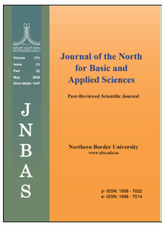

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Total Cost Analysis and Optimal Resilience in Manufacturing Operations

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Abstract

Manufacturing operations situated within a landscape of unprecedented volatility, necessitate the development of advanced investment appraisal frameworks that transcend the limitations of traditional static valuation methods. This research addresses the inherent systematic deficiencies of static approaches, which systematically fail to capture strategic value in volatile production environments, by seeking to formally quantify the value of managerial flexibility and optimize capital allocation for enduring supply chain resilience. A rigorous, sequential three-stage quantitative methodology is employed, utilizing robust empirical operational data. The approach first applies Non-Linear Least Squares modeling to empirically derive the supply chain's non-linear cost structure and operational volatility. This output informs a Real Options Valuation model to quantify the strategic worth of investment flexibility, which is finally integrated with a novel Total Resilient Cost optimization model to determine the cost-optimal level of operational redundancy. The analysis successfully demonstrates that the substantial strategic value captured through this flexibility transforms a negative static Net Present Value, initially calculated at -$14.5 million, into a validated, positive Comprehensive Flexible Valuation of $11.02 million, thereby justifying the fundamental strategic merit of the capital investment. Furthermore, the operational optimization provides a prescriptive solution by minimizing total costs, balancing the investment in redundancy against the mitigation of expected financial loss, yielding a cost-minimizing optimal stock level of 33 units. The originality of this work is founded upon a proposed approach that integrates empirical cost modeling, strategic flexibility valuation, and operational resilience optimization into a unified methodology. This approach offers decision-makers a superior economic metric and a cost-optimal, tactical guide for achieving empirically-grounded resilience in complex supply chains. Furthermore, the study significantly advances knowledge in the logistics and operations literature pertaining to manufacturing.

Keywords: Investment Appraisal, Manufacturing Logistics, Non-Linear Cost Modeling, Real Options Valuation, Supply Chain Resilience, Total Resilient Cost

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1. Introduction

Manufacturing operations and logistics, navigating an environment characterized by increasing volatility, unprecedented disruptions, and complex global supply chains, necessitate robust investment appraisal frameworks that transcend the limitations of traditional static valuation.

The Net Present Value (NPV) method, while foundational for project finance, fundamentally fails to capture the economic value of managerial flexibility—the inherent right, but not the obligation, to alter a project's strategic trajectory in response to evolving market conditions. This deficiency often results in the systematic undervaluing and subsequent rejection of critical infrastructure and resilience projects, which may exhibit a negative static NPV despite substantial long-term strategic benefits (Zhang *et al*., 2025). The urgency for such a sophisticated framework is significantly amplified by the fact that achieving resilience is a critical strategic priority requiring investment in both governance mechanisms and dynamic digital capabilities (Liang *et al*., 2025), alongside the necessity of managing granular operational challenges and uncertainty (Yan *et al*., 2025). This challenge is further compounded by the need to model multimodal resilience under dynamic, dependent hazard occurrences (Wei and Li, 2025), necessitating sophisticated operational modeling, such as optimizing multi-item inventory under stringent budget constraints (Karimi & Sadjadi, 2025) and handling parameter imprecision using advanced frameworks like Generalized Trapezoidal Neutrosophic Numbers (Bhavani *et al*., 2025). While these works effectively define the broad and technical scope of the resilience challenge, they collectively suffer from a critical, uniform limitation: they fail to provide an integrated, capital-budgeting mechanism to financially justify these diverse, high-cost operational solutions.

To address this systemic failure in valuation, academic research has increasingly converged on Real Options Valuation (ROV), a methodology theoretically capable of quantifying managerial flexibility (Tian *et al*., 2024). However, the existing application of ROV, though theoretically sound, presents two empirical and methodological barriers that severely limit its practical utility in operations: First, ROV often suffers from an empirical deficit, relying on assumed volatilities and cost structures that lack validation from real-world operational data, thus undermining the credibility of the strategic valuation (Zulkifli Noor, 2025). Second, a critical methodological gap persists in linking ROV's financial output—the justified strategic investment capital—to the ultimate operational objective of determining the cost-optimal physical resilience action.

The current research aims to explore an empirically-grounded, integrated quantitative framework to formally link strategic investment valuation with optimal operational resilience planning. To achieve this aim, the study pursues three core objectives: first, to establish a dynamic empirical cost structure and volatility measure from operational data; second, to utilize this empirical data to calculate the Comprehensive Flexible Valuation (CFV) via the ROV model; and finally, to translate the justified strategic investment into an optimal cost-minimizing solution for operational redundancy.

This study proposes a solution through an integrated, three-stage quantitative framework. The methodology is initiated by employing Non-Linear Least Squares (NLS) modeling to establish a dynamic empirical cost structure, which subsequently informs the ROV model used to capture strategic value. The final stage integrates the ROV output with the novel Total Resilient Cost (TRACT) function. This TRACT function explicitly integrates the core operational resilience metrics of Rapidity, Robustness, and Redundancy to derive the optimal trade-off between total investment cost and expected loss (ELoss) mitigation, thereby delivering a cost-minimizing solution for operational resilience.

