

# Assessment of Contingency Sum in Buying of Offshore Construction Materials and Its Impact on Total Project Cost to Improve the Inventory Management: A Case Study PT SATM

Veren Priscila<sup>1</sup>, Rhea D. Casela<sup>2</sup>, Nicole Joy M. Realingo<sup>2</sup>

<sup>1</sup>Department of Industrial Engineering, Universitas Atma Jaya Yogyakarta, Indonesia

<sup>2</sup>Department of Industrial Engineering, Bulacan State University, Philippines

Email: verencila@gmail.com, rhea.casela@bulsu.edu.ph, nicole.realingo@bulsu.edu.ph

\*Corresponding author

## ABSTRACT

This study examines the operational challenges faced by an offshore company that has specialized in rigs and floaters, repairs and upgrades, offshore platforms, and specialized shipbuilding over the past seven years. Despite steady growth, the company has encountered significant issues related to contingency fund management during the construction phase. To mitigate unpredictable risk exposure, the company applies a 20% contingency to the total cost estimate of every offshore construction material. However, this approach has led to a consistent 10% surplus, resulting in excessive costs and inventory. The research aims to evaluate the effectiveness of the current contingency allocation strategy and propose solutions to reduce surplus costs and excess inventory. By analyzing the company's data, the study identifies key inefficiencies and suggests optimized approaches to contingency fund management. The findings aim to provide actionable insights for enhancing financial and inventory management practices, ultimately improving the company's overall operational efficiency and profitability.

**DOI:** <https://doi.org/10.24002/ijieem.v7i2.10358>

**Keywords:** contingency fund management, influence diagram, level inventory, Monte Carlo simulation, offshore engineering

**Research Type:** Case Study

**Article History:** Received December 10, 2024; Revised August 4, 2025; Accepted December 17, 2025

**How to cite:** Priscila, V., Casela, R.D., & Realingo, N.J.M. (2025). Assessment of contingency sum in buying of offshore construction materials and its impact on total project cost to improve the inventory management: A case study PT SATM. *International Journal of Industrial Engineering and Engineering Management*, 7(2), 139-147.

© 2025 The Author(s). This work published in the International Journal of Industrial Engineering and Engineering Management, which is an open access article under the CC BY 4.0 license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. INTRODUCTION

The construction phase of any project inherently carries significant risks and expenses, with offshore projects amplifying these challenges due to their complexity and the myriad uncertainties involved. As the offshore industry continues to expand, it necessitates the development of innovative strategies to navigate

constraints and optimize resource utilization.

In the field of Industrial Engineering and Engineering Management, efficient resource planning and cost estimation are essential pillars to ensure optimal performance across the supply chain and throughout the project lifecycle. One of the key issues that intersects both domains is the challenge of managing inventory levels and contingency cost buffers—especially in large-scale,

high-risk environments such as offshore construction projects.

This research is based on a case study of a specific offshore company, an integrated brand offering comprehensive engineering solutions for the offshore, marine, and energy sectors, which has been operational for seven years. The company excels in four primary domains: rigs and floaters, repairs and upgrades, offshore platforms, and specialized shipbuilding. However, from 2016 to 2018, the company faced a recurring issue of excess inventory, leading to significant surplus costs and inefficiencies in project execution.

A critical aspect of project management is the accurate allocation of contingency allowances in project cost estimates (Burroughs & Juntima, 2004). Given the dynamic nature of construction projects, changes are inevitable. The construction industry relies heavily on meticulous planning and financial forecasting to ensure that projects are completed to the desired quality standards, within the stipulated timeframe, while adhering to health and safety regulations, and remaining within the allocated budget (Jimoh & Adama, 2014). The inherent complexity of the construction sector makes accurate cost estimation challenging, prompting the use of contingencies to meet project objectives. According to Watt (2012), if project cost estimates consistently exceed actual expenses, it may indicate that the estimating method is overly conservative.

At this company, a standard 20% contingency is added to the total project cost to account for potential risks. While contingency allowances serve to mitigate uncertainties in cost and time estimates, they can also lead to surplus costs and excess materials, which negatively impact the company's financial performance and inventory efficiency—a direct concern of Industrial Engineering. Figure 1 illustrates the components of total project cost and the role of contingency (England & Moreci, 2012). The total estimated project cost comprises the base cost estimate, representing the expected cost of known scope, and the contingency, covering risk exposure and estimate uncertainty. However, an excessive contingency percentage can lead to overstocking of materials, resulting in unnecessary holding costs and operational waste.

