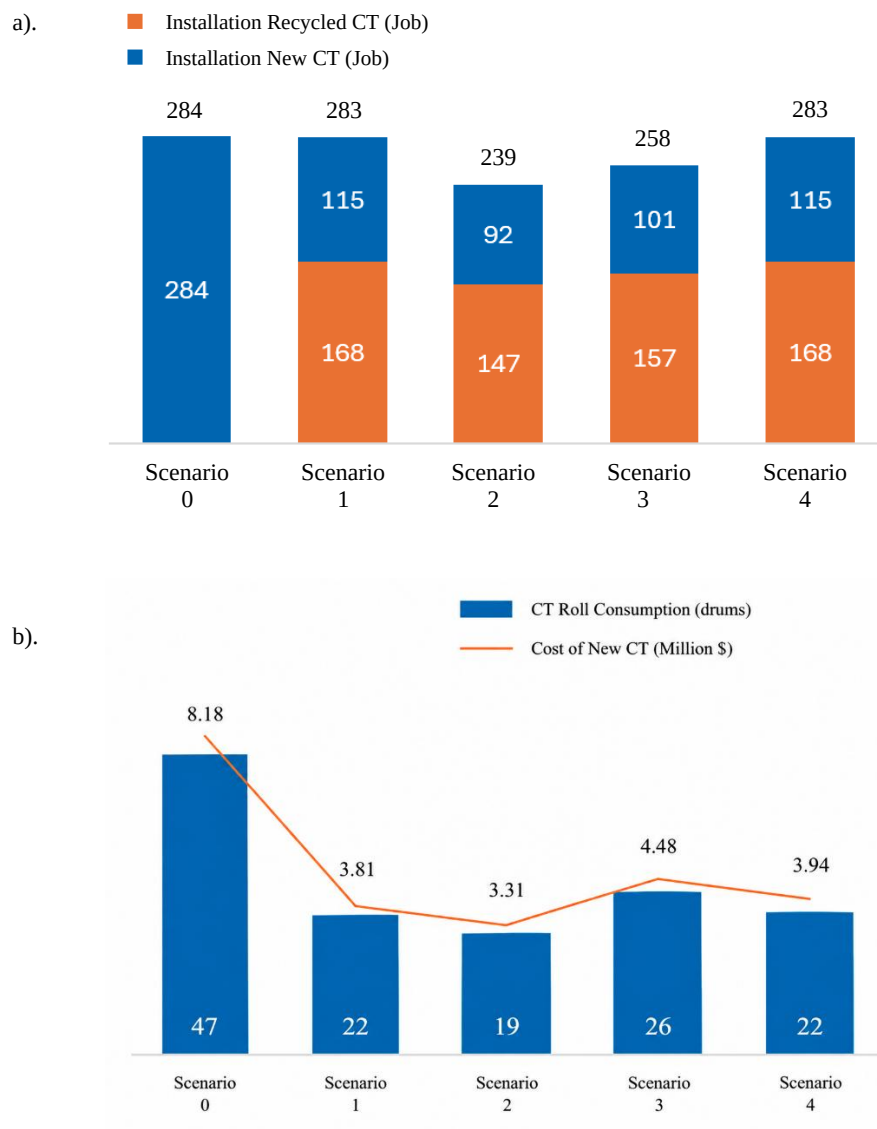


Figure 9.

Coiled tubing consumption breakdown: (a) Installation Job Using New versus Recycled CT; (b) Total new Coiled Tubing consumption.

