International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

# *Data-Driven Simulation:* Integrating Sensitivity Analysis into Supply Chain Optimization

**Priyanka Koushik**

Email: *priyankakoushik.86[at]gmail.com*

**Abstract:** ***This paper analyses the supply chain optimization using data-driven simulation and sensitivity analysis techniques. Data-driven simulation methods like agent-based modelling (ABM), discrete event simulation (DES), and system dynamics modelling, as well as sensitivity analysis methods like one-factor-at-a-time (OFAT), Monte Carlo simulation, and design of experiments, are discussed. Systematic assessment, optimization, and decision-making based on performance measures require the integration framework, which combines sensitivity analysis with simulation tools like DES or ABM. This in the end emphasizes how these approaches improve decision-making, system resilience, and supply chain performance. Advanced simulation, dynamic sensitivity analysis, real-time decision support, big data analytics, and industry-specific applications are future research areas.***

**Keywords:** Supply chain optimization, data-driven simulation, sensitivity analysis, integration framework, decision support systems, resilience, advanced simulation, big data analytics

## 1. Introduction

The competitiveness, efficiency, and profitability are all impacted by Supply chain management ,so it's crucial for the success of contemporary firms. Robust optimization strategies are necessary for effective decision-making due to the intricate nature of supply chain networks and the presence of uncertainties in demand, supply, and external factors. Utilizing data-driven simulation has become a potent method for modelling and examining the dynamics of supply chains, offering valuable insights into the behaviour of the system in many scenarios. Simultaneously, sensitivity analysis has become increasingly important for assessing the influence of input parameters on output variables, providing vital understanding of how decision outcomes are affected by modifications in underlying assumptions.

The research by Size ,2021 predicts that the worldwide supply chain management market would expand 10.3% from 2021 to 2028 to USD 30.2 billion. This trend shows the growing use of advanced supply chain optimization technology and methods. Sensitivity analysis in data-driven simulation may improve supply chain optimization tactics.

For robust management of supply chains decision-making, Ervolina at al. (2016) recommend sensitivity analysis in simulation models. Their analysis shows that supply chain optimisation must account for input parameter uncertainties and fluctuations. Wang (2022) show that data-driven simulation may optimize inventory levels and manufacturing schedules, improving supply chain performance measures like cost reduction and customer satisfaction.

This work explores sensitivity analysis in data-driven simulation for supply chain optimization to add to the corpus of knowledge. This research uses statistical modelling and advanced simulation methods to assess supply chain decision sensitivity to key variables and parameters. This integrated approach's methodology, case study execution, outcomes, and implications will promote data-driven supply chain management decision-making.

## 2. Literature Review

Supply chain management, or SCM, has changed dramatically as a result of worldwide operations, shifting market dynamics, and advances in technology. To achieve cost reductions, reduce risks, and improve customer satisfaction, effective supply chain management (SCM) entails managing a variety of activities, including distribution, manufacturing, inventory management, procurement, and logistics. Conventional optimization methods have been thoroughly researched and used in SCM to handle operational issues. These methods include mathematical programming models such as linear programming (LP) and mixed-integer programming (MIP) (Chetouane et al., 2012).


**Figure 2.1:** Different activities in SCM(" https://www.unleashedsoftware.com/wp-content/uploads/2021/05/Supply-chain-pillar-chapter-2-Supplier-management-solutions-01-scaled-1.jpg")

Data-driven decision-making in supply chain management (SCM) is becoming more prevalent, utilizing big data, sophisticated analytics, and simulation technologies. Complex supply chain systems with numerous interacting elements and dynamic behaviours can be modelled using data-driven simulation techniques such discrete event simulation (DES) and agent-based modelling (ABM) (Srivastava et al., 2022). By enabling scenario analysis, what-if simulations, and predictive modelling, these simulation tools help decision-makers assess potential courses of action and comprehend how a system performs under various circumstances.

