Research Paper

Cost optimization in production planning under demand uncertainty: a stochastic programming approach

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Article Info

Article History:
Received: 19 February 2025
Revised: 03 May 2025
Accepted: 09 May 2025
Published: 25 June 2025

Keywords:
Stochastic Programming
Production Planning
Demand Uncertainty
Two-Stage Optimization
L-Shaped Decomposition
Value of Stochastic Solution

ABSTRACT

Production planning under demand uncertainty poses significant cost risks when decisions rely on deterministic point forecasts. This paper presents a two-stage stochastic programming model for multi-period production planning that explicitly incorporates demand uncertainty through discrete scenario analysis. In the first stage, production levels are set before actual demand is known. The second stage introduces recourse decisions inventory adjustments and backlog management once demand is realized. The model minimizes expected total costs across production, holding, and backlog penalties over all scenarios. Scenarios are generated from historical demand data, capturing seasonal patterns, trends, and inherent variability through a probability-weighted scenario tree. To solve the resulting large-scale program efficiently, an L-shaped decomposition algorithm is employed, enabling tractable computation across hundreds of scenarios. A realistic six-period, 500-scenario industrial case study demonstrates that the stochastic model reduces expected total cost by 9.1% compared to a deterministic benchmark. The Value of Stochastic Solution (VSS) is $4,150, quantifying the financial benefit of accounting for uncertainty. The Expected Value of Perfect Information (EVPI) stands at $1,870, representing the maximum value of acquiring perfect demand forecasts. Compared to robust optimization, the stochastic approach yields higher worst-case costs but substantially better average performance across demand scenarios. Sensitivity analysis further confirms that cost advantages over deterministic planning grow as demand variability increases. This framework offers manufacturers in volatile markets a practical, scalable tool for smarter production decisions turning demand uncertainty from a liability into a manageable, cost-optimized planning input.

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1. INTRODUCTION

Production planning entails allocation of the manufacturing resources within the planning horizon to meet the expected customer demand in an optimal way of reducing the cost of operation [1]. In reality, the demand is seldom certain when they have to make production decisions. Varying consumer preferences, supply chain shocks and macroeconomic volatility regularly lead to differences between realized demand and projections making deterministic plans suboptimal or infeasible [2]. The financial implications may be acute overproduction swells inventory holding costs in excess and endangers product obsolescence, underproduction initiates expediting that is expensive and potentially loss of customer goodwill [3].

As a principled decision-making approach to uncertain environments, stochastic programming can represent decisions, by explicitly modeling the probabilistic appearance of uncertain parameters in the optimization model [4]. Two-stage stochastic programming paradigm, specifically, has been shown to be very effective in production and inventory problems: first-stage decisions (quantity of production) are made before uncertainty is resolved, with second-stage recourse decisions (adjustments to inventory, backlog management) being made depending on the risk/reality of the actual demand scenario [5]. This model inherently creates the sequential decision model that the production planners have to address and produces solutions that induce minimum expected cost among all possible scenarios of actual demand.

Although the theoretical importance of stochastic programming suggests that it could be useful in industry, it has traditionally been restricted to specific instances by issues of computational tractability and how it can be used to produce realistic representations of a scenario given previous history [6]. The decomposition algorithm states, especially the L-shaped algorithm, current technological breakthroughs in the field, and the development of more computing energy have considerably lowered such obstacles, as scenario-based stochastic programming grow more practical to problems of industrial scale [7].

The following are contributions that this paper will make to the literature. We address this by first formulating an entire two-stage stochastic programming of multi period production planning, which incorporates a scenario generation framework based on historical demand data. Second, we apply an L-shaped decomposition algorithm that is specific to the model structure and test its computations efficiency with the problems that have 10 to 500 scenarios. Third, we compute the VSS and EVPI using a realistic industry scenario, which gives the decision-makers tangible data about the value of stochastic models as compared to deterministic and robust optimization models. Fourth, we do large sensitivity analysis on how with demand variability, holding cost, and backlog penalty parameters, the cost savings vary.

