Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395
ISSN (print) 1693-6590 | ISSN (online) 2442-2630
https://journal3.uad.ac.id/index.php/spektrum/index

A Hybrid Stochastic Optimization and Simulation Approach for Multi-Stage Production–Procurement Planning under Uncertainty

Paulina Kus Ariningsih *, Carles Sitompul, Titi Iswari, Giovano Alberto

Supply Chain Center, Fakultas Teknologi Rekayasa, Universitas Katolik Parahyangan, Jawa Barat, 40141, Indonesia
* Corresponding Author: paulina.ariningsih@unpar.ac.id

ARTICLE INFO

Article history
Received May 5, 2026
Revised August 12, 2026
Accepted September 14, 2026

Keywords
Purchasing optimization;
Production scheduling;
Monte Carlo scenario;
Stochastic optimization;
Textile industry.

ABSTRACT

Multi-stage manufacturing firms that source raw materials through both long-lead-time import contracts and volatile spot markets must coordinate procurement and production under supply and demand uncertainty. Managing these decisions separately leads to excessive reliance on spot markets, unstable inventories, and unbuffered downside cost risk. This study aims to develop a novel integrated stochastic optimization framework that jointly plans procurement and multi-stage production for a real-world textile supply chain. The framework's novelty lies in embedding a Conditional Value-at-Risk (CVaR) measure directly into a multi-stage stochastic input–output production–procurement model, so that sourcing-channel selection and production scheduling are optimized jointly rather than sequentially. The approach combines a risk-aware CVaR procurement model with a stochastic input–output production scheduling model that captures material flow across processing stages. The two are accompanied by a Monte Carlo scenario-generation architecture that represents demand and spot-price uncertainty. System performance is evaluated across 100 stochastic scenarios over a 52-week horizon, using a dataset calibrated from an industrial textile system. Results show the framework maintains a 100% service level (zero expected backlog) across all scenarios. As the initial-inventory target rises from 1× to 2× the target Days of Inventory on Hand (DOH), total operational cost increases from about USD 2.15 million to USD 2.80 million (a 30% rise), while the 0.95-level CVaR increases from about USD 1.66 million to USD 2.17 million. This reveals an explicit, quantifiable trade-off between inventory buffering and downside cost risk. The model also shifts sourcing away from expensive spot purchasing as buffering increases. This study contributes to developing a framework that offers a practical, risk-aware decision-support tool for firms balancing import contracts against spot volatility, and demonstrates the value of synchronizing procurement and production rather than planning them in isolation.

©2026 The Author(s)
This is an open-access article under the CC–BY-SA license.

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

1. Introduction

In modern manufacturing systems, firms increasingly operate under significant uncertainty in both supply and demand, particularly in globalized supply chains characterized by long lead times and volatile input prices (Choi et al., 2023). These challenges are especially pronounced in industries such as textiles, where raw materials are often sourced through a combination of long-term import contracts and short-term spot purchasing with volatile prices, each associated with distinct cost structures and risk profiles (Merzifonluoglu, 2026; Mohammadivojdan et al., 2022). At the same time, production systems frequently involve multi-stage processes with strong material flow dependencies, requiring careful coordination to maintain operational efficiency and service reliability (Thürer et al., 2025). The production system consists of multiple sequential stages, including blowing, carding, combing, and spinning, where imbalances in material flow can lead to excess inventory or production delays (Camargo et al., 2021; Zhenglei He et al., 2021). This context provides a representative and practically relevant setting for studying integrated decision-making under uncertainty.

A critical managerial challenge in such environments lies in coordinating procurement decisions with production planning. Procurement strategies determine the availability, timing, and cost of raw materials Parchami et al. (2022); Xu & Song (2022), while production scheduling governs the allocation of these materials across multiple processing stages (Liang et al., 2025). However, existing research largely treats these decisions separately: procurement models typically focus on supplier selection and inventory policies under uncertainty, while production models emphasize scheduling and capacity allocation. This separation can lead to suboptimal decisions, particularly in systems where upstream supply uncertainty directly impacts downstream production feasibility.

A substantial body of research addresses procurement under supply and price uncertainty, typically framed as sourcing-portfolio optimization. Merzifonluoglu (2026) uses multi-stage stochastic programming to optimize replenishment across forward contracts, options, and spot markets under risk-averse objectives, while Mohammadivojdan et al. (2022); Talaba & Koo (2025) study portfolio allocation across unreliable suppliers and spot channels; Conditional Value-at-Risk (CVaR) formulations are widely used within this stream to balance expected cost against downside risk (Taghavi et al., 2023). Industry-specific work, such as Zhang et al. (2021) on textile supply-base risk and Ivanov & Dolgui (2022) on the macro-level "shortage economy," reinforces the operational relevance of sourcing risk in commodity-intensive sectors. A common limitation unifies this stream: production is treated as an exogenous sink for demand, so procured materials are never explicitly allocated across manufacturing stages (Achaw & Danso-Boateng, 2021; Khare, 2021).

Zhang et al. (2021) examine supply chain risk assessment in the apparel and textile industry, employing machine learning on newsfeed data to evaluate long-term supply base risks in low-cost sourcing nations. This study delineates the sector-specific volatility of textile procurement, pertinent to the current research; however, it does not incorporate models for production scheduling decisions or the distribution of bought materials across processing steps. Ivanov & Dolgui (2022) describe the emergence of a "shortage economy" at the macroeconomic level, where the long-held assumption of continuous material availability in supply chain and operations management theory is fundamentally questioned due to geopolitical disruptions and pandemic-induced supply contractions. While this viewpoint underscores the necessity for linked procurement-production frameworks, the study does not formulate a formal optimization model and defers the combined analysis of sourcing and scheduling to other studies. A second, largely separate stream studies multi-stage production planning and control. Thürer et al. (2022), (2025) use simulation to compare shop-floor control systems (Kanban, MRP, DBR, DDMRP) and order-release mechanisms, while Zhiliang et al. (2024) apply reinforcement learning to dynamic production authorization; input–output and MILP formulations are standard for representing inter-stage material dependencies (Guzman et al., 2022; Liang et al., 2025; Parchami Afra et al., 2022). Across this stream, upstream procurement is consistently treated as an unbounded, deterministic input, the model boundary begins at raw-material arrival and excludes contract structure, sourcing channel, and price risk.

However, these models typically assume that material availability is given or exogenously determined (Xu & Song, 2022). A smaller set of studies attempts to bridge the procurement–production interface but stops short of full integration. Raj et al. (2022) analyzes disruption responses empirically without a joint optimization model; Liang et al. (2025) coordinate inbound logistics with multi-stage scheduling but treat procurement decisions (contract type, channel, price) as fixed inputs; and Parchami et al. (2022) confirm in a systematic review that integrated approaches outperform isolated ones on total cost, while noting that such models are largely confined to project scheduling rather than repetitive manufacturing. The closest prior work, Xu & Song (2022) jointly optimizes raw-material procurement and finished-goods production under lead-time and quantity uncertainty using simulation-based optimization with a Genetic Algorithm. However, their procurement sub-model assumes a single sourcing channel with a fixed contract structure and omits the contract-versus-spot choice that is operationally central in textiles.

Thus, treats procurement cost as deterministic rather than price-volatile, and does not represent the sequential inter-stage dependencies (blowing, carding, combing, spinning) where material-flow imbalances generate excess work-in-process or downstream delays (Jayalath et al., 2025; Nalimov & Mulchenko, 1971). The production sub-model fails to depict the sequential dependence structure of multi-stage textile processes, such as blowing, carding, combing, and spinning, where material flow imbalances across stages result in surplus work-in-process inventory or delays in downstream output. These deficiencies collectively necessitate the development of a more robust modeling framework that simultaneously optimizes procurement channel selection and production scheduling across interdependent sequential stages, amid uncertainties on both the supply and price sides (Basu, 2025; Yeshzhanov et al., 2024).

These streams of research reveal a consistent gap: no existing model simultaneously optimizes (a) the choice between contract and spot sourcing under price volatility using a risk measure such as conditional value-at-risk (CVaR), and (b) production scheduling across interdependent multi-stage processes within a single framework evaluated under uncertainty. This study addresses this gap by proposing a novel stochastic optimization framework for integrated procurement and production scheduling.

