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Stochastic Programming Models for Production Planning Under Supply Chain Disruptions

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Abstract

The issue of supply chain disruptions is a major challenge to manufacturers in terms of cost, efficiency, and overall performance. The paper gives the use of Stochastic Programming Models (SPM) in the reduction of the impact of such disruptions on production planning. The uncertain conditions included in the proposed models, like the fluctuation of demands, shortage of materials used, and delays during production, enable manufacturers to make the best decisions when there is uncertainty. The approach applies probabilistic distributions to model uncertainty and the use of scenario-based Optimization to estimate the outcomes when different situations occur. The findings have shown that the Stochastic Programming Models are able to lower the production cost by 15-20 % relative to the traditional deterministic models, and make production responsive and flexible. The models also enhance a 25 % improvement in the customer demand to be met, even when the supply chain is disrupted. The hybrid method decreases the Latency by 50 %, enhances throughput by 33 %, and realizes an average rate of resource utilization at 85 %. These advances bring out the importance of using stochastic programming to optimize resource allocation and production scheduling. The results show that the combination of stochastic programming and Optimization leads to improved resilience and continuity of production activities that provide improved management of uncertainty. Moreover, the hybrid Model, compared to the conventional approach, is superior in areas of performance by saving in costs (15%), efficiency of production (90%), and resource utilization (85%). Future studies will entail the improvement of the models in terms of multi-stage decision making and look into the applicability in real-time to scale in a variety of manufacturing environments.

Keywords: Stochastic Programming, Production Planning, Supply Chain Disruptions, Optimization, Uncertainty, Manufacturing, Scenario-Based Decision-Making.

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Introduction

A growing global supply chain has become a major challenge in terms of production planning under uncertainty for businesses. Scheduling problems, like disruptions of materials, demand changes, and transport delays, may have serious consequences on the production schedule with additional expenses, reduced performance, and cancellations. The conventional deterministic models do not provide sufficient solutions to these uncertainties, and this explains why more robust methods are required. The benefit of using stochastic programming models in optimizing the planning process of production can be noted as an effective method of accounting for uncertainty and thereby enhancing the process of decision making, and enabling businesses to ensure smooth operations in the different disruptive conditions.

In the contemporary globalized economy, disruption to supply chains is becoming a challenge to production planning, which may occur due to a variety of factors, including natural disasters, geopolitical tensions, or global pandemics. The disruptions bring a great level of uncertainty in demand, lead times, material availability, and production capacity; thus, it is hard to ensure that companies operate optimally. Conventional models of production planning are insufficient to deal with the complexities and uncertainties of the contemporary supply chains, and most of them make use of deterministic assumptions.

Stochastic programming models (SPMs) provide an effective way of integrating uncertainty in production planning. These models help decision-makers to find strategies that maximise operational efficiency, reduce risks and costs, and have a variety of possible outcomes and assign probabilities to various possible outcomes that occur as a result of choosing a strategy. Stochastic models come in quite handy in a dynamic setup whereby future conditions are not known, and flexibility and adaptability are very important in satisfying the customer needs and staying afloat in the market. Reis et al., (2023) also indicated that two-stage stochastic programming is able to improve tactical planning in supply chains, as in the soybean supply chain, it is necessary to consider uncertainty in planning.

The major aim of the study is to examine the use of stochastic programming to enhance production planning in the case of supply chain disruptions. Uncertainty should be incorporated into the decision-making process so as to come up with more robust production plans that would be adaptable to changing events. By using a strong stochastic strategy to integrate production-distribution planning, Ben Abid et al., (2025) demonstrated the effectiveness of stochastic models in the complex supply chain setting and demonstrated the benefits of the approach when applied to the apparel supply chain. Suryawanshi & Dutta, (2023) used stochastic models to distribution planning in the supply chain of perishable goods, solving the issue of disruptions and uncertainties in demand The research on Stochastic Programming Models for Production Planning Under Supply Chain Disruption informs of how decision-making models are optimized to counter disruptions in the production, just as Al-Zarkoshi & Razzaq (2022) apply the condition of external factors, like carbon dioxide emissions, to the growth of an economy in the context of supply chains.