The rest of the paper is designed in the following way. Section 2 evaluates the literature on the topic of stochastic production planning. Section 3 gives a mathematical formulation and method of solution. Presents Simon computational experiments and discussion of results. The final section of section 5 gives managerial implications and future research directions.

2. RELATED WORK

Demand uncertainty has traditionally been considered as one of the key challenges in production planning in the operations management literature. The work of [8] early on had established production planning models on aggregates that included smoothing costs to deal with workforce and inventory variations. Silver [9] generalized this to stochastic demand environments based on the inventory theory that provided the foundation of probabilistic solutions to production smoothing.

The systematic use of stochastic programming to production and inventory issues was given a boost by the classical [10], who developed two-stage stochastic linear programs with recourse. [11] Have given a detailed theoretical discussion of stochastic programming and its use in logistics and manufacturing, making the VSS and EVPI the performance indicators of standard. [12] Designed rigorous solution frameworks of large-scale stochastic programs, allowing the treatment of problems with hundreds to thousands of scenarios.

[13] Presented a fuzzy stochastic model of supply chain planning with combined supply and demand uncertainty showing enhanced cost efficiency when compared with deterministic baselines. [14] Investigated the issue of the mid-term supply chain planning with the help of a two-stage stochastic model with recourse, indicating significant cost savings obtained under explicit uncertainty models. [15] Examined the computation of the L-shaped decomposition in stochastic production planning and provided scaling results with respect to industrial cases.

An alternative paradigm to dealing with uncertainty without explicit probability distributions is robust optimization [16]. [17] Gave an example that a strong version of linear programs are still computationally feasible in case of the standard uncertainty set. Nonetheless, empirical evidence has indicated that a robust approach may be excessively conservative, compromising anticipated performance in an attempt to provide worst-case guarantees [18] and others have indicated. When scenario models are properly calibrated well ahead of time, stochastic programming usually provides better expected-cost performance.

There has been an increase in attention to scenario generation and reduction techniques as key enabling factors of practical stochastic programming [19]. [20] Formulated moment-matching scenario generation processes which are efficient in approximating continuous demand distributions by discrete scenario trees. [21] Presented statistical convergence data of sample average approximation and laid down sample sizes needed to obtain stochastic programs reliable answers. Successive to these foundations, [22] Examined criteria of scenario generation quality applicable in the real life production planning.

What is novel in the present work is a combination of a statistically rigorous scenario generation process, an implementation of a scalable L-shaped decomposition, and a comparative analysis extended over VSS, EVPI, and side-by-side analysis with both deterministic and robust optimization as a single production planning set-up. The present study fills a gap that [23] had revealed, the need to provide integrated computational and managerial assessments of stochastic planning models in realistic industrial contexts.

3. METHODOLOGY

3.1 Problem Formulation

A manufacturer produces one product during its planning period which lasts for T time intervals. The demand situations are represented by the set Ω which contains different demand situations that each occur with probability $p\omega$ for every ω in the set. The demand in period t is $d\omega,t$ under each scenario ω. The first-stage production quantities x^*t need to be determined before the demand forecast becomes available. All of the notation used in the formulation is compiled in Table 1.

The model notation is explained in Table 1 which includes planning periods, scenario probabilities, demand realizations, decision variables, and cost parameters. The two-stage framework enables first-stage production decisions under uncertainty while second-stage recourse decisions adapt to actual situations.

