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OPTIMIZATION OF TIN GRANULAR INVENTORY MANAGEMENT THROUGH MODELLING MONTE CARLO SIMULATION

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Abstract

Problems: In the manufacturing industry, uncertainty in raw material demand is a critical challenge that can lead to stockouts and overstocking. The tinplate production line faces an operational scheduling asymmetry: the internal production unit for granular tin raw materials operates only five days a week, while the main production process runs continuously seven days a week.

Purpose: This study aims to design an adaptive and accurate granular tin inventory planning system using a stochastic simulation approach.

Methodology: This study used a Monte Carlo simulation in Python to minimize the margin of error and account for the probabilistic nature of demand uncertainty.

Results/Findings: The Python-based Monte Carlo simulation results achieved an accuracy level of 93.34% with a Mean Absolute Percentage Error (MAPE) of only 7%. These results fundamentally outperform classical forecasting methods such as Moving Average (MAPE 57%), Linear Regression (MAPE 50%), and Holt's Exponential Smoothing (MAPE 53%). This approach has proven effective in minimizing the risk of raw material shortages and optimizing the company's inventory costs. The integration of this simulation enables a transition from static forecasting to scenario-based planning, significantly improving cost efficiency and supply chain resilience amid extreme operational fluctuations.

Paper Type: Quantitative analytical research

***Keywords**:* Forecasting, Inventory, Monte Carlo Simulation, Python, Tin Granular

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A. INTRODUCTION

In the manufacturing industry, supply chain efficiency and operational resilience depend heavily on management's ability to plan raw material supply (Qurthuby et al., 2025). High demand uncertainty creates the risk of stockouts, which can halt production lines and lead to lost sales or higher storage costs. One strategic approach used to address demand and supply uncertainty is accurate, data-driven inventory planning.

Inventory management in the steel manufacturing industry, particularly tinplate production, demands high precision due to the complexity of material flows and the enormous cost of raw material investment. Uncertainty in raw material demand could pose operational risks that halt the main production line. The tinplate manufacturing process is highly dependent on the availability of granular tin as the primary raw material. Based on internal data, the company faces complex challenges in managing its inventory of internally produced granular tin. This situation is influenced by several factors, including the variability in tin coating thickness on tinplate and differences in operational schedules between granular tin production, which runs only five days a week, and tinplate production, which operates continuously (seven days a week). This cycle imbalance creates stochastic challenges that cannot be resolved with static inventory planning.

The complexity of this issue is compounded by technical variability in the production process. Demand for granular tin is greatly affected by fluctuations in coating thickness per customer order, the need for routine furnace maintenance every 2 weeks, and the need for rigid inventory planning with a target of 4 tonnes per day. These production dynamics give rise to several interrelated operational problems. The limited work schedule of Tin Particle Section operators is often not in line with the continuous demand for tinplate production. This problem reflects a high level of uncertainty in raw material requirements, making the conventional approach to inventory planning less effective. It often results in the company facing overstocking, which incurs storage costs, or the risk of stockouts, which threaten the fulfillment of national production targets.

Based on internal company data (Figure 1), there has been a discrepancy between usage and print output over the past year. There were stockouts of granular tin in March 2024, May 2024, July 2024, September 2024, November 2024, and April 2025. Meanwhile, in January 2024, June 2024, August 2024, October 2024, December 2024, and three consecutive months at the beginning of 2025, namely January, February, and March, there was an excess of stock (overstock). This imbalance indicates a discrepancy between demand and supply, which could lead to production inefficiencies,

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increased storage costs, and the risk of stock shortages.

