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Catalyzing resilience: Multi-faceted optimization of single vendor-multi buyer supply chains amidst stochastic demand

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Abstract

In the contemporary supply chain management landscape, the intricacies of managing a single vendor-multi-buyer network amidst stochastic demand pose significant challenges. This paper delves into optimizing such supply chains, emphasizing resilience in the face of uncertain demand scenarios. Leveraging the NSGA-II (Non-dominated Sorting Genetic Algorithm II), a powerful evolutionary optimization technique, we explore the multifaceted dimensions of supply chain optimization. The proposed framework aims to enhance the robustness and adaptability of supply chain networks by simultaneously addressing two key objectives: minimizing costs and maximizing service levels. By considering stochastic demand patterns, inherent uncertainties are meticulously accounted for, ensuring that the optimized solutions are efficient and resilient to unforeseen fluctuations in demand. This study comprehensively evaluates the single vendor-multi buyer supply chain model and highlights the efficacy of the NSGA-II algorithm in navigating the complex trade-offs inherent in supply chain optimization. By generating diverse Pareto-optimal solutions, the algorithm empowers decision-makers with actionable insights, enabling them to make informed choices that balance cost-effectiveness with service quality. Furthermore, this paper contributes to the evolving discourse on supply chain resilience by integrating advanced optimization methodologies with real-world supply chain dynamics. The findings underscore the importance of proactive optimization strategies in building resilient supply chain networks capable of withstanding the volatility of today's global marketplace. In conclusion, this research illuminates the path towards catalyzing resilience in single vendor-multi buyer supply chains, offering a nuanced understanding of the interplay between optimization algorithms, stochastic demand, and supply chain performance. Organizations can fortify their supply chain architectures through continuous refinement and adaptation, fostering agility and competitiveness in an ever-evolving business landscape.

Keywords: supply chain optimization, stochastic demand, NSGA-II algorithm, resilience, multi-objective optimization, single vendor-multi buyer
2020 MSC: 90B06, 90C15, 90C26

1 Introduction

Supply chain management (SCM) is not merely a functional aspect of business operations; it serves as the lifeblood that sustains the modern economy, orchestrating the seamless flow of goods and services across global networks. At its core, SCM embodies a delicate balance of integrity and coordination, weaving disparate elements together into a cohesive efficiency and resilience tapestry. It ensures that every link in the supply chain, from sourcing raw materials

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to delivering the final product to customers, functions harmoniously, optimizing resources, minimizing costs, and maximizing customer satisfaction. This intricate dance of suppliers, manufacturers, distributors, and retailers requires meticulous planning, real-time visibility, and agile responses to disruptions, making SCM a linchpin of economic stability and growth in today's interconnected world [16, 24].

Scholars like Goyal [3, 4] Pan, Yang [15], Lu, Yu-Jen [9], and Lee [7] have illuminated the path toward optimizing supply chain dynamics. Their pioneering research has laid a robust foundation upon which subsequent generations of scholars and practitioners continue to build, each brick adding depth and nuance to the evolving discourse on supply chain optimization.

As the intricacies of global commerce evolve, so do the challenges confronting SCM practitioners. In an era defined by volatility, uncertainty, complexity, and ambiguity (VUCA), the imperative for agile and adaptive supply chain strategies is increasingly evident. Within this dynamic crucible of challenge and opportunity, genetic algorithms (GAs) emerge as a potent catalyst for transformation, providing a ray of hope amid the turbulence of the contemporary business landscape.

In the face of VUCA, traditional supply chain optimization methods often fall short, unable to adapt quickly to fluctuating market conditions and dynamic customer demands. This is where genetic algorithms step in, offering a powerful solution to the complexities of supply chain management. Unlike conventional optimization techniques, GAs mimics the process of natural selection, evolving solutions over successive generations to find the most efficient and effective outcomes.

GAs excel in handling complex, multi-objective optimization problems, which are prevalent in SCM. These problems often involve conflicting objectives, such as minimizing costs while maximizing service levels or reducing lead times while minimizing inventory levels. Traditional optimization methods struggle to find optimal solutions in such scenarios due to their inability to explore diverse solution spaces and handle non-linear relationships between variables. GAs, on the other hand, employ evolutionary principles to search for solutions that balance these competing objectives, enabling SCM practitioners to make informed decisions that drive sustainable value creation.