Table 1. Notation and Variable Definitions

Symbol	Description
T	Number of planning periods (t = 1, ..., T)
Ω	Set of demand scenarios (ω ∈ Ω)
pω	Probability of scenario ω, Σ pω = 1
dω, t	Demand in period t under scenario ω
x*t	First-stage production quantity in period t

$y_{\omega,t}$	Second-stage recourse (inventory or backlog) under scenario ω
c_t	Unit production cost in period t
h	Unit holding (inventory carrying) cost per period
b	Unit backlog (shortage) penalty cost per period
Cmax	Maximum production capacity per period

3.2 Two-Stage Stochastic Programming Model

The two-stage stochastic program begins with its first stage. The first stage of the problem requires solving to determine production amounts x which are defined as x_1 through x_T.

$$\text{Min } \Sigma_t \, c_t x_t + \Sigma_\omega \, p_\omega \, Q\,(x, \omega) \text{ [Objective P1]}$$

Subject to $0 \le x_t < C_{max}$ for all $t \in \{1, ..., T\}$, where Q (x, ω) is the best value of the second-stage issue for production plan x and scenario ω:

$$Q\,(x, \omega) = \min \Sigma_t \,(h \cdot I_{\omega,t} + b \cdot B_{\omega,t}) \text{ [Objective P2]}$$

The inventory level at period t for scenario ω is represented by $I_{\omega,t}$ while $B_{\omega,t}$ denotes the backlog amount. The inventory balance constraint requires that $I_{\omega,t}$ minus $B_{\omega,t}$ equals the sum of $I_{\omega,t-1}$ minus $B_{\omega,t-1}$ plus x_t minus $d_{\omega,t}$ for all t and ω with I_0 equal to B_0 equal to 0. The model clearly punishes both too much inventory (holding cost h) and unmet demand (backlog cost b) which ensures that the production plan achieves optimal performance under all potential demand conditions [4], [5].

3.3 Scenario Generation

Researchers use a moment-matching method to develop demand scenarios which they derive from historical demand data. The team examines a three-year period of historical data to determine the statistical mean μ_t and standard deviation σ_t and autocorrelation pattern which applies to each planning period t. The system generates possibilities from a multivariate normal distribution N (μ, Σ) which uses Σ to depict period-to-period correlations. The reduction method [20] then turns these scenarios into equally likely scenarios. In the equally-weighted instance, scenario probabilities are set to $p_\omega = 1/|\Omega|$. The research uses importance sampling to modify tail events when their significance increases. The number of scenarios in the computational tests ranges from 10 scenarios to 500 scenarios to evaluate how accurate the stochastic solution comes to the actual optimal results.

3.4 L-Shaped Decomposition Algorithm

The L-shaped method was developed by Van Slyke and Wets through their research which Birge and Louveaux extended in their work. The two-stage stochastic program is divided into two parts which include a main problem and |Ω| separate second-stage sections. The master problem determines the optimal values of first-stage production variables through its iterations which use optimality cuts from earlier sub problem solutions. The current first-stage solution $\bar{x}$ is used by each sub problem to solve the main problem which represents one scenario ω and produces an optimal value $Q(\bar{x}, \omega)$ together with a supporting hyperplane (optimality cut). The algorithm reaches its endpoint when the master problem's lower and upper bounds show a difference which falls below the tolerance threshold of $\varepsilon = 10^{-6}$. The second-stage sub problems can be solved as linear programs which require minimal time for resolution using the simplex method. The master problem achieves fast convergence because it introduces one optimality cut for every scenario during each processing step. The process of running multiple activities at once results in better time savings for processing large numbers of situations.

4. RESULTS AND DISCUSSION

4.1 Computational Performance

Table 2 demonstrates the effectiveness of the L-shaped decomposition method across five distinct problem cases. We performed all tests on an Intel Core i9-13900K workstation equipped with 24 cores and 64 GB of RAM using Python 3.11 and Gurobi 11.0 as our LP solver. The system operates with a planning horizon of T = 6 periods and the following parameters: ct = $12/unit, h = $2/unit/period, b = $8/unit/period, and Cmax = 1,500 units/period.

