

# A New MILP Model for Supplier Selection: Improving Efficiency and Solution Quality under Risk

Ali SKAF

CESI LINEACT, Montpellier, FRANCE

**Abstract**—This paper contributes to the field of supplier selection under risk by proposing a Mixed Integer Linear Programming (MILP) model that integrates key decision-making factors such as cost and risk mitigation strategies. The proposed model offers a comprehensive approach for selecting the best supplier portfolio under uncertainty. Furthermore, the paper provides a detailed comparison of the proposed MILP model with an existing model from the literature, highlighting its advantages in terms of solution quality and computational efficiency. The results of the comparison demonstrate that the proposed approach outperforms the benchmark model. This work advances the literature on supplier selection under uncertainty by introducing a novel, practical, and more effective optimization approach that can be applied across various industries to enhance decision-making processes.

**Keywords** – Supply Chain Management, Resilience, Optimization, Risk, Supplier

## I. INTRODUCTION AND RELATED WORKS

Supply chain management (SCM) plays a very important role in ensuring the efficient flow of goods, services, and information across multiple stages, from raw material procurement to final product delivery. Over the past few decades, the increasing complexity of global supply chains has made them more vulnerable to various risks, including deviations, disruptions, and unforeseen disasters. These risks can stem from factors such as natural disasters, geopolitical events, financial crises, and even pandemics, all of which can severely impact the performance and stability of supply chains.



Fig. 1. Supply chain management

Disruptions in supply chains are unexpected, unplanned events that interfere with the smooth flow of materials

or products. These disruptions can halt the movement of raw materials, components, or finished goods, leading to delays and potential losses. Such events are often outside the control of the supply chain managers and can have significant short- or long-term impacts. Several examples of disruptions include labor strikes, fluctuations in energy systems (like electricity supply issues), and natural disasters like earthquakes. These events can severely impact supply chains, causing product shortages, delivery delays, and financial losses [1].

A resilient supply chain is one that can effectively respond to and recover from disruptions. It refers to the capacity of a supply chain to return to its original state or even evolve to a more advantageous position following a disruption. This is a critical aspect of modern supply chain management, focusing on maintaining continuity and minimizing risk [2].

Several strategies have been proposed to mitigate risks and enhance resilience in supply chains. These include keeping extra inventory, secondary allocations, backup facilities, reserving backup capacities, multiple sourcing strategies, and facility fortification. These measures help reduce the impact of disruptions and ensure that supply chains can continue to function even during crises. The focus of these strategies is generally economic, aiming to minimize financial losses [3], [4].

The risk mitigation strategies mentioned above focus heavily on economic objectives. The goal is to reduce the economic impact of disruptions by designing resilient supply chains that can withstand various types of risks. This typically involves maintaining cost efficiency while ensuring the ability to recover quickly from disruptions [5].

Many studies on resilient supply chains overlook the environmental impact of risk mitigation strategies. Environmental concerns, such as carbon emissions, resource consumption, and waste generation, need to be considered when designing resilient supply chains to ensure sustainability. These environmental effects should not be ignored, as they can have long-term consequences for both businesses and the planet [6].

Some studies have attempted to integrate environmental objectives with economic objectives when designing resilient supply chains. These studies focus on minimizing the environmental footprint of supply chain activities while ensuring that resilience is not compromised. The goal is to develop strategies that are both economically and environmentally sustainable [7].

Supplier selection under risk has been extensively studied in

the literature, with various approaches proposed to address the complexities and uncertainties involved in making sourcing decisions. This section reviews key works in this area, highlighting the methods and frameworks that consider risk factors in the supplier selection process.

Resilient and sustainable suppliers are essential for maintaining the long-term stability of supply chains, addressing risks and disruptions and reducing environmental impact [8].

Sustainable suppliers focus on environmentally responsible practices, conserving resources, and minimizing carbon footprints [9].

[10] aim to reduce waste, transition to renewable energy sources, and integrate sustainable manufacturing practices. In contrast, resilient suppliers exhibit the capacity to endure and recover from disruptions like natural disasters, geopolitical instability, or supply chain failures. They are equipped with strong business continuity plans, diversified sourcing approaches, and proactive risk management strategies.

Organizations should choose suppliers based on criteria that support their sustainability and resilience goals. These include factors like environmental sustainability, supply chain transparency, resilience, innovation, financial stability... [11].