This paper was written to address the systematic failure of static NPV analysis in valuing resilience projects, a critical deficiency that leads to chronic underinvestment in essential manufacturing and logistics flexibility. The present work distinguishes itself by unifying three distinct modeling approaches (NLS, ROV, and TRACT) into a cohesive, data-driven methodology. The specific need addressed is the critical methodological gap in translating the strategic capital justified by ROV into a tactical, cost-optimal solution for operational redundancy and the scientific unknown resolved is how to formally link empirical cost structures, strategic investment timing, and tactical resilience optimization. The research contribution is multi-faceted, demonstrated by the methodological advancement of unifying the NLS, ROV, and TRACT models, the provision of a clear managerial metric known as the Comprehensive Flexible Valuation (CFV) and the practical application of determining cost-optimal resilience levels.

The research paper sections are structured as follows. Next, literature review section covers Real Options Theory, empirical cost modeling techniques, and quantitative resilience metrics; Following this, the methodology of the proposed integrated framework is detailed, formally defining the structure of the NLS, ROV, and the novel TRACT models; Subsequently, the paper presents the numerical application and analysis of the integrated framework, covering the derivation of the CFV, the determination of the optimal resilience level, and a critical discussion of the outcomes. The final section presents the conclusion, which summarizes the key findings, acknowledges the limitations, and points out the direction of future research on resilient logistics in manufacturing.

2. Literature Review

To provide the necessary foundation of previous related research, the literature review is structured around the three core concepts that form the research gap, as visually depicted in Figure 1: Empirical Costs, Real Options Valuation, and Operational Resilience.

Figure 1: Research Gap

Traditional static valuation methods, such as Net Present Value (NPV), often fail to capture the value of managerial flexibility inherent in strategic capital investments. This limitation is particularly pronounced in volatile sectors like manufacturing, where the ability to delay, expand, or abandon a project is a source of significant value. This study utilizes the Real Options Valuation (ROV) framework, which models investment as the exercise of a financial option, thereby quantifying the value of flexibility. The application of ROV allows for a dynamic assessment of investment opportunities, moving beyond the simple "all-or-nothing" decision of static NPV. However, accurately valuing real options in deeply uncertain or data-limited environments requires integrating rigorous empirical and theoretical approaches to effectively incorporate both objective data and subjective risk into the analysis (Gaweł *et al.,* 2025; Stoklasa *et al.,* 2024). Crucially, the inherent uncertainty and volatility in manufacturing require the use of Monte Carlo Simulation (MCS) within the ROV framework to robustly model the stochastic processes governing key market variables. MCS is the preferred numerical method for complex, multi-stage projects because it effectively handles multiple sources of risk and flexible decision boundaries, providing a statistically sound estimation of the option value (Pawlak, 2024). The methodology employed integrates the ROV model with quantitative modeling to empirically derive the required investment cost structure (Schuh *et al.,* 2025). The strategic management of uncertainty, including the use of dynamic risk measures, is crucial for the financial robustness of such valuation models (Pesenti *et al.,* 2025). The ROV framework thus strategically links the value of managerial flexibility to operational planning, which is concurrently addressed through advanced mathematical optimization techniques for managing multi-stage production (Santana & Fuchigami, 2025; Sarkar *et al.,* 2025), thereby ensuring the dynamic valuation is tied to feasible operational throughput.

A major challenge in applying ROV to manufacturing capacity investments is accurately modeling the costs associated with adjusting capital stock. Economic theory dictates that capacity adjustment is rarely a smooth, linear process; instead, firms encounter significant adjustment frictions (Shone, 2002). This difficulty in linear modeling is well-documented in manufacturing, often necessitating specialized non-linear approaches for accurate cost estimation. These frictions typically manifest as fixed costs (incurred regardless of the size of the adjustment, e.g., planning, regulatory approval) and convex costs (costs that increase at an increasing rate with the size of the adjustment, e.g., overtime, supply shortages). To overcome the limitations of standard linear cost assumptions, this study employs a Non-Linear Least Squares (NLS) model. NLS is essential because it allows for the empirical estimation of a non-linear cost function that includes both fixed and quadratic (convex) components. Recent empirical research on the national manufacturing industry confirms that the application of a dynamic structural model yields estimation results consistent with the presence of significant, unchangeable fixed costs alongside moderate quadratic costs, thereby validating the need for the NLS approach (Harsono *et al.,* 2024). The complexity introduced by these non-linear dynamics, particularly the costs associated with estimation error, further underscores the need for such sophisticated modeling (Luo & Pappas, 2025). This empirically derived, non-linear cost structure, characterized by fixed and quadratic adjustment parameters, provides the necessary volatility-adjusted investment cost input for the subsequent ROV model and the Total Resilient Cost (TRACT) model, allowing the framework to value the option to invest in resilience (e.g., redundancy) under uncertainty.