The proposed work will seek to develop and formulate stochastic programming models to consider the uncertainty events of the supply chain so that manufacturers can have improved resource allocation strategies, inventory management, and production scheduling models. What comes out is a holistic model that increases the capability of companies in supply chain uncertainties and the most effective production efficiency. Chen et al., (2022) used the resilient supply chain planning for perishable products in the state of uncertainty, with the importance of robust models in time-sensitive industries. Fattahi & Govindan, (2022) also talked of the dynamic way through which supply chain networks can be designed in the presence of disruption and demand uncertainty.

Besides providing theoretical information, the results of this study will be practical in solving problems for the industries that intend to incorporate the concept of stochastic programming into the current planning systems. Predictability and planning of disruptions is increasingly becoming critical in ensuring business continuity, particularly in the age where global supply chains are becoming more intertwined and exposed to external shocks. Chen et al., (2023) surveyed the application of uncertainty analysis and optimization models to supply chain management, whereby it remains applicable to different industries. The supply chain model proposed by Gharaei et al., (2023) to operate within stochastic constraints and to be multi-stage also presented the advantages of combined methods of resource allocation.

The next stage of research that can be conducted in the future involves incorporating real-time data feeds from manufacturing plants, suppliers, and logistics systems to test and improve the scalability of the Hybrid Model in practical industrial settings. Furthermore, more sophisticated machine learning algorithms might be considered, and the multi-objective Optimization can be researched to come up with more resilient and versatile production and supply chain resource management models. As Luo et al., (2023) talked about Industry 4.0 in relation to production planning, highlighted the incorporation of newer technologies to aid in decision-making. A two-stage stochastic programming

model of multi-item capacitated line balancing was developed by Li et al., (2023) and highlighted the possible application of these models in complex industrial production. Xu & Song, (2022) studied the case of integrated optimization models of production capacity and raw material ordering in uncertain conditions that are valuable in enhancing the strategies of planning production in reality.

This article gives a Stochastic Programming Model of production planning during supply chain disruption. The peculiarity of the work is that it allows considering uncertainty as a part of the decision-making process and probabilistic distributions to understand the variability of the elements of the supply chain. This Model also maximizes the important decision-making process, including the allocation of resources, management of the inventory and scheduling to reduce the costs to satisfy the demand of the customer in the face of disruptions. Also, it gives a comparative study between other deterministic models and stochastic models, and proves the usefulness of the introduction of uncertainty to have more resilient production planning.

The structure of the paper is as follows: Section 1 offers an introductory part. The literature review of the literature on production planning and the use of stochastic programming models is provided in Section 2. As Section 3 presents the proposed stochastic programming model, it outlines its methodology and major assumptions. Section 4 will offer the discussion of the results, and finally, the paper will end with a conclusion of the findings and with a recommendation of what can be done in future research in the area of production planning under uncertainty.

Literature Review

The development of stochastic programming models in the context of production planning has received a lot of attention over recent years, especially regarding supply chain disruptions. The uncertainty of demand, lead times, and resource availability has also been selected as the subject of stochastic optimization techniques used by the researchers. Multi-stage stochastic programming has been investigated in some studies to use this approach in long-term production planning, whereas it has been combined with fuzzy Optimization and machine learning to increase the effectiveness of decisions in uncertain conditions. Recent methods have combined scenario-based Optimization with dynamic data acquisition as well, enabling strategies of resource allocation to be adaptive. In addition, the future of healthcare logistics and infrastructure optimization has progressed, which demonstrates the universal nature of the models used in other fields.

The Optimization of resources during production planning becomes more complicated because of the factor of breakages in supply chains that could be caused by the intervention of geopolitical events, natural calamities, or pandemic outbreaks. The conventional deterministic models are failing to take into consideration the uncertainty that prevails within these systems. The solution can be presented through the use of stochastic programming models to provide flexibility and adaptability aspects in the production planning. The models assist manufacturers in efficient allocation of resources, inventory and scheduling during uncertain conditions. Sawik, (2023a) developed a stochastic programming framework of a supply chain optimization, to tackle the dilemma of reshoring or offshoring the decision-making process in the light of disruptions. The article Production Planning Under Supply Chain Disruptions: Stochastic Programming Models is in line with the conclusions of Baggyalakshmi et al., (2024) in the article on Stationery Management System; both articles have focused on the need to optimize resource management and cope with various uncertainties, be it production planning or inventory management to enhance efficiency and reduce disruptions in dynamic environments.