The study makes three main contributions. First, it embeds a CVaR-based risk measure directly into a multi-stage input–output production–procurement model, enabling sourcing-channel selection and stage-level production scheduling to be optimized jointly rather than sequentially. Second, it integrates the model with a Monte Carlo scenario-generation framework that represents demand and spot-price uncertainty through 100 scenarios over a 52-week planning horizon, enabling risk-aware performance evaluation rather than reliance on deterministic point estimates. Third, using data from a real-world textile case, it quantifies the trade-off between inventory buffering, measured in Days of Inventory on Hand (DOH), and downside cost risk, thereby providing managerial insights into sourcing and inventory policies under uncertainty. The remainder of this paper is structured as follows. Section 2 presents the proposed optimization models. Section 3 describes the simulation framework. Section 4 reports the computational experiments and results. Section 5 discusses the managerial implications, and Section 6 concludes the study.

2. Method

This study considers a multi-stage manufacturing system in which procurement and production decisions are tightly coupled under uncertainty. The system is motivated by a textile supply chain, where raw materials are sourced through two distinct channels with different cost and risk characteristics (Alamirew & Tesema, 2024; Islam et al., 2024).

The first sourcing option consists of long-term import contracts with relatively stable prices but long and uncertain lead times (approximately three months, including logistics and clearance). The second option involves local spot purchasing, which offers short lead times (1–2 days) but is subject to significant price volatility. The coexistence of these two sourcing channels introduces a

fundamental trade-off between cost efficiency and supply responsiveness. Here, we assume that the contracted purchase is only assigned to one major supplier only, while the backup supplier shall be assigned to the spot purchasing.

The production system is organized as a multi-stage process with sequential material flow dependencies, including stages such as blowing, carding, combing, drawing, roving, spinning, and finishing. Each stage transforms intermediate products into subsequent forms, and material flows must be balanced to avoid bottlenecks, excess work-in-progress (WIP), or shortages. As observed in the system mapping, imbalances in upstream procurement decisions can propagate downstream, resulting in either excess inventory accumulation or production delays. A key operational challenge lies in determining of three main strategy: (1) The optimal procurement strategy, including the allocation between contract sourcing and spot purchasing under uncertainty; (2) The optimal production schedule across multiple stages, considering capacity constraints and material flow dependencies, (3) The coordination mechanism between procurement and production to maintain stable inventory levels, often measured using Days of Inventory on Hand (DOH), while minimizing total cost.

Meanwhile, uncertainty in the system may arise from three primary sources: (1) Demand variability across planning periods; (2) Price fluctuations in the spot market; (3) Variability in supply lead times and availability. To address these challenges, this study proposes an integrated modeling framework that links procurement and production decisions through two interacting components: a risk-aware procurement optimization model and a dynamic input–output production scheduling model. As mentioned previously, there is uncertainty in the price and demand of the product weekly. Therefore, we introduce the single-product stochastic model to accommodate the uncertainty. The notation, sets, parameters, and decision variables used in the proposed model are as follows.

Sets:

T : The set of weekly planning periods indexed with t, with the horizon of $|T| = 52$
J : The set of the type of product handled, including raw material, intermediate stages, and finished goods, indexed with j
K : The set of sequential production stages, indexed with k. The value $k = 0$ is the inbound raw material, while the value of $k = |K|$ is the outbound finished goods.
S : The set of scenarios for spot price and demand uncertainty, indexed with s

Parameters:

d_{st} : Finished-goods demand in period t for scenario s
$\hat{d}$: Average weekly finished-good demand across all periods and all scenarios
L^{imp} : Lead time of imported order from order placement to arrival
L_k : Internal lead time for production stage k
a_k^w : Waste fraction at production stage k
ρ_k : Chain ratio of material that must enter stage k as the impact of waste fraction for production stage k, formulated as $\rho_k = \prod_{j:k\le j\le|K|} {}^{1}/_{1-a_j^w}$
p_k : processing time per unit of product at the production stage k
$\hat{C}_t$: aggregate capacity of machine in period t
DOH^{target} : target days on hand inventory target
I_k^0 : initial inventory at the beginning of planning horizon for production stage k
$\hat{c}^{con}$: unit price for contracted import
$\hat{c}_{st}^{spot}$: spot price under scenario s at time t
$\hat{c}_k^h$: holding cost per unit at stage k per period
$\hat{c}_k^p$: production cost per unit at stage k
p^b : penalty per unmet demand
α : the CvaR confidence level, with $\alpha = 0.95$

λ : the risk aversion weight, $\lambda = 0$ means that the model is risk neutral (cost minimization), while $\lambda \to 1$ means pure risk minimization (risk-averse model).
π_s : the probability of scenario; in this article, the probability of the scenario is equal for all scenarios

Decision Variable:

q_t^{cont} : Contracted quantity ordered in period t, to be arrived in week $t + L^{imp}$
η : The VaR auxiliary variable for CVaR linearization based on (Rockafellar & Uryasev, 2000)
u_s : The excess scenario cost above the η (CVaR linearization surplus)
q_{st}^{spot} : Spot purchase quantity ordered at period t under scenario of s
r_{st} : The unmet raw material or shortfall at period t under scenario of s
x_{kts} : Production throughput at stage k at period t under scenario s
I_{kts} : End of week inventory at stage k at period t under scenario s
B_{st} : The finished good backlog (unmet demand) at period t under scenario s

It is assumed that there is no loss of raw material during transportation; therefore, the volume of RM received (inbound quantity) at period t under scenario s can be expressed by Eq. (1) as the summation of the quantity of contract as well as spot purchase. It is important to note that the value of q_t^{cont} is easier to determine as the baseline. Therefore, it can be decided regardless of the uncertainty of demand, while the value of q_{st}^{spot} is impacted by the value of demand.

$$RM^{inbound}{}_{st} = q^{cont}_{(t-L^{imp})} + q_{st}^{spot} \text{ with } q^{cont}_{(t-L^{imp})} = 0 \text{ if } t - L^{imp} < 1 \tag{1}$$

The costs involved in this may consist of purchase cost (contract and spot), production, holding, and backlog. Therefore, the total cost for each scenario can be expressed by Eq. (2). Consequently, the objective function is described in Eq. (3).

$$Z_s = \sum_{t\in T}\left(q_t^{cont}\hat{c}^{con} + q_{st}^{spot}\hat{c}_{st}^{spot}\right) + \sum_{k\in K}\sum_{t\in T}\left(x_{kts}\hat{c}_k^p + I_{kts}\hat{c}_k^h\right) + \sum_{t\in T}(B_{st}p^b + r_{st}p^b) \tag{2}$$

$$\min f = (1-\lambda)\sum_{s\in S}\pi_s Z_s + \lambda CVaR_\alpha(Z) \tag{3}$$

$$\text{where: } CVaR_\alpha(Z) = \eta + \frac{1}{((1-\alpha)|S|)}\sum_{s\in S}u_s$$

Whereas the constraints are described through Eq. (4) to Eq. (12).