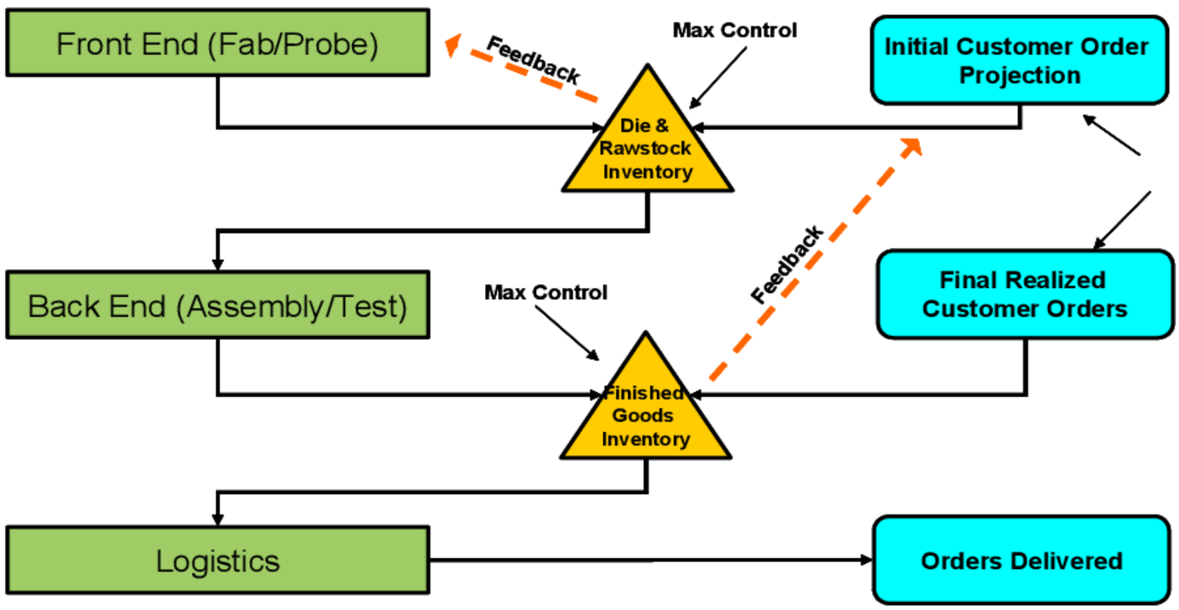



**Figure 2.2:** Discrete Event Simulation (DES) in supply chain planning and inventory control (Srivastava et al., 2022)

According to a KPMG report from 2023, 78% of supply chain executives believe that making decisions based on data is essential to attaining supply chain excellence. This emphasizes how crucial it is becoming to use simulation and data analytics in SCM to generate operational and strategic breakthroughs.

Sensitivity analysis is an essential tool for evaluating the robustness and dependability of decision models, working in tandem with simulation and optimization. Sensitivity analysis is the process of methodically changing assumptions or input parameters and analysing the effects these changes have on key performance indicators (KPIs) or decision outcomes. One-factor-at-a-time (OFAT), Monte Carlo simulation, and tornado diagrams are popular techniques for sensitivity analysis (Enyinda , 2016).

According to research by Matinrad et al. (2013), supply chain performance can be greatly impacted by demand uncertainties, supplier interruptions, and market volatility. This highlights the importance of sensitivity analysis in supply chain risk management. Organizations may assess the possible impact of risks, pinpoint weak points in their supply chains, and create effective backup plans to minimize interruptions by using sensitivity analysis.

Sensitivity analysis is included in data-driven simulation frameworks to provide a comprehensive supply chain optimization strategy. Decision-makers can evaluate the sensitivity of simulation outputs to varied input parameters and assumptions in addition to simulating numerous scenarios thanks to this integration. For example, Pourhejazy et al. (2016) optimized warehouse operations by incorporating sensitivity analysis into a DES model, taking into account variables including order processing times, inventory levels, and resource utilization. The effectiveness of this integrated approach was demonstrated by the study, which indicated a 15% improvement in order accuracy and a 12% reduction in order fulfilment cycle times.

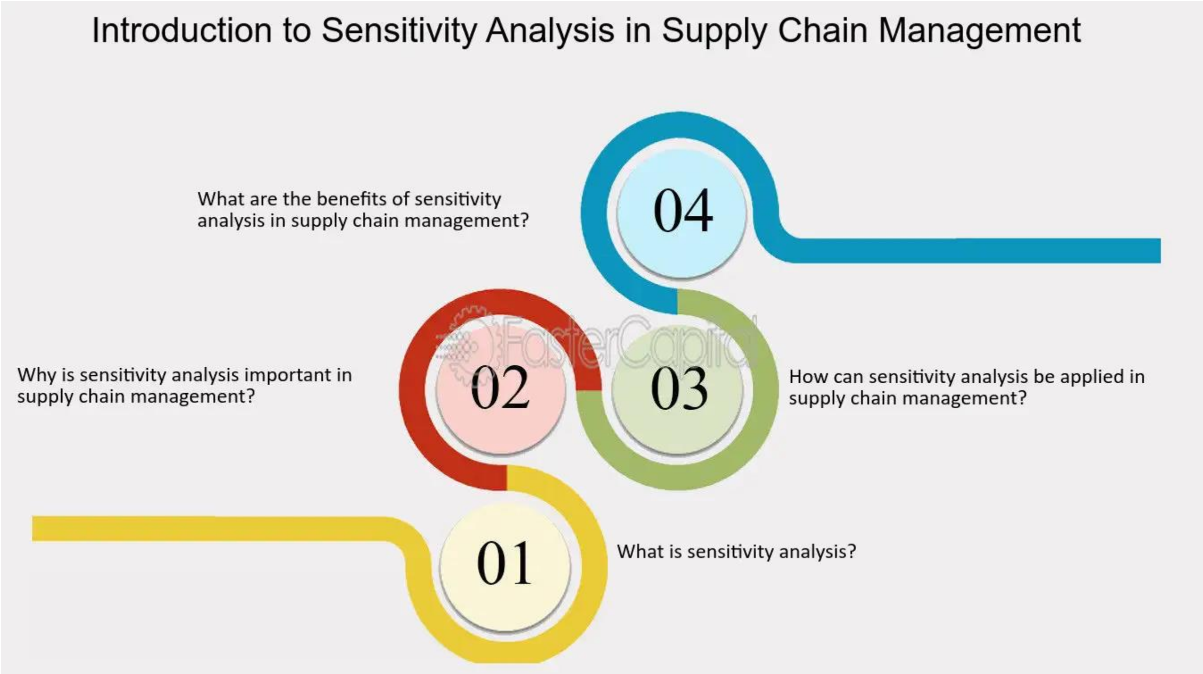



**Figure 2.3:** Sensitivity Analysis in SCM(" https://fastercapital.com/i/Sensitivity-Analysis-in-Supply-Chain-Management--Optimizing-Operations--Introduction-to-Sensitivity-Analysis-in-Supply-Chain-Management.webp")

