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► To cite this version:

Belgacem Bettayeb, Oussama Ben-Ammar, Ilhem Slama, Alexandre Dolgui. Bi-Objective Multi-Period Multi-Sourcing Supply Planning with Stochastic Lead-Times, Degressive Pricing, and Carbon Footprint *. 2024 10th International Conference on Control, Decision and Information Technologies (CoDIT), Jul 2024, Vallette, Malta. pp.2324-2328, 10.1109/CoDIT62066.2024.10708096 . hal-04755968

HAL Id: hal-04755968

<https://imt-mines-ales.hal.science/hal-04755968v1>

Submitted on 23 Jan 2025

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Bi-Objective Multi-Period Multi-Sourcing Supply Planning with Stochastic Lead-Times, Degressive Pricing, and Carbon Footprint*

Belgacem Bettayeb¹, Oussama Ben-Ammar², Ilhem Slama³ and Alexandre Dolgui⁴

Abstract—This article studies a bi-objective stochastic optimization problem for multi-period multi-sourcing supply planning. The formulated problem accounts for stochastic lead times, degressive pricing, holding and backlog costs, delivery flexibility costs, as well as both holding and transportation carbon footprint. The first objective is to minimize the expected total cost, while the second objective is to minimize the expected total footprint. These objectives must be achieved while adhering to suppliers' capacity constraints and meeting customer demand. In this paper, the proposed stochastic integer linear program is detailed, and the ϵ -constraint method used to solve it is described. The first results of experiments are presented and discussed.

I. INTRODUCTION

To remain competitive and maintain a high level of service for their customers, industrial companies must optimize their production processes as well as related upstream and downstream activities, such as replenishment, inventory management, and transportation. At the same time, they are facing growing challenges from environmental sustainability and regulations on carbon emissions. Managing a modern supply chain (SC) efficiently requires balancing economic, customer and environmental objectives in an integrated manner. Therefore, coordinating material, information, and financial flows in an integrated way is essential to ensure a competitive and profitable SC for all stakeholders [1]. However, due to the SC's interdependent network structure, any incident or disturbance in one element can spread and amplify, adversely affecting the entire SC's performance. Such incidents and disturbances are inherent to these complex systems, arising from uncertainties or ignorance regarding one or more influencing parameters of the system, coupled with a lack of countermeasures to predict and prevent them. For several decades, managing uncertainty and mitigating its impact on the SC's performance has been a primary focus for decision-makers and researchers in supply chain management (SCM) [2], [3]. This focus is heightened by the repeated observation of SC vulnerabilities to disruptions caused by uncertainty in certain SC parameters [4], [5]. Numerous sources of

uncertainty have been identified and examined through SC risk analysis, with many being formalized and incorporated into supply planning and inventory control models.

More recently, there is growing recognition of the importance of environmental sustainability for supply chains. Managing carbon emissions from transportation, production and inventory activities is now a strategic priority to meet regulatory compliance and stakeholder expectations [6], [7].

Regarding the uncertainty of lead-times, the literature is rich on approaches such as safety lead-times and safety stocks. However, these well-known approaches to cope with the uncertainty of lead-time are not always time-applicable and advantageous [8], [9], and [10]. Alternative methods utilizing stochastic optimization techniques have also been suggested for supply planning and inventory control. Typically, these models focus on either single-period or multi-period supply planning scenarios with consistent demand and independent, identically distributed lead times. Despite their utility, these models face certain drawbacks regarding optimization and economies of scale, as they often overlook or disregard the influence of dynamic factors like fluctuating demand and varying capacity. Nevertheless, multi-period supply planning that includes stochastic lead times highlights the complexity of managing order crossovers and the inherent randomness in the quantities received over different periods[11]. The crossover problem is typically addressed either by ignoring it or by developing models that mitigate or eliminate its impact [12]. Another common strategy for managing uncertainty in SCM is multi-sourcing, which involves collaborating with several competing suppliers. However, supply chain managers need to formulate effective strategies for selecting and managing multiple suppliers. For supplier selection, various attributes such as quality, price, and delivery performance are commonly considered. Although there is no consensus on the ranking of these attributes, delivery performance is consistently ranked among the top three most important [13]. Another study [14] identifies flexibility as the most important attribute overall, followed by cost and delivery performance.