$$u_s \geq Z_s - \eta \qquad \forall s \in S \tag{4}$$

$$RM^{inbound}{}_{st} + r_{st} \geq d_{st} \qquad \forall s \in S, t \in T \tag{5}$$

$$I_{(k=0)ts} = I_{(k=0)(t-1)s} + RM^{inbound}{}_{st} - x_{(k=1)ts} \qquad \forall s \in S, t > 0 \in T \tag{6}$$

$$I_{kts} = I_{k(t-1)s} + (1 - a_k^w)x_{kts} - x_{k(t+L_k)s} \qquad \forall s \in S, t \in T, k \in K\backslash|K| \tag{7}$$

$$I_{(k=|K|)ts} - B_{st} = I_{(k=|K|)(t-1)s} + \left(1 - a_{(k=|K|)}\right)x_{(k=|K|)ts} - d_{st} \qquad \forall s \in S, t \in T \tag{8}$$

$$p_k x_{kts} \leq \hat{C}_t \qquad \forall s \in S, t \in T, k \in K \tag{9}$$

$$I_{kts} \geq DOH^{target}\hat{d}\rho_k \qquad \forall s \in S, t \in T, k \in K\backslash|K| \tag{10}$$

$$q_t^{cont}, q_{st}^{spot}, r_{st}, x_{kts}, I_{kts}, B_{st}, u_s \geq 0 \qquad \forall s \in S, t \in T, k \in K \tag{11}$$

$$\eta \in \mathbb{R} \tag{12}$$

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

The Eq. (4) denotes the relationship of u_s and η, related to the linearisation of CVaR. Meanwhile, the procurement feasibility constraint is described in Eq. (5), where the total inbound raw material must cover the raw material needed to meet the demand for finished goods. Meanwhile, Eq. (6) emphasizes the raw material balance in the warehouse. It is important to note that the value of $I_{(k=0)(t=0)s} = I^0_{k=0}$. Eq. (7) shows the inter-stage inventory balance for the production stage $k \in K \setminus |K|$, where end-of-period inventory is determined by prior period inventory and the net output after deducting the next stage consumptions during the production lead time of L_k. Here, the value of $I_{k(t=0)s} = I^0_k$. In Eq. (7), the value of $(1 - a^w_k)$ adjusts the input and output proportion due to waste. The relationship between backlog, finished good delivery, and inventory balance is shown in Eq. (8). The production throughput for each production stage k is limited by the available machine capacity, as expressed in Eq. (9).

Here $\hat{C}_t$ denotes the aggregate weekly machine capacity across the three parallel production lines. The constraint is applied per stage; capacity contention between stages running concurrently is not modeled, which is a reasonable approximation when the binding resource differs by stage. This simplification is noted among the study's limitations. The safety-stock requirement is enforced in Eq. (10), which requires end-of-period inventory at each stage to remain at or above the level implied by the target Days of Inventory on Hand (DOH), scaled by the stage's chain ratio's waste coefficient. The non-negativity of all decision variables is stated in Eq. (11), and Eq. (12) defines the CVaR auxiliary variable η as a free (unrestricted) real variable.

2.1. Solution Method

The model written in the previous subsection is a two-stage stochastic program. The contracted order quantity q^{cont}_t is a first-stage (here-and-now) decision: it carries no scenario index and must be committed before the spot price and demand of any given period are known. All remaining variables (q^{spot}_{st}, x_{kts}, I_{kts}, B_{st}, r_{st}) are second-stage (recourse) decisions, indexed by scenario s, and represent how procurement and production adjust once a scenario's demand and spot price are realized. This structure is the reason simulation is required: the underlying demand and price uncertainty is continuous, but the optimization model can only be solved against a finite, discrete set of scenarios. Monte Carlo simulation generates that finite set.

Two sources of uncertainty are represented in the scenario set S: finished-goods demand d_{st} and spot price $\hat{c}^{spot}_{st}$, both varying by period within each scenario. For each scenario, a $|T|$-period path of demand and spot price is generated via independent random sampling from normal distributions calibrated to the case data, with draws drawn independently across periods. A total of $|S|$ scenarios is generated, each assigned equal probability $\pi_s = 1/|S|$. For clarity of scope, import lead time L^{imp} and machine capacity $\hat{C}_t$ are treated as fixed parameters calibrated from historical averages rather than as stochastic quantities; only demand- and price-side uncertainty is represented through the scenario set. This scoping is revisited in the limitations section.

The expected-cost objective is evaluated over the Monte Carlo-generated scenario set S by replacing the expectation with the probability-weighted scenario average as shown in Eq. (3), and the risk term uses the CVaR linearization of Rockafellar & Uryasev (2000), represented through the auxiliary variable η and surplus variables u_s (Eq. 4). Because all |S| scenarios are indexed within a single model and share the common first-stage decision q^{cont}_t. The stochastic program is solved as a single extensive form, known as the deterministic equivalent in (Birge & Louveaux, 2011). Moreover, the scenario-dependent constraints Eq. (5) – Eq. (10) are replicated across all scenarios and optimized jointly in a single pass, rather than scenario by scenario.

This scenario-based formulation yields a globally optimal solution over the sampled scenario set for each parameter configuration, which distinguishes it from simulation-based optimization approaches that embed a simulator inside a metaheuristic search and return a heuristic solution (e.g., the genetic-algorithm scheme of (Xu & Song, 2022). Here, Monte Carlo simulation is used solely to generate the scenario set that represents demand and price uncertainty; the optimization itself is exact

for that set. The extensive form solution method is implemented in Pyomo and solved with the GLPK solver. The complete procedure: scenario generation, model construction, solution, KPI extraction, and repetition across the experimental design, is summarized in Fig. 1.

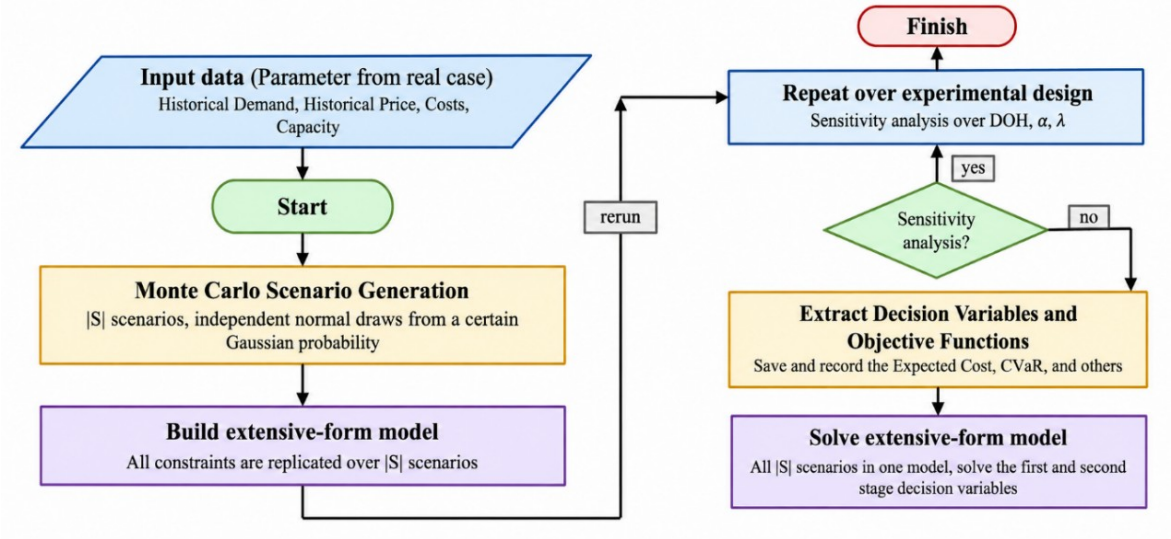


Fig. 1. Simulation Optimization Framework Flowchart

Fig. 1 shows the solution procedure linking Monte Carlo scenario generation with the stochastic optimization model, where the scenarios are generated first, then embedded into a single deterministic-equivalent problem; after solving and extracting performance indicators, the procedure is repeated for each initial-inventory level and each risk-parameter setting in the experimental design.

3. Results and Discussion

The proposed model and solution framework were implemented using a dataset coded from the real-world case of a cotton yarn spinning company in Indonesia. Fig. 2 states the flow of raw material in the factory, where the raw material is processed through a series of processes with different Input-Output Leontief numbers (a_k). It is important to note that the data given in this paper is not the original data due to confidentiality. However, the data are coded, estimated, or approximated from the real-world situation. The company is willing to hold the daily on-hand inventory for a maximum of 18 days. However, due to different utilities and waste ratios, each production process would have different initial inventories, DOH and inventory buffer, and cost value. The details of the data are as shown in Table 1.

