Applying the Monte Carlo Method for Modeling Order Fulfillment with Consideration of Supply Risk

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Abstract — **This paper presents the application of the Monte Carlo method for modelling order fulfilment, taking into account supply risks and delays. The method allows for the consideration of stochastic events and uncertainties in supply chains, which are becoming increasingly complex and vulnerable to various risks, such as production failures, transportation issues, and external factors. Using probabilistic distributions, the Monte Carlo method enables forecasting the frequency and impact of delays, supporting proactive decision-making in logistics management. The developed model assesses the likelihood of on-time order fulfilment under uncertainty, demonstrating the effectiveness of Monte Carlo simulations. The simulation results provide insights into delay patterns, risk factors, and potential strategies for minimizing them, creating opportunities for supply chain optimization.**

Keywords — Monte Carlo method, modelling, supply chain, supply risks, delays, logistics, resilience, uncertainty, stochastic events, forecasting, optimization.

Introduction

The Monte Carlo method is increasingly pivotal in the simulation of order fulfilment processes, particularly within supply chains characterized by numerous risks and uncertainties. In environments where deliveries may be disrupted by a multitude of factors—ranging from production failures and transportation issues to weather events and political instabilities—traditional planning methods often prove inadequate. In contrast, the Monte Carlo approach enables the modelling of a broad spectrum of scenarios, incorporating the stochastic nature of these disruptions effectively. This method's significance lies in its ability to simulate random events and uncertainty, making it especially relevant for contemporary supply chain management. For example, delays can be modelled based on established probabilistic distributions, allowing for the forecasting of both the frequency and severity of potential disruptions. A Poisson distribution, for instance, can be utilized to represent the frequency of delays or failures, enabling a probabilistic assessment of such occurrences. In this framework, each event is treated as an independent simulation, and the larger the number of simulations, the greater the precision in the resulting predictions. This approach provides a strategic advantage in contexts where reactive problem-solving is insufficient or impractical. By employing the Monte Carlo method, organizations are better equipped to anticipate potential disruptions and develop preemptive strategies, thereby enhancing resilience and optimizing overall supply chain performance. The flexibility of the Monte Carlo method is evident in its adaptability to diverse conditions. For instance, if lead times are known to follow a normal distribution, this distribution can be directly applied. Alternatively, in cases where the distribution is asymmetric, a beta distribution may be employed instead. This adaptability makes the Monte Carlo method a versatile tool for analyzing a range of logistics challenges, whether forecasting delivery times, assessing risks associated with product spoilage, or evaluating the impact of delays on the entire supply chain. The results of these simulations provide a strong basis for data-driven decision-making. Management can utilize this information to assess the potential impact of supply chain adjustments on overall order fulfilment times, empowering them to implement strategic policy changes, such as adding contingency routes, increasing inventory levels, or partnering with new suppliers. Simulation analysis also allows for proactive identification and mitigation of supply chain vulnerabilities, helping to enhance overall resilience and efficiency. As global supply chains grow more complex, they face heightened exposure to diverse risks—ranging from financial and political disruptions to environmental and social challenges. This exposure highlights the essential need to incorporate a variety of risk factors and simulate potential scenarios. In this context, the Monte Carlo method is invaluable, enabling the modelling of even rare, high-impact events. By simulating such scenarios, companies can reduce potential losses and build greater resilience into their supply chain, equipping them to respond more effectively to unexpected disruptions. Another significant aspect of the Monte Carlo approach is its application in logistics optimization. When simulations indicate that certain routes may lead to delays, companies can make proactive adjustments to their delivery plans. This not only reduces the costs associated with disruption recovery but also increases the reliability of order fulfilment, an outcome that is particularly valuable for maintaining client satisfaction. Contemporary challenges, including pandemics, climate change, trade conflicts, and other global factors, further underscore the critical importance of Monte Carlo simulations in modern supply chain management. Today's supply chains operate amid unprecedented levels of uncertainty, which conventional planning methods struggle to address comprehensively. The Monte Carlo method, however, enables the modelling of various "what-if" scenarios, providing a robust framework for anticipating a broad spectrum of potential disruptions. Fundamentally, this approach serves as a powerful tool for both risk management and efficiency optimization. By simulating diverse scenarios, the Monte Carlo method enables organizations to evaluate the resilience of their operations under fluctuating conditions, thereby identifying not only risk factors but also opportunities for enhanced efficiency. This capability becomes particularly essential as businesses increasingly pursue flexible, adaptive management strategies, emphasizing a proactive approach to operations rather than merely reactive responses to emerging issues.