The initial techniques for supplier selection presented in the literature predominantly utilize mono- or multi-objective functions optimized in a static environment, with decisions targeting a strategic-level timeframe. Over the past few decades, dynamic supplier selection (DSS) issues have arisen, leading to the development of various models that account for a dynamic environment in which parameters like demand, capacity, and prices change over time. Most DSS approaches aim to minimize the average total cost

*This work was not supported by any organization

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while determining the order quantities for chosen suppliers [15][16]. In the context of stochastic lead-time with multiple suppliers, [17] formulated a mathematical model for a single-item continuous review (s, Q) inventory policy. Similar to our approach, their model allows order replenishment to be distributed among several suppliers. The goal is to optimize the inventory policy parameters, specifically the reorder level and the quantity ordered from each supplier, in order to minimize the expected total cost per time unit. Additionally, [18] introduced a two-phase framework for supplier selection and order allocation, considering various transportation alternatives (TAs) for each supplier. Their optimization model determines the optimal order quantities to allocate to the selected suppliers for each period within the planning horizon.

Regarding the consideration of the environmental aspect, [19] proposed a multi-objective integrated economic-environmental biomass supply chain models using stochastic and fuzzy approaches. A case study is detailed, comparing results from different models and highlighting trade-offs between costs and emissions. [20] presents a novel multi-objective supplier selection model that aims to optimize four objectives simultaneously, namely the minimization of total cost, total carbon footprint, late deliveries, and rejected items. It uses uncertainty theory concepts to handle uncertain parameters and fuzzy logic for linguistic decision-maker preferences.

Recently, the authors of this paper introduced a mathematical model addressing the problem of dynamic supplier selection strategy in multi-period supply planning with uncertain lead times. They developed a stochastic integer non-linear program (SINLP) to optimize the selection of suppliers and the scheduling of lead times, aiming to minimize the expected total cost [21].

This work aims to investigate the problem of bi-objective multi-period replenishment with multiple suppliers, considering stochastic lead times, degressive pricing policies, delivery flexibility costs, and delivery carbon footprint. The objective is to satisfy all demands by distributing them among suppliers while simultaneously minimizing the expected total cost and the expected total footprint.

The structure of the remainder of this paper is as follows. Section II, describes the problem's stochastic integer linear programming formulation of the problem. Then, we report and discuss the first experimental results in section IV. Finally, the the concluding section states the principle conclusions from this work and future research directions.

II. PROBLEM FORMULATION

We address the issue of multi-period replenishment planning in a system involving a single product, a single buyer, and multiple vendors. The demand for each period is known and can be fulfilled by one or more suppliers, each with a stochastic discrete lead-time described by its probability mass function. Additionally, each supplier has a capacity limit for each period and a degressive pricing policy that applies to the total quantity ordered over the

entire planning horizon. Moreover, we consider that each supplier has its own carbon footprint per order delivered, which varies depending on factors such as distance and transportation mode. For this problem formulation, we use the notations presented in Table I for input data and decision variables. We assume that any unfulfilled quantity from each period is carried over as backlogged, incurring corresponding costs. Conversely, quantities held in stock result in inventory holding costs. It is important to note that both backlogged and inventory quantities are subject to stochastic variation due to the unpredictable nature of supplier lead times. We make no restrictive assumptions regarding order crossovers or demand patterns over the planning horizon. Our analysis encompasses scenarios where demand can be divided into smaller batches across different suppliers and/or periods (referred to as splitting), with suppliers releasing deliveries for different batches ordered within the same period incurring an additional cost per batch (termed Delivery Flexibility Cost). In this formulation, we utilize the notations detailed in Table I for both input data and decision variables.