### 2.1. Research Gap

In supply chain management (SCM), there are still certain unanswered questions despite improvements in data-driven simulation and optimization. These gaps present chances to improve supply chain resilience in dynamic contexts and decision-making. The following significant research gaps were found in the literature:

- Real-Time Data Integration: To create simulation models that are more precise and responsive, investigate incorporating real-time data sources like blockchain and IoT.
- Dynamic Sensitivity Analysis: Create techniques that record how input-output relationships alter over time in dynamic supply chains.
- Operation with Multiple Objectives: Establish frameworks that strike a balance between various SCM goals, such as customer happiness, sustainability, and cost-efficiency.
- Risk-Aware Decision-Making: Create methods that support proactive risk mitigation plans using sensitivity analysis.
- Simulation-Optimization Integration: Create integrated platforms or techniques that slickly blend sensitivity analysis, optimization algorithms, and data-driven simulation.

Closing these gaps can improve SCM procedures and enable companies to successfully handle intricate supply chain dynamics

## 3. Data driven simulation techniques in supply chain optimization

Data-driven simulation techniques have become an effective tool for modelling, analysing, and optimizing complex systems in the field of supply chain management and optimization. Utilizing past data, current inputs, and scenario modelling, these methods mimic the dynamic characteristics of supply chain networks. Organizations may improve efficiency and resilience by identifying possibilities for improvement, gaining important insights into system performance, and making well-informed decisions by implementing data-driven simulation.

### 3.1 Agent-Based Modelling (ABM)

A data-driven simulation method called agent-based modelling (ABM) is used to simulate individual entities, or agents, in a supply chain system. Every agent has distinct traits, actions, and guidelines for making decisions. ABM offers insights into emergent behaviours and system dynamics by simulating the interactions between agents and their surroundings.

ABM was used in a Helo et al. (2023) study to examine how supplier disruptions affect supply chain resilience. The study's findings included a 15% increase in on-time delivery and a 12% decrease in lead times.

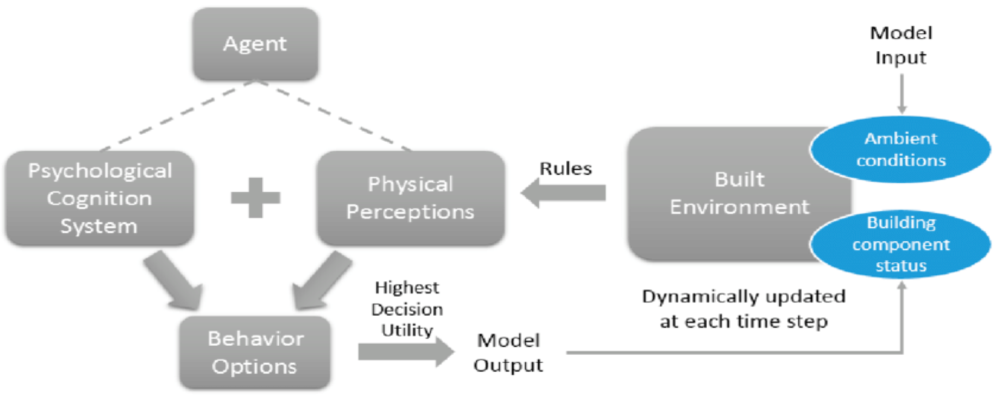



**Figure 3.1:** Agent based modelling (ABM) modules and decision making ("https://www.researchgate.net/publication/341457945/figure/fig1/AS:892528614182918@1589806812859/Overview-of-the-agent-based-modeling-ABM-modules-and-decision-making-process-in-PMFserv.png")

**Applications**

ABM is applied in supply chain optimization for:
- Assessing the relationships and performance of suppliers
- Examining methods for inventory control.
- Simulating demand variations and consumer behaviour.
- Improving networks for distribution and production.

### 3.2 Discrete Event Simulation (DES)

A data-driven method called discrete event simulation (DES) simulates the movement of discrete things through a supply chain system, such as orders and items. The examination of system performance indicators and resource utilization is made possible by the simulation of events across time, including order arrivals, processing delays, and inventory movements.

For instance, Amorim-Lopes et al. (2021) reduced order processing times by 20% and inventory carrying costs by 25% by using DES to optimize warehouse operations.