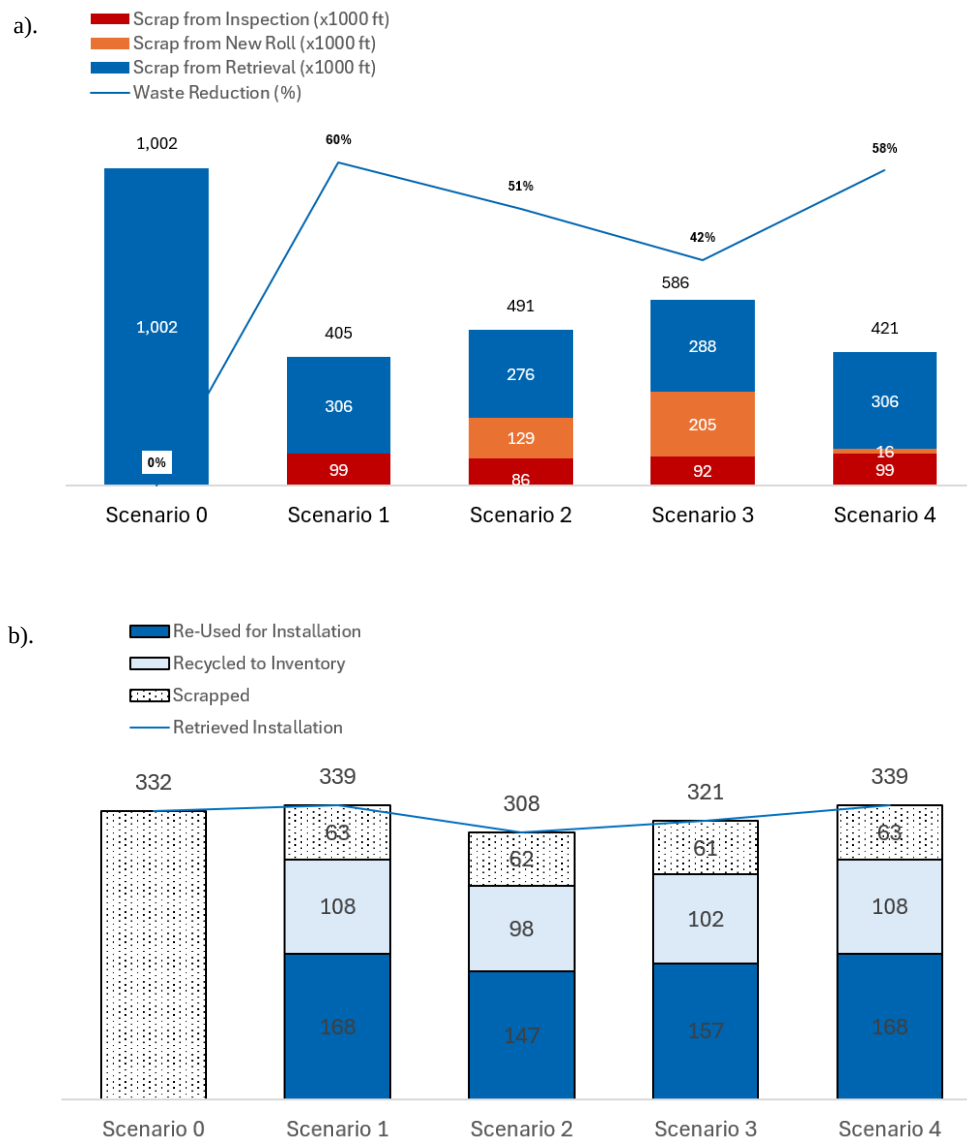


Figure 10.

Waste reduction and circular inventory efficiency illustrate (a) the significant decrease in total scrap length generated and (b) the volume of successfully repurposed coiled tubing per job.

3.5 Cost-benefit and sensitivity analysis

The operational metrics were translated into financial evaluations using Net Present Value (NPV), assessed against a project hurdle rate of \$46.04 million to justify the surface facility and running costs. As illustrated in the NPV evolution and cumulative totals in Figure 11, Scenarios 1 and 4 are the most financially successful, each delivering a peak NPV of \$58.53 million, which represents a 7.62% improvement over the current baseline (Scenario 0). In contrast, the fixed-cutting strategies (Scenarios 2 and 3) proved financially detrimental, yielding lower NPVs of \$49.36 million and \$52.32 million, respectively. These underperformances were directly caused by inventory shortages that led to significant lost revenue opportunities: \$14.25 million for Scenario 2 and \$8.06 million for Scenario 3. This underscores that cutting efficiency must be balanced against inventory availability: a policy that lowers material consumption but cannot service the full range of required lengths destroys more value through rejected jobs than it saves on material.

Table 6.
Summary of simulation result.

