

Article

Sustainable and Resilient Production–Distribution Planning Under Stochastic Demand: A Carbon-Aware MILP Framework with Lost Sales and Rolling Horizon Replanning

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Abstract

Background: Manufacturing supply chains must increasingly coordinate cost, environmental impact, and service continuity under demand uncertainty and limited capacity. **Methods:** This study develops a stochastic mixed-integer linear programming framework for carbon-aware production–distribution planning in an automotive supply chain. The model jointly optimizes production quantities, inventory levels, shipments, truck usage, and lost sales over a multi-period horizon. Demand uncertainty is represented through scenarios, while production- and transportation-related emissions are monetized using an internal carbon price. Lost-sales penalties capture service degradation when demand cannot be fulfilled by the focal plant, and a rolling-horizon analysis evaluates planning responsiveness as demand information is updated. The framework is applied to an industrially inspired, capacity-constrained automotive case with multiple products, production lines, destinations, and demand scenarios. Computational experiments assess carbon pricing, lost-sales penalties, demand volatility, deterministic versus stochastic planning, and rolling-horizon replanning. **Results:** Results show that carbon pricing mainly acts as an economic valuation mechanism under the studied fixed-structure configuration, whereas lost-sales penalties strongly influence service performance. Demand volatility increases unmet demand, and lower emissions may reflect lower fulfilled demand rather than improved efficiency. **Conclusions:** The study provides a decision-support framework for evaluating cost–carbon–service trade-offs under stochastic demand while acknowledging single-plant and fixed-routing limitations.

Keywords: production–distribution planning; stochastic MILP; carbon pricing; lost sales; rolling horizon replanning; supply chain resilience; automotive supply chain



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1. Introduction

Manufacturing supply chains are increasingly required to reconcile economic efficiency, environmental responsibility, and service continuity under uncertain operating conditions. In many industrial sectors, firms are no longer evaluated only on their ability to reduce production and logistics costs, but also on their capacity to reduce carbon emissions, maintain customer service, and adapt their plans when demand or logistics conditions change. This evolution has made green supply chain management and sustainable supply chain planning central research domains, with a growing emphasis on quantitative decision-support models for production, inventory, distribution, and network

planning [1,2]. However, although the literature on sustainable supply chains has considerably expanded, integrating environmental, operational, and service-related decisions remains challenging, particularly at the tactical planning level, where production and distribution decisions must be coordinated over time.

Demand uncertainty is one of the most critical sources of instability in industrial supply chains. It directly affects production loading, inventory positioning, shipment planning, truck utilization, and customer service performance. When environmental considerations are added to this uncertainty, the planning problem becomes more complex because firms must simultaneously manage economic cost, carbon emissions, and service degradation. Previous studies have shown that green supply chain decisions can be highly sensitive to stochastic demand and carbon price assumptions [3]. More recent work also confirms that uncertainty may significantly influence pricing, ordering, greening, and coordination decisions, leading to managerial conclusions that differ from those obtained under deterministic assumptions [4]. These findings suggest that demand uncertainty should not be treated as a secondary modeling feature, but as a structural element of sustainable production–distribution planning.

At the operational level, the need for integration is particularly important. Environmental performance is not determined only by long-term network design or strategic investment decisions. It is also shaped by recurring planning decisions such as production quantities, inventory carryover, shipment timing, and vehicle usage. In this context, carbon pricing is increasingly used as a mechanism to internalize the environmental impact of production and transportation activities. The literature on carbon-aware planning shows that carbon policies can significantly affect total cost, even when their effect on physical operational flows remains limited in capacity-constrained systems [5,6]. This observation is important because it indicates that carbon pricing alone may improve the economic visibility of emissions without necessarily producing substantial short-term decarbonization. Therefore, sustainable planning models should evaluate carbon-related performance jointly with cost, capacity, and service indicators.

In parallel, supply chain resilience has become a major concern for firms operating in uncertain and disruption-sensitive environments. Resilience is commonly associated with the ability of a system to absorb shocks, adapt to changing conditions, and preserve continuity of operations. Recent reviews emphasize the importance of optimization, disruption response, inventory-related flexibility, and adaptive strategies in strengthening supply chain resilience [7,8]. At the same time, the relationship between sustainability and resilience is increasingly viewed as complementary, since firms must often reduce environmental impact while maintaining service continuity under disruptions and uncertainty [9]. For operational planning, this complementarity requires models that cannot only account for emissions but also represent service degradation and adaptive replanning mechanisms.

This study is motivated by an industrially inspired automotive supply chain context involving a Moroccan supplier operating a multi-product and multi-line manufacturing system. The plant serves several destinations through an export-oriented logistics structure and must plan production and distribution under uncertain demand, limited production capacity, and destination-based transportation requirements. This context is particularly relevant because Tanger Med and its associated special economic zones have been identified as a major logistics and industrial hub in the Western Mediterranean, reinforcing the strategic role of export-oriented supply chains in northern Morocco [10]. In such interconnected logistics environments, planning decisions must account not only for cost and emissions but also for service continuity and operational adaptability. In the industrial setting considered in this study, unmet demand does not simply represent a modeling artifact; it reflects a practical service issue where orders not fulfilled by the focal plant may

be redirected to another production site within the industrial network. This situation is modeled as lost sales from the perspective of the focal plant. Consequently, the problem addressed in this paper is not only a green production–distribution planning problem, but also a sustainability- and resilience-oriented decision problem under uncertainty.

To address this issue, this paper develops a stochastic mixed-integer linear programming framework for sustainable and resilient production–distribution planning under uncertain demand. The proposed model jointly optimizes production quantities, inventory levels, shipments, truck usage, and lost-sales decisions over a multi-period planning horizon. The environmental dimension is incorporated through production- and transportation-related carbon emissions valued by an internal carbon price. The service dimension is captured through lost-sales penalties, which allow the model to represent the economic consequences of unmet demand. In addition to the full-horizon stochastic formulation, a rolling-horizon analysis is introduced to reflect industrial replanning practice and to evaluate how adaptive decision-making can support service continuity under changing demand conditions. Rolling-horizon approaches are particularly relevant in uncertain environments because they allow plans to be periodically revised as new information becomes available [11].

Based on the above motivation, this study addresses the following research questions: How can production, inventory, distribution, truck usage, lost sales, and carbon valuation be jointly modeled under stochastic demand in a capacity-constrained production–distribution system? How do carbon pricing, lost-sales penalties, and demand volatility affect total cost, carbon emissions, fill rate, lost sales, and logistics intensity? How can rolling-horizon replanning support responsiveness-oriented decision-making and service-continuity assessment under changing demand conditions?

The contribution of this study is positioned as an integrated modeling and decision-support contribution for sustainable production–distribution planning under uncertainty. Rather than focusing on the development of a new solution algorithm, the study proposes a stochastic MILP-based framework that jointly incorporates production and inventory decisions, destination-based shipments, truck usage, lost-sales-based service degradation, carbon valuation, and rolling-horizon replanning. By integrating these elements within a unified optimization structure, the framework enables the simultaneous assessment of economic cost, carbon emissions, service performance, logistics intensity, and replanning responsiveness in a capacity-constrained automotive supply chain setting.

In this study, resilience is considered from a service-continuity and responsiveness-oriented perspective. Accordingly, the model focuses on how demand uncertainty, capacity restrictions, lost-sales outcomes, and rolling-horizon replanning affect the ability of the production–distribution system to maintain service performance over time. The analysis therefore provides resilience-oriented insights related to adaptive planning under uncertain demand, while more explicit disruption-recovery mechanisms, such as supplier failures, material shortages, or production breakdowns, are identified as relevant extensions for future research.

The computational results show that carbon pricing mainly increases the expected total cost and improves the visibility of emissions, but produces limited short-term operational changes in the studied constrained system. Lost-sales penalties, by contrast, strongly influence service performance and can be used as a managerial lever to encode customer-priority logic into the planning model. The demand-volatility analysis shows that higher uncertainty deteriorates the fill rate and increases unmet demand, while lower emissions under high volatility should not be interpreted as improved environmental efficiency when they result from reduced fulfillment. Finally, the rolling-horizon analysis reveals that service disruptions are concentrated in the early planning windows and progressively

decrease in later periods, highlighting the value of adaptive replanning during the most stressed phases of the horizon.

The remainder of this paper is organized as follows. Section 2 reviews the literature on green supply chain management, stochastic demand, low-carbon production–distribution planning, and resilience-oriented replanning. Section 3 describes the problem setting and presents the stochastic MILP formulation. Section 4 reports the computational experiments and discusses the effects of carbon pricing, lost-sales penalties, demand volatility, deterministic versus stochastic planning, and rolling-horizon replanning. Section 5 concludes the paper and outlines future research directions.

