Preprints of the 23rd IFAC World Congress
Busan, Republic of Korea, August 23-28, 2026

Integrated Optimization–Simulation Framework for Sustainable Sourcing Flow Allocation under Supply and Delivery Risk

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Abstract: This paper addresses sourcing and transportation planning in an aeronautics supply chain under cost, CO_2 emissions, and delivery-risk considerations. We propose the architecture of a hybrid optimization–simulation decision-support framework in which a deterministic mixed-integer linear programming (MILP) model generates sourcing and transport plans, while a discrete-event simulation (DES) model is intended to evaluate their robustness under operational uncertainty. The present paper focuses on the formulation of the MILP decision layer and on the definition of its interaction with an existing DES model previously validated on the same industrial context. Using industrially inspired data, we illustrate how the MILP reacts to changes in service, carbon, and capacity-related parameters, and how such scenario analyses can support sourcing and transport decisions. The automated closed-loop interaction in which DES results are used to update MILP parameters is left for future work.

Keywords: Supply chain optimization; discrete-event simulation; sourcing; carbon footprint; on-time delivery; Aeronautics.

1. INTRODUCTION

Aeronautics supply chains are long, multi-echelon, and tightly synchronized. Minor disruptions in supplier lead times or transport availability can propagate through the system, threatening customer service levels. Meanwhile, manufacturers face growing pressure to minimize their environmental footprint, especially emissions from express air freight. As a result, decisions about "what to source, where to produce, and how to ship" have become complex, multi-criteria problems that must balance cost, service (on-time delivery), and sustainability under risk.

This research was motivated by an industrial case involving an Aeronautics manufacturer aiming to: (i) rationalize the distribution of the sourcing flow in three production/sourcing modes for a specific product family, (ii) decide when to choose air versus sea transport, and (iii) evaluate the impact of the service level of these decisions in scenarios of disruption. An existing discrete-event simulation (DES) model of the supply chain—adapted from Hilali et al. [2024]—was available and could simulate the effects of operational variability on OTD. However, the simulation lacked an optimization layer to suggest optimal flow configurations. Conversely, a purely deterministic optimization model would not capture the stochastic delays observed in real operations. This gap drives the development of a hybrid optimization–simulation framework in which optimization generates prescriptive sourcing and transport plans, while simulation is intended to assess their resilience under uncertainty.

To address this gap, we introduce the architecture of a hybrid optimization–simulation framework in which a mixed-integer linear programming (MILP) model generates prescriptive sourcing and transport decisions, and a DES model is intended to evaluate their robustness under risk. In this paper, we focus primarily on the development and formalization of the optimization component and on the definition of its interaction with the simulation layer. This layered architecture constitutes a first methodological step toward a future Supply Chain Digital Twin [Ivanov, 2021, Tao et al., 2019, Negri et al., 2017]...

Using aggregated industrial data (26 orders, 12 components, 109-day horizon), we illustrate how the MILP can support sourcing and transport decisions by combining production mode selection, multimodal transport choices, delivery-window constraints, and carbon considerations. The DES layer is introduced as the complementary risk-evaluation component intended for future robustness assessment under stochastic lead times and disruptions. Together, the two components define a coherent foundation for a prescriptive and risk-aware decision-support architecture.

The contributions of this paper are threefold. First, we formulate a MILP model for joint sourcing-mode selection, component allocation, and transport decision support under cost, emissions, and delivery considerations. Second,

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we define the interaction logic between this optimization layer and a validated DES model intended to represent stochastic operational risks. Third, we provide a scenario-based illustration of how the optimization layer can support managerial exploration of cost–service–sustainability trade-offs in an aeronautics supply chain. The automated optimization–simulation feedback loop is not implemented in the present paper and is left for future work.

2. LITERATURE REVIEW

In the last two decades, supply chain risk management (SCRM) has evolved into a diverse field combining stochastic programming, robust optimization, simulation, and hybrid methods[Ho et al., 2015, Fahimnia et al., 2015, Fan and Stevenson, 2018]. For supply chain design and tactical planning, mixed-integer optimization remains dominant, as it effectively models multi-echelon networks, capacity constraints, and sourcing flexibility [Sadghiani et al., 2015, Hasani and Khosrojerdi, 2016]. However, optimization models often oversimplify risk by using static or average lead-time values, which fail to capture the true impact of disruptions.