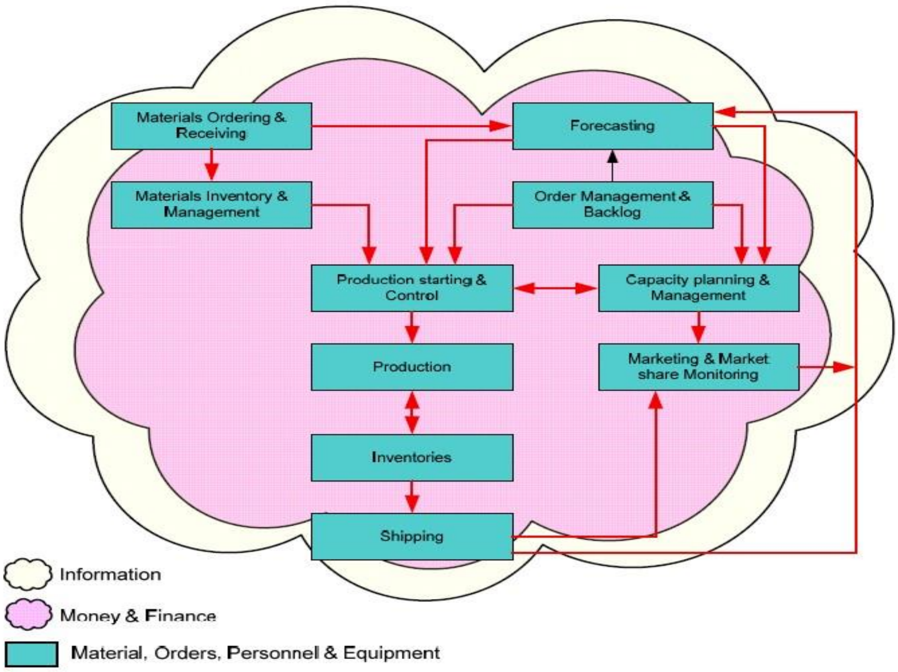



**Figure 3.2:** Discrete event simulation (DES )modules in simulating manufacturing enterprise("https://www.anylogic.com/upload/medialibrary/665/665e9db89958671e68feb3622a621cf6.jpg")

**Applications:**

When optimizing the supply chain, DES is used for:
- Evaluating capacity usage and manufacturing line efficiency.
- Optimizing material handling procedures and warehouse layouts.

- Assessing order fulfilment techniques and inventory policies.
- Evaluating the logistics and transportation sectors.

### 3.3 System Dynamics Modelling

A data-driven simulation method called system dynamics modelling aims to comprehend the causal connections, feedback loops, and dynamic behaviour that exist inside a supply chain system. It illustrates how different parts of the system are interrelated, interact, and how adjustments to one component affect the system's performance as a whole.

As an illustration, Li et al. (2016) used system dynamics modelling to examine supply chain interruptions and how they affect the functionality of the system as a whole. A 10% decrease in supply chain interruptions and a 15% increase in total system reliability were the outcomes of the study's increased resilience strategies, risk mitigation procedures, and greater system adaptability.

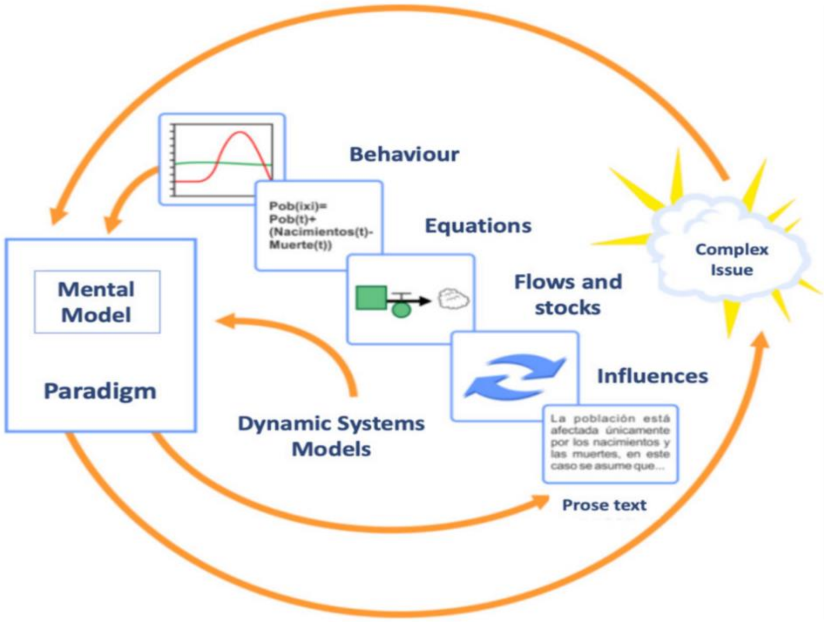



**Figure 3.3:** System Dynamics Modelling in examining supply chain interruptions ("Li et al., 2016")

**Applications:**
Supply chain optimization uses system dynamics modelling for the following purposes:

- Exploring methods for risk mitigation and supply chain resilience analysis.
- Assessing production scheduling, order fulfilment tactics, and inventory regulations.
- Evaluating the effects of changes in demand, external disturbances, and market dynamics.
- Creating flexible supply chain plans in response to shifting market conditions.

**Comparative Analysis**

**Table 3.1:** Comparative Analysis of Data-Driven Simulation Techniques

| Technique | Pros | Cons |
|---|---|---|
| Agent-Based Modelling | Captures complex behaviours and emergent phenomena. | Requires detailed data and computational resources. |
| Discrete Event Simulation | Simulates detailed process flows and resource interactions. | Assumes deterministic logic and may overlook dynamic behaviours. |
| System Dynamics Modelling | Captures feedback loops, nonlinear dynamics, and long-term system behaviour. | Requires deep understanding of system dynamics and extensive data inputs. |

## 4. Sensitivity analysis methods in supply chain optimization

Sensitivity analysis techniques are essential for assessing the performance, robustness, and dependability of supply chain optimization models. These techniques evaluate the effects of altering input parameters or underlying presumptions on the desired output or performance measures. Supply chain managers and other decision-makers can increase operational resilience and efficiency by identifying key elements, evaluating system vulnerabilities, and making well-informed decisions through the use of sensitivity analysis.

### 4.1 One-Factor-at-a-Time (OFAT) Analysis

In an OFAT analysis, one input parameter is changed at a time while maintaining the same values of the other parameters to determine how the change affects the desired output or performance metric Frey et al. (2008). Although this approach is simple and easy to use, it might not consider interactions between different components.