Key Performance	Scenario-0	Scenario-1	Scenario-2	Scenario-3	Scenario-4
Installation (Job/year)	47.3	47.2	39.8	43.0	47.2
New CT Roll (Roll/year)	7.8	3.7	3.2	4.3	3.7
Recycled CT (Job/year)	0.0	28.0	24.5	26.2	28.0
Job Rejected (job/year)	0.0	0.0	7.7	4.3	0.0
Scrap Length (ft)	1,002,270	404,860	490,990	585,710	420,520

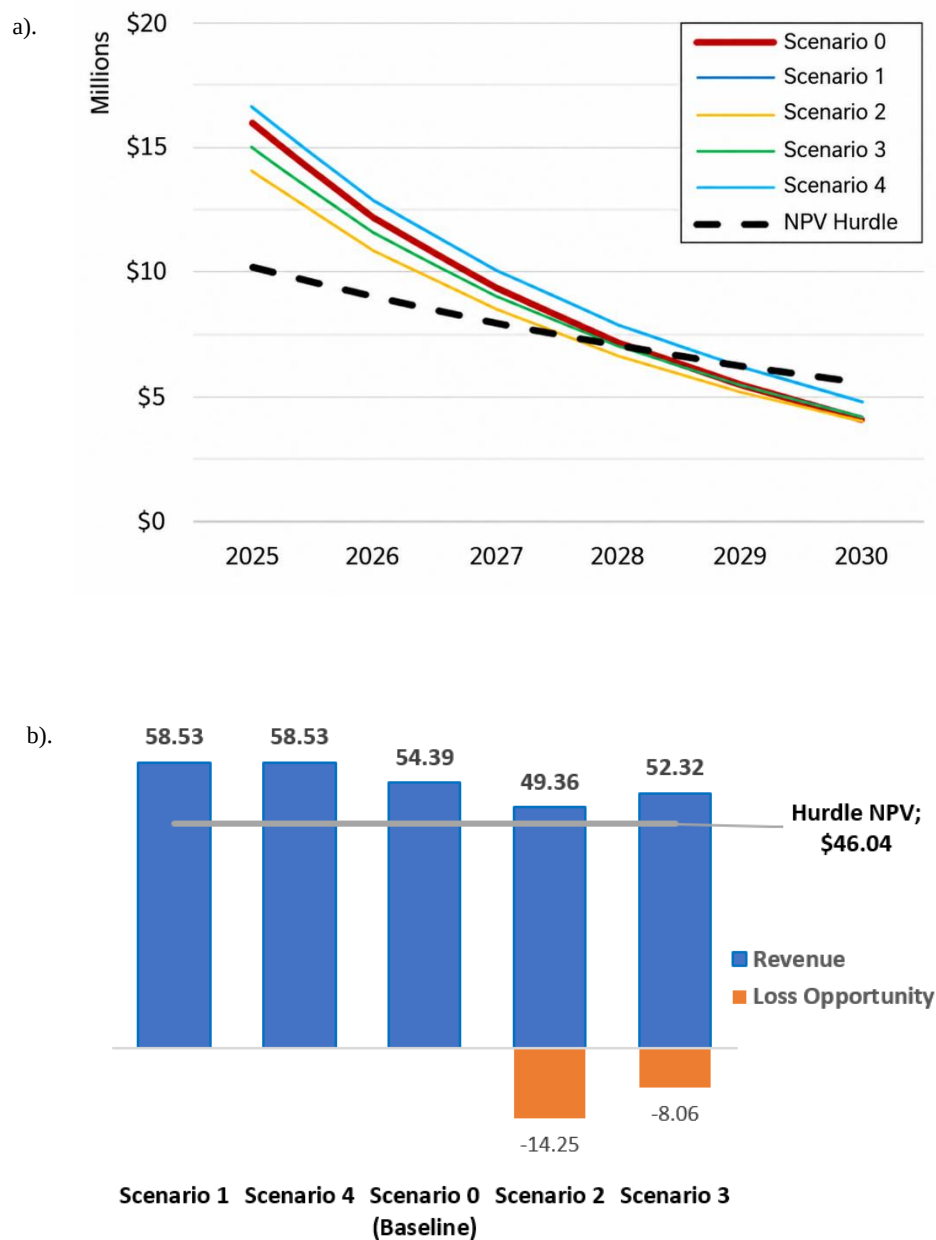


Figure 11.