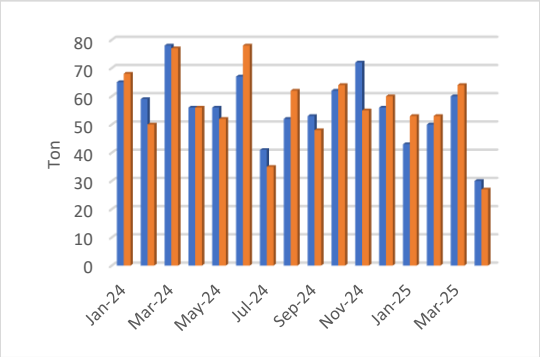


Figure 1. Use of granular tin

Efforts to overcome these challenges have given rise to various forecasting methods, from classical statistical models such as ARIMA and Moving Average to regression models. However, these methods often assume the existence of stable historical patterns that can be extrapolated. This weakness necessitates a more robust approach that is capable of handling the stochastic (random) nature of actual demand data.

Unlike predictive models that attempt to find a single best formula, Monte Carlo simulations build models from empirical probability distributions derived directly from historical data. Monte Carlo simulation is a technique used to predict raw material requirements by modelling and analysing systems that contain uncertainty. Monte Carlo simulation relies on random numbers to estimate the values of uncertain variables, aiming to provide a probabilistic picture of possible outcomes (Rubinstein & Kroese, 2016; Teguh et al., 2022). This method enables more accurate planning by using probabilistic models that account for various random variables that may affect production outcomes. This approach helps companies plan and control more effectively by using more accurate projections of demand and resource requirements (Safitri et al., 2020; Zalmadani et al., 2020).

Efforts to model demand uncertainty have been widely conducted using a range of simulation and forecasting methods. Several previous studies have applied the Monte Carlo method to inventory optimization, but most have focused on smaller businesses or more stable demand patterns. For example, Jufriyanto (2020) applied Monte Carlo to forecast demand in the MSME sector, which has lower disturbance variables. Similarly, Prawita et al. (2020) used a similar approach for pesticide production planning and office stationery stock, where the supply cycle tends to follow a regular seasonal pattern.

This study fills a gap by testing the robustness of Monte Carlo simulations in heavy manufacturing industries facing asymmetric operational constraints. The uniqueness of this study lies in integrating empirical probability distributions to handle demand data with high volatility and zero demand on certain days. Furthermore, this study utilises Python

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to demonstrate that forecasting accuracy in complex systems requires greater computational capacity and more iterations. Through this approach, it is hoped that an inventory planning model will be created that is not only quantitatively accurate but also adaptive to the fluctuating dynamics of steel production floors.

B. LITERATURE REVIEW

Forecasting is an important process in resource management that aims to predict future conditions based on past data and patterns. Good forecasting methods produce predictions that are close to actual needs, thereby minimizing potential risks and improving company performance (Fabianova et al., 2019).

Deterministic approaches such as exponential smoothing and moving averages are often used to achieve the desired level of accuracy. These models assume that each input has a definite value that will produce a definite output (Uusitalo et al., 2015). This approach has limitations, as it is not well suited to forecasts that involve shifts in demand, supply disruptions, or process variability, which could lead to stock shortages or excess inventory (Kumar et al., 2024).

Monte Carlo simulation has the advantage of modelling uncertainty through empirical probability distributions rather than relying on linearity assumptions. Monte Carlo simulation addresses demand uncertainty by simulating many random scenarios based on selected probability distributions, then assessing the distribution of results to evaluate quantitative risk. Several studies show that applying Monte Carlo simulation reduces uncertainty in calibration (García-Berrocal et al., 2024), gas flow (Crowder et al., 2020), EMC (Lee et al., 2003), and environmental modelling (Ciecior et al., 2018). The Monte Carlo method was implemented in a web-based system to predict sales of several components; the predictions achieved high accuracy for different items, enabling stock quantity optimisation (Paixão & Silva, 2019). Monte Carlo applications were also used in pharmacies during the Monte Carlo pandemic to simulate three-month projections and compare EOQ and Min-Max policies, thereby helping to select the EOQ policy that provided the lowest total inventory cost in the study (Hidayatuloh et al., 2023). Monte Carlo simulation can also be applied to inventory planning to address challenges such as demand fluctuations and lead-time variability. Jufriyanto (2020) used this technique to forecast cassava chip demand among MSMEs, achieving an accuracy rate of 98.68%.