2. Literature Review

The literature relevant to this study can be organized into four complementary streams: green supply chain management and sustainable supply chain design, green supply chains under stochastic demand, integrated low-carbon production–distribution planning, and resilience-oriented replanning approaches. These streams have developed substantially in recent years, but they remain only partially integrated at the operational planning level. In particular, relatively limited attention has been devoted to models that jointly capture production, inventory, distribution, carbon-related costs, service degradation, and adaptive replanning under uncertain demand. This section reviews these research streams and positions the contribution of the present study accordingly.

2.1. Green Supply Chain Management and Sustainable Supply Chain Design

Green supply chain management has become a mature research field addressing the integration of environmental concerns into sourcing, production, logistics, distribution, and network design decisions. Recent bibliometric and review studies show that the field has progressively moved from conceptual and compliance-oriented discussions toward quantitative models, optimization approaches, and decision-support tools for sustainable operations [1,12]. This evolution is consistent with earlier review studies that documented the methodological growth of green and sustainable supply chain research, particularly in relation to the modeling of cost–environment trade-offs and the use of optimization-based approaches [13,14].

Sustainable supply chain network design has also received considerable attention because it provides a structured framework for evaluating economic, environmental, and sometimes social objectives in long-term decision-making. Recent reviews confirm that mathematical programming, multi-objective optimization, and life-cycle-oriented indicators are increasingly used to support sustainable supply chain design [2,14]. However, much of this literature remains focused on strategic network configuration, facility location, or network structure. While these decisions are important, they do not fully capture the short- and medium-term operational mechanisms through which sustainability performance is generated in industrial systems.

From an operational perspective, production loading, inventory carryover, shipment planning, vehicle utilization, and service-level decisions also shape environmental performance. These decisions are particularly important in existing industrial networks where the decision-maker cannot redesign the full supply chain structure, but must improve the planning of production and distribution flows under practical capacity and demand constraints. Recent reviews of optimization models in sustainable supply chain management emphasize that the simultaneous treatment of economic performance, environmental impact, and uncertainty remains a relevant research gap [15]. This observation motivates the development of integrated operational planning models that can evaluate sustainabil-

ity not only as a strategic design issue, but also as a recurring production–distribution decision problem.

2.2. Green Supply Chains Under Stochastic Demand

Demand uncertainty is one of the most influential drivers of supply chain performance because it directly affects production quantities, inventory levels, transportation needs, and customer service. In green supply chains, this uncertainty becomes even more critical because demand fluctuations may alter both economic and environmental outcomes. A foundational contribution in this area is the stochastic green supply chain network design model proposed by Rezaee et al., which shows that optimal green supply chain decisions are sensitive to stochastic demand and carbon price assumptions [3]. This result confirms that environmental decisions should not be analyzed in isolation from uncertainty.

More recent research on green supply chains under stochastic demand has extended this perspective by studying decision analysis, coordination, greening efforts, and contractual mechanisms. Wu et al. show that uncertainty can substantially affect pricing, ordering, greening, and coordination decisions, and that deterministic models may lead to different managerial conclusions compared with stochastic settings [4]. This is particularly important for operational planning because it suggests that the representation of uncertainty is not only a technical modeling choice, but also a factor that can change the interpretation of the optimal plan.

Despite these advances, the existing literature still shows an imbalance. Many green supply chain studies under stochastic demand focus on stylized dyadic systems, contract coordination, pricing decisions, or strategic network design. Fewer studies address integrated operational planning models that simultaneously represent production, inventory, transportation, emissions, and service degradation in a realistic multi-product industrial setting. This limitation is relevant to capacity-constrained manufacturing systems, where uncertainty not only affects demand satisfaction but also creates operational consequences, such as production saturation, shipment adjustments, and lost sales.

2.3. Integrated Low-Carbon Production–Distribution Planning

A third research stream focuses on low-carbon production and logistics planning, where manufacturing and distribution decisions are coordinated within a common optimization framework. Compared with strategic network design, integrated production–distribution planning is closer to industrial decision-making because it determines how much to produce, store, and ship over a finite planning horizon. This integration is particularly relevant in carbon-aware planning, since emissions are generated not only by production activities but also by downstream transportation decisions.

Recent work on carbon-conscious manufacturing–remanufacturing–transport planning shows that carbon-related policies can significantly increase total cost, while their impact on physical flows may remain limited when the system is constrained by production, capacity, or logistics restrictions [5]. This insight is important because it shows that carbon pricing does not automatically produce major operational decarbonization in the short term. Instead, carbon pricing can mainly act as a cost-visibility mechanism unless the system has enough structural flexibility to modify production modes, transport patterns, or sourcing decisions.

The literature on carbon policy in green supply chain network design also confirms the importance of environmental regulation mechanisms such as carbon tax, carbon cap, and cap-and-trade systems [6]. However, much of this literature remains concentrated on policy comparison or network design. Less attention has been paid to operational production–distribution planning in existing industrial systems where carbon pricing interacts with

demand uncertainty, limited capacity, truck usage, and service performance. This gap is significant because industrial managers often need tactical decision-support tools that can evaluate cost, emissions, and service continuity without assuming full redesign of the supply chain network.

Carbon emissions in supply chain optimization can be represented through several modeling approaches. A first approach consists of carbon pricing or carbon taxation, where emissions are converted into monetary costs and integrated into the objective function. A second approach uses emission-cap constraints, in which total emissions are limited by a predefined upper bound. A third approach relies on cap-and-trade mechanisms, where firms can purchase or sell emission permits depending on their emission levels. Other studies formulate emissions as a separate objective, leading to bi-objective or multi-objective models that jointly optimize economic cost and environmental impact. In this study, a carbon-pricing approach is adopted because it is consistent with the economic decision-support orientation of the model and allows production- and transportation-related emissions to be internalized within a linear MILP objective function. However, in the absence of alternative low-emission technologies, transportation modes, or routing options, carbon pricing mainly provides an economic valuation of emissions rather than a complete operational decarbonization mechanism.

2.4. Resilience, Service Continuity, and Rolling-Horizon Replanning

In parallel with green supply chain research, supply chain resilience has become a major research domain in operations and logistics. Resilience is generally associated with the ability of a supply chain to prepare for disruptions, absorb shocks, recover from disturbances, and adapt to changing conditions. Recent reviews identify optimization, disruption response, risk mitigation, robust decision-making, and technology-enabled strategies as major streams in supply chain resilience research [7]. From an inventory management perspective, resilience is also linked to stock pre-positioning, flexible capacity, backup sourcing, demand adaptation, and other mechanisms that support service continuity under disruptions [8].

The relationship between resilience and sustainability is increasingly recognized as complementary rather than contradictory. Firms operating in uncertain environments must often reduce environmental impact while preserving service continuity and operational responsiveness. Recent stochastic optimization research on green supply chain resilience shows that disruption mitigation strategies and emission-related policies can interact in complex ways [9]. This confirms that sustainable supply chain planning should not be restricted to environmental cost minimization, but should also account for the system's capacity to maintain service under uncertainty.

For operational planning, rolling-horizon approaches are particularly relevant because they provide a practical mechanism for adaptive decision-making. Instead of solving a static plan once for the entire horizon, a rolling-horizon procedure updates the planning window as new information becomes available. Fattahi and Govindan (2022) demonstrate that rolling-horizon methods are useful for dynamic supply chain distribution network design under disruption and demand uncertainty [11]. From a managerial standpoint, such methods are attractive because they reproduce the way industrial planners revise decisions periodically in response to updated demand, logistics constraints, or operational disturbances.

However, in the literature, rolling-horizon methods are not always connected to green production–distribution planning with explicit service degradation. Many studies use rolling horizons for dynamic network design, disruption response, or inventory control, while fewer integrate this adaptive logic into a carbon-aware production–distribution

model with stochastic demand and lost sales. This represents an important opportunity for research, particularly in industrial settings where sustainability and resilience must be assessed jointly.

2.5. Research Gap and Positioning of the Present Study

The reviewed literature indicates that the individual components addressed in this paper have been widely studied, including green supply chain management, sustainable supply chain design, stochastic demand, carbon-aware planning, resilience, and rolling-horizon replanning [1–4,7–11]. Green supply chain and sustainable supply chain design studies have provided important contributions to environmental decision-making, carbon policy assessment, and network-level optimization [1,2,12–15]. However, many of these contributions remain oriented toward strategic network design, policy analysis, coordination mechanisms, or conceptual sustainability frameworks rather than integrated operational production–distribution planning.