Furthermore, GAs facilitate adaptability and resilience in supply chain operations. In a VUCA environment, where disruptions are frequent and unpredictable, quickly adjusting and optimizing supply chain processes is crucial for maintaining competitiveness. Genetic algorithms enable SCM professionals to rapidly reconfigure routes, adjust inventory levels, and optimize production schedules in response to changing market conditions or unforeseen events. By leveraging data-driven insights and adaptive optimization techniques, GAs empower organizations to react to disruptions and proactively anticipate and mitigate risks, driving continuous improvement and competitive advantage.

By harnessing GAs' computational prowess, researchers have unlocked new frontiers in supply chain optimization. They transcend traditional paradigms to explore innovative inventory management, production planning, and logistics optimization approaches. From the intricacies of inventory routing to the complexities of vendor-managed inventory (VMI) systems, GAs have emerged as indispensable tools in the arsenal of SCM professionals, enabling them to navigate the complexities of the modern supply chain with agility and precision.

One key advantage of genetic algorithms is their ability to handle complex, multi-objective optimization problems. In the context of supply chain management, where multiple objectives such as cost minimization, service level maximization, and risk mitigation often conflict, GAs offer a flexible and efficient means of finding optimal trade-offs. Through exploring diverse solution spaces and applying evolutionary principles, GAs enable SCM practitioners to uncover innovative strategies that balance competing objectives and drive sustainable value creation.

Moreover, GAs facilitate adaptability and resilience in supply chain operations. In a VUCA environment, where disruptions are frequent and unpredictable, quickly adjusting and optimizing supply chain processes is crucial for maintaining competitiveness. Genetic algorithms excel in this regard, providing SCM professionals with the tools to rapidly reconfigure routes, adjust inventory levels, and optimize production schedules in response to changing market conditions or unforeseen events.

As the digital revolution continues to reshape the landscape of global commerce, the role of genetic algorithms in supply chain optimization is poised to become even more significant. With the advent of big data analytics, IoT-enabled devices, and artificial intelligence, GAs offers a scalable and robust solution for managing supply chain networks' increasing complexity and interconnectedness. By leveraging data-driven insights and adaptive optimization techniques, GAs empower SCM practitioners to react to disruptions and proactively anticipate and mitigate risks, driving continuous improvement and competitive advantage.

In conclusion, genetic algorithms represent a transformative force in supply chain management, enabling practitioners to navigate the challenges of a VUCA world with confidence and agility. As we continue to push the boundaries of innovation and explore new horizons in SCM, GAs will undoubtedly remain at the forefront, driving efficiency, resilience, and sustainable growth in the global supply chain ecosystem [20, 22, 23, 25].

The journey undertaken in this paper represents more than a mere academic exercise; it is a quest for enlightenment in the realm of supply chain optimization. As we delve deeper into the intricacies of problem definitions, mathematical models, and solution methodologies, we seek not only to unravel the mysteries of supply chain dynamics but also to illuminate the path forward for practitioners and scholars alike.

Through meticulous analysis and rigorous experimentation, we endeavor to distill insights that transcend the boundaries of theory and practice. We empower stakeholders to make informed decisions that drive sustainable value creation and foster competitive advantage in an ever-changing world. Indeed, the conclusions drawn from this endeavor are not merely endpoints but rather waypoints on a continuous journey of discovery and innovation.

As we embark on this voyage of exploration, let us not lose sight of the ultimate destination: a future where supply chains are not merely efficient and resilient but also compassionate and sustainable, serving as engines of prosperity for all stakeholders involved. With this vision in mind, we embark on our quest, fueled by curiosity, passion, and the relentless pursuit of excellence.

2 Problem definitions

This study focuses on elucidating the complexities inherent in a single vendor-multi buyer supply chain model. This intricate system comprises interconnected components, including production, transportation, and demand dynamics, all of which interact synergistically to determine the system's overall efficiency and effectiveness.

Within this multifaceted framework, each buyer assumes a critical role in influencing demand patterns, thereby exerting a significant impact on the operational dynamics of the supply chain. Concurrently, the vendor shoulders the responsibility of coordinating production activities to fulfill these varied demands within stipulated time constraints, further complicating the operational landscape [11, 29].

At the heart of the problem lies the challenge of harmonizing disparate elements—production, transportation, and demand—into a cohesive and optimized system. This entails devising strategies to synchronize production schedules with fluctuating demand patterns, orchestrating the movement of goods through the transportation network efficiently, and ensuring timely delivery to meet buyer requirements.