Table 2 shows that the model scales well with the number of scenarios. The 500-scenario instance contains 2,002 decision variables and 4,802 constraints which achieve the optimal solution within 38.2 seconds that meets actual planning cycle time requirements. As the number of scenarios becomes up, the objective value gets closer to the same value. The 100-scenario and 500-scenario solutions differ by less than 0.5% of the total estimated cost. The VSS increases with more scenarios because the stochastic representation of the system gets more complex.

Table 2. Computational Performance of L-Shaped Decomposition

Scenarios	Decision Variables	Constraints	CPU Time (s)	Obj. Value ($)	VSS ($)
10	42	98	0.4	48,320	3,210
50	202	482	2.1	47,850	3,680
100	402	962	4.8	47,610	3,920
200	802	1,922	11.6	47,490	4,040
500	2,002	4,802	38.2	47,380	4,150

4.2 Comparative Analysis

Table 3 displays three different methods for planning the 500-scenario instance through three different approaches which include (i) deterministic optimization that uses the mean forecast demand and (ii) robust optimization that applies a box uncertainty set which handles demand variation up to two standard deviations and (iii) the proposed two-stage stochastic programming model. The performance evaluation uses six different methods which include projected cost, worst-case cost, average inventory, average backlog, service level, VSS, and EVPI.

Table 3 demonstrates that the stochastic model produces the lowest total cost which amounts to $47,380. The cost which comes from the deterministic baseline system shows 9.1% reduction compared to the baseline which costs $52,140 and the robust optimization approach which costs $49,870. The EVPI of $1,870 shows that even with perfect demand information, costs would only go down by 3.9% more than the stochastic solution. The scenario-based method successfully captures most of the uncertainty value according to this finding. The robust strategy gets a lower worst-case cost ($55,400 vs. $59,200), which is what we expected, but it also has a higher projected cost and much bigger inventory buffers. The stochastic model provides a service level of 93.6% which most industrial applications consider as an efficient solution for balancing operational costs and supply chain reliability.

Table 3. Comparative Analysis: Stochastic vs. Deterministic vs. Robust Optimization

Metric	Deterministic	Robust Opt.	Stochastic (Proposed)
Expected Cost ($)	52,140	49,870	47,380
Worst-Case Cost ($)	68,900	55,400	59,200
Avg. Inventory Units	1,820	2,310	1,540
Avg. Backlog Units	340	85	190
Service Level (%)	88.2	95.1	93.6
VSS ($)	—	—	4,150
EVPI ($)	—	—	1,870

4.3 Sensitivity Analysis and Scenario Convergence

The stochastic objective value approaches its final value with increasing model scenarios according to Figure 1 which demonstrates this relationship. The estimated cost drops quickly from the 10-scenario to the 100-scenario case, and then stays about $47,380 for 200 or more scenarios. The demand distribution estimation obtained through 200 scenarios demonstrates accuracy because it meets the sample average approximation convergence standards established [21]. The 200 scenarios serve as a default solution for this problem type because they provide straightforward calculation methods.