Inventory management plays a critical role in minimizing excess costs and ensuring efficient operations. According to Shah and Shin (2007), reducing inventory levels can significantly improve a company's financial performance by lowering holding costs and minimizing waste. The Just-In-Time (JIT) inventory system, as discussed by Kannan and Tan (2005), emphasizes the importance of maintaining minimal inventory levels and reducing lead times to enhance efficiency. Additionally, Chikán (2009) highlights that a lean inventory strategy can help companies maintain flexibility and respond quickly to market changes, thereby optimizing resource utilization and reducing the financial burden of holding excess stock.

This study challenges the conventional approach that simply adding a fixed contingency fund (20%) to the total cost estimate is sufficient to cover unpredictable risks. Instead, it proposes a more data-driven and integrated

approach, aiming to reduce contingency levels while considering the implications on inventory and cost efficiency—two key concerns in both Industrial Engineering and Engineering Management. By analyzing the company's historical data from 2016 to 2018, the research evaluates the relationship between contingency planning and surplus costs, and explores strategies to minimize both. The study also seeks to identify the associated risks and propose a more refined methodology for managing contingency funds, thereby enhancing return on investment and reducing inefficiencies in resource allocation.

## 2. LITERATURE REVIEW

Monte Carlo Simulation (MCS) is a widely recognized method in Industrial Engineering and Engineering Management for addressing uncertainties in inventory control, demand forecasting, and project cost estimation. It enables the probabilistic assessment of various outcomes by running numerous simulations, thus offering a comprehensive risk profile for decision-making under uncertainty (Rubio & Jiménez-Parra, 2018). In the context of inventory management, MCS has proven valuable for evaluating the variability in demand and supply, helping companies maintain adequate safety stock levels while minimizing holding and surplus costs (Wakjira, 2021). This capability is particularly important for project-based environments such as offshore construction, where demand is intermittent, and overestimating needs (e.g., via contingency) can lead to excess inventory.

In project cost management, MCS has also been applied to assess the adequacy of contingency reserves, providing a statistical basis to determine whether contingency allowances are too high or too low (Mak & Picken, 2000). Research has shown that using MCS to model cost variability and risk exposure leads to more accurate and justifiable contingency allocations, which can reduce the risk of overbudgeting and material excess (Zhao & Tseng, 2003). This directly supports the application of MCS in this study to reassess the standard 20% contingency policy and its effect on inventory outcomes.

Influence Diagrams (IDs) further enrich the analysis by offering a visual and analytical framework that maps out relationships among decision variables, uncertainties, and outcomes (Shachter, 2019). IDs assist in identifying the most critical factors affecting inventory levels and project performance. When combined with MCS, IDs serve to structure the simulation logic and prioritize variables for scenario analysis (Torra et al., 2018). This integrated use improves clarity in decision-making, especially in environments with multiple interdependent variables like lead time variability, procurement delays, and inventory turnover.

Several scholars have emphasized the synergistic potential of MCS and IDs in complex decision-making contexts. For example, Bozarth et al. (2020) demonstrated the effectiveness of this approach in improving inventory planning accuracy and cost efficiency in volatile environments. Perera et al. (2019) also highlighted the use of MCS in combination with traditional inventory methods (e.g., JIT and EOQ) to better handle demand fluctuations

and optimize ordering strategies.

While traditional inventory control methods such as Just-In-Time (JIT) and ABC analysis offer foundational benefits, they often lack the flexibility to handle high uncertainty without added risk buffers. JIT, for instance, reduces waste and holding costs by aligning production schedules closely with demand (Yang, 2020), but it depends heavily on accurate forecasts and a stable supply chain—both of which can be compromised in offshore project settings (Chen et al., 2019). Similarly, ABC analysis helps categorize items based on value and consumption, allowing targeted management of high-impact inventory (Venkatesan et al., 2019), but it does not inherently account for uncertainty in demand or project timelines.