The primary contributions of this article are as follows:

1. Application of the Monte Carlo method for simulating order fulfilment under supply chain uncertainties.

2. Incorporation of delay and disruption risks into the forecasting model, enhancing its practical applicability.

3. Development of a mathematical model for estimating the probability of on-time order fulfilment, thereby improving planning accuracy.

4. Analysis of the impact of uncertainty on logistics processes, supporting increased resilience and flexibility within supply chains.

The remainder of this article is organized as follows: Section 2 provides a literature review, emphasizing the importance of risk analysis and the application of the Monte Carlo method for assessing risks in supply chains to mitigate delays. Section 3 formulates the research problem, focused on predicting order fulfilment times considering risks and delays, with a formal approach to calculating the probability of timely completion. Section 4 describes the Monte Carlo method for modelling probabilistic scenarios and outlines an algorithm covering the key steps, from initialization to the assessment of statistical characteristics. Section 5 presents the simulation results, demonstrating the impact of uncertainty levels on order fulfilment times and delay risks, supported by diagrams and visualizations. The final Section discusses the Monte Carlo method as an effective tool for risk management and enhancing supply chain flexibility, particularly under conditions of global uncertainty.

2. Relevant work

These articles explore diverse applications of the Monte Carlo method for risk modelling in order fulfilment, offering insight into how this approach facilitates managing uncertainty and mitigating the effects of delays within supply chain operations. Presented here are examples of studies that employ Monte Carlo simulations to model order fulfilment under supply risk conditions. Paper [1] introduces a model for evaluating the impact of tactical procurement risks on order fulfilment in make-to-order production, with a specific focus on risks like delays, price volatility, and quality fluctuations that critically influence timely order completion. In Paper [2], a comprehensive review is conducted on supply chain risk management, emphasizing the role of Monte Carlo simulations in quantifying risks from delivery delays and logistical disruptions. The authors underscore the necessity of quantitative risk assessments in devising effective mitigation strategies. Paper [3] elaborates on the combined use of Monte Carlo and discrete-event simulations to quantitatively assess supply chain disruption risks, proposing a model for analyzing the effects of different types of risks, including delays and operational interruptions, on order fulfilment. Paper [4] examines supplier selection methodologies with a focus on resilience to disruptions, employing Monte Carlo simulations to quantify risk exposure and predict delay probabilities under various disruption scenarios. Paper [5] addresses strategies to mitigate supply chain disruption risks, utilizing Monte Carlo simulations to assess delay probabilities while highlighting practical approaches to risk management and minimizing impacts on business operations. In the paper [6], the authors present a conceptual and analytical framework for supply chain risk management, with a detailed exploration of how Monte Carlo simulations are applied to calculate the likelihood of failures and delays and to evaluate their effects on logistical processes. Paper [7] outlines a systems-based approach to risk modelling in supply chains using Monte Carlo simulations, examining the impact of various uncertainty sources, such as delays and breakdowns, on the efficiency of order fulfilment and supply chain resilience. Paper [8] discusses dynamic recovery strategy development for supply chains susceptible to cascading disruptions, using Monte Carlo modelling to simulate recovery scenarios and evaluate order fulfilment timelines under delay risks. Finally, the paper [10] provides a critical review of methodologies for designing resilient supply chains and value networks, incorporating Monte Carlo simulations to assess and optimize order fulfilment processes amid supply uncertainty.

The objective of this study is to develop and apply the Monte Carlo method for modelling order fulfilment processes undersupply and delay risk conditions. This involves constructing a mathematical framework capable of predicting the likelihood of on-time order fulfilment amid uncertainty and examining the influence of multiple risk factors on logistics. This approach aims to strengthen supply chain resilience and adaptability, providing robust support for decision-making under uncertainty.