At the same time, stochastic demand has been recognized as a major driver of green supply chain performance, since demand variability affects production quantities, inventory levels, transportation requirements, emissions, and service outcomes [3,4]. Carbon-aware production and transportation models also show that carbon-related policies can influence total cost and environmental evaluation, although their operational effect may remain limited in constrained systems without low-emission alternatives or structural flexibility [5, 6]. In parallel, resilience and rolling-horizon approaches have been increasingly used to support adaptive planning and disruption response under uncertainty [7–11]. Nevertheless, these research streams are often treated separately, and fewer studies jointly represent production quantities, inventory flows, destination-based shipments, truck usage, lost-sales-based service degradation, carbon valuation, and adaptive replanning under stochastic demand in a capacity-constrained industrial setting.

This study addresses this gap by proposing an integrated stochastic MILP framework for carbon-aware production–distribution planning under demand uncertainty. The contribution is not positioned as a new solution algorithm or as a new stochastic programming method. Instead, it lies in the joint formulation and analysis of operational, environmental, and service-related dimensions within a unified decision-support model. This integrated structure enables the simultaneous evaluation of cost, emissions, service degradation, logistics intensity, and replanning responsiveness. It also helps avoid misleading interpretations, such as considering lower emissions as an environmental improvement when they result from lower fulfilled demand and higher lost sales.

The positioning of the present study is summarized in Table 1. The table emphasizes that previous studies provide important contributions to green supply chain design, stochastic decision-making, carbon policy analysis, resilience, and rolling-horizon planning [3–6,9,11], but do not fully combine the set of modeling dimensions considered here within the same production–distribution planning framework. The proposed model should therefore be interpreted as an integrated operational planning framework for a specific capacity-constrained automotive setting, with numerical findings that are case-dependent rather than universally generalizable.

Table 1. Positioning of the present study relative to the selected literature.

Reference	Research Scope	Main Dimensions Considered	Contribution and Positioning
Rezaee et al. [3]	Green supply chain network design under uncertainty	Carbon pricing; stochastic demand; network design	Provides a relevant basis for stochastic green supply chain design, but gives less emphasis to operational production–distribution planning, truck usage, and service degradation.
Wu et al. [4]	Decision analysis and coordination in green supply chains	Stochastic demand; green decisions; coordination mechanisms	Highlights the importance of uncertainty in green supply chain decisions, but focuses mainly on coordination rather than integrated industrial production–distribution planning.
Abassi et al. [5]	Carbon-conscious manufacturing–transport planning	Carbon-aware planning, production, and transport decisions	Addresses carbon-aware production and transportation decisions, but with limited integration of stochastic demand, lost sales, and rolling-horizon replanning.
Abbasi and Choukolaei [6]	Review of carbon policies in green supply chain network design	Carbon tax; carbon cap; cap-and-trade mechanisms	Provides a carbon-policy perspective, but remains mainly oriented toward network design and policy analysis rather than tactical operational planning.
Mirzaee et al. [9]	Green supply chain resilience under disruption	Sustainability; resilience strategies; stochastic optimization	Connects sustainability and resilience under disruption, but does not specifically address production–distribution planning with lost-sales-based service degradation.
Fattahi and Govindan [11]	Rolling-horizon distribution network design	Demand uncertainty; disruption response; adaptive replanning	Demonstrates the relevance of rolling-horizon planning, but does not integrate it with carbon-aware production–distribution planning and lost-sales evaluation.
Present study	Sustainable and resilient production–distribution planning	Stochastic demand; carbon pricing; lost sales; truck usage; rolling-horizon replanning	Integrates economic, environmental, service, logistics, and replanning dimensions within a single stochastic MILP framework for a capacity-constrained automotive setting.

It should be noted that the positioning in Table 1 refers to the modeling scope of the proposed framework. The numerical findings of the present study remain case-dependent and should be interpreted within the limits of the single-plant, fixed-routing, and capacity-constrained automotive setting considered in the computational experiments.

3. Problem Description and Mathematical Formulation

3.1. Problem Description

This study considers an integrated sustainable production–distribution planning problem for a single manufacturing plant supplying multiple destinations over a finite planning

horizon. The system is characterized by a multi-product, multi-line, and multi-period structure under uncertain demand. The plant produces a set of automotive components assigned to predefined production lines and destinations. For each planning period, the decision-maker must determine how much to produce, store, and ship, while accounting for production-line capacity, destination-based transportation requirements, service performance, and carbon-related costs.

The planning horizon consists of eight weekly periods. The industrial setting involves 19 production lines, 251 active products, and four destinations. Each product is assigned to one production line and one destination. Therefore, the problem does not involve product–destination reassignment or network redesign decisions. Instead, the focus is on the coordinated planning of production, inventory, shipments, and truck usage under uncertain demand and limited operational capacity.

A key feature of the proposed framework is the explicit integration of environmental considerations into operational production–distribution planning. Carbon emissions arise from two sources: production activities and transportation operations. Production-related emissions are expressed per unit produced, whereas transport-related emissions are associated with the number of truck trips required to serve each destination. These emissions are monetized through an internal carbon price, allowing the model to incorporate carbon-related impact directly into the objective function.

Another important feature is the treatment of unmet demand. In the industrial context motivating this study, demand that cannot be fulfilled by the focal plant may be redirected to another production site within the broader industrial network. From the perspective of the focal plant, this unmet quantity is modeled as lost sales. The model therefore allows partial unmet demand, which is economically penalized through product-specific lost-sales costs.

Demand uncertainty is represented through a finite set of scenarios, each associated with a probability of occurrence. Under this scenario-based stochastic structure, the model jointly determines production quantities, inventory levels, shipped quantities, lost sales, and the number of trucks required for each destination and period. The objective is to minimize the expected total cost while accounting for service performance and carbon-related impacts.

In addition to the full-horizon stochastic model, the study also considers a rolling-horizon implementation over four-week planning windows. This analysis is designed to reproduce industrial replanning practices and to provide resilience-oriented managerial insights into how the planning system behaves under changing demand conditions.

The numerical case study is based on an automotive production–distribution environment whose structure reflects the main operational characteristics of the industrial problem considered in this paper. The case includes a single manufacturing plant, multiple production lines, multiple products, predefined product–line assignments, destination-based distribution flows, truck-capacity requirements, and uncertain customer demand. For confidentiality and reproducibility reasons, some numerical values were anonymized, normalized, or calibrated. Therefore, the computational study should be interpreted as an industrially inspired automotive case study designed to evaluate the behavior of the proposed decision-support framework, rather than as a fully audited industrial deployment.

3.2. Modeling Assumptions

A stochastic mixed-integer linear programming formulation is adopted because the problem combines continuous operational decisions and integer logistics decisions under demand uncertainty. Production quantities, shipments, inventory levels, and lost sales are modeled as continuous non-negative variables, whereas the number of trucks assigned

to each destination and period is modeled as an integer variable. Demand uncertainty is represented through a finite set of scenarios with associated probabilities. The first-period production decision is treated as a here-and-now decision, while subsequent production, inventory, shipment, lost-sales, and truck-usage decisions are scenario-dependent recourse decisions. This structure is suitable for evaluating the expected economic, environmental, logistics, and service performance of the production–distribution system under multiple demand realizations.

The main assumptions of the model are as follows:

- A1—A single manufacturing plant supplies all destinations considered in the planning problem.
- A2—Each product is assigned to exactly one production line, according to the existing industrial configuration.
- A3—Each product is assigned to exactly one destination, meaning that destination reassignment decisions are not considered.
- A4—Production capacity is line-dependent and limited in each planning period.
- A5—Initial inventory is known for each product at the beginning of the planning horizon.
- A6—Inventory can be carried from one period to the next and incurs a product-specific holding cost.
- A7—Transportation is destination-based and performed using trucks with limited capacity.
- A8—The number of trucks used for each destination and period is an integer decision variable.
- A9—Demand is uncertain and represented through a finite set of scenarios with known probabilities.
- A10—Unmet demand is allowed and modeled as lost sales from the perspective of the focal plant.
- A11—Lost-sales penalties are product-specific and reflect the economic and service-related consequences of unmet demand.
- A12—Carbon emissions are generated by production and transportation activities only.
- A13—Production-related emissions are proportional to the quantity produced, while transportation-related emissions depend on the number of truck trips.
- A14—A uniform internal carbon price is applied to monetize carbon emissions in the objective function.
- A15—In the stochastic formulation, the first-period production decision is treated as a here-and-now decision and must be identical across all scenarios.
- A16—Subsequent production, inventory, shipment, lost-sales, and truck decisions are scenario-dependent recourse decisions.