Therefore, the integration of MCS and IDs provides a more robust and dynamic alternative, enabling simulation of diverse risk scenarios and visualization of their implications for inventory outcomes. Marquez et al. (2021) emphasize that probabilistic modeling combined with decision structuring tools enables companies to optimize contingency planning and inventory management simultaneously.

This study proposes the novel application of MCS and IDs to analyze the link between contingency cost allocation and excess inventory in offshore engineering projects—a relationship that has been underexplored in the literature. By revisiting historical project data (2016–2018), this research aims to quantify how overestimated contingencies lead to material over procurement and to offer a data-driven strategy for right-sizing contingencies and aligning them with actual material needs. This approach not only addresses operational inefficiencies but also enhances decision-making under uncertainty, which is a core concern in both Industrial Engineering and Engineering Management.

### 3. METHODOLOGY

This study utilizes a mixed-methods approach, integrating both quantitative and qualitative methodologies to provide a comprehensive analysis of inventory reduction strategies in offshore construction. The research is centered around a case study of a specific offshore construction company, with a focus on the application of Monte Carlo Simulation (MCS) and Influence Diagrams (IDs).

Data were collected from multiple sources to ensure a robust and thorough analysis. A review of company records, project reports, and financial documents from 2016 to 2018 provided historical data on inventory levels, costs, and contingency allocations. Additionally, relevant industry reports and academic literature were consulted to provide context and support the analysis.

The study employs two primary analytical tools: Monte Carlo Simulation (MCS) was used to model the uncertainty and variability in demand and supply chain processes. This approach involved simulating a range of scenarios to provide probabilistic estimates of inventory requirements under various conditions, aiding in the identification of optimal inventory levels that minimize both excess and costs. Influence Diagrams (IDs) were

utilized to map the decision-making processes and visualize the relationships between key variables. This tool helped identify the most influential factors in inventory management and understand the potential outcomes of various decisions.

Compared to deterministic models such as EOQ and basic safety stock calculations, MCS offers superior flexibility in modeling uncertainty and variability (Rossetti, 2008; Davis & Patterson, 2012). It enables companies to simulate dynamic and complex environments, which is particularly relevant in offshore construction, where demand is often project-specific, and supply risks are high.

Influence Diagrams (IDs) were utilized to map the decision-making processes and visualize the relationships between key variables. This tool helped identify the most influential factors in inventory management and understand the potential outcomes of various decisions. IDs strengthen the decision-making framework by clarifying dependencies among variables and supporting scenario analysis. When combined with MCS, IDs improve the structure of probabilistic models and allow decision-makers to focus on high-impact variables (Howard & Matheson, 2005).

**Implementation of Analytical Tools, Monte Carlo Simulation:** Historical data on demand patterns, lead times, and supply chain disruptions were input into the MCS model. The simulation generated a spectrum of possible outcomes, providing a detailed risk assessment and identifying potential inventory shortages or surpluses. Influence Diagrams were developed collaboratively with company stakeholders to ensure accuracy and relevance. The diagrams outlined decision pathways and highlighted the cause-and-effect relationships between variables such as order quantities, lead times, contingency sums, and inventory levels. This method has been shown to improve forecast accuracy and reduce surplus in complex supply chains.

The results from the Monte Carlo Simulation were analyzed to determine the probability distributions of inventory outcomes. Key performance indicators, including stock-out probability and excess inventory costs, were calculated. The Influence Diagrams provided qualitative insights into the interdependencies among variables, complementing the quantitative data.

The integration of MCS and IDs enables companies to navigate uncertainty more effectively, allowing for data-driven decisions that enhance inventory efficiency while reducing project cost risks (Marquez et al., 2021).

### 4. CASE STUDY

This specific offshore company has successfully provided integrated solutions across the energy and utilities value chain. However, along with every project they make, as it many things to consider, a certain contingency percentage was applied, which is 20% in every purchase of materials.