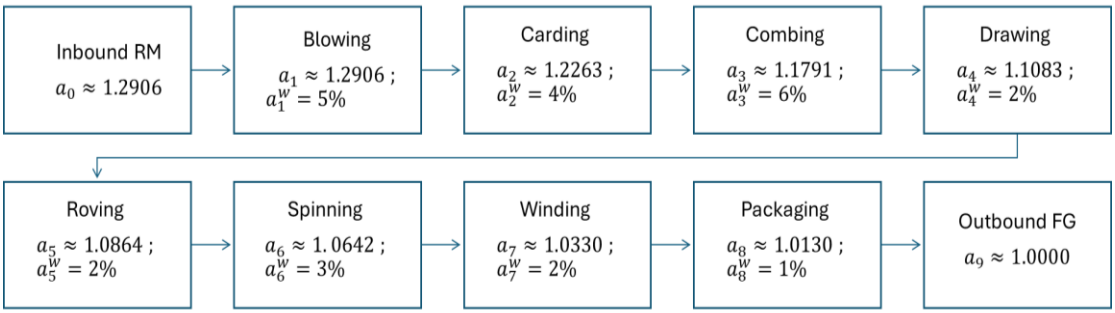


Fig. 2. Production Flow with estimated value of a_k and a_k^w for each production process

Here, we aim to plan for 52 periods; therefore, the value of the spot price is varied. The contract price is available at period $t = 0$, with the value of \$7.5 per unit; meanwhile, the spot price has ranged over \$9.81 ± \$ 1.86, and the backlog penalty is set to \$50. The demand has varied below the

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

average of 102.97 units per period, with a deviation of 16.53 units. The company has three lines with average production capacity per period of 200 units ± 9.2696. The lead time for import is set to 13 periods.

Table 1. Manufacturing parameter list

Process	Cost ($)		Processing time (machine hours)	Inter-stage lead time (period)
	Holding	Production		
0	0.8	-	-	-
1	1.0	2.0	0.9	0
2	1.1	2.5	1.1	1
3	1.2	3.0	1.3	1
4	1.3	1.8	0.8	1
5	1.4	1.6	0.7	1
6	1.5	3.5	1.5	1
7	1.6	1.4	0.6	1
8	1.7	1.0	0.4	0
9	2.0	0.5	0.2	0

We developed 100 scenarios of demand and spot price to be solved using the exact method through the GPLX Solver coded in Pyomo Python. The Monte-Carlo principle is used to develop the scenarios. In the computational experiment, we vary the value of I_k^0 with a multiplier parameter of {1,1.5.2} of DOH to examine the relationship of initial inventory toward the decisions. All runs have obtained an optimal solution. The results of the computational experiment are summarized in Table 2, and the detailed weekly decisions are shown in Fig. 2, Fig. 3, and Fig. 4. Fig. 2 to Fig. 4 depict the dynamics of various performance indicators including raw material purchasing mix, inbound and demand, production schedule, inventory on hand and inventory level, as well as backlog for each initial inventory (I^0) of 1×, 1.5×, and 2× DOH^{target} consecutively.

Table 2 reveals three effects of raising the initial-inventory target, each traceable to the model's constraint structure rather than to description alone. First, total cost rises non-linearly with the inventory target. Increasing the initial-inventory multiplier from 1× to 1.5× raises total cost by 7.8% (from $ 2.155M to $ 2.323M), while the subsequent step from 1.5× to 2× raises it by a further 20.7% (to $ 2.804M). This shows a steepening rather than constant marginal cost. This convexity is consistent with the DOH safety-stock constraint (Eq. 10) being slack at low targets, where early demand can be met from initial stock, and progressively tightening at higher targets, so that additional contract and spot procurement is required, with holding and purchase costs compounding across the 52-week horizon. The non-linearity is managerially important: it suggests diminishing returns to inventory buffering, where each additional unit of target DOH is more expensive than the last.

Table 2. Computational Experiment Result

I_k^0 multiplier	Objective Function ($)		Average Performance		
	Cost	CVaR_0.95	Backlog (unit/period)	RM DOH (days)	FG DOH (days)
1*DOH	2.154.918.61	1.660.507.66	0.0	1.2	0.3
1.5*DOH	2.322,872.29	1.792.873.68	0.0	5.0	0.7
2*DOH	2.804.320.41	2.171.591.56	0.0	17.2	1.4

Second, the raw-material DOH scales disproportionately to the target. RM DOH rises from 1.2 to 5.0 to 17.2 days across the three multipliers. This indicates a 14× increase for a 2× change in the inventory target. This disproportionate response reflects the chain-ratio structure (ρ_k, Eq. 10): because the raw-material stage sits farthest upstream, its safety-stock requirement is inflated by the compounded waste of every downstream stage ($\rho_{RM} \approx 1.29$), so a uniform increase in the DOH target is amplified most strongly at the raw-material end. Finished-goods DOH, by contrast, rises only modestly (0.3 to 1.4 days), because FG carries no downstream waste inflation (ρ_{FG} = 1.0) and the

model minimizes costly late-stage holding. The result is an inventory profile that shifts buffering upstream as the target grows, which is consistent with the operational logic that upstream (cheaper, waste-exposed) stages are the rational place to absorb uncertainty.

Third, the risk composition of cost is nearly invariant. The ratio CVaR_0.95 and expected cost stays almost constant at approximately 0.77 across all three inventory levels (0.771, 0.772, 0.774). This indicates that raising the inventory target scales the entire cost distribution roughly proportionally, so it does not preferentially reduce tail risk. In other words, holding more inventory in this system buys service-level protection (backlog stays at zero throughout) but does not reshape the cost-risk profile: the tail scales with the mean. This is a non-obvious finding, because inventory buffering is often assumed to compress downside risk; here, under a lower-bound DOH constraint and a fixed penalty structure, it does not.