TABLE I: Notations

<i>Parameters</i>	
\mathcal{T}	ordered set of periods indices of the planning horizon
\mathcal{S}	ordered set of suppliers indices
\mathcal{I}_s	ordered set of indices of quantity intervals defining supplier s pricing policy
D_t	demand of period t
C_{st}	capacity limits of suppliers s for each period t
$[l_{si}, u_{si}]$	lower and upper limits of the i -th quantity interval of supplier s pricing policy
c_{si}	unit selling price of the i -th quantity interval of supplier s pricing policy
c_s^o	ordering cost of supplier s
f_s^o	ordering carbon footprint of supplier s
c^h	unit inventory holding cost per time period
f^h	unit inventory holding carbon footprint per time period
c^b	unit backlogging cost per time period
$[L_s^-, L_s^+]$	range of possible discrete lead-time values of supplier s
$L_{s\tau t}^\omega$	actual lead time, in scenario ω , of the quantity released by supplier s at period τ to satisfy demand of period t
$F_s(\cdot)$	cumulative distribution function of supplier s lead-time
<i>Variables</i>	
$Q_{s\tau t}$	integer decision variable that gives the quantity to be ordered from supplier s at period τ to satisfy demand of period t
K_{si}	integer decision variable that gives the total quantity to order from supplier s within the i -th interval of its pricing policy
Y_{si}	binary decision variable indicating if the total ordered quantity from supplier s is within the i -th interval of its pricing policy
$Z_{s\tau t}$	binary decision variable indicating a non-zero quantity is ordered from supplier s at period τ to satisfy D_t
<i>Functions</i>	
$\mathbb{P}(\cdot)$	probability value
$\mathbb{E}(\cdot)$	expected value
$\mathbb{1}_A$	indicator function, equals 1 if event A is true; 0 otherwise

Prior to introducing the problem formulation as a Stochastic Integer Linear Program (SILP) model that incorporates lead time uncertainty and flexibility, let's begin by outlining the following definitions.

Definition 1: For every $s \in \mathcal{S}$ and $(t, \tau, i) \in \mathcal{T}^3$, let define

\mathcal{M}_t as the set of indices for all ordered quantities $Q_{s\tau i}$ that contribute to calculating the backloging level at period t . It is expressed as follows:

$$\mathcal{M}_t = \{(s, \tau, i) : t - L_s^+ + 1 \leq \tau \leq t - L_s^- \text{ and } \tau + L_s^- \leq i \leq \tau + L_s^+\} \quad (1)$$

Definition 2: For every $(s, \tau, i) \in \mathcal{M}_t^3$, let $\alpha_{s\tau i}^\omega$ be a boolean variable indicating for a given scenario ω if the quantity ordered from supplier s at period τ to satisfy the demand of period i arrives before period t . It is formulated as follows:

$$\alpha_{s\tau i}^\omega = \begin{cases} 1 & \text{if } \tau + L_{s\tau i}^\omega \leq t \\ 0 & \text{if } \tau + L_{s\tau i}^\omega > t \end{cases} \quad (2)$$

As $\alpha_{s\tau i}^\omega$ is binary for each triplet (s, τ, i) , the number of possible scenarios is equal to $|\Omega_t| = 2^{|\mathcal{M}_t|}$. A given scenario ω is composed of a set of $\alpha_{s\tau i}^\omega$ for all $(s, \tau, i) \in \mathcal{M}_t$. This allows to define the set of all possible aggregated scenarios as follows:

$$\Omega_t = \left\{ (\alpha_{s\tau i}^\omega)_{(s,\tau,i) \in \mathcal{M}_t} : \omega \in \{1, \dots, 2^{|\mathcal{M}_t|}\} \right\} \quad (3)$$

Each scenario $\omega \in \Omega_t$ has the probability of occurrence p_t^ω defined in Equation (4) below:

$$p_t^\omega = \prod_{(s,\tau,i) \in \mathcal{M}_t} \alpha_{s\tau i}^\omega \times F_s(t') + (1 - \alpha_{s\tau i}^\omega) \times (1 - F_s(t')) \quad (4)$$

where $t' = t - \tau$, $\alpha_{s\tau i}^\omega \in \{0, 1\}$ and $\sum_{\omega \in \Omega_t} p_t^\omega = 1$.

The suggested model formulation presupposes that each demand is divisible into multiple quantities sourced from various suppliers and/or across different time periods. It also permits delivery flexibility, albeit with an extra cost. This means that batches ordered from each supplier at a specific time can be released separately and have their own independent lead times. This approach can be expressed as the bi-objective SILP presented in Equations (5)-(17).

$$\begin{aligned} \text{Min } ETC = & \sum_{t \in \mathcal{T}} \sum_{\omega \in \Omega} p_t^\omega \cdot (c^h I_{t\omega}^+ + c^b I_{t\omega}^-) + \\ & \sum_{s \in \mathcal{S}} \left(\sum_{j \in \mathcal{Z}_s} c_{sj} \cdot K_{sj} + \sum_{t \in \mathcal{T}} \sum_{\tau \in \mathcal{T}} c_s^o Z_{s\tau t} \right) \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Min } ETFP = & \sum_{t \in \mathcal{T}} \sum_{\omega \in \Omega} p_t^\omega f^h I_{t\omega}^+ + \\ & \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} \sum_{\tau \in \mathcal{T}} f_s^o Z_{s\tau t} \end{aligned} \quad (6)$$

s.t.