With this, from the record of the year 2016 – 2018 of buying offshore materials for the project, the total material cost from the purchase order quantity multiplied

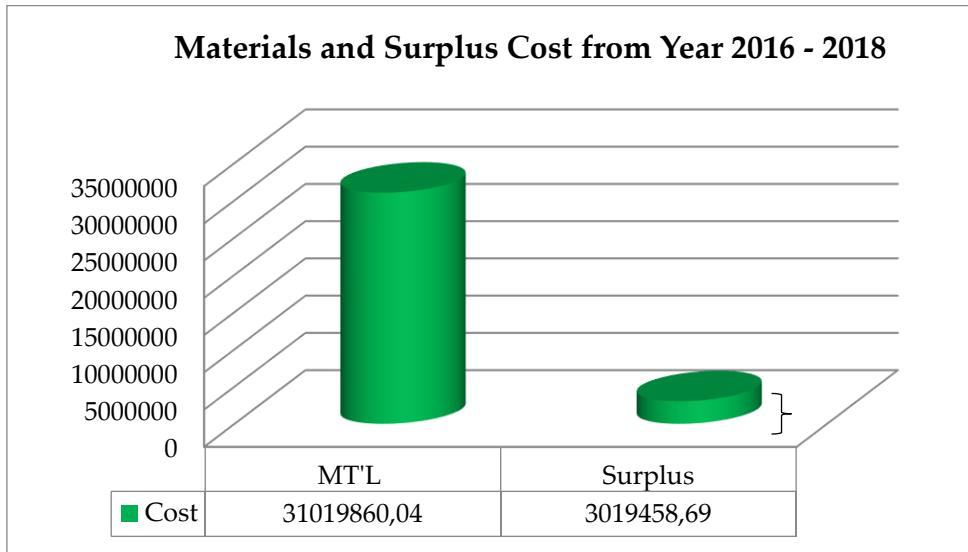


Figure 1. Material and surplus costs from 2016 – 2018

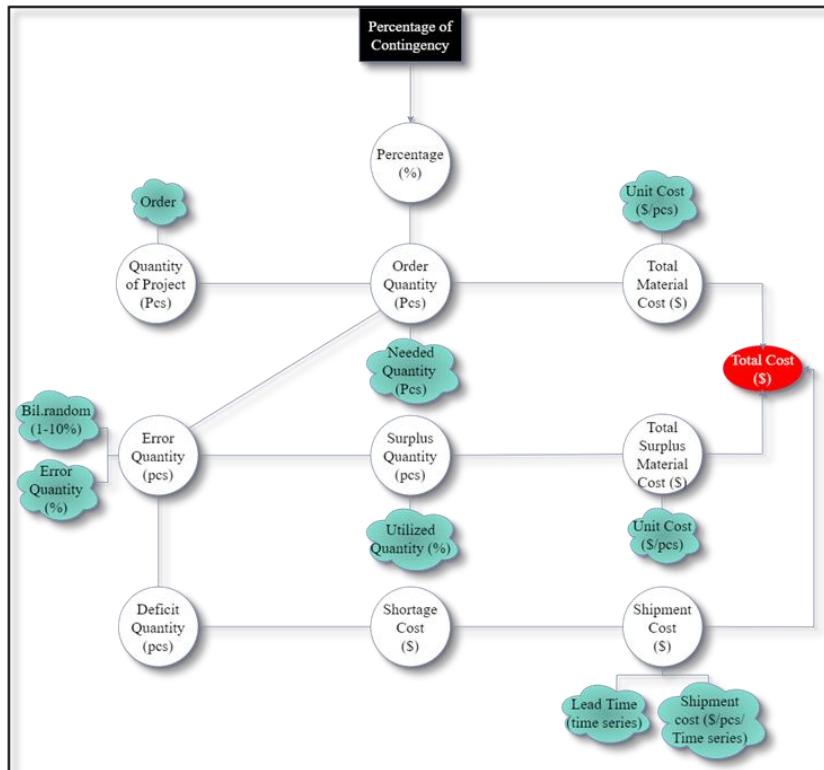


Figure 2. Variables

by the unit cost resulted in \$31,019,860.04, while surplus cost resulted in \$3,019,458.69, as shown in Figure 1, which were computed using the data of the surplus quantity multiplied by the unit cost. There is a 10% surplus cost that exceeds the materials that are utilized. In this regard, excess inventory occurs, often bringing many disadvantages to the company (e.g., capital, storage, service, and inventory risk costs).

The inventory is one of the most crucial components of any operation. Therefore, it is important to use good judgment when deciding how much inventory may be kept on hand and how much to restock. Once a company holds additional stock than what is needed to meet expected demand, this is referred to as excess inventory.