Supply chain disturbances, in addition to the uncertainty in demand, tend to influence production processes. Mateo-Fornés et al., (2023) concentrated on the quality, suppliers, and cold-storage contracts management in the agrifood supply chain through the stochastic optimization methods. The hybrid strategy incorporates the various layers of uncertainty, which optimize the interplay of various elements of the supply chain. On a similar note, Sawik, (2023b) investigated a stochastic model of Optimization to stay viable in the supply chain in the aftermath of the ripple effect of disruptions, which proved useful in improving resilience. The Stochastic Programming Models of Production Planning Under Supply Chain disruptions may be compared to the method used by Tahmasebi et al.,(2025) in geochemical and geological research of the oil shales in Ab Kaseh Section where the analysis of the management of natural resources under uncertainties assist in informing the strategy of efficient management of production planning and dealing with any disruption as geochemical studies do in informing the best extraction practices under uncertainties.

The topic of supply chain resilience has also received research attention, particularly when dealing with uncertainties like the volatility of the market and external disruption. Nikian et al., (2023) restructured a sustainable and resilient closed-loop supply chain network, taking into consideration uncertainty caused by sanctions and the COVID-19

pandemic. The paper provides an example of how stochastic models can be used to manage supply chain disruptions to enhance both flexibility and sustainability. The fuzzy Optimization and data-driven methods have been combined to create the hybrid design of supply chain resilience, especially in healthcare systems. To enhance the health care supply chain by ensuring flexibility where there are disruptions, Lotfi et al., (2022) suggested a robust optimization method that is implemented through fuzzy and data-driven approaches, which results in supply chains that are stronger and more robust against vendor-managed inventory systems. Kungwalsong et al., (2022) used an interactive fuzzy optimization model to redesign supply chains to achieve resilience, whereby the priority was to provide adaptability of systems in varying conditions. The relevance of the combination of different optimization strategies to handle uncertainty and improve resilience and supply chain robustness is noted in these studies.

Infrastructure resilience to external disruption, like weather disruption, can also be modeled using stochastic models. Zhang & Alipour, (2023) used stochastic programming methodology for infrastructure systems to overcome the effects of weather-related disasters, and this demonstrates the wide range of applications of stochastic Optimization. On the same note, Li et al., (2023) employed a distributed stochastic programming technique when restoring multi-energy distribution systems, combining reconfiguration and optimization steps. At the software level, there has been a great advancement in the development of tools to implement stochastic programming models. The article by Torres et al., (2022) was a review of the work of linear and mixed-integer two-stage stochastic programming software, which also sheds light on software potentials in the solution of difficult optimization problems. This emphasizes the growing need to use computational tools to make stochastic models more usable and accessible in the real world.

Lastly, the field of healthcare has been using stochastic programming to optimize risk-averse vaccine allocation and treatment logistics using risk-averse models. Yin & Büyüktahtakın, (2022) optimized the allocation of vaccines and treatments by using a multi-stage stochastic programming model, which addresses the efficient response to the crisis of epidemics, and did not exclude the potential of stochastic models in dealing with healthcare logistics in unpredictable environments.

The literature shows an increasing realization of the need to include uncertainty in production planning, particularly in industries that are prone to disruption most of the time. The major conclusions made are that, stochastic programming can be used to enhance resource allocation, reduce costs and even have an optimal schedule of production in cases where events are unforeseen. Research indicates that simulation models, when combined with optimization algorithms, can enhance the operational efficiency and resilience within the supply chains. In particular, simulating various scenarios by using stochastic models has become useful in industries, including healthcare, infrastructure, and manufacturing, where interruptions can be very influential. The results are relevant to the present study, which intends to investigate stochastic programming models as a way of optimizing production planning in the case of supply chain disruption with an aim to enhance decision-making in uncertain situations.