Financial evaluation using Net Present Value (NPV), illustrating (a) the annual NPV trajectory and (b) cumulative NPV against the \$46.04 million project hurdle rate, identifying Scenarios 1 and 4 as the most profitable strategies.

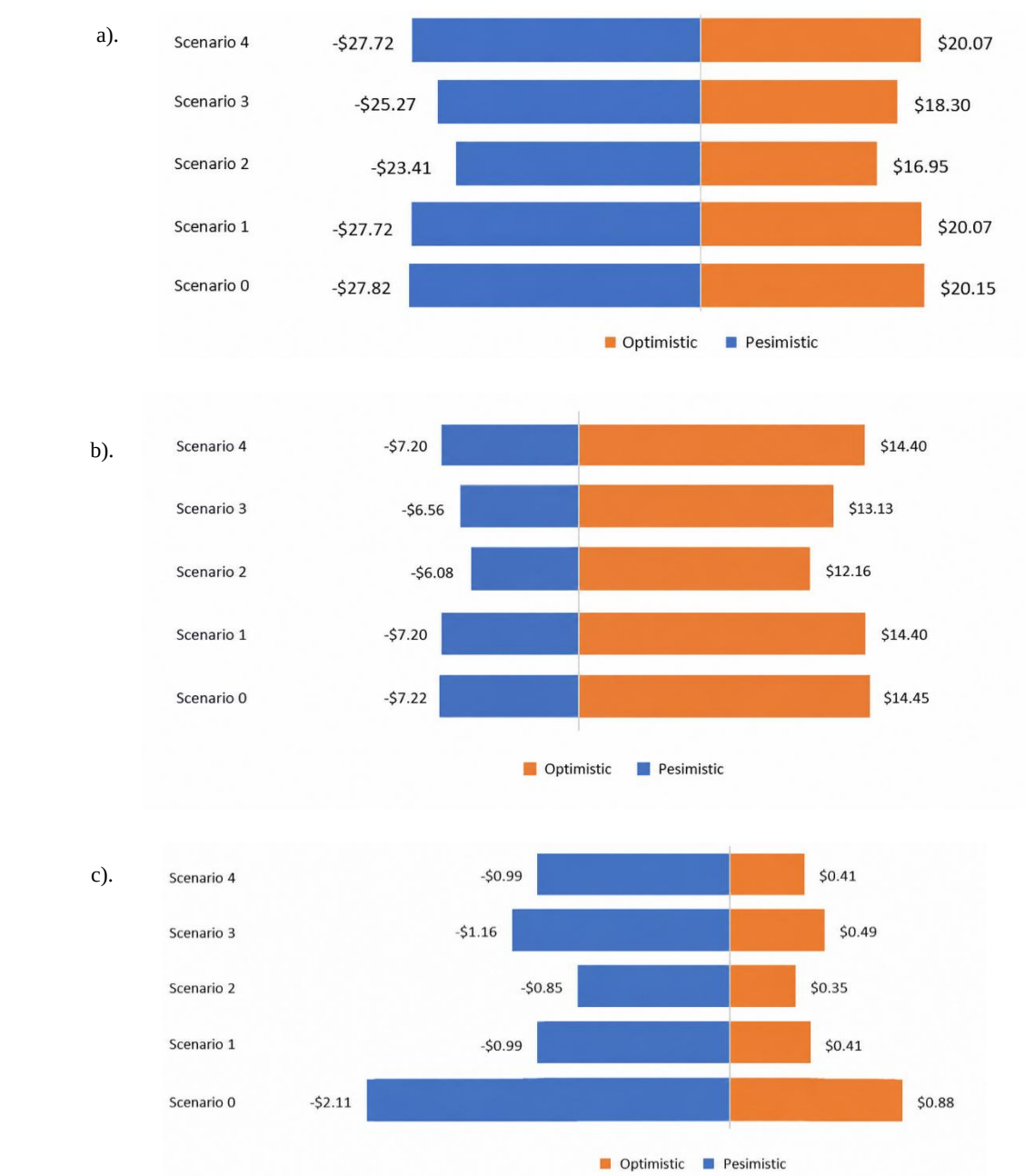


Figure 12.