Moreover, the inherent uncertainties associated with demand variability and transportation constraints add layers of complexity to the problem, necessitating robust optimization techniques to navigate through these uncertainties effectively. Balancing conflicting objectives such as minimizing production costs, optimizing transportation routes, and meeting diverse buyer demands presents a formidable optimization challenge that requires careful consideration and strategic decision-making [13, 18, 28].

In summary, the problem at hand encompasses the intricate interplay of production, transportation, and demand dynamics within a single vendor-multi-buyer supply chain model. By elucidating these problem definitions, we lay the groundwork for a comprehensive analysis to identify optimal solutions to enhance the supply chain system's efficiency, responsiveness, and resilience. Through rigorous investigation and innovative methodologies, we endeavor to unlock insights that drive tangible improvements in supply chain performance and operational excellence [5, 10].

2.1 Assumptions

1. Limited Storage Capacity: Storage space availability is finite within the supply chain. Consequently, strategic allocation of inventory space is imperative to ensure optimal utilization and mitigate the risks associated with stockouts or excessive inventory levels.
2. Stochastic Demand: Variability in buyers' demand patterns introduces inherent uncertainty into the supply chain dynamics. Addressing this uncertainty necessitates the adoption of robust forecasting techniques and adaptive inventory management strategies to navigate demand fluctuations and maintain service levels effectively.
3. Constant Production Rate: A consistent production rate is assumed across all products. This assumption underscores the importance of standardized manufacturing processes and efficient resource utilization to uphold reliability and consistency in product supply and effectively meet demand requirements.
4. Limited Planning Horizon: The planning horizon within the supply chain is bounded, imposing constraints on decision-making processes. Proactive planning and resource allocation are essential to align with demand requirements within specified time frames, ensuring timely response to market dynamics and customer needs.

5. Heterogeneous Transportation Fleets: The transportation fleet comprises vehicles with diverse capacities and capabilities. Optimal route planning and vehicle allocation strategies are indispensable to enhance transportation efficiency, minimize costs, and reduce delivery lead times, thereby optimizing overall supply chain performance.
6. Single Vehicle per Route: Each transportation route is serviced by a single vehicle, simplifying logistics operations and fostering streamlined coordination. This approach maximizes the utilization of transportation resources while minimizing congestion and delays, thereby enhancing operational efficiency and customer satisfaction.
7. Single Meeting per Period: Limiting each buyer to interact with each vehicle once per time period streamlines communication and transactional processes. This simplification enhances logistical efficiency and reduces unnecessary complexity in scheduling and coordination, facilitating smoother operations within the supply chain network.

By delineating these assumptions, this study sets the stage for a comprehensive analysis of the single vendor-multi buyer supply chain model. Through rigorous analysis and simulation, the aim is to unravel the complexities inherent in supply chain operations, identify optimization opportunities, and offer insights and recommendations to drive tangible improvements in performance and resilience.

2.2 Parameters and decision variables

The supply chain operates within an infinite horizon that encompasses buyers, products, and the transportation fleet. A vast array of parameters and decision variables dictate its fluid dynamics and operational efficacy [14, 17, 24].

Parameters:

In an infinite horizon for buyers ($i = 1, 2, ..., N$), products ($p = 1, 2, ..., P$) and fleet of transportation ($k = 1, 2, ..., K$) parameters are:

Q_p: Inventory of product p for vendor,

Q_{ip}: Value of product p ordered by buyer i,

D_p: Demand rate of product p

R_p: Production rate of product p, ($P_i \geq D_i$)

D_{ip}: The demand of products ordered by buyer i, ($D_p = \sum_{i=1}^{p} D_{ip}$)

X_{ip}: Demand in lead-time, $X_{ip} \sim N\{D_{ip}L_{ip}, (\sigma_{ip}\sqrt{L_{ip}})^2)\}$

UL_{ip}: Upper bound for lead-time of product p for buyer i,

A_{ip}: Ordering cost of the product p for buyer i,

A_{vp}: Set-up cost of product p,

C_p^v: Produce cost of each unit of product p,

C_{ip}^B: purchasing cost of each unit of product p, ($C_p^v < C_{ip}^B, \quad \forall i, p$)