These assumptions reflect the case’s industrial structure while preserving the tractability of the stochastic MILP formulation. They also enable the model to jointly evaluate economic costs, carbon-related impacts, service degradation, and adaptive planning behavior under uncertain demand.

In the present formulation, resilience is considered from a service-continuity and responsiveness-oriented perspective. It is represented through the combined use of stochastic demand scenarios, capacity restrictions, lost-sales variables, and rolling-horizon replanning. Demand scenarios expose the system to different operating conditions, capacity constraints limit the ability of the plant and logistics system to absorb demand variations, lost-sales variables quantify service degradation when demand cannot be fulfilled, and the rolling-horizon procedure evaluates how replanning can support adaptive decision-making over time. The model does not explicitly represent disruption-recovery mechanisms such as material shortages, supplier failures, machine breakdowns, or transportation interruptions. These elements are therefore identified as extensions for future research.

3.3. Sets, Indices, and Parameters

The notation used in the stochastic MILP formulation is structured to ensure consistency between the mathematical model and its CPLEX/OPL implementation. Sets and indices define the product, production line, destination, period, and scenario dimensions of the problem. Parameters represent input data related to costs, capacities, demand, emissions, truck capacity, and scenario probabilities. Decision variables represent the operational quantities optimized by the model, including production, shipments, inventory, lost sales, and truck usage. To improve transparency and reproducibility, the main units associated with parameters and variables are explicitly indicated where applicable.

3.3.1. Sets and Indices

$p \in P$: Set of products.

$l \in L$: Set of production lines.

$d \in D$: Set of destinations.

$t \in T$: Set of planning periods.

$s \in S$: Set of stochastic scenarios.

3.3.2. Parameters

C_p^{prod} : Unit production cost of product p .

C_p^{hold} : Unit inventory holding cost of product p .

C_p^{lost} : Unit lost-sales penalty of product p .

c_p^{prod} : Carbon emissions per unit of product p produced.

I_p^0 : Initial inventory level of product p at the beginning of the planning horizon.

Cap_l : Available production capacity of line l in each planning period.

$a_{p,l}$: Binary parameter indicating the assignment of product p to production line l . Takes the value of 1 if product p is produced on line l , and 0 otherwise.

$b_{p,d}$: Binary parameter indicating the assignment of product p to destination d . Takes the value of 1 if product p is delivered to destination d , and 0 otherwise.

$D_{p,t,s}$: Stochastic demand of product p in period t under scenario s .

π_s : Probability of scenario s with $\sum_{s \in S} \pi_s = 1$.

C_d^{trip} : Fixed cost per truck trip to destination d independent of load, as long as truck capacity is not exceeded.

E_d^{trip} : Carbon emissions generated by one truck trip to destination d .

Q_d^{truck} : Maximum number of product units that can be transported to d per truck.

λ : Internal carbon price used to monetize production- and transportation-related emissions in the objective function.

All cost and emission parameters are defined consistently with the unit of the corresponding decision variable. Production cost is expressed per unit produced, inventory holding cost per unit stored and period, lost-sales penalty per unit of unmet demand, and transportation cost per truck trip. Production-related emissions are expressed per unit produced, whereas transportation-related emissions are expressed per truck trip. The internal carbon price converts total emissions into a monetary cost and is applied consistently to both production- and transportation-related emissions in the objective function. This unit structure ensures that all objective-function components are expressed in monetary terms before aggregation.

3.4. Decision Variables

$Q_{p,t,s}$: Amount of product p produced in period t under scenario s .

$S_{p,t,s}$: Amount of product p shipped to its destination in period t under scenario s .

$I_{p,t,s}$: Inventory of product p at the end of period t under scenario s .

$L_{p,t,s}$: Lost sales of product p in period t under scenario s , representing unmet demand from the perspective of the focal plant.

$T_{d,t,s}$: Number of trucks used for destination d in period t under scenario s .

3.5. Objective Function

The objective of the stochastic MILP model is to minimize the expected total cost over all demand scenarios. The total cost includes production costs, inventory holding costs, lost-sales penalties, transportation costs, and the monetized cost of carbon emissions generated by production and transportation activities. Let $E[\cdot]$ denote the expectation with respect to the scenario probabilities π_s . The expected total cost is defined as follows:

$$\min E[TotalCost] = E[C^{Prod}] + E[C^{Hold}] + E[C^{Lost}] + E[C^{Trans}] + E[C^{Carbon}] \quad (1)$$

where each term is defined as follows:

$$E[C^{Prod}] = \sum_{s \in S} \pi_s \sum_{t \in T} \sum_{p \in P} C_p^{prod} Q_{p,t,s} \quad (2)$$

$$E[C^{Hold}] = \sum_{s \in S} \pi_s \sum_{t \in T} \sum_{p \in P} C_p^{hold} I_{p,t,s} \quad (3)$$

$$E[C^{Lost}] = \sum_{s \in S} \pi_s \sum_{t \in T} \sum_{p \in P} C_p^{lost} L_{p,t,s} \quad (4)$$

$$E[C^{Trans}] = \sum_{s \in S} \pi_s \sum_{t \in T} \sum_{d \in D} C_d^{trip} T_{d,t,s} \quad (5)$$

$$E[C^{Carbon}] = \lambda \sum_{s \in S} \pi_s \left(\sum_{t \in T} \sum_{p \in P} e_p^{prod} Q_{p,t,s} + \sum_{t \in T} \sum_{d \in D} E_d^{trip} T_{d,t,s} \right) \quad (6)$$

Equivalently, the full objective can be written in a single expression:

$$\min \sum_{s \in S} \pi_s \left[\sum_{t \in T} \sum_{p \in P} \left(C_p^{prod} Q_{p,t,s} + C_p^{hold} I_{p,t,s} + C_p^{lost} L_{p,t,s} \right) + \lambda e_p^{prod} Q_{p,t,s} \right] + \sum_{t \in T} \sum_{d \in D} \left(C_d^{trip} + \lambda E_d^{trip} \right) T_{d,t,s} \quad (7)$$

This objective function jointly captures the economic, environmental, and service-related dimensions of the planning problem. Production, inventory, and transportation terms represent the operational cost structure, while the carbon term internalizes the environmental impact of production and truck usage. The lost-sales term penalizes unmet demand and allows the model to account for service degradation under capacity limitations and demand uncertainty.

3.6. Constraints

3.6.1. Non-Anticipativity (First-Period Production)

The first-period production decision must be identical across all scenarios because it is made before demand uncertainty is revealed:

$$Q_{p,1,s} = Q_{p,1,1} \quad \forall p \in P, \forall s \in S \quad (8)$$

3.6.2. Inventory Balance

For the first period ($t = 1$), the available quantity is composed of the initial inventory and the quantity produced during the period. This quantity is either shipped or carried as ending inventory:

$$I_p^0 + Q_{p,1,s} = S_{p,1,s} + I_{p,1,s} \quad \forall p \in P, \forall s \in S \quad (9)$$

For all subsequent periods ($t = 2, \dots, T$):

$$I_{p,t-1,s} + Q_{p,t,s} = S_{p,t,s} + I_{p,t,s} \quad \forall p \in P, \forall t \in T, \forall s \in S \quad (10)$$

These constraints ensure the consistency of material flows over the planning horizon.

3.6.3. Demand Satisfaction and Lost Sales

For each product, period, and scenario, realized demand is satisfied through shipments or remains unmet as lost sales:

$$S_{p,t,s} + L_{p,t,s} = D_{p,t,s} \quad \forall p \in P, \forall t \in T, \forall s \in S \quad (11)$$

This constraint allows the model to capture service degradation when demand cannot be fully satisfied because of capacity or logistics limitations.

3.6.4. Production Line Capacity

The total production on each line cannot exceed its per-period capacity:

$$\sum_{p \in P} a_{p,l} Q_{p,t,s} \leq Cap_l \quad \forall l \in L, \forall t \in T, \forall s \in S \quad (12)$$

3.6.5. Truck Capacity and Integrality

Shipments to each destination are aggregated and must be covered by an integer number of trucks. Each truck has a fixed capacity:

$$\sum_{p \in P} b_{p,d} S_{p,t,s} \leq Q_d^{truck} T_{d,t,s} \quad \forall d \in D, \forall t \in T, \forall s \in S \quad (13)$$

This constraint links shipment quantities to destination-based truck usage and ensures that transportation capacity is respected.