Over time, when it is kept by businesses for an overly long period, this item starts to depreciate and becomes worthless.

## 4.1. Influence Diagram

The following are stated on the influence diagram, as shown in Figure 2, are the factors involved that influence and are influenced. This diagram is utilized because it demonstrates how the decisions, variables at work, and desired outcomes relate to one another, making it simple to identify the key variables and their interactions and how each factor impacts the others.

The decision variable is the contingency percentage.

Table 1. The Results of Simulation (Adding Error)

2016			
	Total Cost Re-order	Probability	Expected Return
Average Cost	\$ 567,697	15%	\$ 86,128
Standard Deviation	\$ 2,113		
2017			
	Total Cost Re-order	Probability	Expected Return
Average Cost	\$ 1,003,228	12%	\$ 119,944
Standard Deviation	\$ 2,596		
2018			
	Total Cost Re-order	Probability	Expected Return
Average Cost	\$ 3,595	29%	\$ 1,048
Standard Deviation	\$ 564		

The units are the identified variables that would be significant in determining the objective of the study, which is the optimal contingency percentage in buying offshore materials.

$$Order\ Quantity\ (pcs) = (Needed\ Qty\ (pcs) + \text{Contingency}) \quad (1)$$

Needed Qty (pcs) \* % Contingency

$$Utilized\ Qty(pcs) = Order\ Qty(pcs) * \% Utilized \quad (2)$$

$$Error\ Qty(pcs) = \% Random\ variable + Needed\ Qty\ (pcs) \quad (3)$$

$$Surplus\ Qty(pcs) = Order\ Qty\ (pcs) - Utilized\ Qty\ (pcs) - Error\ Qty(pcs) \quad (4)$$

$$Deficit\ Qty\ (pcs) = Order\ Qty(pcs) - Utilized\ Qty(pcs) - Error\ Qty(pcs) \quad (5)$$

$$Tl.Material\ Cost\ (pcs) = Order\ Qty\ (pcs) * Unit\ cost\ ($/pcs) \quad (6)$$

$$Surplus\ cost\ ($) = Surplus\ Qty(pcs) * Unit\ cost\ ($/pcs) \quad (7)$$

$$Deficit\ cost\ ($) = Deficit\ Qty\ (pcs) * Unit\ cost\ ($/pcs) \quad (8)$$

$$Shipment\ cost\ ($) = 20\% * Unit\ cost\ ($/pcs) \quad (9)$$

$$Shortage\ cost\ ($) = Shipment\ cost\ ($) + Deficit\ cost\ (pcs) \quad (10)$$

$$Total\ Cost\ ($) = Tl.Material\ Cost(pcs) + Surplus\ cost\ ($) + Shortage\ cost\ ($) \quad (11)$$

Each equation reflects a specific phase of the inventory and cost analysis process. Equation (1) calculates the total ordered quantity based on the forecasted need and a contingency buffer. Equation (2) estimates the quantity that will actually be utilized in the project. Equation (3) introduces an error component based on possible unpredictable usage (random variable). Equations (4) and (5) assess whether there is excess or insufficient inventory. Equations (6) through (11) compute the cost implications of each inventory scenario, including surplus and deficit, shipment costs, and ultimately the total cost.

These models serve as the foundation of the Monte Carlo Simulation, allowing for thousands of iterations with randomized inputs to reflect real-world uncertainty. The results aid in determining the optimal contingency percentage that minimizes total inventory cost while ensuring material availability.

#### 4.2. Monte Carlo Simulation

This simulation proposes a probabilistic model to estimate project cost contingency that will happen by considering any risk that can occur on a variety of economic value effects economically. Stochastic quantitative analysis has been performed using Monte Carlo Simulation (MCS) to determine the probability distribution of the contingency cost and the related level of risk coverage.

Data on material usage and project costs were categorized annually (2016–2018). Two levels of contingency percentages were applied: 10% and 20%. These values were determined based on material utilization percentages (Utilized%). The first quartile (utilization  $\leq 89\%$ ) uses a 10% contingency, while values above 89% apply a 20% contingency.

The simulation process follows several distinct steps:

1) Classification of utilization levels using the interquartile range (IQR) to assign appropriate contingency percentages.