On the other hand, discrete-event simulation (DES) has proven effective in analyzing disruption propagation (the "ripple effect"), testing recovery strategies, and validating planning rules in complex supply chains, particularly in Aeronautics and automotive industries [Ivanov, 2017, 2020]. Simulation is well-suited to represent probabilistic delays, resource contention, and the dynamic behavior of supply chain operations.

Recent reviews emphasize the need to integrate optimization and simulation for SCRM. Oliveira *et al.* (2019) highlight that most studies rely exclusively on one method or the other, and few attempt a closed-loop interaction where optimization proposes a plan and simulation evaluates its robustness. Similar hybrid approaches are found in energy and biomass logistics (e.g. Paulo *et al.*, 2023), but remain scarce in Aeronautics.

Carbon-aware supply chain MILP models often incorporate CO_2 through weighted or priced emissions, yet the trade-off between air freight, delivery performance, and environmental impact remains little explored under uncertainty [Zhalechian et al., 2016]. Recent reviews also highlight the limited integration of DES with prescriptive optimization and the growing interest in digitally enabled risk-aware planning [Jerbi and Benjeddou, 2025, Kiani Mavi et al., 2025, Korder et al., 2024]. Accordingly, this paper is positioned at the intersection of multi-mode sourcing, air/sea transport selection, carbon-integrated MILP, and a simulation-based risk-evaluation architecture.

3. PROBLEM STATEMENT

We consider a multi-echelon aeronautics supply chain, delivering a single product family to customers through a set of orders $k \in K$. Each order is characterized by:

- a quantity D_k,
- a target delivery date DC_k,
- an admissible window $[DA_k, DT_k]$.

To assemble each product, a set of twelve components $i \in I$ is required following a fixed bill of materials (BOM). Each component can be sourced or produced through one of three alternative production modes $h \in H = \{1, 2, 3\}$, each representing a different supply strategy:

- Mode 1: internal / regular procurement - components and sub-components are purchased from suppliers, but final assembly and component fabrication occur in the company's internal plants. This mode typically has a longer lead time but gives the company control over production. For transport to the customer, both air and sea shipment are possible for Mode 1 (since production may occur overseas, there are two transport options);
- Mode 2: mixed sourcing (partly external) - the main components are purchased from an external supplier, then the final assembly is done internally. Medium cost, medium lead time;
- Mode 3: fully external / purchased - the finished product is directly purchased from an external supplier and delivered to the end customer. Transport for Mode 3 in our case is often direct delivery (could be considered as a single step).

Each production mode option for the product implies different total lead times, cost structures, and capacity constraints (e.g. limited available volumes from suppliers or internal production limits).

The delivery to the customer can be done by air or by sea. Shipping by air *saves* $TSave_k$ days compared to sea, but incurs an additional cost $\Delta Cost_k$ and additional emissions $\Delta EmCost_k$. The same trade-off structure is assumed for the delivery of components.

In the present study, all customer orders belong to the same product family and share a common bill of materials structure composed of twelve components. The coefficient BOM_i indicates the quantity of component i required per finished product. The formulation considers sourcing and production capacity limitations, but does not explicitly model storage-capacity constraints or intermediate transfers between production sites during execution. These assumptions define the scope of the current decision-support model.

3.1 System KPIs

The company monitors several performance indicators that drive planning decisions:

- Total cost: production + transport + penalties;
- CO_2 emissions: from sourcing mode and transport choice;
- On-Time Delivery (OTD): share of orders delivered on or before DC_k;
- Delay-over-deadline (DoD): average lateness beyond the contractual window.

These KPIs must be balanced to select both sourcing and transport strategies.

3.2 Deterministic vs. Stochastic Parameters

The optimization problem relies on deterministic input parameters such as:

- production lead times LT_{ih},
- transport durations (air/sea),
- sourcing capacities CAP_{iht}.