3.6.6. Variable Domains

Production, shipment, inventory, and lost-sales variables are continuous and non-negative:

$$Q_{p,t,s} \geq 0, S_{p,t,s} \geq 0, I_{p,t,s} \geq 0, L_{p,t,s} \geq 0 \quad \forall p \in P, \forall t \in T, \forall s \in S \quad (14)$$

The number of trucks must be a non-negative integer variable:

$$T_{d,t,s} \geq 0, \quad \forall d \in D, \forall t \in T, \forall s \in S \quad (15)$$

3.7. Performance Metrics (Post-Optimality)

After solving the stochastic MILP model, several post-optimality indicators are computed to evaluate the economic, environmental, and service-related performance of the proposed planning framework. These indicators are used in Section 4 to analyze the effects

of carbon pricing, lost-sales penalties, demand volatility, deterministic versus stochastic planning, and rolling-horizon replanning.

3.7.1. Expected Total Demand

The expected total demand over the planning horizon is defined as:

$$E[D] = \sum_{p \in P} \sum_{t \in T} \sum_{s \in S} \pi_s D_{p,t,s} \quad (16)$$

This indicator represents the average total demand to be served across all scenarios.

3.7.2. Expected Total Lost Sales

The expected total lost sales are computed as:

$$E[L] = \sum_{p \in P} \sum_{t \in T} \sum_{s \in S} \pi_s L_{p,t,s} \quad (17)$$

This indicator measures the expected quantity of unmet demand from the perspective of the focal plant.

3.7.3. Fill Rate

The fill rate is defined as the proportion of expected demand that is satisfied by the focal plant:

$$FillRate = 1 - \frac{E[L]}{E[D]} \quad (18)$$

A higher fill rate indicates better service performance, while a lower fill rate reflects higher demand non-fulfillment.

3.7.4. Expected Total CO₂ Emissions

Expected total carbon emissions include both production-related and transportation-related emissions:

$$E[CO_2] = \sum_{s \in S} \pi_s \left(\sum_{t \in T} \sum_{p \in P} e_p^{prod} Q_{p,t,s} + \sum_{t \in T} \sum_{d \in D} E_d^{trip} T_{d,t,s} \right) \quad (19)$$

This indicator allows the environmental impact of production and distribution decisions to be evaluated jointly.

3.7.5. Expected Number of Trucks

The expected number of trucks used over the planning horizon is calculated as:

$$E[T^{truck}] = \sum_{d \in D} \sum_{t \in T} \sum_{s \in S} \pi_s T_{d,t,s} \quad (20)$$

This metric captures the transportation intensity of the production–distribution plan.

3.7.6. Interpretation of the Performance Metrics

Together, these indicators provide a multidimensional evaluation of the proposed planning framework. Expected total cost captures the economic performance of the optimized plan, expected carbon emissions measure environmental impact, expected lost sales and fill rate evaluate service performance, and expected truck usage reflects the logistics intensity of distribution decisions. This combination of indicators is particularly important because a reduction in emissions may result either from improved operational efficiency

or from lower fulfilled demand. Therefore, environmental indicators must be interpreted jointly with service-level metrics.

The proposed model was validated through a set of logical, computational, and operational consistency checks. First, the material-flow structure was verified by checking that production, initial inventory, shipments, ending inventory, and lost sales are consistently linked through the inventory balance and demand satisfaction constraints. This ensures that each unit of demand is either fulfilled through shipments or recorded as lost sales from the perspective of the focal plant.

Second, feasibility was verified with respect to the main operational constraints. Production quantities were checked against line-capacity limits, shipments were checked against destination-based truck-capacity constraints, and truck variables were restricted to non-negative integer values. Non-negativity conditions were also imposed on production, shipment, inventory, and lost-sales variables to preserve the physical meaning of the solution.

Third, unit consistency was checked across the objective function and the performance metrics. Production, shipment, inventory, and lost-sales variables are expressed in product units, truck usage is expressed as an integer number of truck trips, production emissions are expressed per unit produced, and transportation emissions are expressed per truck trip. The internal carbon price converts emissions into monetary terms, ensuring that production cost, holding cost, transportation cost, lost-sales penalty, and carbon cost are consistently aggregated in the total-cost function.

Fourth, the practical relevance of the model was assessed through post-optimality indicators, including expected total cost, expected CO₂ emissions, expected lost sales, fill rate, and expected truck usage. These indicators allow the optimized plans to be interpreted from economic, environmental, service, and logistics perspectives. The model is therefore intended as a decision-support tool that can help planners evaluate cost–carbon–service trade-offs, test different carbon-price and lost-sales penalty levels, and analyze the effect of demand uncertainty and rolling-horizon replanning on operational performance.

The validation should be interpreted within the scope of the study. The case study is industrially inspired and reflects the structure of an automotive production–distribution environment, but some data are anonymized or calibrated for confidentiality and reproducibility reasons. Therefore, the validation is based on model consistency, feasibility, unit coherence, and operational interpretability rather than on a full industrial deployment.

4. Computational Experiments and Results Discussion

This section evaluates the behavior of the proposed stochastic MILP framework under different computational settings. The objective is to analyze how carbon pricing, lost-sales penalties, demand volatility, stochastic planning, and rolling-horizon replanning affect the economic, environmental, and service-related performance of the production–distribution system.

The computational study is organized around five complementary analyses. First, a carbon-price sensitivity analysis is conducted to assess the impact of environmental cost internalization on total cost, emissions, lost sales, fill rate, and truck usage. Second, a lost-sales penalty sensitivity analysis is performed to evaluate how service-priority calibration influences fulfillment performance. Third, a demand-volatility analysis is used to examine the effect of uncertainty intensity on cost, emissions, and service degradation. Fourth, a deterministic expected-demand baseline is compared with the stochastic model to evaluate the managerial value of explicitly representing uncertainty. Finally, a rolling-horizon analysis is conducted to investigate the adaptive behavior of the planning system over successive planning windows.

These computational experiments are designed not only to report numerical outcomes, but also to assess the internal robustness of the proposed framework under different parameter settings. The carbon-price, lost-sales penalty, and demand-volatility analyses examine how the model responds to changes in environmental valuation, service-priority calibration, and uncertainty intensity. The deterministic-versus-stochastic comparison evaluates the effect of explicitly representing demand uncertainty, while the rolling-horizon analysis examines the behavior of the planning system across successive replanning windows. These analyses provide internal sensitivity and robustness checks within the considered automotive production–distribution case study. However, they should not be interpreted as proof of universal generalizability across all supply chain configurations.

All models were solved to integer optimality using IBM ILOG CPLEX Optimization Studio 22.1.0 with the OPL modeling language. The main results are summarized in Tables 2–6, and each subsection provides a detailed interpretation and managerial insight. The analysis emphasizes the joint evaluation of cost, carbon emissions, service performance, and logistics intensity, since these dimensions may evolve differently under uncertainty and capacity limitations.

Table 2. Carbon-price sensitivity results.

Carbon Price (USD/kgCO ₂)	Expected Total Cost (MUSD)	Expected Total CO ₂ Emissions (Mkg CO ₂)	Expected Lost Sales (Units)	Fill Rate	Expected Trucks
0.0000	26.166	7.4583	26,817.77	0.96149	684.13
0.0578	26.597	7.4578	26,838.67	0.96146	684.00
0.0811	26.771	7.4578	26,838.67	0.96146	684.00
0.1156	27.028	7.4579	26,840.27	0.96146	684.07
0.1503	27.287	7.4577	26,844.57	0.96145	683.97

Table 3. Lost-sales penalty sensitivity results.

Penalty Level	Expected Total Cost (MUSD)	Expected Total CO ₂ (Mkg)	Total Lost Sales (Units)	OEM Lost Sales (Units)	OES Lost Sales (Units)	Fill Rate	Expected Trucks
Low	25.522	7.3860	31,398.47	27,038.07	4360.40	0.95491	673.90
Base	26.597	7.4578	26,838.67	25,432.73	1405.93	0.96146	684.00
High	27.645	7.4617	26,582.53	25,393.87	1188.67	0.96183	684.50

Note: Low, Base, and High penalty levels correspond to 0.8, 1.0, and 1.2 times the baseline lost-sales penalty values, respectively.

Table 4. Demand-volatility sensitivity results.

Volatility Level	Expected Total Cost (MUSD)	Expected Total CO ₂ (Mkg)	Total Lost Sales (Units)	OEM Lost Sales (Units)	OES Lost Sales (Units)	Fill Rate	Expected Trucks
Low	26.580	7.4981	25,811.77	24,889.63	922.13	0.96306	686.87
Base	26.597	7.4578	26,838.67	25,432.73	1405.93	0.96146	684.00
High	27.020	7.3618	32,115.97	30,206.97	1909.00	0.95372	676.17

Note: Low, Base, and High demand levels correspond to 0.8, 1.0, and 1.2 times the baseline demand values, respectively.