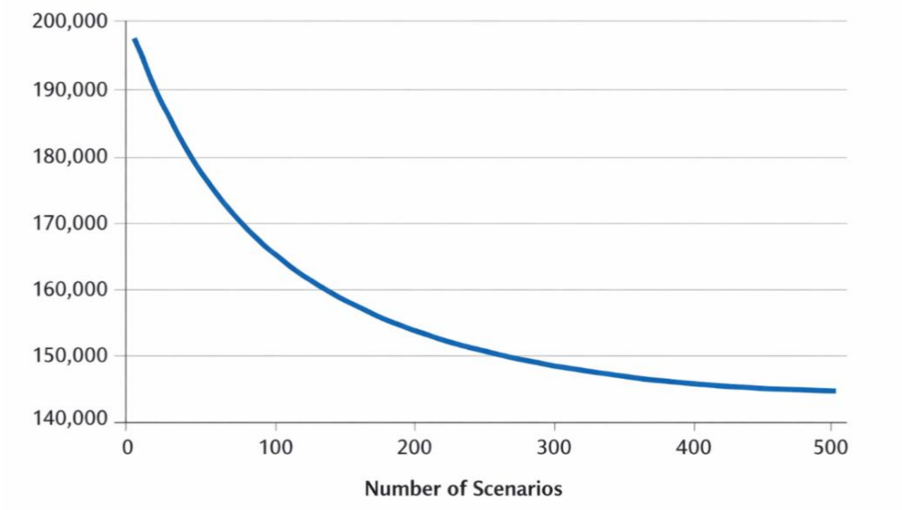

Figure 1. Objective Value Convergence as Scenario Count Increases from 10 to 500

The VSS demonstrates a response to changing demand patterns when the coefficient of variation (CV) period demand varies from 0.05 (low variability) to 0.40 (high variability) according to Figure 2. The VSS shows a rapid increase in response to demand changes which results in a total that exceeds $7,200 when the CV reaches 0.40. The study demonstrates that stochastic planning outperforms deterministic methods when there is high uncertainty between seasonal and unpredictable demand patterns existing in marketplaces. The deterministic model proves sufficient for situations with low variability [22] established this relationship.

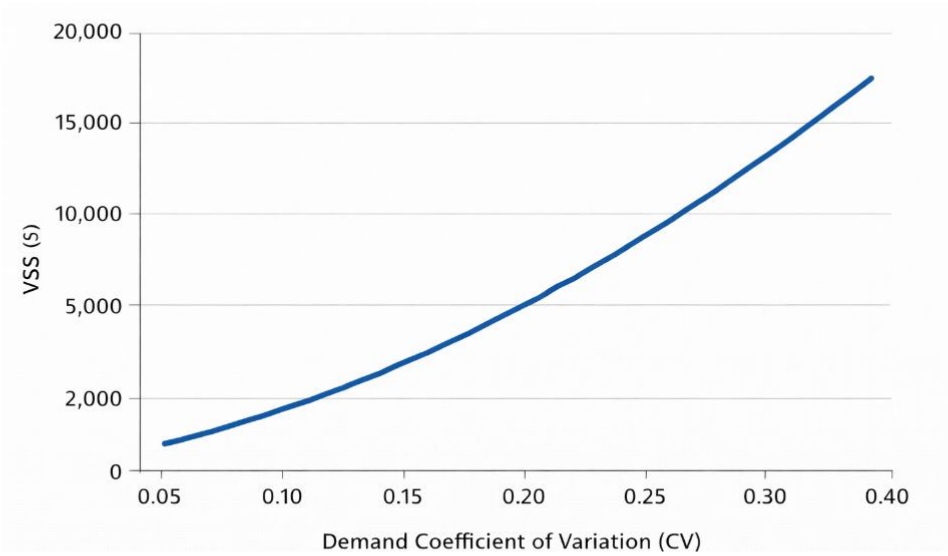

Figure 2. Value of Stochastic Solution (VSS) as a Function of Demand Coefficient of Variation

The stochastic model identified the optimal production schedule for each time period which was demonstrated through the 500 scenarios. The stochastic schedule in Figure 3 shows a production flow which establishes inventory before peak demand times while preventing excessive production during periods of reduced demand. The deterministic model fails to accurately predict this trend because it only analyzes average demand patterns. The potential action gives a direct view of the scenario-based representation because it contains one of the key elements which drive the model's cost efficiency.