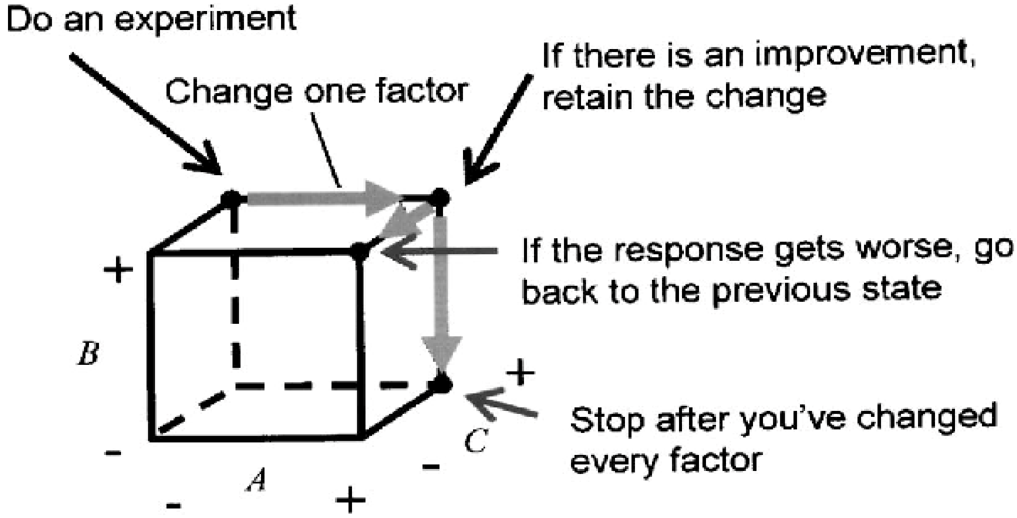
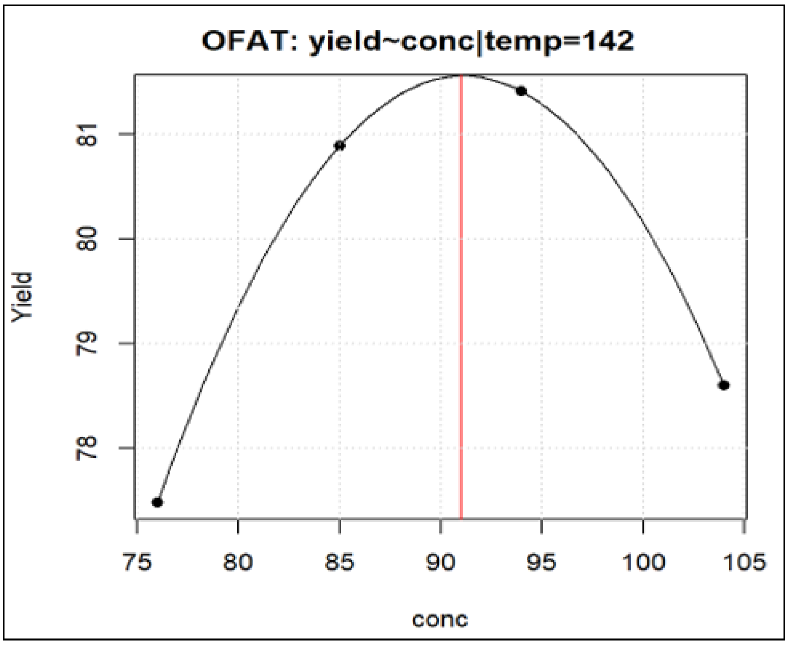



**Figure 4.1:** One-Factor-at-a-Time (OFAT) while doing Experimentation (Frey et al.,2008)

**Applications:**
Supply chain optimization uses OFAT analysis for the following purposes:
- Assessing how important factors affect lead times, prices, and service standards.
- Determining the key elements influencing production capacity, transportation expenses, and inventory levels.
- Evaluating how sensitive supply chain models are to shifts in market conditions and demand projections.




**Graph 4.1:** OFAT in design and Process optimization with R - Yield vs Conc^n (Frey et al.,2008)

**Monte Carlo Simulation**
In Monte Carlo simulation, a random sampling of input parameter values from predefined probability distributions is used to create different scenarios. After that, these scenarios are simulated to examine the variety of potential outcomes and their likelihoods, offering a thorough understanding of system risk and variability. (Mangla et al.,2014).