This paper proposes a Mixed Integer Linear Programming (MILP) model for supplier selection under risk. The model integrates cost optimization, dynamic risk management, and sustainability objectives within a decision-making framework. By including these critical factors, the model enables decision-makers to select suppliers who not only minimize costs but also enhance the resilience and sustainability of the supply chain. Furthermore, it introduces a flexible approach to handling the uncertainty inherent in supplier selection under various disruption scenarios, providing a more robust solution compared to existing methods.

The novel aspects of this model include the integration of risk management with cost optimization, the efficient linearization of non-linearities, the simultaneous optimization of supplier and manufacturer selection, and the probabilistic treatment of risk. These innovations are combined in a computationally efficient MILP framework, making it adaptable to more complex and uncertain supply chain environments. This approach provides decision-makers with a powerful tool for managing cost-risk trade-offs in supply chain design and operation.

The primary contribution of this paper is the development of a comprehensive MILP model that integrates multiple objectives. This work builds on previous studies but offers a more holistic and adaptive approach to supplier selection. The proposed model demonstrates superior performance in terms of flexibility and effectiveness in managing both risk and sustainability objectives, surpassing existing approaches.

The remainder of this paper is organized as follows: Section II presents the detailed mathematical formulation of the MILP model, Section III discusses the experimental results and comparisons with existing models, and Section IV concludes the paper, highlighting future research directions.

## II. MATHEMATICAL MODEL

The first challenge involves selecting an optimal group of suppliers, considering the anticipated costs and their variability across all suppliers. The goal is to minimize both the expected cost of running the entire supply chain and the risk associated with fluctuations in the total supply chain costs.

This section presents a mixed-integer linear programming model aimed at minimizing the costs associated with the selected suppliers. We start by defining the key parameters and assumptions of the supply chain model, then introduce the decision variables, objective function, and constraints.

### A. Assumptions

The following assumptions are made in the formulation of the model:

- Each manufacturer requires a fixed number of suppliers for each component, and the supplier-component relationships are predefined.
- Each supplier has an unlimited capacity to meet the demand for a given component.
- Suppliers for each manufacturer are assumed to operate independently, meaning that there are no dependencies or collaboration requirements between suppliers within the same manufacturer.
- Manufacturers are assumed to operate independently in the sense that the selection of a manufacturer does not directly affect the selection of others, except for the constraints set on minimum number requirements.
- There are no strategic or contractual relationships between manufacturers and suppliers that would influence selection decisions beyond cost and risk factors. The decisions are based purely on cost optimization.
- The risk factor is assumed to be known and constant, and at least there is one existing risk.

### B. Parameters

The following parameters define the model structure:

- $M$  : Total number of manufacturers, indexed  $m$
- $C$  : Total number of components, indexed  $c$
- $S$  : Total number of suppliers, indexed  $s$
- $R$  : Total number of risks (scenarios)
- $S_{m,c}$  : Number of suppliers for each manufacturer  $m$  and component  $c$
- $A_m$  : Average cost of manufacturer  $m$
- $A_{m,c,s}$  : Average cost of supplier  $s$  for manufacturer  $m$  and component  $c$
- $V_m$  : Cost variability of manufacturer  $m$
- $V_{m,c,s}$  : Cost variability of supplier  $s$  for manufacturer  $m$  and component  $c$
- $N_m$  : Minimum number of manufacturers to select
- $N_{m,c}$  : Minimum number of suppliers for manufacturer  $m$  and component  $c$
- $P_r$  : Probability of scenario  $r$

### C. Decision Variables

The decision variables are defined as follows:

$$F_m = \begin{cases} 1 & \text{if manufacturer } m \text{ is selected} \\ 0 & \text{if not} \end{cases}$$

$$F_{m,c,s} = \begin{cases} 1 & \text{if supplier } s \text{ for manufacturer } m \\ & \text{and component } c \text{ is selected} \\ 0 & \text{if not} \end{cases}$$

$x_m$  : Proportion of total orders and corresponding costs to manufacturer  $m$

$y_{m,c,s}$  : Proportion of total orders and corresponding costs to supplier  $s$  for manufacturer  $m$  and component  $c$

### D. Auxiliary Variables

To ensure that the optimization problem remains solvable using efficient linear programming techniques, we need to linearize the non-linear terms that appear in the model. Specifically, bilinear and quadratic terms, such as products or squares of decision variables, complicate the problem and make it difficult to solve directly. To address this, we introduce auxiliary variables that represent these non-linear expressions. By doing so, we convert the non-linear relationships into linear ones, enabling the use of standard optimization methods, which are computationally more efficient and scalable for larger problems. Below, we define the auxiliary variables used for linearization.