$$\begin{aligned} I_{t\omega}^+ - I_{t\omega}^- = & \sum_{s \in \mathcal{S}} \sum_{\tau=1}^{t-L_s^+} \sum_{i=\tau+L_s^-}^{\tau+L_s^+} Q_{s\tau i} + \sum_{(s,\tau,i) \in \mathcal{M}_t} \alpha_{s\tau i}^\omega Q_{s\tau i} \\ & - \sum_{\tau=1}^t D_\tau \quad \forall t \in \mathcal{T}, \forall \omega \in \Omega_t \end{aligned} \quad (7)$$

$$Q_{s\tau t} \leq D_t \quad \forall s \in \mathcal{S}, \forall t, \tau \in \mathcal{T} \quad (8)$$

$$\sum_{t \in \mathcal{T}} Q_{s\tau t} \leq C_{s\tau} \quad \forall s \in \mathcal{S}, \forall \tau \in \mathcal{T} \quad (9)$$

$$\sum_{s \in \mathcal{S}} \sum_{\tau=t-L_s^+}^{t-L_s^-} Q_{s\tau t} = D_t \quad \forall t \in \mathcal{T} \quad (10)$$

$$\sum_{j \in \mathcal{Z}_s} Y_{sj} \leq 1 \quad \forall s \in \mathcal{S} \quad (11)$$

$$l_{sj} Y_{sj} - K_{sj} \leq 0 \quad \forall s \in \mathcal{S}, \forall j \in \mathcal{I}_s \quad (12)$$

$$K_{sj} - l_{sj} Y_{sj} \geq 0 \quad \forall s \in \mathcal{S}, \forall j \in \mathcal{I}_s \quad (13)$$

$$\sum_{j \in \mathcal{Z}_s} K_{sj} - \sum_{t \in \mathcal{T}} \sum_{\tau \in \mathcal{T}} Q_{s\tau t} = 0 \quad \forall s \in \mathcal{S} \quad (14)$$

$$\sum_{i \in \mathcal{T}} D_i \cdot Z_{s\tau t} - Q_{s\tau t} \geq 0 \quad \forall s \in \mathcal{S}, \forall t, \tau \in \mathcal{T} \quad (15)$$

$$Y_{sj}, Z_{s\tau t} \in \{0, 1\} \quad \forall s \in \mathcal{S}, \forall j \in \mathcal{I}_s, \forall t, \tau \in \mathcal{T} \quad (16)$$

$$I_{t\omega}^-, I_{t\omega}^+, K_{sj}, Q_{s\tau t} \in \mathbb{N} \quad \forall s \in \mathcal{S}, \forall j \in \mathcal{I}_s, \forall t, \tau \in \mathcal{T} \quad (17)$$

In the SILP model described by Equations (5)-(17), we consider all possible aggregated scenarios (see Definition 2) and simultaneously minimize the ETC and the ETFP while determining the proportion of a given D_t to be ordered from a specific supplier s during a particular period τ . The ETC in Eq. 5 comprises the expected inventory holding and backlog costs, in addition to the purchasing costs. The latter include the direct cost of the items purchased, which depends on the degressive pricing applied, and the ordering costs, both of which vary based on the selected supplier. The ETFP in Eq. 6 consists of two main components: the first term corresponds to the expected footprint from inventory holding, and the second term accounts for the cumulative footprint incurred by transporting each ordered quantity, which varies depending on the chosen supplier. Constraints (7) specify the inventory level $I_{t,\omega}$ at the end of each period t for each scenario ω . Constraints (8) ensure that the quantity ordered from supplier s during period τ to meet the demand for period t does not exceed D_t . Constraints (10) mandate that the total quantity ordered to meet the demand for period t equals D_t , thus ensuring that all demands are met. Constraints (11) to (14) facilitate the selection of the pricing level applied by each supplier based on the total ordered quantities. Constraint (15) ensures that $Z_{s\tau t}$ is set to 1 if $Q_{s\tau t}$ is non-zero. Constraints (16) and (17) define the domains of the decision variables.