$C_{ip}^v(L_{ip})$: Violation cost of lead-time for the product p for buyer i,

h_{ip}: Holding cost of the product p for buyer i,

h_{vp}: Holding cost of product p for vendor

h'_{vp}: Safety coefficient of product p for buyer i,

K: Maximum capacity of transportation vehicles,

q_k: Maximum capacity of vehicle k,

t_{ij}: Travel time from vertex i to vertex j,

a_i: Receiving time to vertex i,

g_{ik}: Service time of vehicle k to vertex i,

w_{ik}: Lead-time of the vehicle k in vertex i,

τ_k: Longest permitted route time for vehicle k,

f_{ik}: Servicing time of the vehicle k in vertex i,

z_{0k}: Leaving time of vehicle k from purchasing storage,

e_i: The earliest time that the buyer i received goods,

l_i: the latest time that the buyer i received goods,

f: Fix the cost of using vehicles on the routes,

F^v: Maximum capacity of vendor capacity,

F_i^B: Maximum capacity of buyer i,

S_{ip}: Safety stock of product p for the buyer i,

v_p: The ratio for a volume of product p to basis product,

ct: Fix cost of each transportation time unit,

TEC_0^V: The expected total cost of each time unit for the vendor,

TEC_0^B: The expected total cost of each time unit for a buyer,

TEC_A^V: Expected fixed set-up cost of each time unit for the vendor,

TEC_H^V: Expected holding cost of each time unit for the vendor,

TEC_H^B: Expected holding cost of each time unit for buyer,

TEC_O^B: Expected ordering cost of each time unit for buyer,

TEC_T^B: Expected transportation cost of each time unit for buyer,

P_i: Production rate of buyer i,

D_i: Demand rate of buyer i,

σ_{ip}: The standard deviation of product p for buyer i,

n: Number of transportations from vendor to buyer,

r_{ip}: Re-order point of the product p

L_{ip}: Lead-time of product p for buyer i,

x_{ijk}: Binary variable, if vehicle k travel from vertex i to vertex j is equal to 1, else is equal zero, $(i, j \neq 0,\ i \neq j)$

The mathematical model is as follows [6, 8]:

Mathematical model

The inventory pattern of the vendor and buyer i for the product p is presented in figure 1.

$$\begin{aligned} Z_1 = \min \left(\sum_{p=1}^{P} \frac{D_p}{Q_p} \left(\frac{A_{vp}}{n} + \sum_{i=1}^{N} (A_{ip} + C_{ip}(L_{ip})) \right) \right) &+ \sum_{i=1}^{N} \sum_{p=1}^{P} \left(h_{ip} C_{ip}^{B} \left(\frac{Q_p}{2R_p} D_{ip} + k'_{ip} \sigma_{ip} \sqrt{L_{ip}} \right) \right) \\ &+ \sum_{p=1}^{P} \frac{Q_p}{2} h_{vp} C_p^V \left(n \left(1 - \frac{D_p}{R_p} \right) - 1 + \frac{2D_p}{R_p} \right) \\ &+ \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} x_{ijk} t_{ij} ct_k \end{aligned} \tag{2.1}$$

$$Z_2 = \min \max_i \left\{ \sum_{p=1}^{P} \frac{D_p \sigma_{ip} \sqrt{L_{ip}} \psi(k'_{ip})}{D_{ip} Q_p} \right\} \tag{2.2}$$

$$\sum_{j=1, i \neq j}^{N} x_{ijk} = \sum_{j=1, i \neq j}^{N} x_{jik} \leq 1, \quad \forall i;\ i = \{0, 1, ..., N\},\ \forall k; k = \{1, ..., K\} \tag{2.3}$$

$$\sum_{k=1}^{K} \sum_{j=0, j \neq i}^{N} x_{ijk} = 1, \quad \forall i;\ i = \{1, ..., N\} \tag{2.4}$$

$$\sum_{k=1}^{K} \sum_{i=0, i \neq j}^{N} x_{ijk} = 1, \quad \forall j;\ j = \{1, ..., N\} \tag{2.5}$$