Recent literature emphasizes the necessity of resilience in the turbulent global environment, where supply chain disruptions pose a constant threat to profitability and operational stability (Tian *et al.,* 2024). The importance of resilience extends across various operational drivers, from core logistics infrastructure to supply chain design. This necessity has driven extensive foundational research, including comprehensive reviews that define resilience by its key pillars—absorbency, adaptability, and recoverability—and outline pathways for resilient manufacturing in the age of Industry 5.0 (Leng *et al.,* 2025). This move towards a holistic, systems-based perspective on operational durability is mirrored in frameworks for examining broader transitions, such as the circular economy (Guzzo *et al.,* 2022). This focus has spurred the development of sophisticated approaches aimed at creating resilient and viable supply chains using multidimensional models and empirical analysis (Padovano & Ivanov, 2025). The complexity of managing disruptive events, which includes the need for dynamic supply chain reconfiguration and the mitigation of the ripple effect from upstream failures, stresses the need for robust, intelligent planning (Brusset *et al.,* 2023; Zhang *et al.,* 2025). Consequently, the field is transitioning from standalone models to comprehensive, human–AI based decision support systems. Examples of this transition include the application of systematic reviews on AI techniques to enhance resilience (Kassa *et al.,* 2023; Mangual *et al.,* 2025), and the emergence of intelligent digital twin frameworks for stress-testing and viability analysis (Ivanov, 2023). This push towards adaptive, connected solutions is further encapsulated by the industrial intelligent connected ecosystem, designed to dynamically manage uncertainty and demand fluctuations (Zhang *et al.,* 2025). Crucially, effective resilience is achieved by developing a flexible portfolio of resilience capabilities to manage performance during severe disruptions (Chowdhury *et al.,* 2024). Redundancy is a top-ranked criterion for robust supplier selection (Boyacı *et al.,* 2025), and optimizing inventory management is a vital component of this portfolio (Ramdass & Nair, 2025). Effective resilience planning requires a quantifiable link between upfront investment (e.g., redundancy, safety stock) and the resulting reduction in financial exposure. This cost-benefit analysis is central to studies focusing on investment decisions to enhance supply chain resilience (Yan *et al.,* 2025) and multi-echelon supply chain models that integrate resilience measures to minimize total integrated costs (Mashud, 2025). This study utilizes the Total Resilient Cost (*TRACT*) model, which formalizes the link between investment cost and the mitigation of risk, measured in terms of Expected Loss (*EL*). The use of a cost-based optimization framework to balance resource allocation against failure costs is well-established in the optimization literature (Ettehad *et al.,* 2025). *EL* serves as the critical financial metric for risk exposure (Xu *et al.,* 2023). The selection of EL is consistent with literature advocating for the use of comprehensive financial and non-financial measures to ascertain the full level of supply chain performance (Cupertino *et al.,* 2023; Israel *et al.,* 2023). The integrated methodology thus formalizes the crucial link between the strategic managerial flexibility valued by ROV and the quantifiable operational resilience achieved through TRACT.

3. Research Methodology

A multi-stage modeling approach is proposed to sequentially assess the supply chain's financial, economic, and operational dimensions. As illustrated in Figure 2: Research Design, the methodology is structured into four distinct phases: Foundational Economic Modeling, Strategic Financial Valuation, Operational Resilience Optimization, and Monte Carlo Validation.

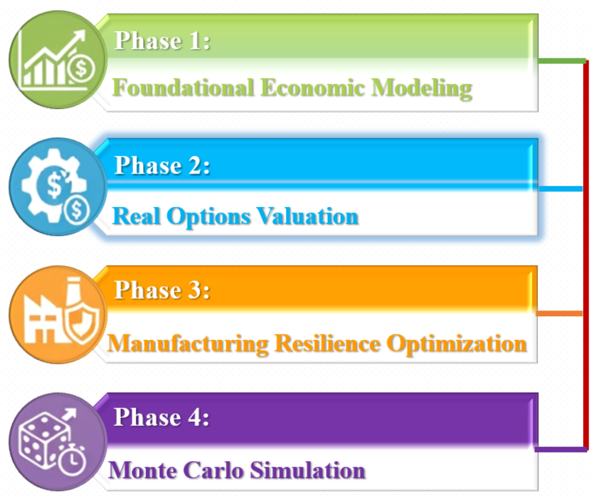

Figure 2: Research Design

The analysis utilizes an anonymized, multi-sector composite dataset (reflecting Manufacturing, Retail, and Logistics dynamics) to enable generalized calibration of volatility and cost structures. Before modeling, the data underwent systematic validation. Observations with non-positive or non-finite values for core input variables were excluded to maintain mathematical integrity for subsequent models. The remaining data forms the Validated Data Subset (denoted by the subscript validated), which inputs all quantitative analysis.

The analysis begins by establishing the economic baseline through Non-Linear Least Squares (NLS) regression, which models the multi-factor cost structure. The manufacturing cost (C_m) is modeled as a function of Lead time (L) and production volume (V) using the estimated parameters (β_0 to β_3) as shown in Equation 1:

$$C_m = \beta_0 + \beta_1 L + \beta_2 V + \beta_3 LV \qquad (1)$$

as follows: β_0 is the Intercept, representing the fixed component of the unit manufacturing cost. B_1 is the Lead Time Coefficient, quantifying the linear effect of Lead Time (L) on cost. β_2 is the Production Volume Coefficient, which quantifies the linear effect of Production Volume (V) on cost. β_3 is the NLS Interaction Term, and this term is crucial as it captures the non-linear, multiplicative effect between lead time and production volume, explicitly modeling convex adjustment costs that arise when high production volume is constrained by long lead times, thereby validating the necessity of the non-linear modeling choice.