III. RESOLVING APPROACH

To solve our bi-objective problem, we exploit the the ϵ -constraint method, which is powerful approach commonly used for solving multi-objective optimization problems. It allows decision makers to explore trade-offs between conflicting objectives, namely in our case the expected total cost incurred by purchasing and holding inventory and the expected total carbon footprint incurred by transporting and holding. Let $f_1(X)$ and $f_2(X)$ denote respectively ETC and $ETFP$ with $X = (Q, K, Y, Z)$ the vector of all decision

variables. The ϵ -constraint approach is then composed of the following steps:

- 1) determine $e_0 = f_2(\arg \min_X \{f_2(X) \text{ s.t. (7 - 17)}\})$
- 2) determine $e_1 = f_2(\arg \min_X \{f_1(X) \text{ s.t. (7 - 17)}\})$
- 3) determine the set of points defining the Pareto front: $\{(f_1(X^*), f_2(X^*)) : X^* = \arg \min_X \{f_1(X) \text{ s.t. (7 - 17)} \text{ and } f_2(X) \leq \epsilon \ \forall \epsilon \in [e_0, e_1]\}$

IV. NUMERICAL EXAMPLE AND DISCUSSION

The SILP model of the problem has been coded in C++ and solved using the ϵ -constraint approach with the IBM ILOG CPLEX solver. The numerical example involves a test instance with a 10-period planning horizon, 5 non-zero demands (see Table II), and 3 suppliers. Inventory cost parameters are $c_h = 10$ and $c_b \in \{10, 15\}$. Concerning carbon footprint, the test parameters are $f^h = 1$ and $f_1^o = 10$, $f_2^o = 15$ and $f_3^o = 7$ for suppliers 1 to 3, respectively. Suppliers have constant capacities, with $C_{1,t} = 60$, $C_{2,t} = 50$ and $C_{3,t} = 100$ for all $t = 1, \dots, 10$, and uncertain lead-times, which are characterized by their probability distributions given in Table III. The pricing policies and their parameters are given in Table IV.

TABLE II: Vector of demands

Periods	5	6	7	8	9
Demand	180	100	30	10	80

The optimal solution for the numerical example with $c_b = c_h = 10$ and $\epsilon = e_1$ is presented in Table V. The last five rows of the table display the optimal quantities to order from each supplier for each period. Despite the third supplier having the highest price (75) and ordering cost (1000), it is chosen for three orders ($Q_{346}=100$, $Q_{356}=80$, $Q_{357}=20$, $Q_{367}=80$ and $Q_{368}=20$) which sum to 300, representing 75% of the total demand. This demonstrates that selecting a supplier should not be determined only by the selling price and ordering cost. Moreover, relying solely on one supplier isn't optimal for reducing costs and managing uncertainties. The suggested model enables identifying a balanced approach to address inventory, procurement, and ordering expenses effectively.

The details of the optimal solution of the numerical example with $c_b = c_h = 10$ and $\epsilon = e_0$ are presented in Table VI. It reveals that the third supplier is chosen to fulfill the entire demands, despite not having the lowest transportation mode carbon footprint per delivered order compared to other suppliers. Although Supplier 3 has the lowest carbon footprint per delivered order $f_3^o = 7$, it is not

TABLE III: Lead-times probability distributions.

s	$\mathbb{P}(L^s = l)$	l : lead-time possible values			
		1	2	3	4
1	$\mathbb{P}(L^s = l)$	0.24	0.76	-	-
2	$\mathbb{P}(L^s = l)$	-	0.53	0.16	0.31
3	$\mathbb{P}(L^s = l)$	0.95	0.05	-	-

TABLE IV: Pricing policies parameters.

s	Pricing levels						c_s^o
	level 1			level 2			
	l_{s1}	u_{s1}	c_{s1}	l_{s2}	u_{s2}	c_{s2}	
1	1	20	69	21	500	65	800
2	1	30	67	31	500	65	700
3	1	500	75	-	-	-	1000

TABLE V: Solution of the numerical example with $\epsilon = e_1$.

t	1	..	5	6	7	8	9	10	11	12
D_t	-	-	180	100	30	10	80	-	-	-
$\mathbb{E}(I_t^+)$	-	-	-	-	-	-	-	-	-	-
$\mathbb{E}(I_t^-)$	-	-	180	280	130	40	100	100	30	20
Q_{19t}	-	-	-	-	-	-	-	60	-	-
Q_{26t}	-	-	-	-	10	10	20	-	-	-
Q_{34t}	-	-	-	100	-	-	-	-	-	-
Q_{35t}	-	-	-	80	20	-	-	-	-	-
Q_{36t}	-	-	-	-	80	20	-	-	-	-