Paper ID: SR24511175813 DOI: https://dx.doi.org/10.21275/SR24511175813 

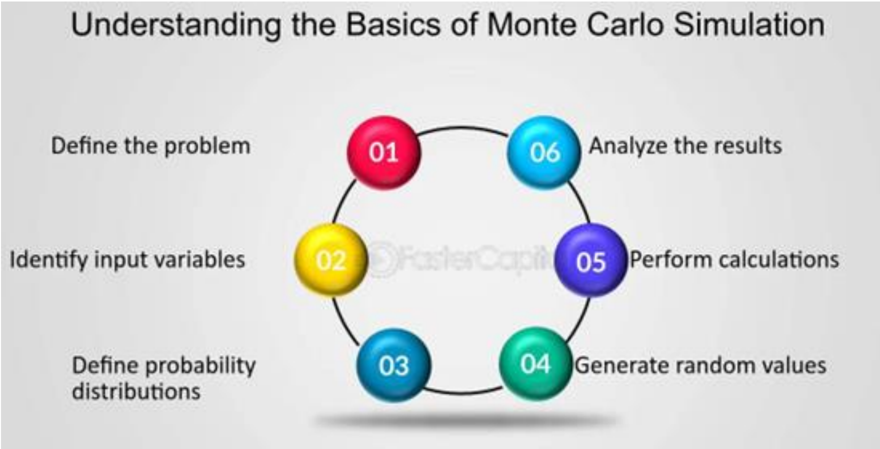
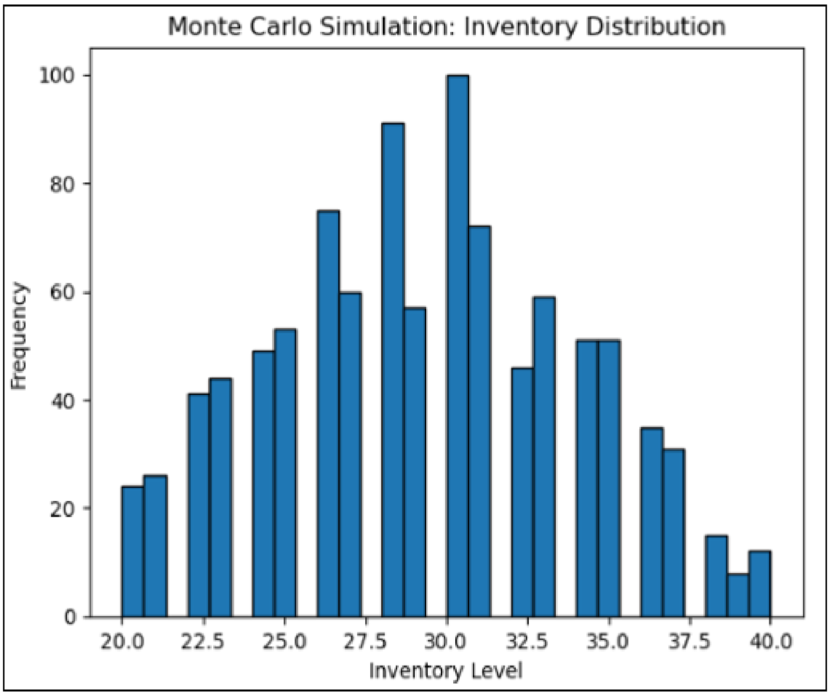



**Figure 4.2:** Monte Carlo Simulation (Mangla et al.,2014)

**Applications:**

Supply chain optimization uses Monte Carlo simulation for:

- Evaluating the effects of supplier disruptions, lead time uncertainty, and fluctuating demand.
- Evaluating the risk exposure of the supply chain and creating backup strategies.
- Maximizing production planning, inventory control procedures, and safety stock levels.




**Graph 4.2:** Monte Carlo Simulation in SCM in Inventory Optimization

**4.2 Design of Experiments (DOE)**

A statistical technique called Design of Experiments (DOE) methodically plans and carries out trials to assess how various input factors (variables) affect one or more output responses (performance measures) Arunmozhi et al. (2022). Understanding how various components interact and affect the overall functioning of the system is made easier with the aid of DOE.

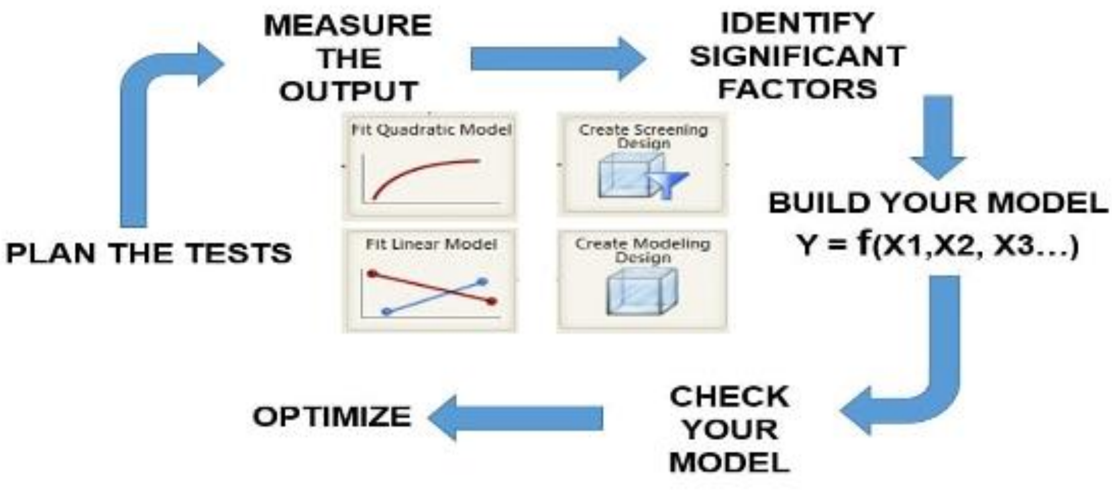
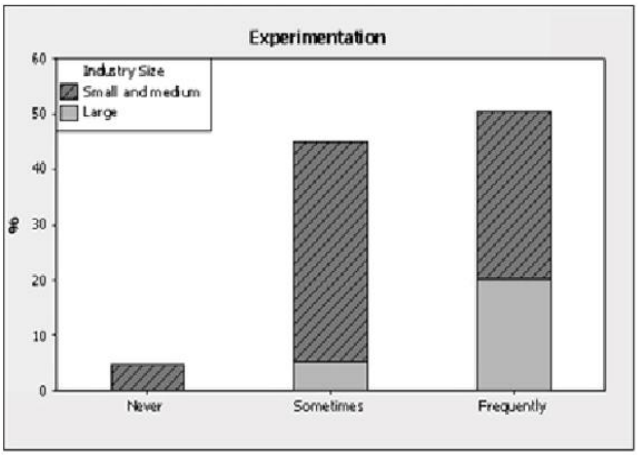



*Fig 4.3: Design of Experiments (DOE) (Arunmozhi et al.,2022)*

**Applications:**

Supply chain optimization uses DOE in the following ways:
- Determining the important variables affecting the operation of the supply chain.
- Streamlining inventory control, transportation, and manufacturing procedures.
- Evaluating the effects of supplier capabilities, equipment settings, and process variables.