The Monte Carlo method does not focus solely on simple random sampling but also on integrating complex operational parameters (Luengo et al., 2020). Monte Carlo simulations are highly dependent on an accurate representation of input distributions

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because input model uncertainty directly affects the output. In the manufacturing industry, discrete distributions are more representative than normal distributions because they can capture outlier phenomena, such as spikes in demand or unstable production conditions.

Although Microsoft Excel remains popular for small-scale simulations, its limitations in handling large iterations are an obstacle to achieving statistical convergence (McEwan et al., 2010). The use of computing enables the efficient execution of large iterations (Kurniawan & Silalahi, 2023), thereby reducing the margin of error compared to limited spreadsheet-based simulations. This computational advantage enables model validation with greater confidence.

C. METHODS

This study uses a quantitative, comparative case study to objectively evaluate and compare the performance of Monte Carlo Simulation with three classical time series forecasting methods. The case study was applied to daily granular tin usage data that faced challenges related to uncertainty in raw material demand. The data were taken from the production recording system for the period January 2024 to April 2025, totaling 486 data points.

The proposed method is the development of a discrete empirical probability distribution derived directly from historical data. The process begins by grouping the frequency of each daily usage value (ton) to calculate its relative probability. Next, a cumulative distribution is formed to map random numbers to the corresponding demand values.

This method involves several stages that must be followed to ensure accurate, reliable results. The Monte Carlo simulation method is a highly effective technique for dealing with complex problems involving uncertainty, and is used in various fields such as finance, engineering, and risk analysis. The following are the main steps in data processing using Monte Carlo simulation:

1. Density Distribution
   Once the daily frequencies are known, they are converted into probabilities by dividing each demand value's frequency by the total number of data points.
2. Cumulative Distribution
   The probabilities of each demand value are gradually added up to form a cumulative distribution. This distribution will be used to map random numbers to demand values.
3. Random number
   To generate random numbers, Microsoft Excel uses the RAND() formula, and Python uses standard modules such as random or numerical libraries such as numpy to generate numbers between 0 and 1. The number of random numbers generated is adjusted to the number of simulation periods.

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4. Simulating demand
   Each random number is mapped to a cumulative distribution range to determine the simulated demand. Simulation results can be organised in tables or graphs to analyse demand projections.
5. Evaluation
   Evaluation is conducted using a Monte Carlo simulation to test whether the established policy can maintain optimal inventory levels, avoiding stockouts and overstocking.

In this study, the number of iterations was set in the range of 50,000 to 100,000 times. This number was selected based on the Law of Large Numbers (Daulay et al., 2023), which states that as the number of trials increases, the average simulation results will converge towards the expected value. The use of 50,000 iterations through a Python script minimises standard error and ensures statistical stability (convergence). In Microsoft Excel, a very large number of iterations often degrades computational performance and limits data visualisation. In contrast, the vectorised operations approach in Python allows simulations to be run repeatedly quickly, providing higher confidence.

This study uses three standard error metrics to evaluate and compare the accuracy of each forecasting method quantitatively. Mean Absolute Error (MAE) measures the average absolute error without regard to direction. Mean Squared Error (MSE) squares the error before averaging it. The Mean Absolute Percentage Error (MAPE) measures error as a percentage of the actual value.

D. RESULTS AND DISCUSSION

The Tin Particle Section is where the tin granulation process takes place. Metal granulation generally involves breaking down or spraying molten metal into fine droplets, which then solidify into granules, thereby increasing the surface area and ease of processing. Granular tin is tin that has been processed into small particles or granules. This process involves spraying molten tin into a cooling medium, such as water, to form particles. Granular tin has several advantages, including ease of storage, transportation, and further processing.