3. Problem Statement

The task of applying the Monte Carlo method for simulating order fulfilment while accounting for supply risks and delays is formulated as follows: Given a set of orders N, the goal is to determine the probability of each order being completed within specified deadlines. T_i. The order completion time D_i has a distribution $f(D_i)$, that incorporates uncertainties. Additionally, delay risks. P_j And delay time distributions. L_j Are introduced, which are associated with various types of failures. The simulation involves repeatedly generating random variables representing. D_i and L_{ij}, whereL_{ij} Is the delay caused by the j -th risk for order i. The total completion time of an order in each iteration of the simulation is $D_i + \sum_j L_{ij}$, where the probability of L_{ij} Occurring is determined by parameters. P_j . After performing a large number of iterations K , the distribution of total completion times is assessed, along with the probability that it does not exceed T_i. Based on the statistical data obtained during the simulation, metrics are calculated, such as the probability of on-time completion. $P_{execution}(T_i)$, the mean completion time, and measures of variability.

4. Materials and methods

4.1 Monte Carlo method

The Monte Carlo method was first proposed in the 1940s by physicists Stanislaw Ulam and John von Neumann. The name "Monte Carlo method" was introduced because it was associated with the gambling activities at the Monte Carlo casino, reflecting the use of random (stochastic) processes in the method. The first systematic description and application of the Monte Carlo method were presented in the work [10]. The Monte Carlo algorithm involves using random simulation to numerically solve various problems involving uncertainties and probabilistic processes. In this context, it is used to estimate event probabilities or statistical characteristics of complex systems. The algorithm includes several key steps, which can be detailed as follows:

Step 1: Initialization

Setting the initial state of the system. The initial state of the system is determined X(0), including the values of all state variables (e.g., initial resource stocks). This can be a single vector of values or a set of initial conditions considering different possible initial situations.

Definition of distributions of random variables. Defines probability distributions for all random variables involved in the model, such as resource supply$Q_i(t)$ and demand $D_i(t)$. These can be normal, lognormal, Poisson or any other distributions reflecting the nature of stochastic processes in the system.

Determination of time parameters. The time step is set Δt and the total number of modeling steps N_t , to set the duration of the simulation $T = N_t \Delta t$.

Step 2: Trajectory generation. For each simulated scenario, time-step iteration is performed to simulate the evolution of the system state. This process can be detailed as follows:

Trajectory Initialization. Starts from the specified initial state X(0).

1. **Time iteration.** Для каждого временного шага $t = 0, \Delta t, 2\Delta t, \ldots$,T:

- **Generation of random variables.** Random values are generated for all quantities such as $Q_i(t)$ and $D_i(t)$, using the given probability distributions.
- **b. Solving the dynamic model.** The system status is updated $X(t)$ According to a dynamic model described by a system of stochastic differential equations (SDE):

$$(t) = f(X(t), t)dt + G(X(t), t)dW(t) \quad (1)$$

Or, in discrete form:

$$X_{t+\Delta t} = X_t + f(X_t, t)\Delta t + G(X_t, t)\Delta W \quad (2)$$

,

where $f(X_t, t)$ describes the deterministic evolution of the system, and $G(X_t, t)\Delta W_t$ There's a stochastic component.

2. **Trajectory Recording.** The values obtained are stored $X(t)$ for each time step to fully describe the trajectory of the system state.

Step 3: Repeat trajectory generation.

The trajectory generation process from Step 2 is repeated many times (e.g., N times) to construct a statistically significant sample of possible system evolutions. Each trajectory represents one possible realization of the system evolution taking into account random perturbations.

Step 4: Estimation of probabilities or statistical characteristics.

Defining the target event. A criterion is specified for the event whose probability is to be estimated. For example, event A may represent a situation where the stocks of all resources remain above zero throughout the simulation period:

$$A = \{X_i(t) > 0, \forall i, \forall t \in [0, T \quad (3)$$

Counting successful realizations. The number of trajectories is determined. N_A , for which the event A occurred, i.e. the conditions of the task were fulfilled.