However, in real operations, these parameters are stochastic and influenced by:

- supplier variability and shortages,
- internal production disruptions (machine downtime, rework),
- transport delays (customs, port congestion),
- external disruptions (regulatory changes, geopolitical events).

These uncertainties generate lead-time variability and may significantly degrade OTD performance. A purely deterministic MILP cannot capture such risks and would produce plans that appear optimal but may fail under realistic conditions.

3.3 Decision Problem

Given these elements, the company wants to decide:

(1) the sourcing mode used for each component i;
(2) the production quantities per mode;
(3) whether each customer order k should be shipped by air or sea;
(4) while minimizing total cost and CO_2 emissions and minimizing late deliveries;
(5) and while ensuring high service performance within the delivery windows.

Although several extensions of MILP exist to model uncertainty (e.g., stochastic programming or robust optimization), they remain impractical for the considered aeronautical system. Capturing correlated delays across suppliers, internal fabrication, assembly stages, and transport activities would require a large number of scenarios, leading to an exponential increase in model size. Moreover, operational disruptions in aeronautics are characterized by heavy-tailed and non-stationary delay distributions, which cannot be represented accurately in tractable stochastic MILP forms. Robust models, on the other hand, tend to be overly conservative and ignore the dynamic propagation of disruptions (ripple effect). For these reasons, deterministic MILP is considered for generating baseline sourcing and transport plans, while a discrete-event simulation (DES) model is intended to evaluate their robustness under realistic uncertainty. This motivates the hybrid optimization-simulation framework developed in this study.

4. OPTIMIZATION–SIMULATION INTERACTION FRAMEWORK

The proposed framework combines a deterministic MILP decision layer and a DES evaluation layer. The MILP is intended to generate nominal sourcing and transport plans, while the DES is intended to assess how such plans behave under operational uncertainty. In the present paper, the interaction logic between the two layers is defined, but the automated closed-loop implementation is left for future work. Accordingly, this section describes the intended workflow and decision logic rather than a fully deployed bidirectional coupling.

4.1 Workflow

The intended interaction between optimization and simulation is illustrated in Fig. 1 and consists of the following steps:

(1) **Optimize.** Solve the MILP with nominal inputs to obtain sourcing and transport decisions and the implied delivery times.
(2) **Simulate.** Use these decisions as inputs to the DES model and run multiple replications in order to estimate service and risk-related KPIs such as OTD and DoD.
(3) **Diagnose.** Identify the main sources of service degradation, such as transport delays, supplier variability, or capacity bottlenecks.
(4) **Update policy.** Adjust selected MILP parameters or constraints, for example lateness penalties, carbon weights, transport restrictions, or capacity limits.
(5) **Re-solve and re-evaluate.** Repeat the process until the decision-maker is satisfied with the trade-off between cost, emissions, and service performance.

4.2 Stopping criteria

In the intended closed-loop version of the framework, a candidate plan would be accepted when the lower bound of the confidence interval associated with the simulated OTD reaches the target service level and when the corresponding cost and emission levels remain acceptable for the decision-maker. To avoid endless iterations in cases where no satisfactory plan can be obtained under the selected policy adjustments, a maximum number of iterations and a fall-back rule returning the best compromise solution should be defined. Since the automated loop is not implemented in the present paper, these stopping rules are described here as part of the future coupling logic.

4.3 Toward a Digital Twin

The proposed interaction logic provides a basis for future digital-twin-oriented coupling between optimization, simulation, and operational data.

5. MILP OPTIMIZATION MODEL

The first component of the proposed framework is a deterministic mixed-integer linear programming (MILP) model that prescribes the allocation of sourcing modes, component production volumes, and transport choices for each customer order. The objective is to minimize total cost—including production, transport, carbon emissions and delay penalties—while ensuring that all orders respect their delivery windows and that sourcing decisions remain within the capacity of each production mode. The formulation captures the structural couplings between Bill-of-Materials (BOM), production lead times, transport times, and air–sea trade-offs, thereby providing a coherent baseline plan from which operational performance can be evaluated. Although the MILP does not model stochastic delays explicitly, it establishes a deterministic decision core that can subsequently be stress-tested through the DES model.