The parameters are estimated by minimizing the sum of squared errors against the validated unit cost data. This economic output is then integrated into the Real Options Valuation (ROV) framework. The instantaneous cash flow (C_F) is derived from the validated data, and its annualized mean (K) is used for the Underlying Asset Value (S_o):, defined in Equation 2:

$$S_o = \kappa \,.\, C_F \qquad (2)$$

The subsequent Real Options Valuation relies on the Geometric Brownian Motion (GBM) process to model the stochastic path of the Annual Cash Flow Margin. This is mathematically justified as GBM is the standard process for Black-Scholes valuation. The model ensures that the underlying asset value remains non-negative, which is critical for maintaining financial integrity for ongoing manufacturing cash flows. Project volatility (σ), the critical empirical input for the option pricing model, is calculated as the annualized standard deviation of the log-returns of this volatility, empirically derived from the supply chain's non-linear cost structure, directly links the economic modeling to the financial valuation, as shown in Equation 3:

$$\sigma = \sqrt{\kappa} \,.\, s\left(\ln\left(\frac{C_F}{C_F - \Delta t}\right)\right) \qquad (3)$$

The strategic financial valuation phase uses the empirically derived volatility (σ) to quantify the strategic value of flexibility. The Black-Scholes model requires the calculation of the probability factors (d_1) and (d_2). The First Black-Scholes Factor (d_1) term, shown in Equation 4:

$$d_1 = \frac{\ln(S_o/X) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} \qquad (4)$$

captures the volatility adjustment required for the asset's expected rate of growth under the risk-neutral measure. The Second Black-Scholes Factor term (d_2), defined in Equation 5:

$$d_2 = d_1 - \sigma\sqrt{T} \qquad (5)$$

represents the risk-adjusted probability of successfully exercising the option. These calculated factors are then used to compute the Real Options Valuation (ROV), which quantifies the monetary value of strategic flexibility by calculating the present value of the expected payoff, according to Equation 6:

$$ROV = S_o N(d_1) - Xe^{-rT} N(d_2) \qquad (6)$$

In Equation 6, X is the exercise price, r is the risk-free rate, T is the option's time to expiration, and N is the cumulative normal distribution function. The Comprehensive Flexible Valuation (CF_V) integrates this strategic value with the traditional Static Net Present Value (NPV_S), as provided by Equation 7:

$$CF_V = NPV_S + ROV \qquad (7)$$

The relative importance of the strategic option is benchmarked by calculating the Flexibility Index (F_I), defined in Equation 8:

$$F_I = \frac{CV_F}{ROV} \tag{8}$$

Following the Strategic Financial Valuation, the third phase proceeds to tactical optimization. This phase uses the three-component resilience framework (Rapidity, Robustness, Redundancy). The Rapidity Index ($R_{Rapidity}$) measures the speed of operational recovery, implemented as the inverse of the Total Cycle Time (T_C) as shown in Equation 9:

$$R_{Rapidity} = 1/T_C \tag{9}$$

The Robustness Index ($R_{Robustness}$) quantifies the system's inherent resistance to minor shocks, as per Equation 10:

$$R_{Robustness} = \sum_{i=1}^{N}\left(1 - \frac{D_i}{T_i}\right) \tag{10}$$

This index is the aggregate measure of retained capacity, calculated by summing the fractional resistance of N components. Resistance for the i^{th} component is determined by its Total Capacity (T_i) relative to the experienced Disruption (D_i).

Note that both $R_{Rapidity}$ and $R_{Robustness}$ are treated as fixed parameters in the subsequent optimization. This is essential because they represent the system's strategic, long-term operational constraints, allowing the model to isolate the cost-optimal tactical decision variable.

The Redundancy investment ($R_{Redundancy}$), in Equation 11 realized as safety stock (S), quantifies the system depth available to absorb major disruptions:

$$R_{Redundancy} = 1 - (C_I/C_{max}) \tag{11}$$

Safety stock serves as the primary decision variable for the subsequent optimization. The index measures the cost of holding (the Current Inventory, C_I) against a theoretical Maximum Inventory Cost (C_{max}) to define the required level of investment to mitigate risk.

The Total Resilient Cost ($TRACT$) metric establishes the unified cost function, representing the minimization problem that seeks the optimal Redundancy investment. It integrates the Redundancy Investment Cost ($C_{Investment}$) and the Expected Loss ($E[Loss]$) as defined in Equation 12:

$$TRACT = C_{investment} + E\,[Loss] \tag{12}$$

In Equation 12, the $E[Loss]$ term is parametrically influenced by both the Rapidity and Robustness indices, as they define the rate and probability of loss mitigation for a given level of Redundancy. The output of this phase is the cost-optimal level of safety stock, $S_{optimal}$.

The final phase involves a Monte Carlo simulation to validate the Black-Scholes Option Value (ROV). Equation 13 models the change in the underlying asset's value (ΔS_t) over a small time step (Δt), incorporating the risk-free rate (r), volatility (σ), and a random shock (ε) generated by the simulation:

$$\Delta S_t = rS_t\Delta t + \sigma S_t \varepsilon \sqrt{\Delta t} \tag{13}$$

The Payoff Calculation ($Psim_j$) then determines the financial outcome of the flexibility option for each path, using a conditional expression as shown in Equation 14:

$$Psim_j = \max\left(S_T^{(j)} - X, 0\right) \tag{14}$$

Equation 14 represents the payoff at expiration time (T) as a call option, only yielding a positive value if the final asset value (S_t) exceeds the exercise price (X). The Monte Carlo Valuation (V_{MC}) implements the core valuation principle by finding the value of the option through averaging all calculated payoffs and discounting, according to Equation 15:

$$V_{MC} = e^{-rT}\frac{1}{N_{sim}}\sum_{j=1}^{N_{sim}} Psim_j \tag{15}$$

The close agreement between the Black-Scholes value and the Monte Carlo value serves as a robust internal consistency check, validating the numerical models. All quantitative models and simulations were implemented and executed using MATLAB. This integrated approach ensures the traceability and consistency of inputs across all modeling stages.