2) Addition of random error ranging from 1–10%, simulating unforeseen variations in demand or logistical issues.

3) Calculation of re-order needs using the mathematical model referred to equation 1 – 8.

4) Estimation of probabilities and financial impact using:  $Probability\ (%) = Frequency\ of\ deficit\ cost / Sum\ data\ of\ the\ year$   $(12)$

$Expected\ Return\ ($) = Probability\ (%) * Total\ Shortage\ Cost\ ($)$   $(13)$

The simulation identifies materials resulting in deficit costs after random error is added. Table 1 presents the results. Lowering the contingency percentage reduces surplus cost. This surplus reduction is treated as an investment, which can be used to finance future reorders in case of deficits. To measure the associated risk, a Value at Risk (VaR) analysis was conducted based on "Surplus plus Error" data. This simulation outputs the probability of investment risk across confidence intervals of 90%, 95%, and 99%." The data will be categorized by the year. The average surplus quantity also shows the deficit quantity. This simulation will show the percentage of risk

Table 2. Deficit quantity (Surplus + Error)

Surplus plus error	2016	2017	2018
Average	2	2	0
Standard Deviation	11	11	1
Simulation 1	6	0	0

Table 3. Result from the Monte Carlo Simulation (500 iterations)

	2016	2017	2018	
Expected Return	2	2	0	
Standard Deviation	11	12	1	
90%	-12	-13	-1	
Variance	95%	-16	-17	-2
99%	-23	-25	-3	
Simulation (1 million)	\$119,223	\$126,055	\$13,701	
	\$159,800	\$168,704	\$17,762	
	\$234,372	\$247,087	\$25,225	

Table 4. The results from the pipes each year

2016			
	Total Cost Re-order	Probability	Expected Return
Average Cost	\$552,550	15%	\$83,530
Standard Deviation	\$2,144		
2017			
	Total Cost Re-order	Probability	Expected Return
Average Cost	\$943,738	13%	\$125,303
Standard Deviation	\$2,855		
2018			
	Total Cost Re-order	Probability	Expected Return
Average Cost	-	0%	\$0
Standard Deviation	-		

Table 5. Deficient quantity of pipes each year

Surplus plus error	2016	2017	2018
Average	1	2	0
Standard Deviation	6	12	0
Simulation 1	4	-8	0

affecting the company's investment to decrease the surplus cost.

There will be a comparison of the expected value from simulation and the expected value of the probability that we count from how many deficits happened in that year, as shown in Table 2, the expected value with probability.

The simulation will run until 500 hundred data points that will be used the result of the simulation will be shown in Table 3. Confidence intervals that will be used are 90%, 95%, and 99%. The company will have many options to see the risk from the investment. The researchers assumed that the company would invest the decrease in surplus cost, which is 1 million, along with these are the values

that represent the risks each year in its respective variance.

The researchers specified the results by categorizing the materials into two (2): the pipe and pipe fitting, each year from 2016 to 2018.

#### 1. Pipe

The researchers assume that the cost surplus that has been reduced is an investment. The investment will have risk each year. Therefore, we simulate to see how much of the investment the company will spend to cover the reorder cost (Tables 4, 5, 6).

#### 2. Pipe fitting

The researchers assume that the cost surplus that has been reduced is an investment. The investment will

have risk each year. Therefore, we simulate to see how much of the investment the company will spend to cover the reorder cost. (Table 7, 8, 9)

The application of a 20% contingency percentage in purchasing offshore construction materials led to significant surplus costs and excess inventory for the company. Recognizing these disadvantages, the company aimed to determine an optimal contingency sum to reduce the 10% surplus cost. By employing Monte Carlo simulation, the researchers successfully lowered the surplus cost from 10% to 9%, along with the overall material cost.

Rather than relying on a single contingency percentage, the researchers utilized two different percentages based on the level of material utilization. The interquartile range (IQR) method was employed to establish variability around the median, with quartiles determined as Q1 = 84%, Q2 = 87%, and Q3 = 92%. This classification led to two contingency classes.

1) **First Class:** For utilization percentages  $\leq 89\%$ , a 10% contingency is applied.