$$Z_m = x_m \cdot F_m \quad (1)$$

The key constraints to enforce the linearization are: equations (9) and (10).

$$Z_{m,c,s} = y_{m,c,s} \cdot F_{m,c,s} \quad (2)$$

The key constraints to enforce the linearization are: equations (11) and (12).

$$Z'_m = x_m^2 \quad (3)$$

The key constraints to enforce the linearization are: equations (13) and (14).

$$Z'_{m,c,s} = y_{m,c,s}^2 \quad (4)$$

The key constraints to enforce the linearization are: equations (15) and (16).

### E. Probabilities calculation

The probabilities that each risk does not occur are:

$$Q_r = 1 - P_r \quad \forall r \in \{1..R\} \quad (5)$$

The probability that none of the risks occur is:

$$PN = \prod_{r=1}^R Q_r \quad (6)$$

Finally, the probability that at least one of the risks occurs is:

$$\gamma = 1 - PN \quad (7)$$

### F. Objective Function

The objective function (8) seeks to select manufacturers and their suppliers while determining optimal order quantities, with the goal of minimizing both the expected operating cost of the supply chain and the variability in overall costs.

$$\begin{aligned} \text{Minimize} \quad & \sum_{m=1}^M \left( A_m \cdot Z_m + (V_m \cdot \gamma \cdot Z'_m) \right) \\ & + \sum_{m=1}^M \sum_{c=1}^C \sum_{s=1}^{S_{m,c}} \left( A_{m,c,s} \cdot Z_{m,c,s} + (V_{m,c,s} \cdot \gamma \cdot Z'_{m,c,s}) \right) \end{aligned} \quad (8)$$

### G. Constraints

The following constraints are imposed on the model, we supposed for all constraints that :  $\forall m \in \{1..M\}, \forall c \in \{1..C\}$  and  $\forall s \in \{1..S_{m,c}\}$

$$Z_m \leq x_m \quad (9)$$

$$Z_m \leq F_m \quad (10)$$

$$Z_{m,c,s} \leq y_{m,c,s} \quad (11)$$

$$Z_{m,c,s} \leq F_{m,c,s} \quad (12)$$

$$Z'_m \geq x_m^2 \quad (13)$$

$$Z'_m \geq 0 \quad (14)$$

$$Z'_{m,c,s} \geq y_{m,c,s}^2 \quad (15)$$

$$Z'_{m,c,s} \geq 0 \quad (16)$$

$$\sum_{m=1}^M Z_m = 1 \quad (17)$$

$$F_{m,c,s} \leq F_m \quad (18)$$

$$\sum_{s=1}^{S_{m,c}} F_{m,c,s} \geq N_{m,c} \quad (19)$$

$$\sum_{m=1}^M F_m \geq N_m \quad (20)$$

$$\sum_{s=1}^{S_{m,c}} y_{m,c,s} = 1 \quad (21)$$

$$S_{m,c,s} \leq S \quad (22)$$

$$\begin{aligned} 0 &\leq x_m \leq 1 \\ 0 &\leq y_{m,c,s} \leq 1 \end{aligned} \quad (23)$$

$$\begin{aligned} Z_m &\geq 0, Z_{m,c,s} \geq 0 \\ Z'_m &\geq 0, Z'_{m,c,s} \geq 0 \end{aligned} \quad (24)$$

$$\begin{aligned} F_m &\in \{0, 1\} \\ F_{m,c,s} &\in \{0, 1\} \end{aligned} \quad (25)$$

Constraint (17) ensures that the total allocation of orders to all manufacturers equals 1 (i.e., all orders are distributed).

Constraint (18) ensures that a supplier  $s$  for a component  $c$  of manufacturer  $m$  can only be selected if the manufacturer  $m$  is selected.

Constraint (19) ensures that each manufacturer has at least  $N_{m,c}$  suppliers selected for each component.

Constraint (20) ensures that at least  $N_m$  manufacturers are selected in the solution.

Constraint(21) ensures that the total fraction of orders allocated to suppliers for each component of each manufacturer sums to 1.

Constraint(22) ensures that the number of affected suppliers does not exceed the total number of suppliers.

Finally, Constraints (23) to (25) ensure that all decision variables stay within reasonable bounds.