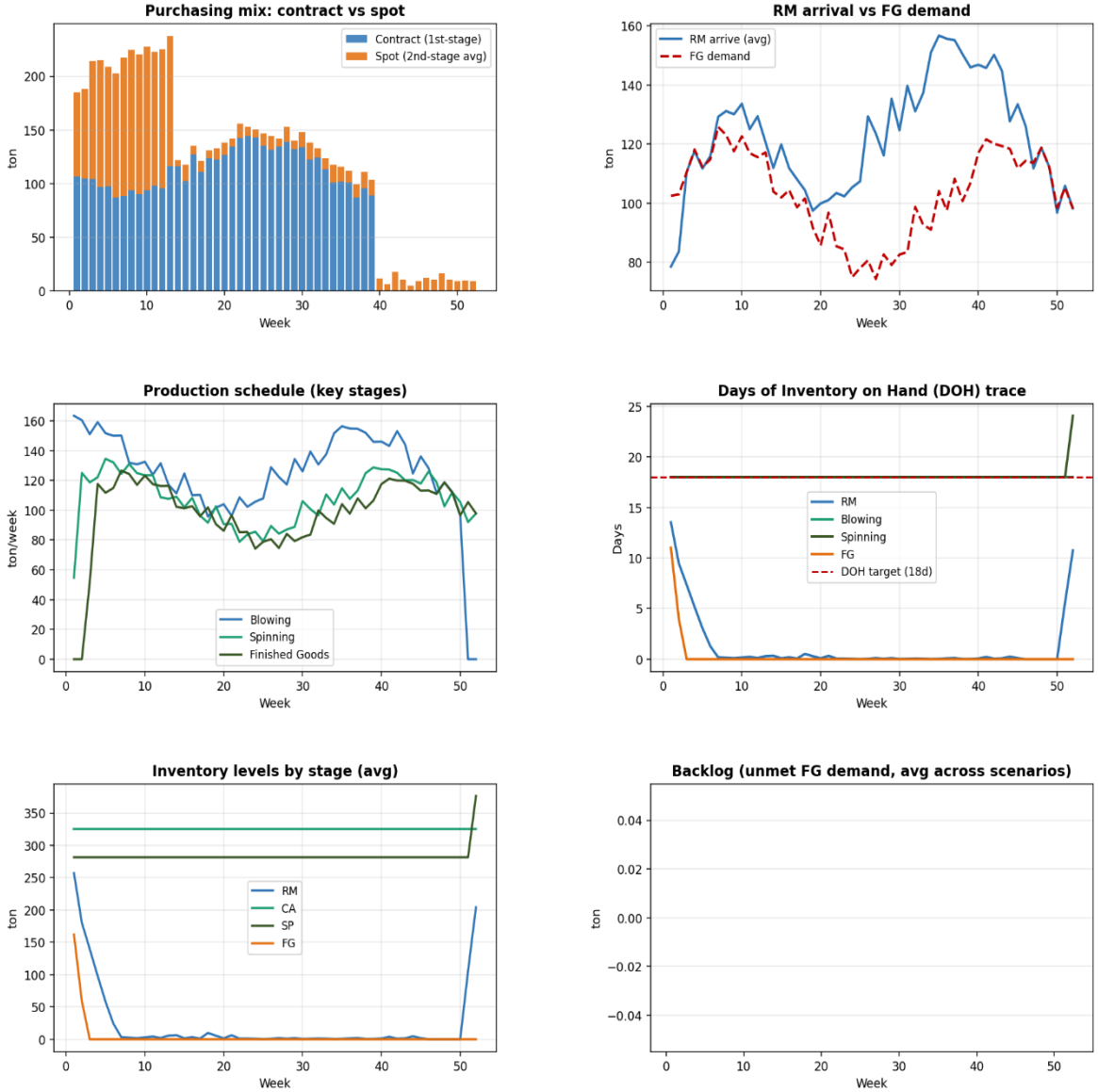


Fig. 3. Result of the Model Implementation with $I^0 = DOH^{target}$

Across all configurations, expected backlog remains zero. This is a direct consequence of the cost parameters: the backlog penalty ($ 50/unit) exceeds the highest holding cost ($ 2.0/unit at the finished-goods stage) by more than an order of magnitude, so the optimizer always finds it cheaper to serve demand than to defer it. The zero-backlog result is therefore not a coincidence of the data but a

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

structural outcome of the penalty-to-holding ratio; it would change only if that ratio fell below the point where deferring demand became locally cheaper than holding stock.

The weekly DOH traces (see Fig. 3–Fig. 5) show a consistent pattern that finished-goods and raw-material inventories are drawn down to near zero for most of the horizon and only approach their DOH targets near the planning boundary, whereas intermediate stages such as blowing and spinning hold their targets throughout. This asymmetry is consistent with the inventory-balance constraint (Eq. 10) being a lower bound ($I_{kts} \geq$ target) rather than an equality: the model may hold more than the target when doing so is cheaper than the alternative, and may sit at the target otherwise. Finished goods, carrying the highest holding cost, are held near the minimum feasible level, while intermediate stages, where holding is cheaper and downstream lead-time coupling is tighter, are maintained closer to target to keep material flowing without downstream starvation. The end-of-horizon rise in FG and RM inventory is a terminal effect: with no demand beyond the horizon, there is no incentive to draw stock down further, so inventory settles at the DOH lower bound.

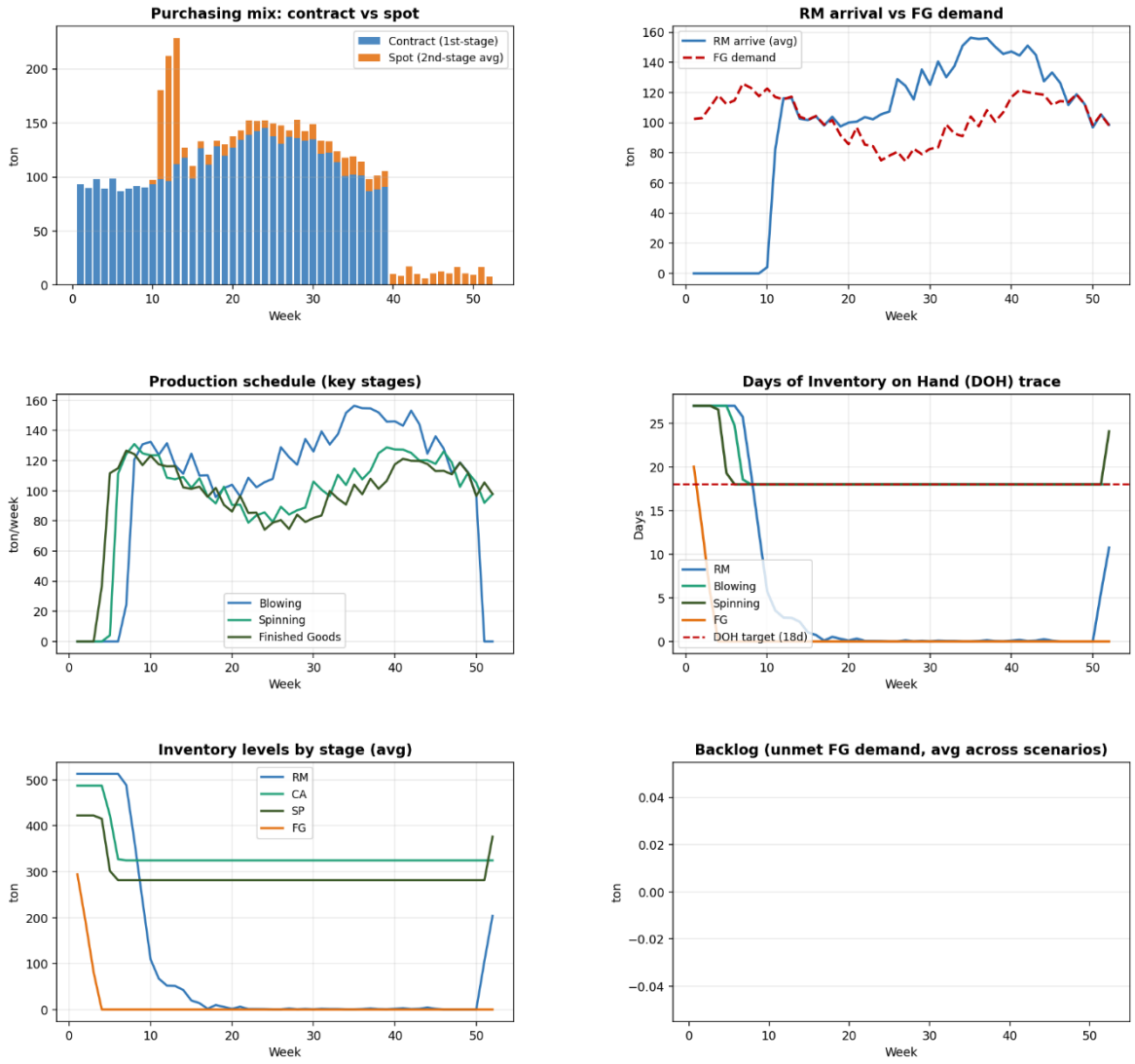


Fig. 4. Result of the Model Implementation with $I^0 = 1.5 * DOH^{target}$

We also perform a sensitivity analysis to check the impact of the CVaR parameter (α, λ) towards the objective function of cost and also CVaR_0.95. Fig. 6 and Fig. 7 depict the results of the sensitivity analysis for each value of α, λ toward cost (Fig. 6) and CVaR (Fig. 7). The figures clearly show that the value of the objective function increases along with the increase of the (α, λ) parameters for all

types of I_k^0 multipliers. The sensitivity analysis (Fig. 6–Fig. 7) shows total cost rising with both the confidence level α and the risk-aversion weight λ, across all inventory multipliers, expected, since a higher λ places more weight on the CVaR term and a higher α widens the tail being penalized, both of which trade expected cost for tail protection. More informative is that CVaR_0.95 is relatively insensitive to α. This occurs because of the Rockafellar–Uryasev linearization (Eq. 4), noting that the auxiliary variable η is optimized jointly with the production and procurement decisions, so as α changes, the model re-selects the η that minimizes the CVaR estimate for that confidence level, partially absorbing the change. The practical implication is that, for this cost structure, the risk-averse solution is robust to the precise choice of confidence level. Consequently, a manager need not tune α finely to obtain stable risk-aware decisions, though the weight λ remains a meaningful lever.