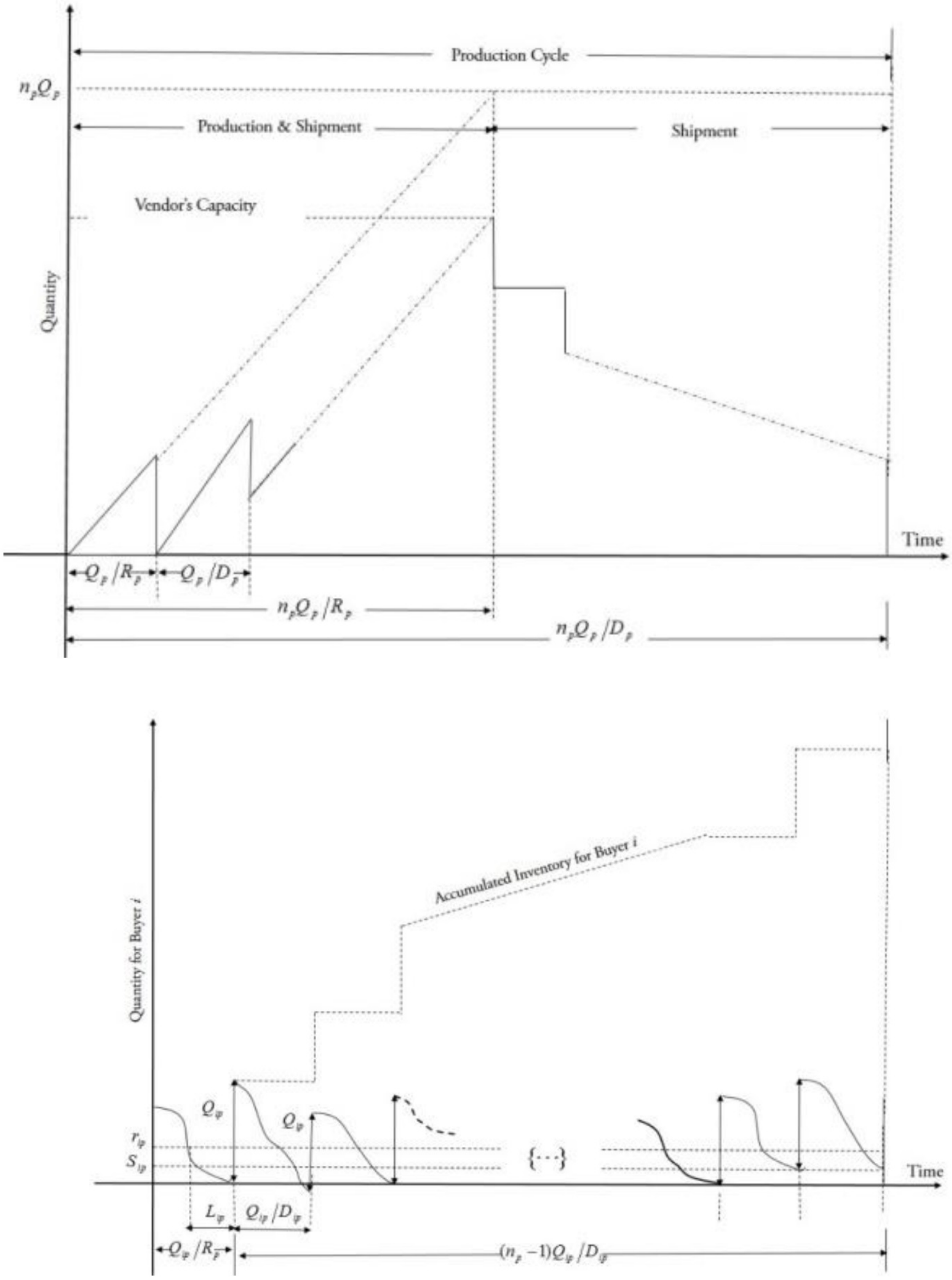

Figure 1: The inventory pattern of the vendor and buyer i for the product p

$$\sum_{i=1}^{N}\sum_{p=1}^{P} Q_{ip}v_p \sum_{j=0}^{N} x_{ijk} \leq q_k, \quad \forall k;\ k=\{1,...,K\} \tag{2.6}$$

$$\sum_{i=0}^{N}\sum_{j=0,j\neq i}^{N} x_{ijk}(t_{ij}+g_{ik}+\omega_{ik}) \leq \tau_k, \quad \forall k;\ k=\{0,1,...,K\} \tag{2.7}$$