Tornado charts representing sensitivity analysis, the financial impact of (a) production forecast accuracy, (b) oil price volatility, and (c) coiled tubing material cost inflation on the project's robustness.

This research conducted three sensitivity evaluations to assess each scenario's simulation results under varying conditions. Because marginal field projects operate under inherent uncertainties, a Monte Carlo sensitivity analysis (10,000 iterations) was conducted to assess each scenario's financial robustness against three major external factors: production forecasting accuracy, oil price volatility, and CT material cost inflation. The resulting Tornado Charts (Figure 12) reveal that production forecasts and external oil prices are the most critical risks, each capable of swinging the project's NPV by more than \$20 million.

Crucially, the sensitivity to CT price increments highlights the extreme vulnerability of the current "use-and-dispose" practice; Scenario 0 relies entirely on purchasing new materials, causing its NPV to plunge below the \$46.04 million hurdle rate if CT prices increase by 20% in the fifth year. By drastically reducing reliance on new materials, Scenario 1 acts as a strong financial hedge against supply chain inflation, keeping NPV well above the hurdle.

Based on this financial benefit and its sensitivity, two recommendations emerge for this project related to best-scenario and retrieval-strategy optimization. Consequently, implementing the dynamic recycling strategy alongside a "lean retrieval" policy where CT is retrieved only when necessary to replenish inventory is strongly recommended to protect long-term project viability and profitability. The company should avoid treating retrieval as a standalone service and instead schedule it only when necessary to replenish recycled CT inventory, as this minimizes costs and protects the project's high NPV.

4. Discussion

Previous studies on coiled tubing have predominantly focused on isolated technical parameters such as plastic-elastic deformation and corrosion failure mechanisms. Meanwhile, DES has been widely and successfully implemented in other sectors such as healthcare and logistics to manage uncertainty and optimize complex supply chains (Ala & Chen 2020; Coelho et al., 2021). The contrast with the deterministic approach ordinarily applied to this decision is substantive. A static payback or average-cost comparison evaluates a single expected demand path and would rank the fixed-cut policies favorably because they consume the fewest new rolls per installation; it has no mechanism to represent the stochastic arrival of job lengths and therefore cannot expose the rejected jobs those policies generate. The DES formulation surfaces exactly that failure mode, and the \$14.25 million and \$8.06 million of lost revenue opportunity attached to Scenarios 2 and 3 are visible only because demand is modeled as a stochastic process rather than an average. By integrating DES, the best-performing Dynamic Cutting model (Scenario 1) proves that flexible inventory routing can fully satisfy stochastic well demands without job rejections. Consistent with broader inventory optimization studies where simulation methods significantly lowered average holding costs and material volumes (Chen et al., 2022; Mitrovi et al., 2021), Scenario 1 leverages dynamic flexibility to deliver a reduction in metal scrap and NPV improvement through avoided new material purchases.

The simulation results for and strongly support a fundamental shift from the current linear "take-make-dispose" framework to a circular asset management model. The superior Net Present Value (NPV) achieved by the dynamic cutting strategies (Scenarios 1 and 4) represents more than a marginal operational improvement; it significantly enhances the asset's overall value. This value creation is driven by two primary mechanisms: massive cost avoidance through a dramatic reduction in the procurement of expensive new Coiled Tubing (CT) rolls, and revenue assurance by ensuring all job demands are met. By fulfilling 100% of operational demands, the dynamic reutilization project goes beyond simple cost-saving to become a value-creation engine that improves both the top and bottom lines of marginal field operations.

Beyond base-case profitability, the sensitivity analysis provides critical insights into the strategic value of operational resilience. While the baseline practice (Scenario 0) is profitable under ideal conditions, it is extremely vulnerable to external market shocks. In contrast, the dynamic recycling models proved highly resilient because their reduced dependence on new materials acts as a powerful hedge against supply chain volatility and material cost inflation. In an oil and gas industry defined by uncertainty, particularly regarding production forecasts and oil prices, this resilience is arguably as important as the initial NPV, making dynamic reutilization the most strategic choice for long-term planning.