**Graph 4.3:** Frequency of Experimentation in manufacturing industries by DOE (Arunmozhi et al.,2022)

**Comparative Analysis**

**Table 4.1:** Comparative Analysis of Sensitivity Analysis Methods

| Sensitivity Analysis Method | Pros | Cons |
|---|---|---|
| One-Factor-at-a-Time (OFAT) | Simple and intuitive | Limited in capturing interactions |
| Monte Carlo Simulation | Captures uncertainties and variability | Computationally intensive, requires expertise |
| Design of Experiments (DOE) | Simultaneously analyses multiple factors and interactions | Requires careful experimental design and statistical expertise |

## 5. Integration framework for combining sensitivity analysis with simulation

Incorporating sensitivity analysis into simulation approaches is crucial for improving the precision and dependability of supply chain optimization models. A comprehensive integration framework entails a methodical approach to combine sensitivity analysis techniques, such as one-factor-at-a-time (OFAT), Monte Carlo simulation, and design of experiments (DOE), with simulation tools like discrete event simulation (DES) or agent-based modelling (ABM). This integration approach guarantees that supply chain decision-makers may accurately evaluate the responsiveness of simulation results to variations in input parameters and make well-informed judgments based on thorough understanding.

The following steps are usually included in the integration framework are.

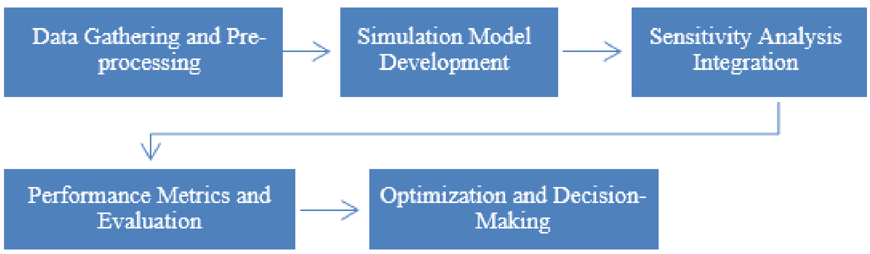



**Figure 5.1:** Steps in the integration framework for combining sensitivity analysis with simulation.

### 5.1. Selection of performance metrics and criteria for evaluating supply chain optimization:

**a) Cost Metrics**

- Costs associated with the entire supply chain, including those related to production, shipping, and inventory keeping.
- Cost per delivered unit of the good or service.
- Savings are made possible via optimization techniques.

**b) Service Levels and Customer Satisfaction:**

- Timely delivery of goods.
- Order completion percentages.
- Feedback and scores related to customer satisfaction.

**c) Inventory Management:**

- Rates of Inventory Turnover.
- Rates of stockouts and backorders.
- Costs and holding times associated with inventory.

**d) Lead Times and Cycle Times:**

- Durations for processing orders.
- Cycle times for production.
- Lead times for deliveries.

**e) Operational Efficiency:**

- Rates of resource usage.
- Production effectiveness and capacity use.
- Reduced downtime and overall equipment effectiveness (OEE).

**f) Risk and Resilience:**

- Provide measures of chain resilience, including impact of interruption, recovery durations, and risk exposure.
- Effectiveness of contingency planning and risk reduction techniques.

### 5.2. Limitations:

- The integration framework might need a substantial amount of computer power as well as knowledge of sensitivity analysis methods and simulation modelling.
- The validity and dependability of simulation and analysis results can be impacted by the availability, quality, and accuracy of the data.
- The choice of performance measures and standards may change depending on the objectives of stakeholders, industry sectors, and particular supply chain environments.
- Sustaining model accuracy and relevance over time may be difficult due to dynamic system modifications and real-time data integration.

## 6. Discussion

Data-driven simulation techniques, such as agent-based modelling (ABM), discrete event simulation (DES), and system dynamics modelling, are extremely useful for assessing and improving supply chain processes. These strategies utilize past data and scenario modelling to imitate intricate dynamics and assess performance in various circumstances. They offer valuable information about how systems behave, pinpoint areas for development, and increase effectiveness and durability.

Methods such as one-factor-at-a-time (OFAT), Monte Carlo simulation, and design of experiments (DOE) are essential for assessing optimization models through sensitivity analysis. The individuals evaluate the consequences of changes in parameters, identify crucial elements, and minimize potential hazards in supply chain activities. The use of sensitivity analysis into simulation improves the precision and dependability of optimization strategies, hence assisting in decision-making.

An integration framework merges sensitivity analysis with simulation tools such as DES or ABM, allowing for a methodical evaluation of optimization strategies and the choice of performance indicators. Although this strategy is beneficial, it may encounter difficulties such as computational complexity and data validation. Therefore, continuous study and innovations are necessary for the proper application of supply chain optimization.