Table 5. Deterministic versus stochastic planning results.

Planning Approach	Expected Total Cost (MUSD)	Expected Total CO ₂ (Mkg)	Total Lost Sales (Units)	OEM Lost Sales (Units)	OES Lost Sales (Units)	Fill Rate	Expected Trucks
Deterministic demand	26.673	7.5198	26,290.40	25,424.00	866.40	0.96253	686.00
Stochastic baseline	26.597	7.4578	26,838.67	25,432.73	1405.93	0.96146	684.00
Weekly full-horizon stochastic	26.597	7.4578	26,838.67	25,432.73	1405.93	0.96146	684.00

Table 6. Rolling-horizon results.

Rolling Window	Expected Total Cost (MUSD)	Expected Total Demand	Expected Lost Sales (Units)	Fill Rate	Expected Trucks
1–4	15.296	390,426.40	26,210.20	0.93287	370.17
2–5	12.679	331,318.40	12,695.46	0.96168	323.23
3–6	10.721	316,205.43	506.81	0.99840	323.90
4–7	10.012	303,095.27	236.37	0.99922	310.23
5–8	10.329	305,955.77	324.72	0.99894	314.33

4.1. Carbon Price Sensitivity Analysis

To assess the effect of carbon valuation on the production–distribution plan, five internal carbon price levels were tested, ranging from 0 to 0.1503 USD/kgCO₂. This experiment evaluates whether increasing the monetary value assigned to emissions significantly modifies operational decisions or mainly affects the economic structure of the optimized plan.

The results in Table 2 show that increasing the internal carbon price raises the expected total cost from 26.166 MUSD to 27.287 MUSD. However, the physical response of the system remains very limited. Expected CO₂ emissions remain almost unchanged, decreasing only marginally from 7.4583 Mkg to 7.4577 Mkg. Similarly, expected lost sales, fill rate, and truck usage remain nearly stable across all carbon-price levels.

The limited operational response to carbon pricing should be interpreted with caution. In the present formulation, carbon emissions are generated by production quantities and destination-based truck usage, while the model does not include alternative low-emission production technologies, transportation modes, routing options, or emission-cap constraints. Consequently, the carbon-price parameter mainly changes the economic valuation of emissions in the objective function, rather than creating a strong operational incentive to reconfigure production or distribution flows. This result is therefore partly structural: under fixed product–line assignments, fixed product–destination relationships, and limited logistics flexibility, carbon pricing alone has a limited ability to modify physical decisions. Its main value in the current framework is to make the cost of emissions visible and to support cost–carbon trade-off assessment. Stronger operational decarbonization effects would require additional decision alternatives, such as cleaner fleet options, modal shifts, flexible routing, alternative production allocations, or explicit emission-cap constraints.

This result indicates that, in the studied production–distribution system, carbon pricing mainly affects the economic valuation of emissions rather than the operational structure of the plan. The limited variation in emissions and truck usage suggests that the system has little short-term flexibility to modify production and transportation patterns in response to carbon-price signals. This behavior is consistent with the presence of

fixed product–line assignments, destination-based flows, capacity constraints, and limited alternatives for transport reconfiguration.

From a sustainability perspective, this finding is important. Carbon pricing improves the visibility of environmental impact by translating emissions into economic terms, but it does not automatically generate substantial operational decarbonization when the system is structurally constrained. Therefore, managers should not interpret the implementation of an internal carbon price as sufficient by itself to reduce emissions. In such contexts, structural and operational levers, such as production-capacity redesign, shipment consolidation, cleaner transportation options, routing flexibility, or supplier and plant reallocation, should complement carbon pricing.

Overall, the carbon-price analysis shows that the proposed framework can quantify the financial impact of carbon valuation while also revealing the limited short-term decarbonization potential of the existing production–distribution configuration. This confirms the importance of evaluating carbon-related costs jointly with operational feasibility and service-performance indicators.

4.2. Lost-Sales Penalty Sensitivity Analysis

This experiment evaluates the impact of lost-sales penalty calibration on the behavior of the production–distribution system. Three penalty levels are considered: low, base, and high. The objective is to analyze how the economic valuation of unmet demand affects service performance, lost-sales allocation, carbon emissions, total cost, and truck usage.

For the lost-sales penalty sensitivity analysis, the labels Low, Base, and High refer to three levels of the product-specific lost-sales penalty parameter used in the objective function. The Base level corresponds to the reference penalty values used in the baseline model. The Low and High levels are obtained by multiplying the baseline lost-sales penalty values by 0.8 and 1.2, respectively, corresponding to -20% and $+20\%$ variations around the baseline values. These variations directly affect the lost-sales cost component of the objective function and modify the economic pressure placed on unmet demand.

The results in Table 3 show that lost-sales penalties have a significant effect on service performance and fulfillment behavior. When the penalty level increases from low to base, total lost sales decrease from 31,398.47 units to 26,838.67 units, while the fill rate improves from 0.95491 to 0.96146. A further increase from the base to the high penalty level leads to a smaller additional improvement, with total lost sales decreasing to 26,582.53 units and the fill rate reaching 0.96183. This indicates that lost-sales penalties are effective in improving service performance, but that their marginal impact decreases once the system approaches its capacity and logistics limits.

The disaggregated results by product category provide an additional managerial interpretation. The largest improvement is observed for OES products, whose lost sales decrease from 4360.40 units under the low penalty setting to 1188.67 units under the high penalty setting. By contrast, OEM lost sales decrease more moderately, from 27,038.07 to 25,393.87 units. This suggests that OEM demand is already strongly protected under the baseline configuration, whereas OES demand is more sensitive to changes in the penalty structure. Therefore, lost-sales penalties can be used as a practical mechanism to encode customer or product-priority rules into the optimization model.

From an economic perspective, improving service performance comes at a cost. The expected total cost increases from 25.522 MUSD under the low penalty setting to 27.645 MUSD under the high penalty setting. This increase reflects both the direct effect of higher lost-sales penalties and the operational adjustments required to satisfy additional demand. Expected CO₂ emissions also increase slightly, from 7.3860 Mkg to 7.4617 Mkg, while the expected number of trucks rises from 673.90 to 684.50. This confirms that improving service

levels may require additional production and transportation activity, which can increase both cost and environmental impact.

From a sustainability perspective, this result highlights an important trade-off. A higher lost-sales penalty improves service continuity and reduces unmet demand, but it may also increase emissions because more demand is fulfilled through additional production and shipment operations. Therefore, service improvement should not be evaluated independently from environmental performance. In sustainable supply chain planning, lost-sales penalties should be calibrated jointly with carbon pricing and capacity constraints to avoid improving customer service at the expense of disproportionate environmental impact.

From a managerial standpoint, the lost-sales penalty acts as a service-prioritization lever. Firms can use penalty levels to translate commercial priorities, customer criticality, or product importance into operational planning decisions. In constrained environments, penalty calibration helps determine which demand categories should be protected first when full demand satisfaction is not feasible. This makes the proposed model useful not only for cost minimization but also for supporting differentiated service strategies under uncertainty.

4.3. Demand-Volatility Sensitivity Analysis

This experiment analyzes how different levels of demand volatility affect the behavior of the production–distribution system. Three volatility levels are considered: low, base, and high. The objective is to evaluate the impact of uncertainty intensity on expected total cost, carbon emissions, lost sales, fill rate, and truck usage.

For the demand-volatility sensitivity analysis, the labels Low, Base, and High refer to three demand levels generated from the baseline demand values. The Base level corresponds to the reference demand scenario used in the baseline model. The Low and High levels are obtained by multiplying the baseline demand values by 0.8 and 1.2, respectively, corresponding to -20% and $+20\%$ demand variations. These variations modify the scenario-dependent demand parameter used in the demand-satisfaction constraints and allow the model behavior to be evaluated under different demand-intensity conditions.

The results in Table 4 show that increasing demand volatility significantly deteriorates service performance. Total lost sales increase from 25,811.77 units under the low-volatility setting to 32,115.97 units under the high-volatility setting. At the same time, the fill rate decreases from 0.96306 to 0.95372. This confirms that higher uncertainty creates stronger fulfillment pressure on the production–distribution system, especially when production capacity and destination-based transport resources are limited.

The disaggregated results show that both OEM and OES lost sales increase with demand volatility. OEM lost sales rose from 24,889.63 units to 30,206.97 units, while OES lost sales increased from 922.13 units to 1909.00 units. This indicates that demand volatility affects all product categories, although the absolute level of OEM lost sales remains dominant. The higher sensitivity of service performance under high volatility suggests that the planning system becomes less able to absorb demand fluctuations when uncertainty intensifies.