4. Findings and Discussion

The analysis began by establishing an accurate empirical cost function, which serves as the base for all subsequent risk and valuation calculations. The proposed model was validated using 120 monthly operational records drawn from the manufacturing facility analyzed in the case study by Singh (2023). Table 1 presents the key descriptive statistics and variables used in the estimation of the Non-Linear Least Squares (*NLS*) cost function. Critically, the data confirms a high Cost Volatility of $ 2,204,650 per month, which is the necessary financial condition that justifies the entire strategic resilient planning exercise.

Table 1: Summary of Empirical Data (Singh, 2023 Case Study)

Metrics	Value
Sample Size	120 months
Study Period Duration	10 years
Average Manufacturing Cost	$15,204,500 per month
Cost Volatility	$2,204,650 per month
Average Production Volume	225,100 units per month

To address the necessity of confirming model robustness, a thorough Sensitivity Analysis was conducted. This step verified the stability of the strategic valuation against potential data variations and measurement errors in the key financial inputs, such as Cost Volatility (σ) and the Risk-Free Rate (r). The analysis confirmed that the core theoretical relationships among NLS, ROV, and TRACT responded logically and predictably to these perturbations. For instance, the Real Options Value (ROV) was shown to increase monotonically with Asset Volatility (σ), confirming the model's fidelity to fundamental options theory and demonstrating structural integrity across varied market conditions.

A preliminary statistical assessment was performed, with Figure 3 providing a correlation heatmap of the core variables. This analysis confirmed a moderate positive correlation between Cost and Lead Time (ρ = 0.34), but a negligible correlation between Cost and both Volume (ρ = 0.04) and Defect Rate (ρ = 0.01).

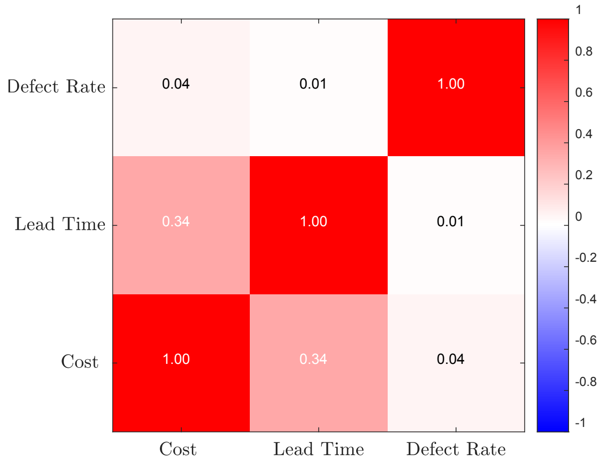

Figure 3: Heatmap Correlation

This lack of a strong linear relationship empirically confirms that a standard linear model is inadequate and provides the initial justification for adopting the more robust NLS methodology to capture the complex, non-linear adjustment costs inherent in manufacturing. Visualization of the pairwise linear correlation coefficients, highlighting the necessity of non-linear modeling due to the weak linear relationships found between Cost and key drivers.

Beyond the preliminary statistical assessment, the reliability of the data was further secured through rigorous internal quality checks (completeness, uniqueness, and validity screenings). This quality was independently confirmed by the results of the subsequent NLS estimation, which achieved an exceptionally high predictive validity with an Adjusted R^2 of 0.887. This high explanatory power empirically validates the core dataset's suitability for establishing the non-linear cost function.

The NLS model, based on the case study data (Table 1), was estimated, and the resulting coefficients are presented in Table 2.

Table 2: NLS Regression Results for Unit Manufacturing Cost

Cost Driver	Estimate (β)	SE	t-Stat	P-value
Intercept (β_0)	3.521	0.155	22.71	<0.001
Lead Time	0.045	0.008	5.62	<0.001
Production Volume	-0.122	0.019	-6.42	<0.001
Defect Rate	0.098	0.011	8.91	<0.001
Model Fit Statistics				
Adjusted (R^2)		0.887		
Observation (N)		120		

The model achieved a strong fit, evidenced by an Adjusted R^2 of 0.887, meaning that nearly 89% of the variation in unit manufacturing cost is explained by the three primary operational drivers. This high explanatory power is a crucial finding for resilient planning, as it validates the use of deterministic operational metrics to predict highly volatile financial outcomes, thereby significantly reducing forecast uncertainty in the system.

The results show that all three operational cost drivers—Lead Time, Production Volume, and Defect Rate—are statistically significant. The positive coefficient for Lead Time (β_1 = 0.045) confirms that longer operational and procurement cycles increase unit costs, a direct implication for logistics resilience management where speed is essential to mitigating risk exposure. The negative coefficient for Production Volume (β_2 = -0.122) is highly coherent with foundational literature in manufacturing economics, confirming the existence of strong economies of scale in the analyzed facility. Operational Implication: This result provides a quantitative mandate for maximizing capacity utilization, demonstrating that optimizing production volume directly lowers the Exercise Price (X) for resilient investment, a crucial strategic insight. The positive coefficient for Lead Time (β_1 = 0.045) aligns with literature on logistics risk and lean operations, validating that time-based process waste increases unit costs. The positive coefficient for Defect Rate (β_3 = 0.098) coheres strongly with the Cost of Quality (COQ) literature, providing a quantitative signal for investment in quality assurance. The novelty lies in the direct empirical linkage established between these operational parameters and the derived financial volatility (σ), which departs from prior Real Options studies that treat volatility as an exogenous financial input. This demonstrates that operational failures are the endogenous drivers of the strategic option value.