Calculating the probability of an event. The probability of the target event is estimated using the formula:

$$P(A) \approx \frac{N_A}{N}, \quad (4)$$

where N_A is the number of trajectories that satisfy the criterion, a N is the total number of generated trajectories.

Step 5: Estimation of statistical indicators

If it is required to estimate not only the probability of an event, but also other characteristics (e.g., mean, variance), the correspondig indicator is calculated for each trajectory, and a statistical characteristic is calculated from the results of all trajectories. For example, the mean value $\hat{\mu}$ and dispersion $\hat{\sigma}^2$ are estimated according to the formulas:

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} X_i, \quad (5)$$

$$\hat{\sigma}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \hat{\mu})^2, \quad (6)$$

where X_i is the result of the ith trajectory.

Thus, the Monte Carlo method can be used to numerically solve problems related to uncertainties and random processes, allowing us to estimate probabilities of complex events and calculate statistical characteristics. Its application is also appropriate for logistic activities.

4.2 Modeling of order fulfillment

To mathematically describe the steps of the algorithm aimed at modelling possible delivery delays using the Monte Carlo method, we present the main steps:

1. Problem statement and initial data

The task of modelling delivery delays is defined as a random process depending on the probability of delays and delivery lead time. Input data include:

Lots of orders $O = \{o_1, o_2, \dots, o_n\}$, where every order o_i characterized by:

Expected lead timeT_i,

Probability of delayR_i .

Multiple deliveries $S = \{s_1, s_2, \dots, \}$, where for each delivery s_j delay probability is set P_j and the length of the delay D_j.

2. Delay modelling by Monte Carlo method

At each modeling stage for each order o_i one of the possible delay scenarios is selected. For this purpose, a sample of delays is created, where:

The delay scenario is sampled according to the law of probability distribution$\{P_j\}$ per shipment s_j:

$$\Delta T_i = \begin{cases} D_j, \text{with a probability } P_j \\ 0, \text{with a probability } 1 - P_j \end{cases} \quad (7)$$

Here ΔT_i denotes a random delay value for the order o_i in the event of a delay event.

Updated delivery time T_i' for ordering $o_i$on account of the delay ΔT_i is calculated as:

$$T_i' = T_i + \Delta T_i. \quad (8)$$

This value represents the order fulfillment time including possible delays.

3. Estimation of entropy as an indicator of uncertainty

For an order with multiple possible outcomes (e.g., on-time delivery or delays of different durations), entropy can be calculated for the total uncertainty estimate based on the probability distribution of different delay scenarios. Formally, if X is a random variable denoting the fulfilment status of an order with n possible outcomes, then the entropy H(X) is defined as:

$$H(X) = -\sum_{k} p(x_i)_k \log(p(x_i)) \quad (9)$$

where $p(x_i)$ there is a probability of delay for each scenario x_i in a sample of possible outcomes. This indicator is a metric of randomness and allows quantifying the impact of uncertainty on the expected lead time.

Calculation of metrics to analyze results

Statistical measures such as average latency are calculated to evaluate the performance of the models and analyze the data:

$$Average\ delay = \frac{1}{N}\sum_{i=1}^{N}\left(T_{fact}^{(i)} - T_{plan}^{(i)}\right) \quad (10)$$

Where: N is the total number of orders; $T_{fact}^{(i)}$ is the actual execution time of order i ; $T_{plan}^{(i)}$ is the planned time of fulfilment of order i.

Deviations and standard errors can also be accounted for to analyze in detail the probability distribution of lead times, allowing the impact of delays on operational processes and supply chain resilience to be assessed.

Analysis and interpretation of results

The simulation results are analyzed to identify delay patterns and examine their distribution. Using visualizations of order fulfilment time distributions and entropy metrics, risks and their potential impact on fulfilment times can be assessed.

Thus, the proposed approach, based on the Monte Carlo method, enables the modelling of probabilistic delay scenarios in the supply chain by using uncertainty metrics to quantify risk. This method allows for the exploration of delay distributions and supports informed management decisions to minimize negative impacts on the supply chain.