An important result concerns the environmental indicator. Expected CO₂ emissions decrease from 7.4981 Mkg under low volatility to 7.3618 Mkg under high volatility. However, this reduction should not be interpreted as an improvement in environmental efficiency. It is mainly associated with lower fulfilled demand, reduced production, and fewer truck trips. This is confirmed by the decrease in expected trucks from 686.87 to 676.17. Therefore, the apparent environmental improvement is service-driven rather than efficiency-driven.

This finding is particularly important for sustainable supply chain evaluation. If emissions are analyzed in isolation, the high-volatility case may appear environmentally favorable because it generates lower total CO₂ emissions. However, when emissions are interpreted jointly with lost sales and fill rate, it becomes clear that the reduction is caused by service deterioration. In other words, the system emits less because it serves less demand, not because it operates more efficiently.

From a managerial standpoint, this result confirms that demand uncertainty should be monitored through a combined set of environmental and service indicators. Managers should avoid evaluating sustainability performance solely through total emissions, especially in disruption-prone or capacity-constrained systems. A robust interpretation requires simultaneous monitoring of CO₂ emissions, fill rate, lost sales, and truck usage. This supports the need for integrated planning models that can distinguish between genuine environmental efficiency and emission reductions caused by unmet demand.

Overall, the demand-volatility analysis shows that uncertainty intensity is a major driver of service degradation. It also demonstrates that sustainability assessment under uncertainty must account for fulfillment performance, because lower emissions may conceal reduced service continuity rather than improved operational sustainability.

4.4. Deterministic Versus Stochastic Planning

This experiment compares the stochastic MILP baseline with a deterministic expected-demand baseline. The objective is to assess the managerial value of explicitly representing demand uncertainty in the production–distribution planning process. In the deterministic baseline, demand is replaced by its expected value, whereas the stochastic model considers multiple demand scenarios and their associated probabilities.

The results in Table 5 show that the deterministic expected-demand baseline achieves a slightly higher fill rate and lower total lost sales than the stochastic baseline. The fill rate is 0.96253 in the deterministic case, compared with 0.96146 in the stochastic baseline. Similarly, total lost sales are lower in the deterministic case, reaching 26,290.40 units compared with 26,838.67 units in the stochastic model.

However, this apparent service improvement comes with a higher expected total cost and higher carbon emissions. The deterministic baseline generates an expected total cost of 26.673 MUS\$D, compared with 26.597 MUS\$D for the stochastic baseline. It also produces higher expected CO₂ emissions, increasing from 7.4578 Mkg in the stochastic model to 7.5198 Mkg in the deterministic case. The expected number of trucks is also higher in the deterministic baseline, with 686.00 trucks compared with 684.00 trucks in the stochastic baseline.

These results suggest that the deterministic model tends to produce a slightly more service-oriented plan, but at the expense of higher cost, higher emissions, and higher logistics intensity. By contrast, the stochastic model provides a more balanced compromise between cost, environmental impact, and service performance. Although its fill rate is marginally lower, it explicitly accounts for demand uncertainty and avoids relying on a single expected-demand representation.

From a methodological perspective, this comparison highlights the importance of stochastic modeling in uncertain production–distribution environments. A deterministic expected-demand approach may mask the variability of demand and lead to planning decisions that are less representative of real operating conditions. In contrast, the stochastic formulation provides a more realistic decision-support framework because it evaluates decisions over a set of possible demand scenarios.

The equality between the stochastic baseline and the weekly full-horizon stochastic baseline confirms the internal consistency of the implementation. Both approaches produce

identical values for expected total cost, CO₂ emissions, lost sales, fill rate, and truck usage, which indicates that the stochastic model is solved consistently across the full planning horizon.

The relatively small differences between the deterministic expected-demand baseline and the stochastic formulation should be interpreted carefully. These results do not indicate a strong numerical superiority of the stochastic model in the present case. Instead, they reflect the constrained structure of the studied production–distribution environment. Products are assigned to predefined production lines and destinations, routing flexibility is not considered, and the recourse decisions are limited by production-line capacity and destination-based truck requirements. Under such conditions, the model has limited flexibility to substantially modify production and distribution decisions across scenarios.

Therefore, the value of the stochastic formulation in this study lies primarily in its ability to provide an uncertainty-aware evaluation of expected cost, emissions, lost sales, fill rate, and truck usage, rather than in producing large numerical improvements over the deterministic baseline. The stochastic model evaluates planning performance across multiple demand realizations, while the deterministic baseline relies on a single expected-demand representation. The close results observed in Table 5 are thus interpreted as a consequence of limited recourse flexibility in the studied case, not as evidence that stochastic modeling is unnecessary in general.

This finding also highlights an important limitation of the current model structure. The value of stochastic modeling is expected to become more visible in systems with higher demand variability, flexible product allocation, alternative routes, multiple plants, differentiated transportation modes, or richer recourse decisions. These extensions are therefore relevant directions for future research.

4.5. Rolling Horizon Analysis

A rolling-horizon procedure was implemented to evaluate the adaptive behavior of the production–distribution system over successive planning windows. Instead of solving the full eight-week horizon as a single static plan, the analysis considers overlapping four-week windows. This structure reflects industrial replanning practice, where decisions are periodically revised as updated demand information becomes available.

The objective of this experiment is to assess how service performance, lost sales, logistics intensity, and expected cost evolve across successive replanning windows. The rolling-horizon analysis is particularly relevant from a resilience perspective because it provides insight into periods when the system is most exposed to service disruption and when adaptive replanning is most valuable.

The results in Table 6 show that service disruption is strongly concentrated in the first rolling window. In the 1–4 window, expected lost sales reach 26,210.20 units, and the fill rate is only 0.93287. This indicates that the beginning of the planning horizon represents the most constrained and vulnerable phase of the system. The high level of expected demand in this first window, combined with limited production and distribution flexibility, creates significant service pressure.

A clear recovery pattern appears in the following windows. Expected lost sales decrease from 26,210.20 units in the 1–4 window to 12,695.46 units in the 2–5 window. The fill rate also improves from 0.93287 to 0.96168. This improvement becomes even stronger in the later windows, where expected lost sales fall below 600 units and the fill rate approaches complete demand fulfillment. In the 3–6, 4–7, and 5–8 windows, the fill rate reaches 0.99840, 0.99922, and 0.99894, respectively.

This evolution suggests that the system progressively stabilizes as the planning horizon advances. The early windows are characterized by stronger demand pressure and higher

service disruption, while later windows allow the planning system to recover and achieve near-complete fulfillment. From a resilience perspective, this result is important because it shows that service vulnerability is not uniformly distributed across the planning horizon. Instead, the most critical tensions are concentrated in the earliest replanning periods.

It is important to emphasize that the rolling windows overlap. Therefore, the results reported in Table 6 should not be summed across windows. Each window represents a separate replanning exercise over a four-week horizon. The purpose of the rolling-horizon analysis is not to compute an aggregate full-horizon cost or demand value, but to observe how the planning system behaves when the decision horizon is progressively updated.

From a managerial standpoint, the rolling-horizon results suggest that adaptive replanning is most valuable during the early and most stressed periods of the horizon. Managers should intensify monitoring, demand review, and production–distribution adjustment during these critical windows. Once the system stabilizes and service performance improves, replanning intensity may be gradually reduced or focused on exception management.

Overall, the rolling-horizon analysis provides resilience-oriented insights by identifying when the system is most vulnerable and how service performance evolves over successive replanning iterations. This confirms the value of combining stochastic optimization with rolling-horizon logic for sustainable and resilient production–distribution planning under uncertainty.

The rolling-horizon results should be interpreted as responsiveness-oriented indicators rather than as a complete disruption-recovery assessment. The analysis does not simulate explicit disruptions such as supplier failures, machine breakdowns, material shortages, or transportation interruptions. Instead, it evaluates how the planning system behaves when the decision horizon is updated under changing demand conditions. From this perspective, the rolling-horizon procedure provides useful information on the temporal distribution of service vulnerability. The early windows show higher lost sales and lower fill rates, indicating that the system is more exposed to service pressure at the beginning of the horizon. Later windows exhibit improved service performance, suggesting that replanning can support progressive recovery of the production–distribution plan when updated demand information becomes available.

This interpretation is consistent with the service-continuity perspective adopted in this study. Rolling-horizon replanning is therefore not presented as a complete resilience mechanism, but as a practical planning tool that helps identify when adaptive decision-making is most valuable in a capacity-constrained automotive production–distribution environment.