These findings both confirm and extend prior work. Most directly, the study in spinning industry by Camargo et al. (2021) find that coordinating production scheduling with cotton-blending decisions yields fewer unfulfilled demands than a hierarchical scheme that sequences the two separately. Our results converge on the same conclusion from an entirely different modeling route: where their integration is deterministic and internal to production (blending and lot-sizing), ours couples upstream contract-versus-spot procurement to multi-stage production and holds expected backlog at zero across all scenarios. The disproportionate upstream buffering echoes the flow-imbalance mechanism identified by Thürer et al. (2025), but quantifies it through the chain-ratio structure rather than shop-floor control rules. The near-constant CVaR-to-cost ratio contrasts with the risk-compression benefit often attributed to inventory in newsvendor-style settings (e.g., Taghavi et al. (2023), suggesting that in a multi-stage system with a binding DOH constraint, inventory's role is service protection rather than risk reshaping, a distinction that is not made explicit in single-stage procurement models such as in (Merzifonluoglu, 2026) or (Xu & Song, 2022).

3.1. Managerial Implications

The results of this study provide several important managerial insights for firms operating in multi-stage manufacturing environments under supply uncertainty. Procurement and production decisions should not be managed independently Xu & Song (2022), particularly in systems with long lead times and multi-stage material dependencies, since decoupled decision-making tends to produce systematic inefficiencies such as excessive spot reliance and unstable inventory (Merzifonluoglu, 2026). Consistent with this, the integrated framework anticipates downstream production requirements when setting upstream sourcing Zamani et al. (2023), producing coordinated material flows across the 52-week horizon while holding expected backlog at zero in every tested configuration. Managers should therefore treat sourcing and production as a single decision: a contract quantity set without reference to downstream stage requirements is the root cause of the spot-reliance and inventory instability the literature warns against.

The analysis reveals a critical trade-off between cost efficiency and supply flexibility. Spot purchasing provides responsiveness under uncertain demand, but excessive dependence exposes firms to significant price volatility (Talaba & Koo, 2025). The CVaR-based procurement strategy proposed here lets decision-makers explicitly control this downside risk, particularly valuable where input prices are highly volatile Liang et al. (2025), by balancing expected cost against protection from extreme scenarios (Merzifonluoglu, 2026). The results quantify this control: across the risk-aversion sweep, tail cost stays in a stable proportion to expected cost, roughly 0.77 at every inventory level, confirming that the model reshapes the cost distribution rather than merely shifting its mean. The practical implication is that the risk-aversion weight λ, not the confidence level α, is the effective control dial. Because CVaR proved insensitive to α, effort spent fine-tuning the confidence level yields little, whereas λ directly sets the trade-off between expected cost and tail protection.

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

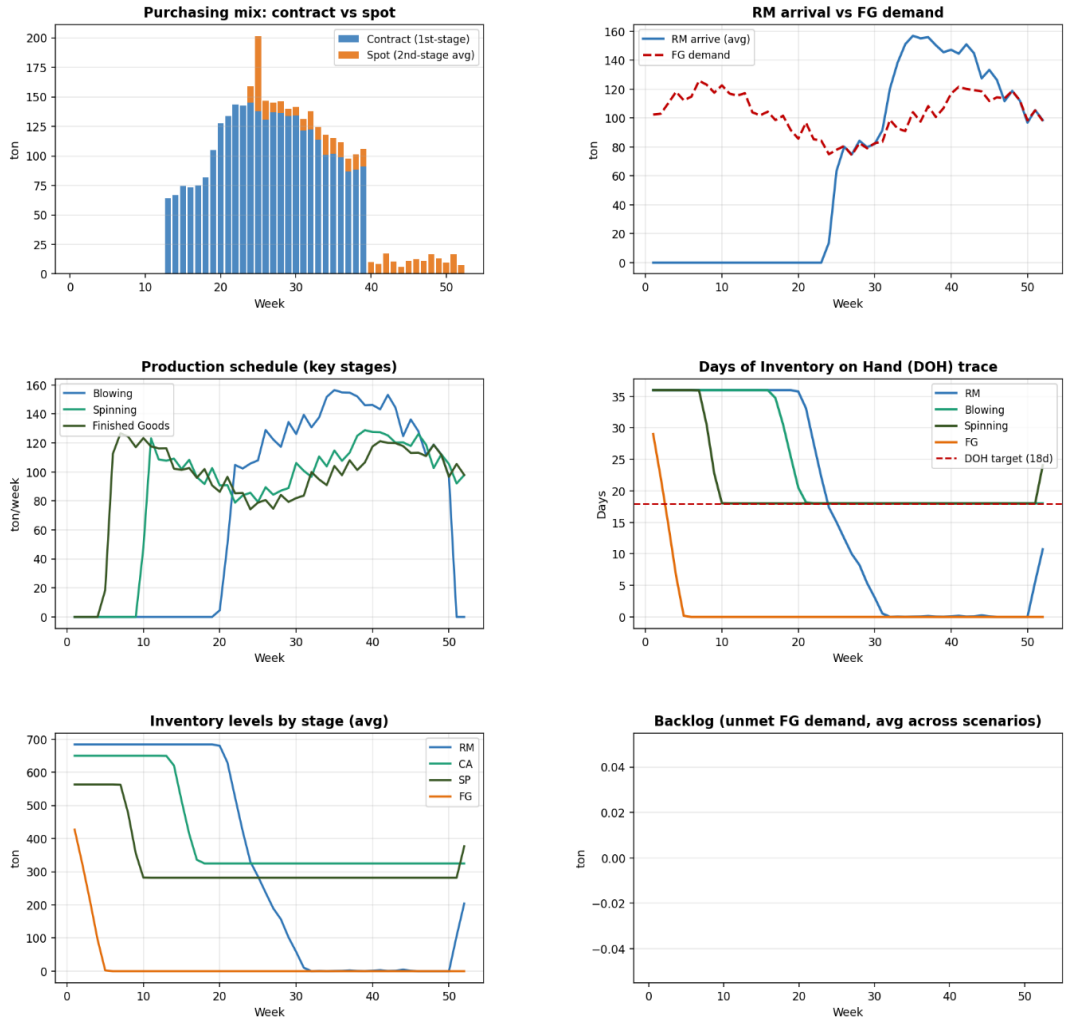


Fig. 5. Result of the Model Implementation with $I^0 = 2 * DOH^{target}$

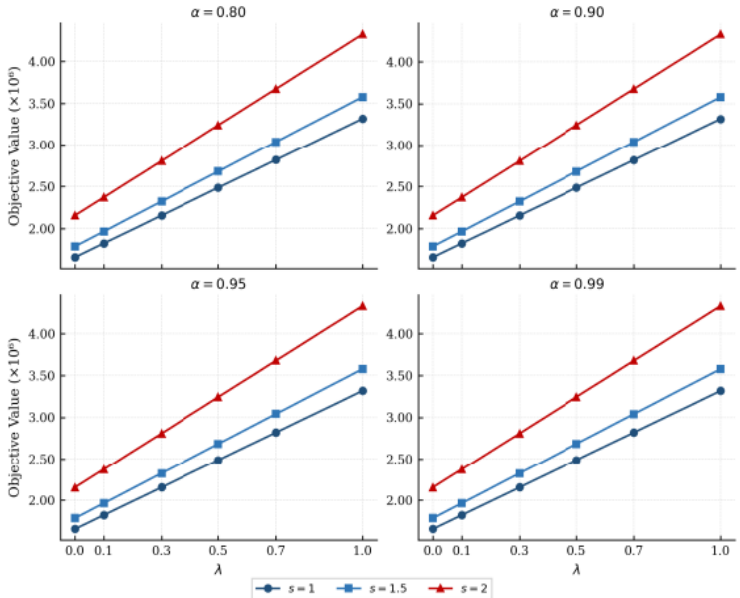


Fig. 6. Result of the Sensitivity Analysis toward Cost with s indicates the I_k^0 multiplier

The results also emphasize maintaining stable inventory rather than minimizing it in isolation. Traditional lean approaches prioritize inventory reduction, yet in uncertain environments with long replenishment lead times, overly aggressive minimization invites frequent stockouts and costly emergency sourcing (Choi et al., 2023). The framework shows that an appropriate level of Days of Inventory on Hand (DOH) buffers production flow and reduces reactive decisions (Thürer et al., 2025). However, the buffer is not free, and its cost accelerates. Raising the initial-inventory target from 1× to 1.5× of target DOH increased total cost by 7.8%, while raising it to 2× added a further 20.7%: the second increment of safety stock costs roughly two-and-a-half times the first.