Algorithm 1: Monte Carlo Simulation for Delivery Delay Modeling

```
Input: order_data, supplies_data, iterations = 1000
Output: Array of total delays for each iteration
Initialize delays array to store results for each iteration;
Set current_risk ← order_data.supply_risk[1];
Set current_delivery_time ← order_data.delivery_time[1];
while i ≤ iterations do
    Set base_delay ← 0;
    if runif(1) < current_risk then
        Set base_delay ← rpois(1, lambda = 3);
    end
    Initialize supplier_delays array;
    for each supplier j in supplies_data do
        if runif(1) < supplies_data[j].delay_probability then
            Append supplies_data[j].delay_days to
             supplier_delays;
        end
    end
    Calculate total_delay ← base_delay + sum(supplier_delays);
    Append total_delay to delays;
    Increment i;
end
return delays;
```

Explanation of Key Steps

1. **Initialization**: Sets up the delay array and retrieves the current supply risk and delivery time.

2. **Iteration with while...do**: Repeats the delay calculations for a set number of iterations.

3. **Conditional Delay Calculation**: Uses random values to determine if base and supplier delays occur.

4. **Aggregation**: Combines base and supplier delays to produce a total delay for each iteration.

This pseudocode provides a formal outline of the algorithm for simulating delivery delays with Monte Carlo methods, using structured logic and probability checks.

5.EXPERIMENT AND RESULTS

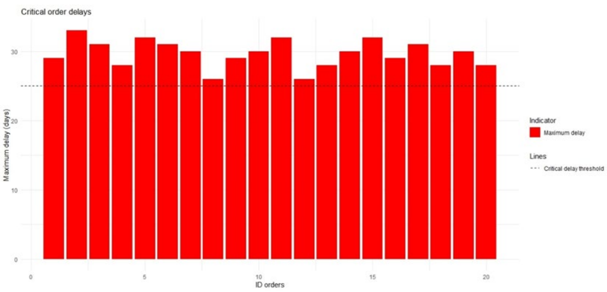

Fig.1 Visualization of critical order delays – 25 days (X-axis shows order number)

The chart provides a detailed illustration of critical order delays, with each order ID displayed on the x-axis and the corresponding maximum delay duration (in days) on the y-axis. Each bar represents the peak delay recorded for a particular order, highlighted in red to denote critical delays. A dashed horizontal line indicates an arbitrary "Critical Delay Threshold" (set at 10 days for this analysis), functioning as a benchmark to identify orders that surpass an acceptable delay limit. Any bar that exceeds this threshold denotes an order with a delay surpassing the critical level, which may signal potential operational disruptions, decreased customer satisfaction, or increased costs.

Upon examining the chart, it becomes evident that all orders experience delays significantly beyond the critical threshold. This observation suggests persistent and substantial issues within the supply chain or logistics processes. Potential underlying causes may include unreliable supplier performance, logistical bottlenecks, or inefficiencies in order handling and processing. To address these concerns, a deeper investigation into the root causes of these delays is recommended, followed by the development of targeted strategies to mitigate their impact and enhance supply chain resilience.