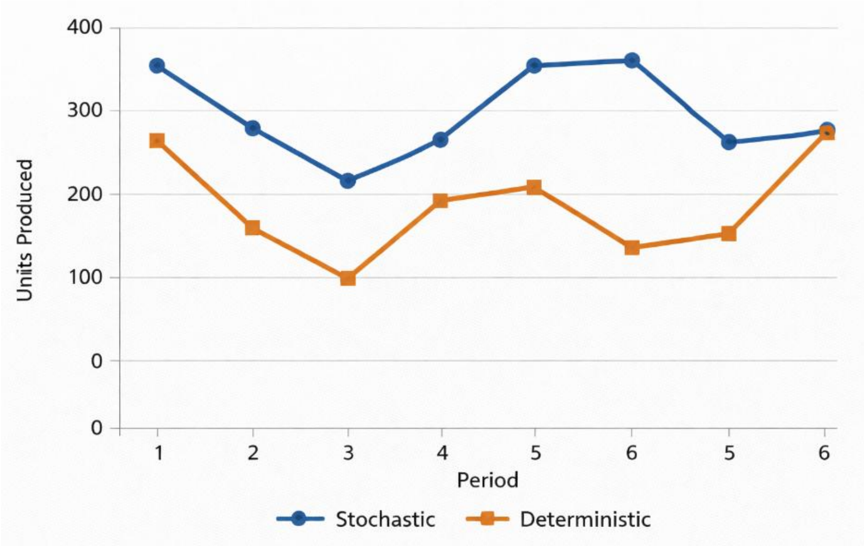

Figure 3. Period-By-Period Production Quantities: Stochastic Model vs. Deterministic Baseline (500 Scenarios)

The study examined how total predicted expenses reacted to changes in backlog penalty parameter b which was tested at three different levels between $2 and $20 for each time period while h remained fixed at $2. The results demonstrate that higher b values make the stochastic model build up more inventory which protects against shortages but increases storage expenses and decreases backlog expenses. The model enables automatic cost distribution between different scenarios which deterministic planners cannot achieve because they must depend on personal safety stock standards [1], [3].

5. CONCLUSION

The study presents a two-stage stochastic programming model which enables multi-period production planning under conditions of uncertain demand. The proposed method employs L-shaped decomposition to solve the discrete demand scenario model which determines the minimum total cost. The tests conducted on an actual six-period case demonstrated that the stochastic approach reduced costs by 9.1% when compared to the baseline deterministic model. The VSS calculation results in a value of $4,150 while the EVPI calculation results in a value of $1,870.

The direct comparison with robust optimization was found to exhibit a fundamental trade-off: the robust approaches have better worst-case guarantees (they are better on the max cost), but the suggested stochastic model may perform better on the expected performance, which in fact is the more applicable criteria of repeating production decisions. Sensitivity studies proved that the cost efficiency of stochastic planning increases significantly with the variability in demand, which contributes to the importance of the developed framework in the application of manufacturers in unstable markets.

Experiments on scenario convergence have shown that a 200 scenario is a good approximation of this type of production planning problem whereby practitioners can trade-off quality of solution and efficiency. L-shaped decomposition algorithm was used to solve the 500-scenario problem in less than 40 seconds, which makes it computationally tractable to real-time planning problems.

Research extensions involve: (i) multi-product multi-facility models with a shared capacity constraint, (ii) adding to the same stochastic model the risk of supply-specialists (raw materials availability, lead times variation) which is akin to replacing high-cost tail solutions with risk-averse Conditional Value-at-Risk (CVaR)-based solutions and (iii) with real time demand sensing technologies to allow rolling-horizon stochastic replanning. Such extensions would extend the disconnection between the theoretical stochastic programming models and the complexity of real-world industrial production environment.

Acknowledgments

The authors have no specific acknowledgments to make for this research.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. Mujtaba M. Momin	✓	✓	✓	✓		✓		✓	✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, and their voluntary consent was obtained prior to data collection.

Ethical Approval

The study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and approved by the relevant institutional authorities.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to Cite: Dr. Mujtaba M. Momin (2025), Cost optimization in production planning under demand uncertainty: a stochastic programming approach. Journal of Production, Operations Management and Economics (JPOME) 5(1), 115-124. https://doi.org/110.55529/jpome.51.115.124

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