Managers should therefore set target DOH at the point where added stability no longer justifies the steepening cost, rather than maximizing it by default. The study further demonstrates that multi-stage systems require flow synchronization rather than local optimization. Bottlenecks and excess work-in-progress (WIP) arise less from capacity shortages than from imbalances in material flow across stages (Thürer et al., 2022). The dynamic input–output model lets managers align production rates so upstream and downstream processes stay coordinated (Zhiliang He et al., 2024), which is critical in sequential processing structures, where disruption in one stage propagates through the system. The results make the direction of this coordination concrete: raw-material DOH scaled far more steeply than finished-goods DOH (1.2 to 17.2 days versus 0.3 to 1.4 days across the multipliers), because upstream stages absorb the compounded waste of every stage below them. Managers should therefore position protective stock upstream rather than uniformly: in a 13-week-lead-time textile chain, buffer belongs in raw cotton and early intermediates, where holding is cheap and waste compounds, not in finished yarn, where holding is most expensive and adds least flow protection.

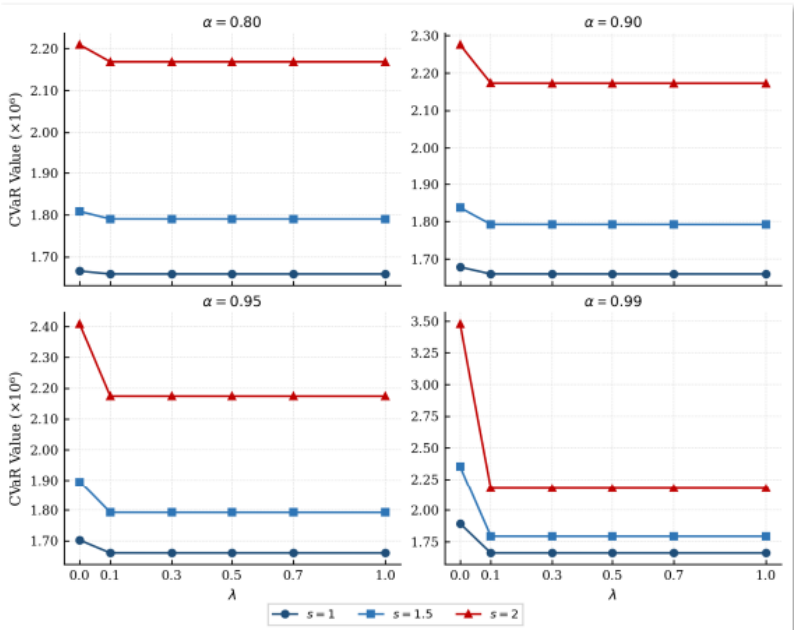


Fig. 7. Result of the Sensitivity Analysis toward CVaR with s indicates the I_k^0 multiplier

Integrating Monte Carlo scenario generation gives the model a practical mechanism for handling uncertainty. Rather than relying on deterministic planning, managers can evaluate policies across many possible scenarios to gauge robustness, which is especially useful for stress-testing procurement under extreme price or demand shifts (Xu & Song, 2022). Evaluating decisions across 100 demand and price scenarios, rather than a single point forecast, is what allowed the zero-backlog service level and the stable cost-risk profile to be verified under uncertainty rather than assumed. Managers can use this scenario layer as a pre-commitment stress test and run candidate contract quantities against extreme scenarios before signing, since a plan that looks optimal against an average forecast may hide tail costs that a scenario-based evaluation would expose.

Spektrum Industri
Vol. 24, No. 2, 2026, pp. 379–395

Operating at the tactical level, the framework can be adopted as a decision-support tool without overhauling existing systems, embedding into planning cycles such as monthly procurement and production planning to improve coordination across sourcing, production, and inventory (Goyal, 2021; Kanon et al., 2023). Finally, the proposed framework can be adopted as a decision-support tool that operates at a tactical planning level. The company does not need to overhaul its entire planning systems; instead, the model can be integrated into existing planning cycles (e.g., monthly procurement and production planning) to improve coordination between functions such as sourcing, production, and inventory management.

Despite its contributions, this study has several limitations that also frame directions for future work, including: data, model assumptions, computational complexity, multi-product model, and future manufacturing challenges. The experiments use a scenario-based dataset calibrated from an industrial context rather than proprietary real-time data; live-dataset validation is a natural next step. Three modelling assumptions also apply: deterministic import lead time (13 weeks) and machine capacity; only demand and spot price are modelled stochastically. Thus, adding stochastic lead time and capacity would extend the scope; machine capacity is an aggregate weekly limit applied per stage, omitting contention between concurrently running stages; and decision-making is assumed centralized, whereas authority is often distributed, motivating a decentralized or multi-agent extension.

Solved as the extensive form of a two-stage stochastic program, problem size grows linearly with scenario count; the sensitivity grid used a reduced count (S = 30) for tractability while baseline results used S = 100. For larger scenario sets, longer horizons, or the multi-product case, decomposition methods (Benders/L-shaped or progressive hedging) would likely be needed. The model treats a single (aggregated) product, whereas real textile operations run multiple yarn counts sharing capacity and raw material; a multi-product extension would add shared-resource contention, product-mix decisions, and correlated demand. Finally, integrating real-time analytics and digital-twin technologies for adaptive replanning and sustainability measures such as carbon emissions, would align the framework with green supply chain objectives (Corsini et al., 2024; Kim et al., 2025).

4. Conclusion

This study proposed an integrated stochastic optimization framework for procurement and production planning in multi-stage manufacturing under supply and demand uncertainty. It combined a CVaR-based stochastic procurement model with a dynamic input–output production scheduling model, linked through Monte Carlo scenario generation and solved as the extensive form of a two-stage stochastic program. Applied to a cotton-yarn spinning case over a 52-week horizon with 100 scenarios, the framework produced three explicit findings. First, it maintained a 100% service level (zero expected backlog) across all tested configurations, because the backlog penalty exceeds the highest holding cost by more than an order of magnitude, making demand fulfillment always locally optimal. Second, it quantified the cost of inventory buffering as non-linear: raising the initial-inventory target from 1× to 2× of target DOH increased total cost by 30% (from USD 2.15M to USD 2.80M) and CVaR_0.95 by a comparable 31%, with the marginal cost of buffering steepening rather than constant. Third, it showed that buffering is optimally positioned upstream, raw-material DOH scaled roughly fourteen-fold while finished-goods DOH changed little, reflecting the compounded-waste (chain-ratio) structure of the multi-stage process.

Beyond these numerical results, the study contributes a modeling approach that explicitly links risk-aware sourcing (contract versus spot under price volatility) to multi-stage production feasibility within a single framework, and a managerial tool that lets firms read off the cost–risk consequences of their inventory and sourcing policies rather than relying on fixed heuristics or deterministic planning. The framework's practical value lies in supporting coordinated, risk-aware tactical planning: firms facing long import lead times and volatile spot prices can use it to set contract quantities, position safety stock across stages, and stress-test procurement policies against extreme scenarios. Realizing

this value at scale, for multi-product systems, stochastic lead times, and real-time replanning, defines the research agenda outlined in the limitations, including the integration of digital-twin and simulation-optimization capabilities now emerging in manufacturing supply chains. Future research should focus on realizing this value at scale by extending the framework to multi-product systems, incorporating stochastic lead times, and enabling real-time replanning, including the integration of digital-twin and simulation-optimization capabilities now emerging in manufacturing supply chains.

Author Contribution: All authors contributed to this paper. All authors read and approved the final paper.

Funding: "This research was funded by the name of Institution of Research and Community Services, Universitas Katolik Parahyangan under the scheme of Skema Pengabdian Lembaga."

Acknowledgment: Allow us to express our sincere gratitude to PT. X, which has been providing insights and case studies for this research.

Conflicts of Interest: The authors declare no conflict of interest.

Declaration of AI-Tool Usage: AI-assisted tools were used to support manuscript proofreading, verify the consistency of variables and mathematical notation, and check reference formatting. All outputs were reviewed and verified by the authors, who take full responsibility for the accuracy and integrity of the final manuscript.