4.6. Overall Discussion

The computational experiments provide a multidimensional assessment of the proposed stochastic MILP framework by jointly considering economic cost, carbon emissions, service performance, logistics intensity, and replanning behavior. The results show that these indicators should not be interpreted independently, since improvements in one dimension may be associated with deterioration in another. This is particularly important in capacity-constrained production–distribution systems, where service degradation, carbon emissions, and logistics activity are strongly interrelated.

Table 7 summarizes the main findings obtained from the five computational analyses. The carbon-price sensitivity analysis shows that increasing the internal carbon price mainly affects the economic valuation of emissions, while physical flows remain nearly unchanged under the current fixed-structure configuration. The lost-sales penalty analysis shows that higher penalties improve service performance, but may increase cost and emissions. The demand-intensity analysis confirms that higher demand levels increase unmet demand and reduce the fill rate. The deterministic-versus-stochastic comparison indicates that

the numerical difference between the two approaches remains limited because of fixed assignments and restricted recourse flexibility. Finally, the rolling-horizon analysis shows that service vulnerability is concentrated in the early planning windows and decreases in later periods.

Table 7. Summary of the main computational findings and managerial interpretation.

Analysis	Main Finding	Interpretation
Carbon-price sensitivity	Higher carbon prices mainly increase total cost, while emissions and physical flows remain nearly stable.	Carbon pricing acts primarily as an economic valuation mechanism in the current fixed-structure model.
Lost-sales penalty sensitivity	Higher penalties reduce unmet demand and improve the fill rate.	Service performance can be improved through penalty calibration, but this may increase cost and emissions.
Demand-intensity sensitivity	Higher demand levels increase lost sales and reduce the fill rate.	Demand pressure directly affects service continuity under limited production and logistics capacity.
Deterministic versus stochastic planning	The two approaches produce close aggregate results.	The value of stochastic modeling is mainly related to uncertainty-aware evaluation rather than strong numerical improvement in this constrained case.
Rolling-horizon replanning	Early planning windows show higher service disruption than later windows.	Replanning analysis helps identify when the system is most vulnerable to service degradation.

Overall, the results confirm the need to evaluate sustainable production–distribution planning through combined indicators rather than isolated performance measures. In particular, lower emissions should not automatically be interpreted as improved environmental efficiency if they result from lower fulfilled demand. Similarly, service improvement should be assessed together with its cost and carbon consequences. The proposed framework therefore provides an integrated basis for analyzing cost–carbon–service trade-offs under stochastic demand.

The findings should also be interpreted within the scope of the model. The computational study is based on a single-plant, fixed-routing, and capacity-constrained automotive production–distribution environment. Therefore, the results demonstrate the internal behavior of the proposed framework under different parameter settings, but they do not establish universal generalizability across all supply chain configurations. Broader validation would require additional industrial cases, flexible routing structures, alternative transportation modes, multi-plant configurations, and explicit disruption scenarios.

4.7. Managerial and Practical Implications

The computational results provide several practical implications for production, logistics, and sustainability managers operating in capacity-constrained automotive production–distribution environments. First, the carbon-price sensitivity analysis shows that internal carbon pricing can improve the economic visibility of emissions, but it does not necessarily generate substantial operational changes when the system has fixed product–line assignments, fixed destination flows, and limited low-emission alternatives. Managers should therefore interpret carbon pricing as an accounting and decision-support mechanism, and not as a sufficient decarbonization strategy by itself. Stronger emission reductions would require complementary operational levers, such as cleaner transportation

options, shipment consolidation, routing flexibility, alternative production allocations, or emission-cap policies.

Second, the lost-sales penalty analysis shows that the economic valuation of unmet demand can strongly influence service performance. From a managerial perspective, lost-sales penalties can be used to translate customer criticality, product priority, or commercial commitments into the optimization model. In constrained systems, this allows planners to identify which demand categories should be protected first when full demand satisfaction is not feasible. However, improving service levels may increase production and transportation activity, which can raise both cost and emissions. Therefore, service-priority decisions should be evaluated jointly with environmental and logistics indicators.

Third, the demand-intensity analysis highlights the need to interpret sustainability indicators together with service indicators. Lower emissions are not necessarily evidence of better environmental efficiency if they result from lower fulfilled demand and higher lost sales. Managers should therefore monitor emissions, fill rate, lost sales, truck usage, and total cost simultaneously. This is particularly important in uncertain environments, where demand fluctuations can create misleading sustainability signals.

Fourth, the deterministic-versus-stochastic comparison suggests that the value of stochastic planning should not be assessed only through immediate numerical improvement over a deterministic baseline. In fixed-routing and capacity-constrained systems, deterministic and stochastic solutions may be close because recourse flexibility is limited. Nevertheless, the stochastic formulation remains useful because it evaluates expected performance across different demand scenarios and provides a more uncertainty-aware basis for decision-making.

Finally, the rolling-horizon analysis provides practical insight into when adaptive replanning is most valuable. The results show that service vulnerability is concentrated in the early planning windows, where lost sales are higher and fill rate is lower. This suggests that managers should intensify monitoring, demand review, and production–distribution adjustment during the most constrained periods of the horizon. Once the system stabilizes, replanning efforts can be focused on exception management and service-risk monitoring.

5. Conclusions

In this study, we developed a stochastic MILP-based decision-support framework for carbon-aware production–distribution planning under uncertain demand in an automotive supply chain environment. The proposed model jointly considers production quantities, inventory levels, destination-based shipments, truck usage, lost sales, and carbon-related costs over a multi-period planning horizon. Demand uncertainty is represented through a finite set of scenarios, while a rolling-horizon analysis is used to examine the responsiveness of the planning system as updated demand information becomes available.

The contribution of the study lies in the integrated formulation and analysis of economic, environmental, service, logistics, and replanning dimensions within a single production–distribution planning framework. The work does not claim novelty in the use of scenario-based stochastic programming or in the solution method, since the model is solved using a standard MILP implementation. Rather, its contribution is to show how carbon valuation, lost-sales-based service degradation, stochastic demand, truck-capacity decisions, and rolling-horizon replanning can be jointly evaluated in a capacity-constrained automotive production–distribution environment.

The computational experiments provide several findings. First, carbon pricing mainly increases the economic valuation of emissions, while its effect on operational decisions remains limited under the fixed-structure configuration considered in this study. This indicates that carbon pricing alone is not sufficient to generate substantial operational

decarbonization when alternative low-emission production or transportation options are not available. Second, lost-sales penalties strongly influence service performance and can be used to represent customer or product-priority logic in the optimization model. Third, higher demand levels increase unmet demand and reduce the fill rate, confirming the strong link between demand uncertainty and service degradation. Fourth, the deterministic and stochastic solutions remain close in aggregate terms because the studied system has limited recourse flexibility. Therefore, the value of the stochastic formulation should be interpreted mainly as an uncertainty-aware evaluation capability rather than as a guaranteed source of large numerical improvement. Finally, the rolling-horizon analysis identifies early planning windows as the most vulnerable periods in terms of service continuity, highlighting the relevance of adaptive replanning for monitoring and responding to changing demand conditions.

From a practical perspective, the proposed framework can help production, logistics, and sustainability managers evaluate cost–carbon–service trade-offs before implementing planning decisions. It supports the assessment of carbon-price effects, the calibration of lost-sales penalties, the analysis of demand-pressure scenarios, and the identification of periods where replanning efforts should be intensified. The results also show that carbon emissions should be interpreted jointly with service indicators, since lower emissions may reflect reduced fulfillment rather than improved environmental efficiency.

The study has several limitations. The computational analysis is based on a single-plant, fixed-routing, and capacity-constrained automotive production–distribution environment. Product–line assignments and product–destination relationships are predefined, and the model does not include alternative low-emission technologies, modal choices, flexible routing, or explicit emission-cap constraints. In addition, the case study is industrially inspired and some data were anonymized or calibrated for confidentiality and reproducibility reasons. The model also focuses on demand uncertainty and does not explicitly represent material shortages, supplier failures, machine breakdowns, or transportation disruptions.

Future research could extend the proposed framework in several directions. First, multi-plant and multi-echelon configurations could be considered to assess the generalizability of the model across broader supply chain structures. Second, carbon-responsive decision variables, such as alternative transportation modes, cleaner fleet options, emission caps, cap-and-trade mechanisms, or differentiated production technologies, could be integrated to evaluate stronger decarbonization strategies. Third, explicit disruption scenarios involving material availability, production capacity reduction, supplier unreliability, or logistics interruptions could be incorporated to move from responsiveness-oriented resilience toward disruption-based resilience modeling. Finally, future studies could validate the framework using additional industrial datasets and compare the proposed approach with alternative planning policies or heuristic solution methods for larger-scale applications.

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