$$z_{0k}=\omega_{0k}=g_{0k}=0, \quad \forall k;\ k=\{1,...,K\} \tag{2.8}$$

$$\sum_{k=1}^{K}\sum_{i=0,j\neq i}^{N} x_{ijk}(a_i+t_{ij}+g_{ik}+\omega_{ik}) \leq a_j, \quad \forall j;\ j=\{i,...,N\} \tag{2.9}$$

$$e_i \leq (a_i+\omega_{ik}) \leq l_i, \quad \forall i;\ i=\{1,...,N\},\ \forall k; k=\{i,...,K\} \tag{2.10}$$

$$\sum_{p=1}^{P}(S_{ip}+Q_{ip})V_p \leq F_i^B, \quad \forall i;\ i=\{1,...,N\} \tag{2.11}$$

$$\begin{aligned}
&\sum_{p=1}^{P} nV_p\left(Q_p-\frac{Q_pD_p}{R_p}\right)\leq F^V\\
&1\leq L_{ip}\leq UL_{ip}\\
&Q_{ip},n\geq 0; x_{ijk}\in\{0,1\}, \quad \forall i,j;\ i,j=\{1,...,N\}
\end{aligned} \tag{2.12}$$

3 Solving algorithm

The NSGA (Non-dominated Sorting Genetic Algorithm) introduced by Srinivas and Deb [27] represents a significant advancement in the realm of multi-objective optimization algorithms. Building upon Goldberg's non-dominant criterion [1, 2] this algorithm revolutionized the approach to solving complex optimization problems by efficiently ranking solutions based on their dominance status.

However, despite its efficacy, the NSGA algorithm exhibited high sensitivity to the parameters of shared fitness. In response to this limitation, Deb et al. embarked on a quest to refine and enhance the algorithm's performance, culminating in the development of NSGA-II.

NSGA-II represents a quantum leap forward in multi-objective optimization, offering improved robustness and stability compared to its predecessor. By leveraging innovative techniques and methodologies, NSGA-II overcomes its predecessor's shortcomings, providing more reliable and accurate solutions to complex optimization problems [12].

Through a meticulous blend of evolutionary principles and computational ingenuity, NSGA-II has indeed risen as a cornerstone in the arsenal of optimization algorithms. This powerful tool empowers researchers and practitioners alike to confront real-world challenges with unparalleled efficiency and precision. Its versatility and adaptability make it the preferred choice for addressing many optimization problems across diverse domains, spanning from engineering and finance to logistics and beyond [19, 21, 26].

For the presented model, the algorithm chromosome encapsulates crucial parameters essential for optimizing the supply chain dynamics. These parameters include each product's production value, production cycle, lead time, safety coefficient, and routes. Figure 2 illustrates the schematic chromosome structure tailored for a scenario involving 3 products, 5 buyers, and 3 vehicles.

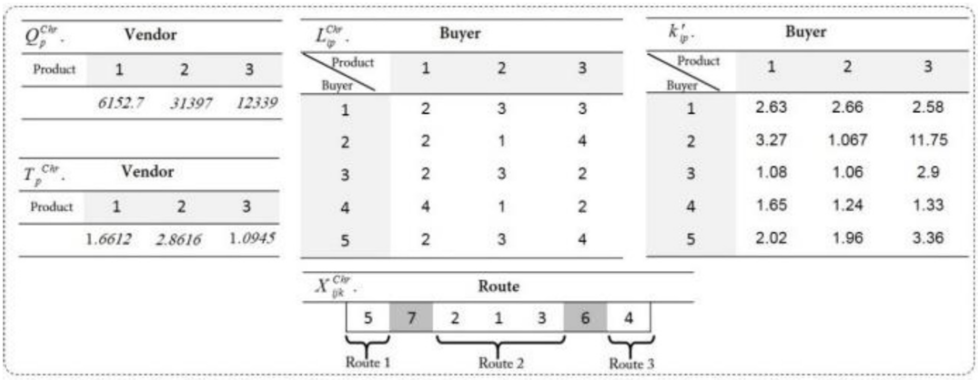

Figure 2: Chromosome Structure of Presented Model

Each component plays a pivotal role in shaping the optimization process in this chromosome structure. The production value and cycle dictate the manufacturing schedule and volume for each product, while the lead time parameter influences the timing of product delivery to buyers. Additionally, the safety coefficient ensures buffer stock levels to mitigate risks associated with demand variability.