References

Achaw, O. W., & Danso-Boateng, E. (2021). Textile and fabric manufacture. *In: Chemical and Process Industries*. https://doi.org/10.1007/978-3-030-79139-1_3

Alamirew, A. T., & Tesema, G. B. (2024). Optimizing Carding Speed Parameters and C-60 RSB Draft to Improve Sliver Quality. *Journal of Natural Fibers*. https://doi.org/10.1080/15440478.2024.2337044

Basu, A. (2025). Compact spinning: new developments. *Developments in Yarn Spinning Technologies*. https://doi.org/10.1016/B978-0-443-13887-4.00005-3

Birge, J. R., & Louveaux, F. (2011). *Introduction to Stochastic Programming*. Springer New York. https://doi.org/10.1007/978-1-4614-0237-4

Camargo, V. C. B., Almada-Lobo, B., & Toledo, F. M. B. (2021). Integrated Lotsizing, Scheduling and Blending Decisions in the Spinning Industry. *Pesquisa Operacional*, *41*(spe). https://doi.org/10.1590/0101-7438.2021.041s1.00233486

Choi, T. Y., Netland, T. H., Sanders, N., Sodhi, M. S., & Wagner, S. M. (2023). Just-in-time for supply chains in turbulent times. *Production and Operations Management*, *32*(7), 2331–2340. https://doi.org/10.1111/poms.13979

Corsini, R. R., Costa, A., Fichera, S., & Framinan, J. M. (2024). Digital twin model with machine learning and optimization for resilient production–distribution systems under disruptions. *Computers & Industrial Engineering*, *191*, 110145. https://doi.org/10.1016/j.cie.2024.110145

Goyal, A. (2021). Management of spinning and weaving wastes. *Waste Management in the Fashion and Textile Industries*. https://doi.org/10.1016/B978-0-12-818758-6.00003-X

Guzman, E., Andres, B., & Poler, R. (2022). Models and algorithms for production planning, scheduling and sequencing problems: A holistic framework and a systematic review. *Journal of Industrial Information Integration*, *27*, 100287. https://doi.org/10.1016/j.jii.2021.100287

He, Zhenglei, Xu, J., Tran, K. P., Thomassey, S., Zeng, X., & Yi, C. (2021). Modeling of textile manufacturing processes using intelligent techniques: a review. *The International Journal of Advanced Manufacturing Technology*, *116*(1–2), 39–67. https://doi.org/10.1007/s00170-021-07444-1

He, Zhiliang, Thürer, M., & Zhou, W. (2024). The use of reinforcement learning for material flow control: An assessment by simulation. *International Journal of Production Economics*, *274*, 109312. https://doi.org/10.1016/j.ijpe.2024.109312

Islam, M. R., Hasan, A. Al, Afrose, T. D., Hasan, M. S., & Sikdar, H. (2024). Sustainable development of three distinct starch based bio-composites reinforced with the cotton spinning waste collected from fiber preparation stage. In *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e31534

Ivanov, D., & Dolgui, A. (2022). The shortage economy and its implications for supply chain and operations management. *International Journal of Production Research*, *60*(24), 7141–7154. https://doi.org/10.1080/00207543.2022.2118889

Jayalath, M. M., Perera, H. N., Ratnayake, R. M. C., & Thibbotuwawa, A. (2025). Harvesting sustainability: Transforming traditional agri-food supply chains with circular economy in developing economies. In *Cleaner Waste Systems*. Elsevier. https://doi.org/10.1016/j.clwas.2025.100264

Kanon, T. A., Rashid, M. E., Haque, R. U., Islam, M. A., & Khan, M. R. (2023). Double air suctioned carding process: A method for achieving improved quality ring-spun carded yarn. In *Heliyon*. cell.com. https://www.cell.com/heliyon/fulltext/S2405-8440(23)00303-1

Khare, A. R. (2021). *Principles of spinning: fibres and blow room cotton processing in spinning*.

Kim, D.-H., Kim, G.-Y., & Noh, S. Do. (2025). Digital Twin-Based Prediction and Optimization for Dynamic Supply Chain Management. *Machines*, *13*(2), 109. https://doi.org/10.3390/machines13020109

Liang, T., Zhou, L., & Jiang, Z. (2025). Integrated scheduling of production and material delivery for the intelligent manufacturing system. *International Journal of Production Research*, *63*(3), 882–903. https://doi.org/10.1080/00207543.2024.2363435

Merzifonluoglu, Y. (2026). Procurement portfolio management for resilient supply chains: value of information for risk averse decision making. *Annals of Operations Research*, *356*(2–3), 1059–1088. https://doi.org/10.1007/s10479-024-05918-5

Mohammadivojdan, R., Merzifonluoglu, Y., & Geunes, J. (2022). Procurement portfolio planning for a newsvendor with supplier delivery uncertainty. *European Journal of Operational Research*, *297*(3), 917–929. https://doi.org/10.1016/j.ejor.2021.05.026

Nalimov, V. V. ., & Mulchenko, Z. M. (1971). Measurement of Science. Study of the Development of Science as an Information Process. *Foreign Technology Division*.

Parchami Afra, A., Kheirkhah, A., & Ahadi, H. (2022). Systematic literature review of integrated project scheduling and material ordering problem: Formulations and solution methods. *Computers & Industrial Engineering*, *173*, 108711. https://doi.org/10.1016/j.cie.2022.108711

Raj, A., Mukherjee, A. A., de Sousa Jabbour, A. B. L., & Srivastava, S. K. (2022). Supply chain management during and post-COVID-19 pandemic: Mitigation strategies and practical lessons learned. *Journal of Business Research*, *142*, 1125–1139. https://doi.org/10.1016/j.jbusres.2022.01.037

Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk*, *2*(3), 21–41. https://doi.org/10.21314/JOR.2000.038

Taghavi, S. M., Ghezavati, V., Bidhandi, H. M., & Al-e-Hashem, S. M. J. M. (2023). Green-Resilient Supplier Selection and Order Allocation Under Disruption by Utilizing Conditional Value at Risk: Mixed Response Strategies. *Process Integration and Optimization for Sustainability*, *7*(1–2), 359–380. https://doi.org/10.1007/s41660-022-00298-4

Talaba, N. A., & Koo, P.-H. (2025). Portfolio Procurement Strategies with Forward and Option Contracts Combined with Spot Market. *Systems*, *13*(3), 210. https://doi.org/10.3390/systems13030210

Thürer, M., Fernandes, N. O., Lödding, H., & Stevenson, M. (2025). Material flow control in make-to-stock production systems: an assessment of order generation, order release and production authorization by simulation. *Flexible Services and Manufacturing Journal*, *37*(1), 1–37. https://doi.org/10.1007/s10696-024-09532-2

Thürer, M., Fernandes, N. O., & Stevenson, M. (2022). Production planning and control in multi-stage assembly systems: an assessment of Kanban, MRP, OPT (DBR) and DDMRP by simulation. *International Journal of Production Research*, *60*(3), 1036–1050. https://doi.org/10.1080/00207543.2020.1849847

Xu, W., & Song, D.-P. (2022). Integrated optimisation for production capacity, raw material ordering and production planning under time and quantity uncertainties based on two case studies. *Operational Research*, *22*(3), 2343–2371. https://doi.org/10.1007/s12351-020-00609-y

Yeshzhanov, A., Murzabayeva, G., & Togataev, T. (2024). The influence of increasing the productivity of the carding machine on the quality indicators of the card sliver. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202447401024

Zamani D. D., Moradi, S., & Alizadeh, B. (2023). Simultaneous planning of purchase orders, production, and inventory management under demand uncertainty. *International Journal of Production Economics*, *265*, 109012. https://doi.org/10.1016/j.ijpe.2023.109012

Zhang, Y., Huang, M., Tian, L., Jin, D., & Cai, G. (2021). Build or join a sharing platform? The choice of manufacturer's sharing mode. *International Journal of Production Economics*, *231*, 107811. https://doi.org/10.1016/j.ijpe.2020.107811