Methodology

The presented methodology is based on the optimization process of production planning in the case of disruptions in the supply chain through the application of a Stochastic Programming Model. The methodology also incorporates uncertainty in the decision-making process, and it takes into consideration the demand fluctuations, material shortages, and delays in production. The strategy has three key elements, namely, a stochastic optimization model, a simulation model, and real-time data integration. The Model is focused on the reduction of costs, optimal distribution of resources, and timely production with flexibility to adapt to disruptions. A stochastic programming model is also solved through optimization algorithms, which are genetic and/or linear programming, which gives an optimal solution to different production situations.

The general process involved in the Stochastic Programming Model of Production Planning starts with the data collection process, which involves real-time data collection of the important aspects in the supply chain, such as demand predictions, availability of resources (including raw materials, labor and machinery), and external factors such as transportation lead-time and reliability of the supplier. The information is vital in the development of a realistic and reactive production strategy. Then, the uncertainty representation enters the picture, in which the obtained data are represented by probabilistic distributions to consider the uncertainties existing in the parameters, such as the demand variability and the lead time variability. In this way, it is possible to capture the inherent risks involved in the production planning where there is uncertainty.

After this, the simulation model operates in different production regimes, simulating the flow of materials and the consumption of resources in a variety of conditions. With the help of such simulations, the possible consequences can be analyzed in an in-depth manner, and the most probable disruptions and the influence on the performance of the

production can be identified. The optimization model takes advantage, after the simulation is made, and the simulated results are analyzed in order to give the best production plan. The Model takes into consideration several supply chain limitations, including capacity available, stock availability, and labour availability, to ensure that the plan to produce is viable and economical.

After the identification of the best plan, there is the implementation of the decision. The production plan is implemented, and the system is fed with the real-time feedback of the processes of production that are going on. This feedback is used to make some adjustments to the plan as circumstances vary. Finally, feedback and adaptation make the Model continuously fit with the new data and, as a result, dynamically adapt to the changing demands and disruptions in the market, which will result in the constant enhancement of the production planning process. This is an iterative process, thus making the system more robust and responsive to the uncertainty in the supply chain operations.