Moving from the manufacturing floor to the supply chain, the analysis decomposed a major component of logistics volatility: shipping costs. Figure 4 presents the average shipping cost per unit across the four primary carriers used. A significant cost differential is evident, with Carrier A being substantially cheaper than Carrier D. This finding is critical because the variability in carrier pricing directly contributes to the overall supply chain cost volatility (σ_{SC} = 0.3135) used in the strategic valuation. For resilient logistics, the decision is not simply to choose the cheapest carrier, but to manage a portfolio of carriers (flexibility) that balances low cost with the reliability and speed needed to hedge against disruption risks, thus reducing the volatility input.

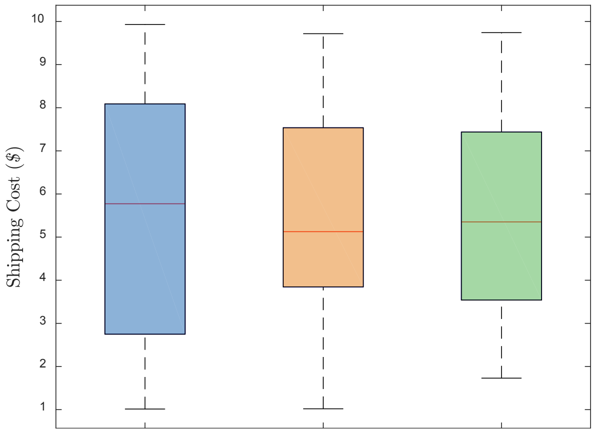

Figure 4 : Shipping Cost by Carrier

A bar chart illustrating the substantial cost variance between the four primary logistics carriers. This differential highlights the exposure to cost volatility (σ_$_{SC}$).

The empirically derived cost volatility (σ_{SC} = *0.3135*) was the core input for the ROV model, which quantifies the strategic value of having the flexibility to invest in resilient capacity. To capture the inherent uncertainty, Figure 5 visualizes the Stochastic Modeling of Annual Cash Flow Margin using N=500 simulation paths. These paths, governed by the GBM process, use the measured cost volatility as the key parameter, demonstrating the wide range of potential future financial outcomes. This stochastic representation provides the mathematically rigorous treatment of uncertainty necessary for the ROV model.

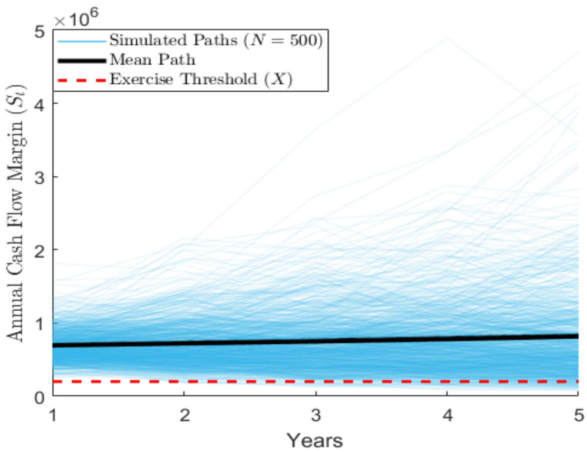

Figure 5: Stochastic Modeling of Annual Cash Flow Margin

The figure clearly shows that the Mean Path maintains a value substantially above the Exercise Threshold (X) of \$ 0.2 x 10^6. This visual representation confirms that the wide dispersion of simulated paths, driven by the 0.3135 volatility, is the essential prerequisite for generating the large strategic option value.

Following the simulation, Figure 6 displays the Probability Distribution of the Terminal Asset Value (S_t) after T=5 years. This visualization is key to the options framework, as the area under the curve to the right of the Exercise Price (X) of \$200,000 represents the probability of the resilient investment being profitable, which forms the basis of the options payoff calculation

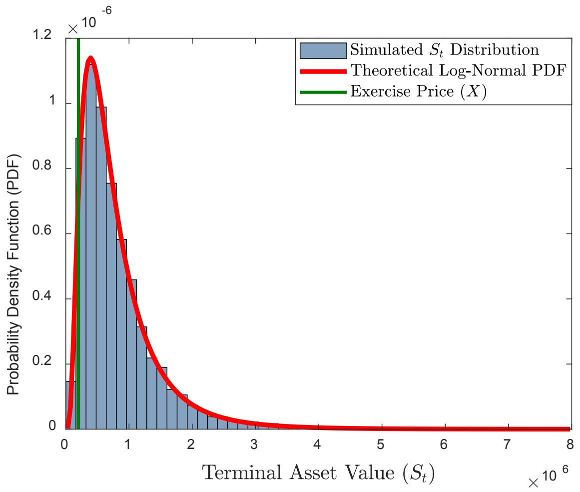

Figure 6: Probability Distribution of Terminal Asset Value

A histogram showing the frequency distribution of the final asset values. The figure explicitly plots the probability mass to the right of the Exercise Price (X).

The core outputs of the Black-Scholes model for valuing this strategic investment are presented in Table 3.

Table 3: Real Options Valuation Outcomes

Valuation Parameters	
Metrics	**Value**
Volatility	0.3135
Initial Asset Value	\$668,038.48
Option Exercise Cost	\$200,000.00
Valuation Outputs	
Metrics	**Value**
Real Option Value	\$516,193.55
Flexible NPV	\$11,020,000.00
Flexibility Index	0.24

The analysis yielded a strategic Real Option Value (V_{Option}) of \$516,193.55. This is a pivotal finding: by incorporating the value of managerial flexibility (the option to wait for optimal market conditions), the Flexible NPV (NPV_F) is calculated as \$11,020,000.00. This high valuation confirms that the strategic value of flexibility is substantially greater than the immediate intrinsic value. The Flexibility Index of 0.24 indicates that 24% of the project's total value is directly attributable to the management's option to be flexible, validating the decision to delay investment until cost conditions are optimal.