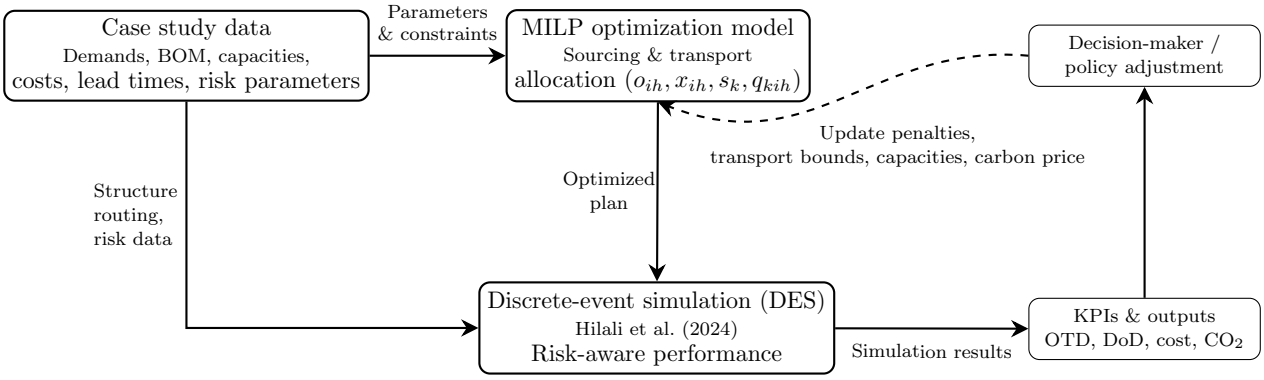


Fig. 1. Architecture of the proposed optimization–simulation framework.

The following subsections present the indices, parameters, decision variables, objective function, and constraints that define the optimization problem.

5.1 Indices and Parameters

$k \in K$	customer orders (26 in case study)
$i \in I$	components (12)
$h \in H$	sourcing / production modes (3)
$t \in T$	time periods (days, horizon 109)

Parameters:

- D_k: demand of order k;
- BOM_i: units of component i per finished product;
- CAP_{iht}: capacity of component i in mode h at period t;
- LT_{ih}: production lead time of i in mode h (days);
- $Tship_k$: sea shipping time for order k;
- $TSave_k$: time saved if order k is shipped by air;
- $Cost_{ih}$: production cost of component i in mode h;
- EC_{ih}: emissions of component i in mode h;
- $\Delta Cost_k$: extra cost for shipping k by air;
- $\Delta EmCost_k$: extra emissions for shipping k by air;
- $LateCost_k$: penalty per day of delay (within window);
- $LTCost_k$: cost associated with lead time (stock keeping, organizational);
- Pen_k: penalty if k is delivered after DT_k;
- Em: weight (price) of emissions.
- $\Delta\text{DelCost}_{ih}$: Additional cost of shipping component i produced with mode h by air (currency per unit).
- DLT_h : Baseline delivery time by sea for production mode h (days).
- DLTSave_h : Delivery time saved when shipping by air for items produced with mode h (days).
- ΔEmCost_{ih} : Additional CO_2 emission (monetized emission cost) for shipping component i by air instead of sea when produced under mode h.

5.2 Decision Variables

- $x_{ih} \geq 0$: quantity of component i produced in mode h;
- $o_{ih} \in \{0,1\}$: 1 if component i uses mode h;
- $s_k \in \{0,1\}$: 1 if order k is shipped by air;
- $y_{k,i,h}$: lead time for producing the component i of the order k with mode h;
- $w_{k,t} \in \{0,1\}$: 1 if order k is completed in the period t;
- $z_k \geq 0$: lead time for producing and shipping the order k;
- $\delta_k \geq 0$: delay of order k beyond DC_k;
- $\pi_k \in \{0,1\}$: 1 if order k is late beyond DT_k.
- $q_{k,i,h} \in \{0,1\}$: Binary variable indicating if component i of order k, produced by mode h, is shipped by air (as opposed to sea). This variable represents inbound expediting decisions, which are distinct from the outbound transport decision for the finished customer order.