The simulation reveals two unexpected yet pivotal findings. First, the detrimental performance of the fixed-cutting strategies (Scenarios 2 and 3) proved that a poorly implemented reutilization strategy lacking adequate inventory management introduces a new mode of failure (rejected jobs), which entirely negates the benefits of recycling. Second, the analysis revealed that the program successfully reframes a liability into a financial asset. The baseline practice incurred \$8.81 million in scrap costs over six years from over one million feet of discarded tubing, recovering zero value. In contrast, the optimal recycling strategies not only reduced scrap costs to \$3.6 million but simultaneously generated \$4.04 million in value from the reutilized CT. This new concept shift proves the initiative is a profitable, self-sustaining component of the business.

From a management perspective, this study validates Discrete Event Simulation (DES) as a critical tool for de-risking decisions. It allows decision-makers to quantify trade-offs and test complex operational changes in a risk-free virtual environment before committing substantial capital. However, to maintain practical integrity, the model's limitations must be acknowledged. The assumption of zero material cost for recycled CT is a deliberate simplification for modeling purposes. In actual field applications, nominal costs associated with storage space, logistical handling, and non-destructive inspection of retrieved tubing would apply. Furthermore, while this model successfully demonstrates the economic viability of CT reutilization, it currently assumes an unconstrained inspection capacity. Future iterations should incorporate physical resource limitations to identify potential operational bottlenecks.

5. Conclusion

This study was initiated to address the critical business challenge of declining production contributions from CTGL installations in marginal fields, necessitating significant cost-efficiency improvements to maintain project viability. The comprehensive DES evaluation conclusively proves that shifting from a "use and scrap" to a "use and recycle" approach through a dynamic cutting strategy is the optimal path forward. Scenario 1 raises NPV from \$54.39 million to \$58.53 million, an improvement of 7.62% or \$4.14 million, while cutting new coiled tubing consumption by 53% and metal scrap by 60% and servicing 100% of job demand. By synthesizing the simulation outcomes, this study establishes DES as a robust decision-support tool that effectively bridges technical asset evaluation with long-term economic planning. The findings highlight a critical implication for oil and gas operators: rigid inventory policies are fundamentally detrimental in stochastic circumstances. Meanwhile, adopting reutilization strategies transforms retrieved coiled tubing from a waste liability into a high-value financial hedge. Ultimately, implementing a robust recycling inventory with dynamic cutting minimizes vulnerability to market shocks and maximizes long-term financial returns.

Moving forward, future research should refine the model's precision by transitioning from deterministic inputs to fully stochastic variables for process times and future job planning. To address operational realities, subsequent models must incorporate resource constraints to accurately identify potential physical bottlenecks in the retrieval and inspection phases. Finally, expanding the scope of the key performance indicators to quantify environmental benefits such as CO₂ emission reductions and avoided waste handling costs will provide a more holistic validation of the circular economy's value within the oil and gas industry.

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7. Declarations

7.1 Author contributions

Warno contributed to the conception and design of the study, data collection, data analysis, and the initial drafting of the manuscript. Suharjito provided data validation, critical review, and overall supervision of the research process. Both authors discussed the results, contributed to the refinement of the manuscript, and approved the final version for submission.

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7.3 Competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

7.4 Data availability

The data supporting this study were obtained from the corresponding author upon reasonable request and subject to permission from the data owner, due to commercial confidentiality.

7.5 The use of AI or AI-assisted technologies

During the preparation of this manuscript, the authors used AI-based writing and editing tools to support language refinement, formatting, and reference organization. All scientific content, data interpretation, and conclusions are sole responsibility of the authors, who reviewed and edited all AI-assisted output and take full responsibility for content of this publication.

8. Glossary of terms and symbols

Terms & Symbols	Definition	Unit
CTGL	Coiled Tubing Gas Lift	-
DES	Discrete Event Simulation	-
DCF	Decline Curve Forecasting	-
NPV	Net Present Value	-

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