2) **Second Class:** For utilization percentages  $> 89\%$ , a 20% contingency is applied. (Figure 3)

This refined approach to contingency management, which moves away from a standard flat rate, provides a more nuanced and effective method for addressing the inherent risks and complexities of offshore construction projects. By implementing two distinct classes of contingency, the company can better tailor its risk management strategies according to project-specific factors. This differentiation helps ensure that excess inventory and surplus costs are minimized, thereby optimizing the overall budget and project performance.

The study's findings emphasize the importance of a well-calibrated contingency plan, which not only mitigates financial risks but also aligns with project timelines and objectives. The introduction of a dual-class contingency model offers a strategic advantage, providing clear guidelines for decision-making based on utilization rates. This approach ensures that the company is prepared for potential risks, with a predefined strategy to address issues as they arise, thus safeguarding both financial

Table 6. Result from the Monte Carlo simulation of the pipes each year

	2016	2017	2018	
Expected Return	2	2	0	
Standard Deviation	6	12	0	
90%	-6	-14	0	
Variance	95%	-8	-18	0
	99%	-12	-27	0
Simulation (1 million)	\$58,015	\$136,606	0	
	\$79,704	\$182,130	0	
	\$119,565	\$265,797	0	

Table 7. The results from the pipe fitting each year

	2016	2017	2018
Average Cost	Total Cost Re-order	Probability	Expected Return
Average Cost	\$277,876	16%	\$44,515
Standard Deviation	\$1,448		
	2017	2018	
Average Cost	Total Cost Re-order	Probability	Expected Return
Average Cost	\$1,002,337	12%	\$118,910
Standard Deviation	\$2,609		
	2018	2018	
Average Cost	Total Cost Re-order	Probability	Expected Return
Average Cost	\$3,202	13%	\$426
Standard Deviation	\$599		

Table 8. Deficient quantity of pipe fittings each year

Surplus plus error	2016	2017	2018
Average	1	2	0
Standard Deviation	11	11	1
Simulation 1	8	-2	1

Table 9. Result from the Monte Carlo simulation of the pipes fitting each year

	2016	2017	2018	
Expected Return	2	2	0	
Standard Deviation	11	12	1	
90%	-12	-13	-1	
Variance	95%	-16	-18	-2
	99%	-24	-26	-3
Simulation (1 million)	\$121,277	\$132,790	\$14,377	
	\$161,849	\$177,073	\$18,650	
	\$236,415	\$258,459	\$26,503	

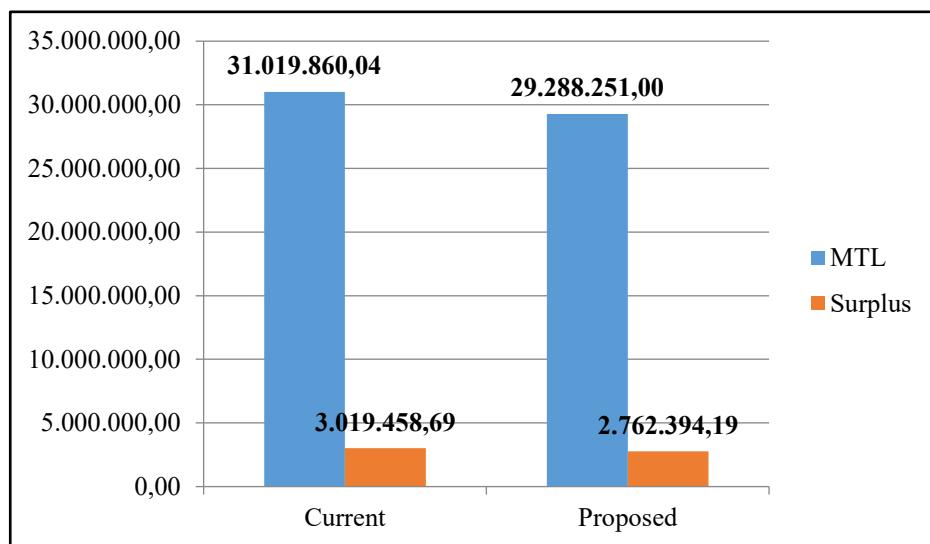


Figure 3. Comparison of the material and surplus cost

stability and operational efficiency.