The formulation distinguishes two transport-related decision levels. The first concerns the expedited transport of components or subassemblies on the upstream part of the supply chain. The second concerns the outbound shipment of the finished customer order. In addition, the additional air-freight cost represents the premium tariff associated with choosing air instead of sea transport on the relevant leg; consolidation economies or aircraft loading effects are not explicitly modeled in the present formulation.

5.3 Objective Function

The objective is to minimize the total cost, including production costs, additional air shipment cost, CO_2 emissions cost, and delay penalties:

$$
\begin{aligned}
\min\ Z \;=\; & \underbrace{\sum_i \sum_h x_{ih} \cdot Cost_{ih}}_{\text{Production cost}} \\
& + \underbrace{\sum_k s_k \cdot (\Delta Cost_k + \Delta EmCost_k)}_{\text{Extra cost if entire order } k \text{ is shipped by air}} \\
& + \underbrace{\sum_k (LateCost_k \cdot \delta_k + Pen_k \cdot \pi_k)}_{\text{Delay penalty \& very late penalty}} \\
& + Em \cdot \underbrace{\sum_i \sum_h o_{ih} \cdot EC_{ih}}_{CO_2 \text{ emissions from production mode}} \\
& + \underbrace{\sum_k z_k \cdot LTCost_k}_{\text{Lead time cost}}
\end{aligned}
$$

$$+\underbrace{\sum_{k}\sum_{i}\sum_{h} q_{kih}\cdot(\Delta DelCost_{ih}+\Delta EmCost_{ih})}_{\text{Additional air freight \& } CO_2 \text{ cost per component/mode}}. \tag{1}$$

5.4 Constraints

- *Demand and BOM:*

$$\sum_{h\in H} x_{ih} \;\geq\; \left(\sum_{k\in K} D_k\right) BOM_i, \quad \forall i\in I. \tag{2}$$

- *Capacity:*

$$\sum_{t',k|t'\leq t} w_{k,t'} D_k BOM_i \; CAP_{iht} \;\leq \sum_{h,t'\leq t} CAP_{iht'}, \quad \forall i,t. \tag{3}$$

$$x_{ih} \;\leq \sum_{t\in T} CAP_{iht}, \quad \forall i,h. \tag{4}$$

- *Mode selection linking:*

$$x_{ih} \leq M\, o_{ih}, \quad \forall i,h \tag{5}$$

with M a sufficiently large number.

- *Delivery time:*

$$y_{kih} = LT_{ih}\cdot(D_k\cdot BOM_i)\cdot\frac{x_{ih}}{\sum_k D_k\cdot BOM_i} + DLT_h\cdot o_{ih} - DLTSave_h\cdot q_{kih}, \qquad \forall k,i,h \tag{6}$$

$$z_k \geq y_{kih} + Tship_k - s_k\cdot TSave_k, \qquad \forall k,i,h \tag{7}$$

- *Order completion time:*

$$\begin{cases}\sum_t w_{kt} = 1,\\ \sum_t t\cdot w_{kt}\geq z_k,\end{cases} \qquad \forall k \tag{8}$$

- *Delay:*

$$\begin{cases}\delta_k \geq \sum_t t\cdot w_{kt} - DC_k,\\ \delta_k \geq DC_k - \sum_t t\cdot w_{kt},\end{cases} \qquad \forall k \tag{9}$$

- *Very late delivery window:*

$$\begin{cases}DA_k - \sum_t t\cdot w_{kt}\leq M\cdot\pi_k,\\ \sum_t t\cdot w_{kt} - DT_k\leq M\cdot\pi_k,\end{cases} \qquad \forall k \tag{10}$$