Based on the company's internal reports, the data were grouped by daily frequency to facilitate the simulation process. The daily usage frequency data, in tonnes, for the 2024–2025 period totalled 486 observations. The data distribution showed a tendency for the highest frequency to occur at 2 and 3 tonnes per day. There is extreme variation in the usage pattern, with 0 tonnes on 105 days and 7 tonnes on 1 day (Table 1). The validity of this data is the main foundation for Monte Carlo simulation, where random number intervals (0-100) are mapped to cumulative frequency distributions to

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ensure the model reflects the real dynamics of the production floor.

Table 1. Frequency of tin granular use

Daily Frequency	
Amount (Tons)	**Frequency**
0	105
1	62
2	145
3	148
4	22
5	3
7	1
Total	486

The density distribution is obtained by dividing the frequency of each demand value by the total number of data points.

$$P(x) = \frac{f(x)}{n} \quad (1)$$

where P(x) = Probability of using x tonnes; f(x) = Frequency of using x tonnes; and n = Total frequency

The density distribution serves as the basis for determining the relative probability of each possible outcome in a random process (Table 2).

The cumulative distribution can be obtained by sequentially summing the density distribution (Table 3). This distribution serves as the basis for the Monte Carlo simulation process, converting random numbers into daily usage values (tonnes) based on historical data. This cumulative function is used to divide the range of random numbers between 0 and 1 into several intervals, each representing a specific usage value (Table 4). The main function of this tag number is to ensure that the simulation results reflect historical patterns realistically while remaining based on a random process, so they can be used for more accurate decision-making.

To generate random numbers in Monte Carlo simulations, use Python. According to the Excel Monte Carlo Resource Centre guide, to achieve good accuracy in simple simulations, it is recommended to perform at least 50,000 iterations. However, Microsoft

Table 2. Density distribution

Amount (Tons)	Frequency	Density Distribution
0	105	105/486 = 0.216
1	62	62/486 = 0.127
2	145	145/486 = 0.298
3	148	148/486 = 0.304
4	22	22/486 = 0.045
5	3	3/486 = 0.006
7	1	1/486 = 0.002
Total	486	

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Table 3. Cumulative distribution

Amount (Tons)	Frequency	Density Distribution	Cumulative Distribution Function
0	105	0.216	0.216
1	62	0.127	0.343
2	145	0.298	0.641
3	148	0.304	0.945
4	22	0.045	0.990
5	3	0.006	0.996
7	1	0.002	0.998
Total		486	

Excel has limitations in handling very large numbers of iterations. For complex simulations with many random variables, it is more advisable to use Python (Table 5).

Table 4. Tag number

Tag Number	Amount (Tons)
00 – 0.216	0
0.217 – 0.343	1
0.344 – 0.641	2
0.642 – 0.945	3
0.946 – 0.990	4
0.991 – 0.996	5
0.997 – 0.998	7

The optimal number of iterations (randomization) in Monte Carlo simulations depends heavily on the model's complexity. Based on previous studies, it is recommended that the number of iterations be between 10,000 and 100,000, depending on the model's complexity. Hu et al. (2022) recommend 10,000 iterations to obtain an error of <2% in adequate probability distribution simulations. A similar approach was reported in a manufacturing study, which suggested a minimum of 50,000 iterations (Kurniawan & Silalahi, 2023).

Overall, these studies confirm that there is no single universal iteration number, but in general, it is recommended that 1,000–10,000 iterations are sufficient for simple simulations. For high accuracy or extreme analysis, it is recommended to use ≥50,000 iterations. In this study, 50,000–100,000 iterations were run in Python to obtain the best results.

After generating random numbers in Python, they were assigned to predetermined tag numbers. Based on Monte Carlo simulations using Python to generate random numbers, the tin granule requirement for May 2025 was

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32 tonnes, while the actual tin granule usage in May 2025 was 30 tonnes (Table 6).