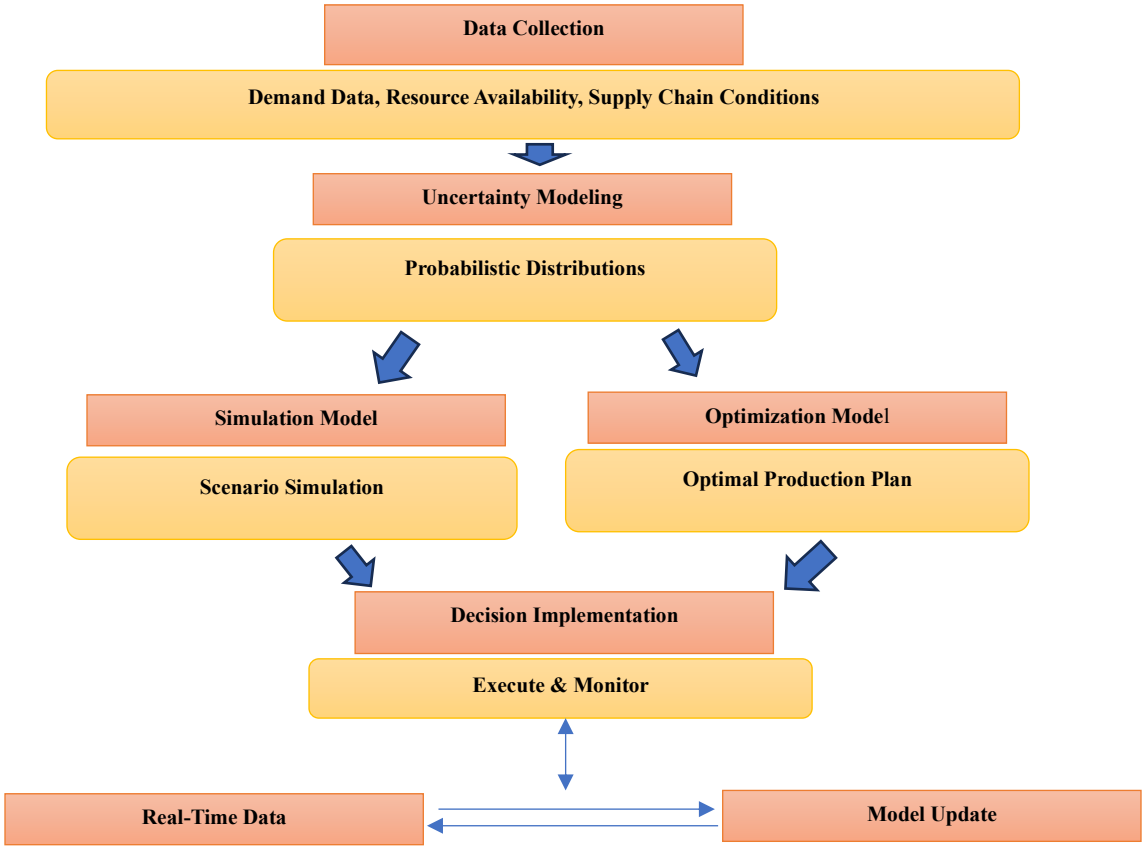


Fig. 1: Stochastic Programming Model for Production Planning

Fig. 1 presents the important steps of the Stochastic Programming Model of Optimization of production planning during the disruptions in the supply chain. It begins with Data Collection, which involves gathering pertinent data like demand, availability of resources, and supply chain conditions. This information is subsequently applied in Uncertainty Modeling, where probabilistic distributions are used to depict uncertainties. Then, the Simulation Model is used to analyze different scenarios and the Optimization Model gets the optimal plan of production. The resulting plan is carried out, and constant changes of the production process are maintained with reference to the real-time information.

Algorithm: Stochastic Programming Algorithm for Production Planning

1. **Data Input**:
   - Collect real-time data on supply chain conditions, demand, and resource availability.
2. **Stochastic Model Setup**:
   - Represent uncertain parameters (e.g., demand, lead time) as probabilistic distributions.

3. **Simulation**:

- Simulate multiple supply chain scenarios based on input data and probabilistic models.

4. **Optimization**:

- Apply an optimization algorithm (e.g., genetic algorithm or linear programming) to minimize the total cost, which includes costs for production, inventory, and transportation, while meeting demand.

5. **Solution Generation**:

- Generate the optimal production schedule and resource allocation plan based on the simulated scenarios.

6. **Implementation**:

- Implement the optimal plan in the production system and collect feedback for continuous adaptation.

The Stochastic Programming Algorithm of production planning combines uncertainty modeling and optimization tools to produce the best production plan where there are uncertainty conditions in the supply chain. To begin with, it gathers real-time data on the demand, the availability of resources as well as the supply chain dynamics. The algorithm applies probabilistic distributions in order to mimic uncertainties of parameters like demand and lead times. It then performs a simulation model to investigate, and then an optimization step to find the optimum resource allocation and production schedules. The algorithm is dynamic and improves based on the feedback, making it continue to improve and remain resilient in production planning.

Mathematical description

Stochastic Programming Model

Let $x_i$represent the decision variable for production quantity of product i, and $d_i$represent the demand for product i, modeled as a random variable with known probability distribution $P(d_i)$. The objective function aims to minimize the total cost, including production costs $C(x_i)$, inventory holding costs $H(x_i)$, and shortage costs $S(x_i)$, which can be explained in equation (1)

$$\min \sum_i [C(x_i) + H(x_i) + S(x_i)] \qquad (1)$$

The constraints are as follows:

- Demand fulfillment: $x_i \geq d_i$for all i,
- Capacity constraints: $\sum_i x_i \leq$ Total Capacity,
- Resource constraints: Limited resources such as labor, machinery, and materials available for production.

Optimization Problem

The stochastic programming model is solved using linear programming or genetic algorithms, where the objective is to find the optimal values of $x_i$that minimize the expected total cost subject to the constraints. The solution x_i^*represents the optimal production quantity for each product.