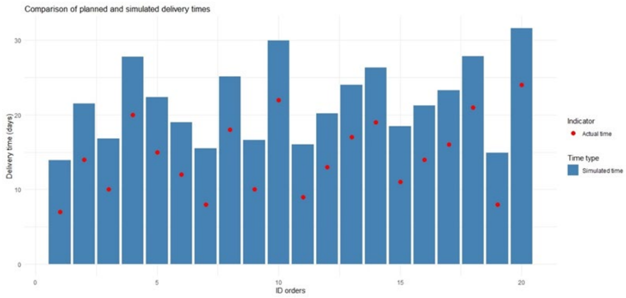

Fig. 2 Visualization of Planned vs. Simulated Delivery Times Comparison

The chart presents a comparison of planned and simulated delivery times across various orders, facilitating a deeper analysis of the predictive accuracy and practical applicability of the forecasting model in supply chain management. The x-axis displays order identifiers, while the y-axis represents delivery time in days, enabling a quantitative assessment of the temporal deviations between planned and simulated values. Red dots, representing the actual (or expected) delivery times, are overlaid on blue bars that depict the simulation results for each order. The visual distance between the position of these dots and the height of the bars allows for an immediate evaluation of how closely the model simulates delivery times. When the red dots align with or are very close to the top edge of the blue bars, a high level of predictive accuracy can be inferred. Such alignment suggests that the model effectively captures the key parameters and factors influencing delivery, indicating its potential applicability for planning purposes. Conversely, where red dots deviate significantly from the bar edges—especially when the simulated times either overestimate or underestimate actual times—discrepancies arise, signalling potential model deficiencies or incomplete input data. These differences highlight the need for further investigation: what caused these deviations? Potential explanations include unanticipated delays, unmodeled logistical factors unique to certain orders or delivery contexts, or limitations within the simulation model itself, such as inadequate handling of stochastic variables. This chart serves both a visual and analytical function, providing a clear indication of where the model requires refinement or recalibration. If certain orders consistently exhibit large discrepancies between simulated and actual delivery times, this may indicate systemic causes, suggesting that model adjustments are necessary.

Conversely, significant alignment across most data points indicates high model validity for the given dataset. In both academic and practical contexts, this approach allows for more than just average-level model evaluation; it enables a critical examination of its accuracy on a case-by-case basis, which is especially valuable for achieving adaptive and predictive management in supply chains.

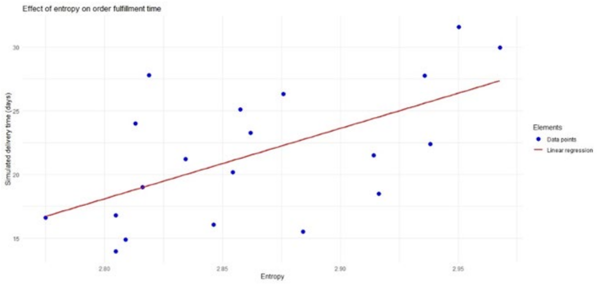

Fig. 3 Effect of entropy on order Fulfillment time

This chart presents a detailed examination of the relationship between entropy levels and simulated order execution times, intending to evaluate how randomness or unpredictability within a system impacts delivery timelines. The X-axis, representing entropy, likely serves as an indicator of the degree of uncertainty or complexity embedded in the order execution process. Higher entropy values typically reflect increased unpredictability, which theoretically correlates with a higher degree of procedural complexity. The Y-axis denotes the simulated delivery times in days, providing a quantitative measure of order completion time under varying conditions of system entropy.

The red regression lines suggest a positive association between entropy and order execution times, highlighting a trend where greater unpredictability in the system correlates with extended average delivery times. This observation can have meaningful implications for logistics management and decision-making processes, suggesting that highly complex or stochastic processes may inherently demand longer durations for completion. Notably, the dispersion of data points (blue markers) around the regression line illustrates considerable variance, indicating that while there is an observable trend, the dependency is not strictly linear. This variability implies that entropy, while influential, is likely not the sole determinant of order execution time. Other factors, potentially structural or external, may significantly contribute to variations in delivery timelines. From an academic perspective, this chart underscores the potential necessity for more sophisticated models to account for additional variables and interactions within the order execution process.

In sum, while the observed correlation offers valuable insights, it warrants further investigation to validate its reliability and applicability. A deeper analysis incorporating additional parameters may enhance the accuracy of predictions, thus advancing the understanding of factors influencing logistical efficiency and system responsiveness.

Fig.4 Relationship between supply chain entropy, delivery delay time, delivery risk and delay probability

The presented petal chart illustrates the complex interrelationships between supply system entropy (risk), delivery delay time, supply risk, and delay probability. This diagram visualizes the influence of entropy levels on delivery time, factoring in supply risk and delay probability, allowing for an analysis of how these variables interact to create a multi-layered picture of delivery parameter dependency on system randomness or uncertainty, symbolized by entropy. Entropy, represented on the X-axis, can be viewed as an indicator of logistical system complexity or unpredictability, suggesting high uncertainty and an increased likelihood that delivery times and reliability may deviate from expected parameters. The higher the entropy value, the greater the system uncertainty, which, in turn, creates conditions for various disruptions in the logistics chain that could lead to longer delivery times (displayed on the Y-axis), especially under high-risk and delay-probability conditions.