The model is subject to the above constraints, which guarantee feasibility and consistency of the sourcing and delivery decisions. Constraints (2) and (4) ensure that all ordered quantities are produced and that production remains within the available capacity of each sourcing mode. The linking constraint $x_{ih}\leq M\cdot o_{ih}$ enforces mode selection logic by activating sourcing mode h only if production is assigned to it. Constraints (6)–(7) compute the lead time of each component and derive the total delivery lead time of each order, taking into account production, transport mode decisions, and benefit of air shipment. Equation (6) should be understood as an aggregate deterministic approximation of the component-related contribution to the lead time of order k. Since the MILP does not represent detailed production sequencing or event-level operational dynamics, the nominal lead-time contribution associated with mode h is allocated proportionally according to the component requirement of the considered order within the total demand. This surrogate expression is used only to estimate nominal completion times in the optimization layer; the detailed stochastic behavior of the supply chain is intended to be represented by the DES model. Constraints (8) assign each order to one (and only one) completion time period. The delay constraints (9) compute lateness with respect to the target delivery date DC_k, while constraints (10) activate the binary variable π_k when the delivery date exceeds the acceptable delivery window $[DA_k, DT_k]$. Overall, the constraint set enforces the structural feasibility of the plan, while the objective function evaluates the impact of sourcing mode and transport decisions on total cost, service level, and environmental performance. Unlike classical sourcing or transport optimization models, this formulation integrates component-level production choices and order-level delivery commitments in a unified structure, which will enable the subsequent simulation module to evaluate the robustness of optimized solutions under uncertainty.

6. DISCRETE-EVENT SIMULATION MODEL

The second component of the framework is a discrete-event simulation (DES) model. It represents the same sourcing and transport planning problem described in the previous sections, but with explicit consideration of operational risks and stochastic lead-time variability. The model was originally developed by Hilali et al. [2024] in collaboration with the same industrial partner and has been validated using extensive historical data, demonstrating its ability to reproduce the behavior of the real supply chain with high accuracy.

These outputs are intended to be used to assess the robustness of deterministic MILP plans under operational uncertainty.

7. ILLUSTRATIVE SCENARIO ANALYSIS OF THE MILP LAYER

The case study is based on an industrially inspired dataset including 26 customer orders, 12 components, three sourcing modes, two transport modes, and a finite planning horizon. The corresponding data structure includes demand quantities, bill-of-material coefficients, sourcing capacities, nominal lead times, transport parameters, and cost/emission coefficients.

At the present stage of the research, the numerical section is intended to illustrate the behavior of the MILP decision layer and the types of managerial levers that the overall framework is expected to exploit. It does not constitute a full experimental validation of the closed-loop optimization–simulation framework.

To support this illustration, five representative scenarios are defined:

- **Scenario 1 – Baseline.** Nominal parameter setting.

- **Scenario 2 – Service-oriented.** Increased lateness penalties to favor faster but potentially more expensive decisions.
- **Scenario 3 – Carbon-oriented.** Higher carbon-emission weight to reduce recourse to high-emission transport or sourcing options.
- **Scenario 4 – Capacity perturbation.** Modified sourcing capacities to represent bottlenecks or temporary flexibility.
- **Scenario 5 – Combined policy adjustment.** Simultaneous changes in service, carbon, and capacity parameters to illustrate multi-criteria trade-offs.

These scenarios are not presented as validated performance results. Rather, they define a structured experimental logic for exploring how the MILP reacts to changes in service, sustainability, and operational constraints. In the complete version of the framework, candidate plans generated by the MILP would then be evaluated in the DES in order to quantify their robustness under stochastic disruptions through indicators such as OTD and DoD.

8. CONCLUSION AND FUTURE WORK

This paper presented the architecture of a unified hybrid optimization-simulation framework for sourcing and transport planning in an aeronautics supply chain under cost, emissions, and delivery-risk considerations. The main contribution of the present work is the formulation of the MILP decision layer together with the definition of its intended interaction with a DES evaluation layer. The scenario-based analysis illustrates how the optimization model can support the exploration of cost–service–sustainability trade-offs, while also clarifying the role that simulation is expected to play in future robustness assessment. Future work will implement and test the automated optimization–simulation feedback loop, in which simulated performance indicators are used to update planning parameters and improve decision robustness under uncertainty.

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