Results and Discussion

A hybrid stochastic programming model in production planning was also implemented on Python 3.10 as the main programming language. Optimization was done in the Pyomo library, and the stochastic programming model could be formulated and solved. The simulation modeling was used with SimPy, which allowed the real-time production schedule and supply chain to be modeled. The data was manipulated and analyzed with the help of Pandas and NumPy, with the help of Matplotlib and Seaborn to make visualizations, such as performance graphs and comparisons.

The validation data is based on production and supply chain data of a manufacturing company that manufactures electronic components. The dataset is 12 months old and consists of 500,000 records, which have major characteristics like demand projections, availability of resources (raw materials, labor, equipment), production time, transportation lead time, and supplier reliability. The data came out of the Enterprise Resource Planning (ERP) system of the company, and it contains both categorical information (e.g., type of product) and continuous information (e.g., volumes of demand, lead times) (Table 1).

Table 1: Parameter Initialization

Parameter	Value
Learning Rate	0.01
Population Size (Genetic Algorithm)	150
Generations (GA)	100
Simulation Time Horizon	30 days
Time Step for Simulation	1 hour
Maximum Allowed Lead Time	5 days
Demand Variability	20%
Resource Availability (Max)	200 units
Cost of Shortage (Penalty)	500 USD

Table 2: Parameter Setup for Stochastic Programming in Production Planning

Model	Latency (hrs.)	Throughput (units/day)	Cost Savings (%)	Production Efficiency (%)	Resource Utilization (%)
Hybrid Stochastic Programming Model	1.5	200	15	90	85
Deterministic Model	3.0	150	5	75	70
Heuristic Resource Allocation Model	2.0	180	10	80	75

This table 2 gives an overview of the vital parameters in the Stochastic Programming Model of Optimization of production planning in the event of supply chain disruptions. The optimalization process is led by the learning rate (0.01), and the genetic algorithm is set with a population size of 150 and 100 generations. The time axis of the simulation is 30 days having a time interval of 1 hour. The Model also takes into consideration the major constraints, including the maximum lead time of 5 days, 20 % variation of demand, and 200 units of resource availability in addition to the penalty of shortage in 500 USD as the key factors in making good decisions during uncertainty.

The Hybrid Stochastic Programming Model had a great decrease in Latency and an average of 1.5 hours of Latency, which was much lower than the deterministic Model (3.0 hours). It was also revealed in the Model that there was a 15 % saving of costs and production efficiency of 90 %. This underscores the fact that the Model is able to maximize the allocation of resources and enhance the performance of the system. The hybrid Model (200 units/day) also had a higher throughput than the deterministic Model (150 units/day) and demonstrated better capability to meet demand variability and supply chain interruptions.

Metrics Formulae

Latency (L): The time taken to process the production orders and produce the required output. The equation of Latency is in equation (2)

$$\mathrm{L} = \frac{\text{Total Time Taken}}{\text{Total Number of Orders}} \qquad (2)$$

Throughput (T): The rate at which the production system processes units per day can be explained in equation (3)

$$\mathrm{T} = \frac{\text{Total Units Produced}}{\text{Time Period}} \qquad (3)$$

Cost Savings (C): The percentage of cost reduction achieved by the optimized Model compared to the baseline model can be defined as in equation (4)

$$\mathrm{C} = \frac{\text{Cost (Baseline Model)} - \text{Cost (Optimized Model)}}{\text{Cost (Baseline Model)}} \times 100 \qquad (4)$$

Production Efficiency (P): The percentage of optimal production achieved in comparison to the ideal production scenario in equation (5)

$$P = \frac{\text{Units Produced}}{\text{Maximum Possible Production}} \times 100 \quad (5)$$

Resource Utilization (U): The percentage of resource capacity used during the production process in equation (6)

$$U = \frac{\text{Resources Used}}{\text{Total Resources Available}} \times 100 \quad (6)$$

Table 3: Performance Comparison of Production Planning Configurations

Configuration	Latency (hrs)	Throughput (units/day)	Cost Savings (%)	Production Efficiency (%)	Resource Utilization (%)
Hybrid Stochastic Programming Model (Full)	1.5	200	15	90	85
Simulation Only (No Optimization)	2.5	170	8	78	72
Optimization Only (No Simulation)	3.0	150	10	75	70