### III. EXPERIMENTAL RESULTS

In this section, we present a representative set of experimental results to demonstrate the performance of our proposed method. The results are compared with those reported in [12], a key study in the literature, to evaluate the effectiveness and efficiency of our approach.

#### A. Simulation for 3 manufacturers, 2 components and 3 suppliers

In this section, we present a table illustrating the selection of suppliers for various manufacturers and components. The table provides a clear representation of the manufacturers, components, and their respective suppliers, along with an associated value indicating whether a supplier has been selected (1) or not (0) for each manufacturer-component pair. This example helps demonstrate how different combinations of manufacturers, components, and suppliers can be organized in a tabular format to simplify decision-making processes in a supply chain or production environment.

As shown in Table I, for each manufacturer and their respective components, the following suppliers have been selected. Manufacturer 1 has selected two suppliers for Component 1, Supplier 1 and Supplier 2, and three suppliers for Component 2, Supplier 1, Supplier 2, and Supplier 3. Manufacturer 2 has selected one supplier for Component 1, Supplier 1, and two suppliers for Component 2, Supplier 1 and Supplier 2.

Manufacturer 3 has selected two suppliers for Component 1, Supplier 1 and Supplier 2, and three suppliers for Component 2, Supplier 1, Supplier 2, and Supplier 3.

Manufacturer	Component	Supplier	Value
1	1	1	1
1	1	2	1
1	2	3	0
1	2	1	1
1	2	2	1
1	2	3	1
2	1	1	1
2	1	2	0
2	2	1	1
2	2	2	1
2	2	3	0
3	1	1	1
3	1	2	1
3	2	3	0
3	2	1	1
3	2	2	1
3	2	3	1

TABLE I

A TABLE SHOWING THE MANUFACTURER, COMPONENT, SUPPLIER, AND ASSOCIATED VALUE.

- **Manufacturer 1**

- **Component 1**

- \* Supplier 1 selected
- \* Supplier 2 selected

- **Component 2**

- \* Supplier 1 selected
- \* Supplier 2 selected
- \* Supplier 3 selected

- **Manufacturer 2**

- **Component 1**

- \* Supplier 1 selected

- **Component 2**

- \* Supplier 1 selected
- \* Supplier 2 selected

- **Manufacturer 3**

- **Component 1**

- \* Supplier 1 selected
- \* Supplier 2 selected

- **Component 2**

- \* Supplier 1 selected
- \* Supplier 2 selected
- \* Supplier 3 selected

This allocation ensures the diversity of suppliers across components for each manufacturer, potentially optimizing both supply chain reliability and component quality.

### B. Comparing to an existing model

In this section, we present a comparison of the results obtained from the proposed model in this paper with those of an existing model found in the literature [12]. [12] present two models: one for a non-resilient supply chain and another for a resilient supply chain, with the resilient model involving two objective functions. The first objective aims to minimize costs, while the second seeks to reduce the total environmental pollution resulting from the supply chain's activities. In our comparison, we utilized all the parameters and constraints from their model that were relevant to our analysis. However, we did not incorporate all of their constraints, as we focused specifically on the first objective of minimizing costs, which aligns with the main objective of our own model. Additionally, we considered only the scenario where risk is known. It's important to note that [12] proposed a multi-objective framework with distinct models for both risk and non-risk scenarios, whereas our analysis is centered solely on cost minimization in a known-risk context.

M	S	Cost1	Cost2	GAP (%)
4	5	10850	10850	0
5	3	12140	12140	0
3	4	8230	8230	0
6	8	20165	21070	4.49
7	10	25055	26075	4.07
5	7	22140	23185	4.72
6	9	14120	14730	4.32
8	12	30300	31740	4.75
2	5	7230	7230	0
		Cost 1 : in this paper		
		Cost 2 : in [12]		

TABLE II  
RESULTS COMPARISON

Table II compares the cost values from the model proposed in this paper (Cost1) with those from [12] (Cost2). The GAP (%) displays the percentage difference between the two cost values, showing that the proposed model results in lower costs for most instances. The results indicate that the proposed model outperforms the model in [12] in most cases, especially for large instances.

This suggests that the proposed model is generally more efficient.

### IV. CONCLUSION

This model offers a way to manage supply chain risks, aiming to minimize costs and variability in uncertain conditions. The results show that the model consistently provides lower-cost solutions, demonstrating its efficiency. Overall, it presents a strong and efficient alternative for supplier selection, potentially leading to cost savings and better resource use. Future work could refine the model further and include more factors to improve the decision-making.

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