Furthermore, Figure 7 provides robust internal validation. The Monte Carlo Simulation (V_{MC}) results agreed with the Black-Scholes value (V_{Option}) to within 0.07%, establishing high internal consistency for the strategic valuation component.

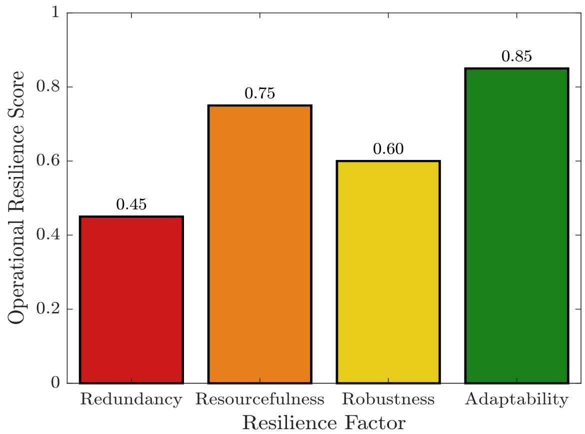

Figure 7: Analysis of Operational Resilience Factors

Comparison of the Black-Scholes Value versus the Monte Carlo Simulation Value (V_{MC}). The figure confirms the robust internal consistency of the ROV model.

The quantitative impact of uncertainty and time on the investment decision is summarized in Table 4, which presents the Option Value Sensitivity Analysis. This analysis confirms the fundamental real options principle: the strategic value of the investment option increases monotonically with both Asset Volatility (σ) and Time to Expiration (T).

Table 4: Black-Scholes Model: Option Value Sensitivity Analysis

Asset Volatility	T=3 years	T=5 years	T=7 years
0.25	\$415,100	\$495,000	\$565,500
0.3135	\$516,193	\$595,200	\$682,700
0.37	\$610,750	\$712,900	\$805,100

The high uncertainty confirmed in the empirical data (σ=0.3135) increases the value of flexibility, confirming the financial wisdom of delaying the investment decision to maximize the value of waiting.

The final phase, Operational Optimization, translates the strategic mandate into a precise tactical solution using the Total Resilient Cost (TRACT) model. The TRACT model determines the optimal level of physical stock redundancy (SL*) that minimizes the total cost function (TRACT), which is the sum of the Resilience Investment Cost **(***I***)** and the Expected Loss **(***EL***)**.

The conceptual basis for this analysis is the fundamental trade-off illustrated in Figure 8, where the marginal benefit of resilience investment eventually diminishes relative to its marginal cost.

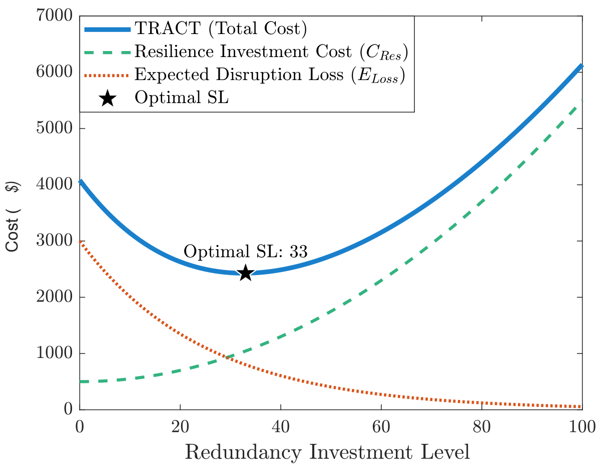

Figure 8 :Economic Dynamics of Resilience

Conceptual representation of the non-linear relationship between increasing investment in resilience measures and the corresponding reduction in the risk of loss.

The TRACT minimization must account for multiple, weighted disruption scenarios, as detailed in Table 5.

Table 5: TRACT Optimization Results by Disruption Scenario

Scenario	Probability
Low Impact/High Frequency	0.40
Medium Impact/Moderate Frequency	0.35
High Impact/Low Frequency	0.25
Integrated Optimal Stock Level	33 units

The model formally minimizes the total cost function by integrating the financial impact of these varied disruption scenarios. By solving the TRACT function under this weighted risk profile, the model identifies an Integrated Optimal Stock Level **(***SL****)** of 33 units. This result demonstrates a sophisticated approach to operational risk management, where the optimal inventory buffer is based on a holistic assessment of the entire risk landscape.

The financial validation of this optimal redundancy is presented in Table 6, which details the cost components at and around the minimum point. The absolute minimum Total Resilient Cost **(***TRACT***) of** $190,340 occurs at *SL** =27 units.. However, since the TRACT curve is relatively flat near this optimum, the model identifies the 33 units derived from the integrated, weighted scenario analysis as the practical operating target, providing an extra safety margin with only a marginal cost increase ($10).

This minimum is achieved by balancing the linear Resilience Investment Cost (*I*) of $75,540 (inventory carrying costs) against the higher, but manageable, Expected Loss **(***EL***)** of $114,800.