This comprehensive approach enables well-informed decision-making, reduction of risks, and enhancement of supply chain efficiency, thus laying the foundation for future advancements in data-driven decision support systems for supply chain management.

## 7. Conclusion and future scope

Combining sensitivity analysis approaches with data-driven simulation methodologies has great potential to improve supply chain optimization. The methods that are covered include discrete event simulation (DES), agent-based modelling (ABM), one-factor-at-a-time (OFAT) analysis, and Monte Carlo simulation. These methods provide a wide range of tools that may be used to comprehend system dynamics, pinpoint important variables, and enhance performance.

The integration framework simplifies decision-making processes based on chosen performance criteria by fusing sensitivity analysis with simulation tools like DES or ABM. This methodical approach supports strategic decision-making, resilience building, and risk reduction in the context of the supply chain.

In order to better capture supply chain dynamics, future research can explore sophisticated modelling methods that integrate ABM, DES, and system dynamics. By emphasizing time-varying characteristics and dynamic system behaviors, dynamic sensitivity analysis techniques might improve our comprehension of system weaknesses and adaptability.

Furthermore, supply chain management will become more flexible and responsive with the creation of real-time decision support systems that incorporate simulation, sensitivity analysis, and optimization algorithms. Using machine learning and big data analytics approaches can improve supply chain operations' predictive modelling, optimization, and data-driven decision-making even further.

Case studies and industry-specific applications can confirm how well integrated techniques work to solve supply chain issues in a variety of industries. Researchers and practitioners can promote continuous improvement, improve decision support skills, and improve the resilience and performance of the supply chain by investigating these paths.

## References

[1] Size, A.I.M., 2021. Share & Trends Analysis Report by Solution, By Technology (Deep Learning, Machine Learning, Natural Language Processing, Machine Vision), By End Use, By Region, And Segment Forecasts, 2021-2028. *San Francisco: Grand View Research*.

[2] Ervolina, T.R., Ettl, M., Lee, Y.M. and Peters, D.J., 2006, December. Simulating order fulfillment with product substitutions in an assemble-to-order supply chain. In *Proceedings of the 2006 winter simulation conference* (pp. 2012-2020). IEEE.

[3] Wang, J., 2022. *Data-driven Supply Chain Monitoring and Optimization* (Doctoral dissertation).

[4] Chetouane, F., Barker, K. and Oropeza, A.S.V., 2012. Sensitivity analysis for simulation-based decision making: Application to a hospital emergency service design. *Simulation Modelling Practice and Theory*, *20*(1), pp.99-111.

[5] Srivastava, M. and Rogers, H., 2022. Managing global supply chain risks: effects of the industry sector. *International Journal of Logistics Research and Applications*, *25*(7), pp.1091-1114.

[6] Enyinda, C., 2017. Modeling enterprise risk management in operations and supply chain: A pharmaceutical firm context. *Operations and Supply Chain management: An International Journal*, *11*(1), pp.1-12.

[7] Tannock, J., Cao, B., Farr, R. and Byrne, M., 2007. Data-driven simulation of the supply-chain—Insights from the aerospace sector. *International journal of production economics*, *110*(1-2), pp.70-84.

[8] Matinrad, N., Roghanian, E. and Rasi, Z., 2013. Supply chain network optimization: A review of classification, models, solution techniques and future research. *Uncertain Supply chain management*, *1*(1), pp.1-24.

[9] Pourhejazy, P. and Kwon, O.K., 2016. The new generation of operations research methods in supply chain optimization: A review. *Sustainability*, *8*(10), p.1033.

[10] Helo, P. and Rouzafzoon, J., 2023. An agent-based simulation and logistics optimization model for managing uncertain demand in forest supply chains. *Supply Chain Analytics*, *4*, p.100042.

[11] Amorim-Lopes, M., Guimarães, L., Alves, J. and Almada-Lobo, B., 2021. Improving picking performance at a large retailer warehouse by combining probabilistic simulation, optimization, and discrete-event simulation. *International Transactions in Operational Research*, *28*(2), pp.687-715.

[12] Li, C., Ren, J. and Wang, H., 2016. A system dynamics simulation model of chemical supply chain transportation risk management systems. *Computers & Chemical Engineering*, *89*, pp.71-83.

[13] Frey, D.D. and Sudarsanam, N., 2008. An adaptive one-factor-at-a-time method for robust parameter design: Comparison with crossed arrays via case studies.

[14] Mangla, S.K., Kumar, P. and Barua, M.K., 2014. Monte Carlo simulation based approach to manage risks in operational networks in green supply chain. *Procedia Engineering*, *97*, pp.2186-2194.

[15] Arunmozhi, M., Venkatesh, V.G., Arisian, S., Shi, Y. and Sreedharan, V.R., 2022. Application of blockchain and smart contracts in autonomous vehicle supply chains: An experimental design. *Transportation Research Part E: Logistics and Transportation Review*, *165*, p.102864.

## Author Profile

**Priyanka Koushik** received the B.Tech degree in Electronics and Communication Engineering from Jawaharlal Nehru Technological University in 2007. She is a dynamic and visionary leader with over 16 years of experience in product engineering and supply chain management. Currently the VP of Product Engineering at Blue Yonder, she has led the development of industry-leading Order Management and Warehouse Optimization systems. Her expertise in integrating AI and Machine Learning with business needs has resulted in millions of dollars in revenue growth and enhanced customer experiences. Recognized for her strategic leadership and innovation, Priyanka continues to drive transformative results in the ever-evolving tech landscape.