In summary, the research successfully met its primary objective of assessing the impact of contingency sums on project material procurement and identifying methods to reduce surplus costs. The study also highlighted the benefits and drawbacks of maintaining an adequate contingency percentage. The methodologies and tools developed can serve as valuable references for other companies facing similar challenges with contingency percentages, surplus costs, and excess inventory. The comprehensive analysis and solutions provided offer a robust framework for optimizing inventory management and enhancing project outcomes.

## 5. CONCLUSIONS

This study demonstrated that optimizing contingency percentages can significantly reduce surplus costs and excess inventory in offshore construction projects. By implementing a dual-class contingency model 10% for utilization rates  $\leq 89\%$  and 20% for rates  $> 89\%$  the company effectively lowered surplus costs from 10% to 9%. These findings highlight the importance of tailored contingency management in achieving cost efficiency and operational effectiveness, providing a valuable framework for other companies to enhance their inventory and risk management strategies.

## REFERENCES

Bozarth, C.C., Handfield, R.B., & Chandrasekaran, A. (2020). *Introduction to operations and supply chain management*. Pearson.

Burroughs, S.E., & Juntima, G. (2004). Exploring techniques for contingency setting. *AACE International Transactions*, ES31.

Chen, C., Chen, M., & Zhao, X. (2019). Impact of lead time uncertainty and lead time reduction on the performance of inventory control policies. *International Journal of Production Economics*, 218, 214–223.

Chikán, A. (2009). *Managing inventory: Concept, theories, and practices*. Springer.

Davis, K., & Patterson, D. (2012). *Ethics of big data: balancing risk and innovation*. O'Reilly Media.

England, A., & Moreci, J. (2012). *Project cost estimating and control*. AACE International.

Howard, R.A., & Matheson, J.E. (2005). Influence diagrams. *Decision Analysis*, 2(3), 127-143.

Jimoh, R.A., & Adama, U.J. (2014). Assessment of contingency sum in relation to the total cost of renovation work in public schools in Abuja, Nigeria. *International Journal of Managerial Studies and Research*, 2(10), 55-63.

Kannan, V. R., & Tan, K. C. (2005). Just in time, total quality management, and supply chain management: Understanding their linkages and impact on business performance. *Omega*, 33(2), 153–162.

Mak, S., & Picken, D. (2000). Using risk analysis to determine construction project contingencies. *Journal of Construction Engineering and Management*, 126(2), 130-136.

Marquez, P.C., Agustina, D., & Amin, S.H. (2021). Integrated vendor-managed inventory and supply chain coordination models: A review. *Computers & Industrial Engineering*, 159, Article 107526.

Perera, H.S.C., Samarasinghe, G.D., & Samarasinghe, D. (2019). Predictive analytics and risk analysis in supply chain management. *International Journal of Supply Chain Management*, 8(2), 91–97.

Rubio, J. L., & Jiménez-Parra, J. F. (2018). A new Monte Carlo simulation approach for inventory management in retailing. *Mathematics*, 6(11), 248-260.

Rossetti, M.D. (2008). *Simulation modeling and arena*. John Wiley & Sons

Shachter, R.D. (2019). Influence diagrams for representing and solving decision problems. *Communications of the ACM*, 32(5), 408–415.

Shah, R., & Shin, H. (2007). Relationships among information technology, inventory, and firm performance. *Production and Operations Management*, 16(5), 577–593.

Torra, V., Narukawa, Y., Aguiló, I., & González-Hidalgo, M. (2018). *Modeling decisions: Information fusion and aggregation operators*. Springer.

Venkatesan, M., Prajapati, P., & Raj, T. (2019). Analysis of inventory turnover as a measure of inventory performance: An empirical study. *Materials Today: Proceedings*, 18, 1826–1831.

Wakjira, M.T. (2021). Application of Monte Carlo simulation for inventory management. *American Journal of Operations Management and Information Systems*, 6(1), 1–6.

Watt, A. (2012). *Project management*. B.C. Open Textbook Project.

Yang, X. (2020). Just-in-time inventory management system and business performance: The moderating role of demand uncertainty. *International Journal of Production Economics*, 230, Article 107861.

Zhao, T., & Tseng, C.L. (2003). Valuing flexibility in infrastructure expansion. *Journal of Infrastructure Systems*, 9(3), 89-97.

*This page is intentionally left blank*