Table 5. Random number table

Date	Random Number
05/01/2025	0.596917
05/02/2025	0.921498
05/03/2025	0.027378
05/04/2025	0.076205
05/05/2025	0.950270
05/06/2025	0.073283
05/07/2025	0.012675
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05/23/2025	0.138310
05/24/2025	0.064434
05/25/2025	0.410850
05/26/2025	0.515099
05/27/2025	0.475214
05/28/2025	0.059240
05/29/2025	0.022049
05/30/2025	0.034010
05/31/2025	0.187394

This study found significant differences in performance between spreadsheet use (Excel) and programming (Python). Although Excel is capable of executing basic simulations with the =VLOOKUP and =RAND() functions, this platform experiences performance degradation when the number of iterations is increased above 10,000. In contrast, Python scripts enable the simultaneous execution of 50,000 to 100,000 iterations with high stability. Python's technical advantage lies in its ability to run multiple trials to automatically obtain a convergent expected value. It provides greater academic value it minimising the subjective bias that often arises in manual data processing.

Table 6. Forecast for granular tin python in May 2025

Date	Random Number	Ton
05/01/2025	0,200917	0
05/02/2025	0,474498	2
05/03/2025	0,051378	0
05/04/2025	0,229205	1
05/05/2025	0,354270	2
05/06/2025	0,488283	2
05/07/2025	0,269675	1

05/23/2025	0,353310	2
05/24/2025	0,134434	0
05/25/2025	0,127850	0
05/26/2025	0,407099	2
05/27/2025	0,306214	1
05/28/2025	0,092240	0
05/29/2025	0,604049	2
05/30/2025	0,502010	2
05/31/2025	0,077394	0

The accuracy of a Monte Carlo simulation using Python to generate random numbers for planning granular tin supplies in May 2025 reached 93.34%. This result is better than when using Microsoft Excel to generate random numbers. The random numbers are found in iteration 1363 as

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Table 7. Comparison of tin granular forecasts for May 2025

Method	Demand (Ton)	Forecast	MAD	MSE	MAPE
Monte Carlo	30	32	2	32	7%
Moving Average	30	47	17	289	57%
Linear Regression	30	45	15	225	50%
Holt's Exponential Smoothing	30	46	16	256	53%

an initial indicator of model stability, but the results' validity still relies on the Law of Large Numbers.

The comparison results show that the Monte Carlo simulation method provides the most accurate prediction, namely 32 tonnes with a MAPE of 7%, thus having the lowest error rate compared to other methods. Moving Average predicts 47 tonnes with a MAPE of 57%, Linear Regression produces 45 tonnes (MAPE 50%), and Holt's exponential smoothing produces 46 tonnes (MAPE 53%) (Table 7). The failure of these classical methods is due to the linear nature of the data and their tendency to smooth all data points. In contrast, the stochastic Monte Carlo method captures these random characteristics, resulting in a demand projection of 56 tonnes for June 2025 with a much higher confidence level. It proves that the probabilistic approach is the most reliable solution for inventory optimization amid operational uncertainty (Zhang et al., 2025).

D. CONCLUSION AND RECOMMENDATION

This study shows that Monte Carlo simulation is a much more reliable forecasting tool than conventional deterministic methods for handling the intermittent and fluctuating dynamics of raw material demand. A Python-based Monte Carlo simulation achieved an accuracy rate of 93.34% with a Mean Absolute Percentage Error (MAPE) of 7%. This performance significantly outperforms the Moving Average, Linear Regression, and Holt's Exponential Smoothing methods, which have error margins above 50%. For the June 2025 period, the simulation results project a total requirement of 56 tons of granular tin, which can serve as a basis for procurement planning to ensure the continuity of tinplate production. The application of this simulation provides a concrete solution to the problem of operational asymmetry between the raw material production unit (5 working days) and the main production line (7 working days). This model allows the company to shift from a static stock policy to a more adaptive risk-based inventory management.

Although demonstrating high accuracy, the simulation model developed is based solely on historical

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demand probability distributions (internal factors) and does not yet integrate external variables, such as fluctuations in the global tin price. Further research is recommended to integrate the Monte Carlo method with a Machine Learning approach or dynamic system modelling in order to capture the interaction between internal operational variables and external market volatility more comprehensively.

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