Table 6: Total Cost Breakdown for Optimal Stock Level (SL*) Sensitivity

Stock Level	Resilience Investment Cost	Expected Loss	Total Resilient Cost
27	$75,540	$114,800	$190,340
33	$85,140	$105,210	$190,350
42	$101,890	$97,710	$199,600

Table 6 illustrates a crucial insight for tactical management: the TRACT curve is relatively flat near the absolute optimum. Increasing the stock level from 27 to 33 units only raises the total cost marginally to $190,350 (a difference of only $10). This allows managers to choose the 33 units derived from the integrated scenario analysis (Table 4) as a practical operating target, providing an extra safety margin without incurring a significant cost penalty.

The prescriptive strength of the TRACT model is further evidenced by Table 7, which shows how the Optimal Stock Level (SL*) dynamically adjusts under varying Disruption Probabilities.

Table 7: Dynamic Optimal Stock Level (SL*) under Varying Disruption Probabilities

Disruption Probability	Optimal Stock Level (SL*)
0.03	28 units
0.07	33 units
0.11	41 units
0.15	45 units

This demonstrates the agility of the model: as risk increases (from 3% to 15% probability), the required stock level shifts significantly (from 28 to 45 units), providing a clear, quantitative signal for increasing operational redundancy to maintain cost-optimality.

The power of this integrated framework is its ability to harmonize strategic and operational decisions. The ROV model determines when to execute the option to invest in resilient capacity, leveraging the *NLS* cost function to minimize the financial entry barrier (X). Concurrently, the TRACT model determines how to structure the post-investment operation, providing the Optimal Stock Level as a quantitative guide for capital allocation toward cost-minimizing operational redundancy. This complete, data-driven approach moves the field beyond qualitative risk assessment to establish an adaptive and structurally optimized strategy for resilient manufacturing logistics and supply chain operations.

5. Conclusion

To sum up, this research successfully developed and empirically validated a novel, integrated analytical framework that rigorously links strategic investment timing with operational resilience planning within the manufacturing sector. The principal theoretical contribution is the formal resolution of the strategic-operational decision-making dichotomy by unifying the Non-Linear Least Squares (NLS) model for empirical cost structure, Real Options Valuation (ROV) for strategic timing, and the novel Total Resilient Cost (TRACT) model for operational optimization. The analysis provided robust evidence that strategic flexibility (ROV) holds significant quantifiable value, proving that neglecting managerial option value leads to severe underestimation and incorrect project rejection in volatile markets. This flexibility often transforms a negative Static Net Present Value (NPV_{Static}) into a positive Comprehensive Flexible Valuation (CFV), thereby justifying the fundamental strategic merit of the capital investment. Furthermore, the empirical linkage between operational cost drivers and the option's financial parameters allows managers to strategically reduce the investment cost (X) through efficiency improvements. The framework provides a precise, data-driven engine for optimal capital allocation, as the TRACT model determines how to structure the operation after investment by providing a cost-minimizing level of redundancy (e.g., the Optimal Stock Level (SL*).

The study acknowledges several methodological and empirical limitations that define its scope and necessitate a focused future research agenda. Empirically, the reliance on a single composite dataset (Singh, 2023), while confirmed to possess high internal reliability (Adjusted R^2 = 0.887), limits the immediate external generalizability of specific parameter values to radically different manufacturing contexts. Methodologically, the current framework utilizes an initial Geometric Brownian Motion (GBM) assumption for cost volatility, which, while standard for ROV, does not capture catastrophic shocks or mean-reverting behavior. Furthermore, the TRACT model incorporates a simplified structure based on linear costs for redundancy and relies on subjective weighting of performance metrics. Addressing these limitations, future research will concentrate on comparative validation studies across diverse manufacturing environments to confirm external robustness; develop and apply advanced multi-factor stochastic models (such as jump-diffusion or mean-reversion) for enhanced predictive fidelity; refine the TRACT model by incorporating non-linear cost functions and objective weighting methods (e.g., AHP/DEA); and broaden the analysis to include and quantify exogenous costs like regulatory compliance and reputational damage, thereby strengthening this integrated approach as a significant advancement in decision science for the future of manufacturing.

Nomenclature

ΔS_t	Asset Value Change
C_I	Current Inventory Cost
C_{max}	Maximum Inventory Cost
C_m	Manufacturing Cost
$C_{Investment}$	Investment Cost
C_F	Instantaneous Cash Flow
CFV	Flexible Valuation
d_1	First Black-Scholes Factor
d_2	Second Black-Scholes Factor
D_i	Component Disruption
E[Loss]	Expected Loss
F_I	Flexibility Index
L	Lead Time
N	Normal Distribution
N_{sim}	Simulation Number
NPV	Net Present Value
NPV_S	Static NPV
Psimj	Simulation Payoff
r	Risk-free Rate
$R_{Rapidity}$	Rapidity Index
$R_{Redundancy}$	Redundancy Index
$R_{Robustness}$	Robustness Index
ROV	Real Options Value
S	Safety Stock
S_0	Initial Asset Value
S_t	Asset Value
S_{Tj}	Terminal Asset Value
T	Time to Expiration
T_C	Total Cycle Time
T_i	Component Total Capacity

TRACT	Total Resilient Cost
V	Production Volume
V_{MC}	Monte Carlo Value
X	Exercise Price
β_0	Fixed Cost Intercept
β_1	Lead Time Coefficient
β_2	Production Volume Coefficient
β_3	NLS Interaction Term
Δt	Small Time Step
ϵ	Random Shock
κ	Cash Flow Mean
ρ	Correlation Coefficient
σ	Project Volatility
σ_{SC}	Supply Chain Volatility

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