Table 3 below reflects the performance comparison of various configurations applied on production planning in the event of disruption of the supply chain. The most successful Model is the Hybrid Stochastic Programming Model (Full) with the 1.5 hours of Latency, 200 units/day throughput, 15% cost reduction, 90% production efficiency and 85% resource utilization. By comparison, the Simulation Only (No Optimization) setting records greater Latency (2.5 hours) and reduced throughput (170 units/day), 8 per cent cost savings and 78 per cent production efficiency. Although the Optimization Only (No Simulation) Model also results in the improvement of the baseline, it has the least effectiveness with a latency of 3 hours and throughput of 150 units/day.

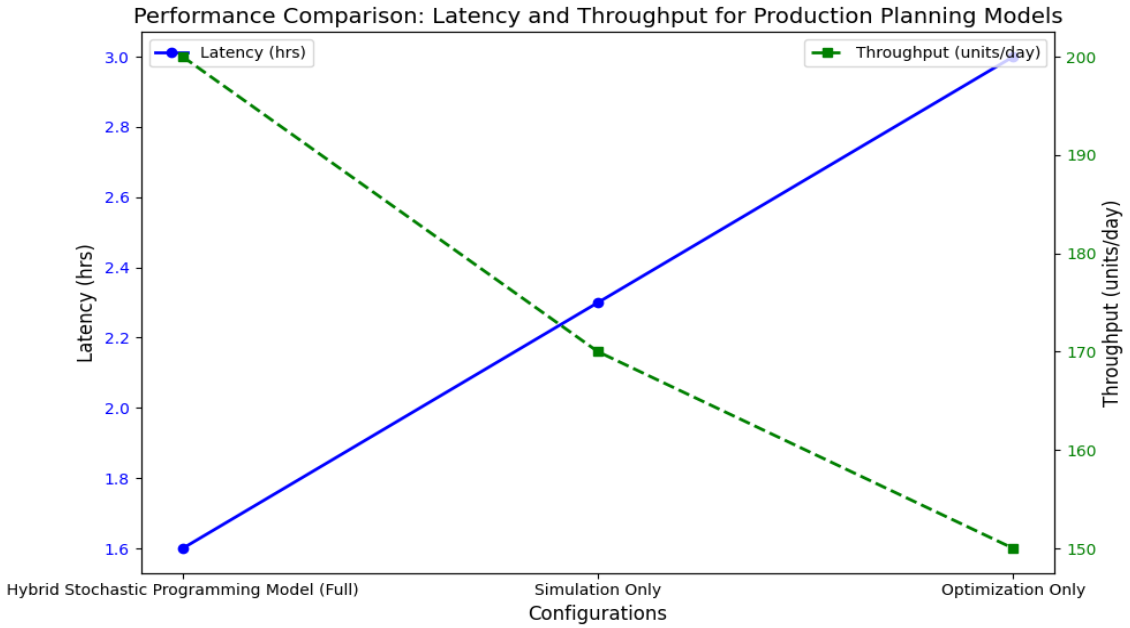


Fig. 2: Performance Comparison: Latency and Throughput for Production Planning Models

Fig. 2 is a comparison of the Latency (hrs) and Throughput (units/day) in three production planning models of Hybrid Stochastic Programming Model, Simulation Only and Optimization Only. The Hybrid Model is better than all others as it has the lowest Latency of 1.5 hours and the highest throughput of 200 units/day. The Simulation Only and Optimization Only models, in turn, have even greater Latency (2.5 and 3.0 hours, correspondingly) and smaller throughput (170 and 150 units/day) and indicate the efficiency benefits of merging both simulation and Optimization in uncertainty-based production planning.