A close examination of specific data points reveals clustering at certain entropy levels. For instance, at lower entropy levels, delivery times remain relatively stable, not exceeding 25-27 days. However, with increased entropy, data dispersion is observed, indicating a broader distribution of delivery times. This reflects the heightened variability of the system—higher entropy makes delivery less predictable, and order fulfilment time can vary significantly, often exceeding 30 days. Colour coding in the diagram illustrates the level of supply risk: from blue and purple for low risk to bright red for high risk. Thus, at low entropy levels, blue and purple points dominate, symbolizing relatively low risk. However, with higher entropy values, the number of red points sharply increases, highlighting a direct relationship between uncertainty and risk. This suggests that complex and unstable systems are more often exposed to high supply risks, a key factor in delays. Additionally, the point size on the chart reflects delay probability, with larger points indicating higher delay probability, clustering in areas with high entropy and high risk. This suggests that delay probability rises as both risk and entropy increase. Highly chaotic and uncertain systems likely face not only greater challenges in supply control but also an increased tendency for disruptions, resulting in delays.

In sum, the diagram reveals a complex and nonlinear relationship between entropy level, supply risk, delay probability, and delivery time. Rising entropy leads to increases in both risk and delay probability, ultimately affecting delivery time. This insight emphasizes the importance of managing uncertainty in logistics, as even a small increase in entropy can lead to a significant decline in delivery reliability and increased time costs.

6. Conclusion

The research findings presented in the article allow for more comprehensive conclusions regarding the application of the Monte Carlo method for modelling order fulfilment while considering risks and uncertainties in supply chains:

1. The Monte Carlo method has confirmed its capability to model complex supply chains that are subject to significant risks. In a globalized environment, where supply chains often depend on multiple factors (including logistics, politics, climate conditions, and production disruptions), this method enables the consideration of various scenarios that reflect real uncertainty. Thus, it becomes indispensable for companies operating in unstable and dynamic markets.

2. The study demonstrates that accounting for the risks of delays and supply disruptions allows for a more accurate prediction of potential disruptions in the supply chain and their impact on order fulfilment timelines. Risk-aware modelling methods not only identify potential weak points but also forecast the likelihood of delays. Consequently, company executives can proactively develop strategic measures to prevent potential losses—such as ensuring backup routes or increasing inventory levels, thereby enhancing supply reliability.

3. The use of various probability distributions within the Monte Carlo method allows for the consideration of the specifics of particular risks and delays. For example, a normal distribution may describe more predictable risks, while beta or Poisson distributions can be employed for rarer but significant events. This flexibility renders the model universal and more precise, as it enables adaptations to the conditions of specific supply chains, which is particularly important when assessing rare and catastrophic events.

4. The Monte Carlo method, as part of the proposed model, facilitates more informed managerial decision-making. Through this approach, companies can not only anticipate how various risks will impact order fulfilment timelines but also take preemptive measures. Executives can utilize simulation results to optimize logistics—revising routes, increasing stock levels, or establishing agreements with alternative suppliers. This enhances supply chain resilience and minimizes potential financial losses in the face of global and regional crises.

5. The application of the Monte Carlo method as a tool for risk and uncertainty analysis strengthens the resilience of logistics systems. The article notes that this method can model even extremely rare events that, nonetheless, may have significant impacts on business. This capability allows companies to prepare in advance for potential crises, including climate disasters, epidemics, and political conflicts, making their logistics processes more flexible and adaptable to external threats.

6. In light of the rising global risks (such as pandemics, climate change, and trade wars), the article emphasizes the importance of a proactive approach to logistics management facilitated by the Monte Carlo method. It assists companies in planning their logistics processes ahead of time, minimizing reactive decisions that may be less efficient and more costly. This provides businesses with an advantage in rapidly changing market conditions, allowing them to better manage risks and adapt to new challenges.

Thus, this study substantiates the application of the Monte Carlo method as a tool for enhancing the reliability of supply chains for logistics companies. The use of this method not only mitigates the impact of delays and disruptions on order fulfilment but also fosters a more resilient and adaptive logistics strategy, which is especially relevant in the context of global instability and increasing uncertainties.

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