ETC= 74400; ETFP=46 ; CPU time = 7.08 seconds

TABLE VI: Solution of the numerical example with $\epsilon = e_0$.

t	1	..	5	6	7	8	9	10	11	12
D_t	-	-	180	100	30	10	80	-	-	-
$\mathbb{E}(I_t^+)$	-	-	-	-	-	-	-	-	-	-
$\mathbb{E}(I_t^-)$	-	-	180	280	130	40	90	80	-	-
Q_{34t}	-	-	-	80	-	-	-	-	-	-
Q_{35t}	-	-	-	100	-	-	-	-	-	-
Q_{36t}	-	-	-	-	100	-	-	-	-	-
Q_{37t}	-	-	-	-	-	30	10	-	-	-
Q_{38t}	-	-	-	-	-	-	-	80	-	-

ETC= 77000; ETFP=35 ; CPU time = 3.17 seconds

selected to supply any quantity due to its considerably higher ordering cost compared to Suppliers 1 and 2.

The results of the ϵ -constraint method gives the Pareto fronts for $c_b = 10$ and $c_b = 15$ that plot in Figure 1. It demonstrates the marginal impact of increasing backlog costs, resulting in an increase in both objectives. Furthermore, it is noteworthy that with higher backlog costs, a solution is identified that reduces the ETFP from 46 to 38, with a relatively smaller increase in the ETC compared to scenarios with lower backlog cost.

Figure 2 illustrates the impact of incorporating carbon footprint criteria as a secondary objective on the selection rates of suppliers. When prioritizing ETC, all suppliers are utilized, even with minimal selection rates for suppliers 1 and 2. Conversely, to minimize the ETFP, the selection is restricted, utilizing only the third supplier.

V. CONCLUSION

This paper presents a bi-objective stochastic optimization model for multi-period, multi-source supply planning under uncertainty. The model formulated the problem as a SILP and solved it using the ϵ -constraint method. The numerical results provided insight into the trade-offs between costs and emissions when selecting suppliers and ordering policies. While effectively demonstrating the concepts, the study focused on a small problem instance with limited parameters.

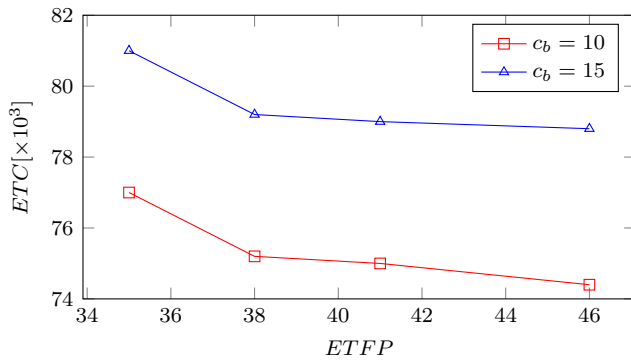


Fig. 1: Effect of backlog cost on the Pareto front.

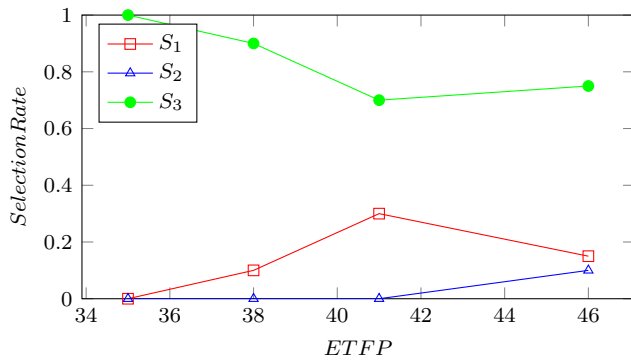


Fig. 2: Effect of carbon footprint on suppliers' selection rates.

To address real supply chain planning challenges, more advanced modelling and solution approaches are needed.

Future work will continue to focus on improving the model and its resolution approach to study larger instances. The weakness of the current model lies in the exponentially increasing number of scenarios with the number of suppliers and their lead-time distribution ranges. Some multi-objective meta-heuristics will also be explored.

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