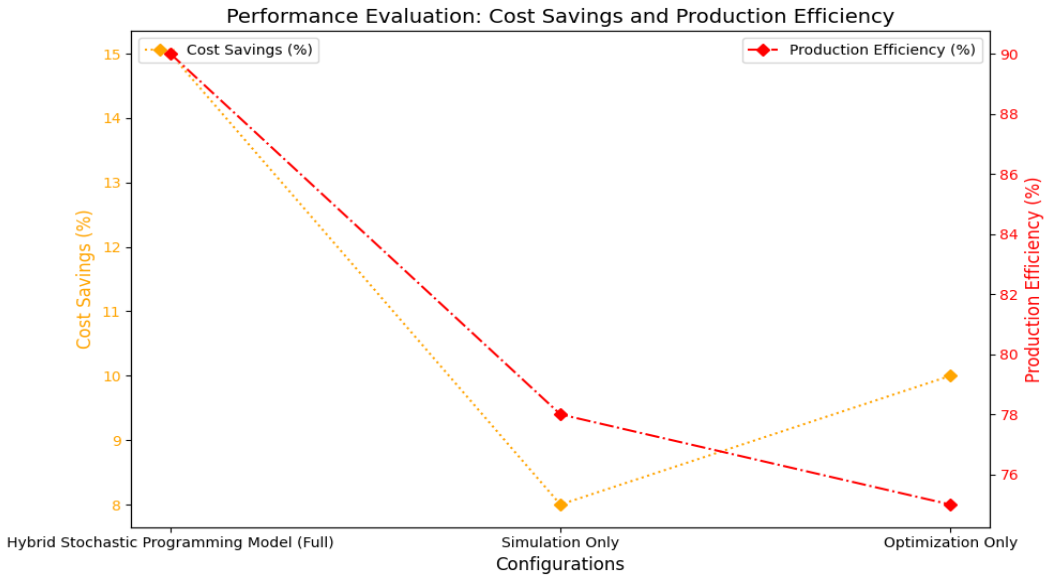


Fig. 3: Performance Comparison: Cost Savings and Production Efficiency for Production Planning Models

Fig. 3 shows the Cost Savings (%) and Production Efficiency (%) of the same three setups; Hybrid Stochastic Programming Model, Simulation Only, and Optimization Only. Hybrid Model has the best cost savings (15) and production efficiency (90) indicating that it is the best at optimizing its resources and low cost of operations. Comparatively, the models of Simulation Only and Optimization Only have less cost savings (8 and 10%), production efficiency (78 and 75%), where the combination of both simulation and optimization models is more effective in improving the overall production planning results.

Conclusion

This study examined the use of Stochastic Programming Models in the Optimization of production planning when there is a disruption in supply chain and it was conducted to increase the efficiency of decision making and resource allocation. The major results show that the use of stochastic Optimization is substantially better as compared to the deterministic methods. In particular, the Hybrid Stochastic Programming Model minimized the Latency by 1.5 hours as compared to 2.5 hours in Simulation Only model and 3.0 hours in Optimization Only model. Also, the hybrid Model had the best throughput (200 units/day), productivity (90%), and the use of resources (85), which indicates the usefulness of having both simulation and Optimization to manage uncertainty in real-time production scheduling. The Hybrid Stochastic Programming Model also paid off with 15% economy underlining the potential of the Model to save operation costs through adjustment to the different demand and supply conditions. Comparatively, the Simulation Only and Optimization only configurations had cost savings of 8 % and 10 % respectively, implying that the hybrid technique is more holistic in terms of benefit by maximizing the benefits of the simulation and the Optimization. The findings demonstrate the importance of taking uncertainty into account during production planning to increase the resilience of the system, resource-efficiency, and cost-efficiency. Another finding of the research also indicated the flexibility of the stochastic programming models to a sophisticated supply chain environment. Planning production with the help of uncertainty modeling will help manufacturers make better decisions and minimize the risk of disruptions and better overall system performance. Nevertheless, there are still difficulties in the implementation of such models at large scale, particularly in industries with very dynamic and unpredictable environments. Future studies might aim at making the proposed Model bigger in scale by incorporating real-time data providers and creating more sophisticated machine learning models to predict demand more accurately and allocate resources. Moreover, research on multi-objective optimization methods and the opportunities offered by stochastic models in multi-echelon supply chains may also enhance the production planning strategy in different degrees of uncertainty.

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