Furthermore, the incorporation of routes within the chromosome enables the optimization algorithm to explore various transportation strategies, considering factors such as vehicle capacity, distance, and efficiency. By integrating these diverse parameters into a unified chromosome structure, the optimization algorithm can navigate the complexities of the supply chain model with precision and effectiveness, ultimately driving toward enhanced efficiency and performance.

4 Numerical example

This section presents a numerical example with 8 buyers, 3 products, and 3 vehicles. Tables 1 to 7 present all the parameters of this problem, and Table 8 contains the results of the NSGA-II algorithm. Figure 3 presents the Pareto front of this problem [6].

Table 1: Ordering cost, demand rate, purchasing cost, and standard deviation of products for buyers

A_{ip}	Product		
Buyer	1	2	3
1	26	26	24
2	27	29	22
3	19	30	20
4	25	23	28
5	25	17	24
6	17	17	23
7	16	19	29
8	22	18	19
9	30	19	27
10	20	28	27
11	24	18	21
12	18	29	24
13	27	20	16
14	19	18	15
15	23	19	23

D_{ip}	Product		
Buyer	1	2	3
1	4117	3757	4100
2	4736	3993	4270
3	1519	2802	4475
4	3275	1335	1337
5	2878	1916	2599
6	1047	4654	2039
7	2348	4304	2726
8	1648	4304	2726
9	4177	3153	4643
10	2245	4985	1727
11	3114	1312	2055
12	1662	2771	1582
13	3408	1426	1544
14	2052	4848	4478
15	3616	1018	3319

C^B_{ip}	Product		
Buyer	1	2	3
1	25	20	27
2	28	39	40
3	32	35	20
4	25	30	38
5	32	32	39
6	34	24	36
7	24	29	22
8	22	40	25
9	26	31	27
10	26	30	34
11	28	24	22
12	30	30	35
13	21	33	22
14	25	34	33
15	36	28	30

σ_{ip}	Buyer		
product	1	2	3
1	20	18	10
2	16	20	11
3	11	17	19
4	13	10	17
5	16	19	13
6	20	20	20
7	20	17	10
8	11	18	14
9	20	18	14
10	20	14	18
11	15	17	18
12	18	11	12
13	11	17	15
14	14	10	14
15	20	13	17

Table 2: Holding cost, lead-time and service time

h_{ip}	Product		
Buyer	1	2	3
1	o.1567	0.3453	0.1691
2	0.3060	0.3384	0.3533
3	0.1551	0.2933	0.1584
4	0.2105	0.2136	0.1678
5	0.2877	0.3435	0.1512
6	0.3341	0.2598	0.1683
7	0.1243	0.2052	0.2307
8	0.3788	0.3817	0.1933
9	0.3327	0.3628	0.3770
10	0.2460	0.2650	0.2291
11	0.2308	0.2867	0.1554
12	0.2340	0.2761	0.3715
13	0.1919	0.1623	0.3939
14	0.2526	0.1904	0.2317
15	0.2532	0.2413	0.1333

w_{ik}	Product		
Buyer	1	2	3
1	4	3	2
2	4	2	4
3	3	5	5
4	4	3	1
5	1	3	1
6	2	5	5
7	3	2	4
8	2	3	2
9	4	5	3
10	5	1	1
11	2	5	2
12	4	1	2
13	1	4	2
14	5	3	1
15	1	4	2

g_{ik}	Product		
Buyer	1	2	3
1	2	4	4
2	4	10	8
3	1	2	5
4	6	8	5
5	5	7	7
6	10	9	10
7	9	4	4
8	5	8	9
9	9	9	8
10	2	4	10
11	4	6	1
12	10	10	4
13	10	6	7
14	8	4	3
15	7	7	3

Table 8 provides a comprehensive overview of key performance metrics used to evaluate the results of multi-objective algorithms. These metrics include the mean ideal distance (MID), diversity, algorithm implementation time, and the number of Pareto solutions (Nos). By analyzing these metrics, researchers can gain valuable insights into the efficiency and effectiveness of optimization algorithms in addressing complex multi-objective optimization problems.

Table 3: Safety stock, upper bound for lead-time and violation cost of lead-time

S_{ip}	Product			UL_{ip}	Product			$C_{ip}^{V}(L_{ip})$	Product		
Buyer	1	2	3	Buyer	1	2	3	Buyer	1	2	3
1	324	220	309	1	3	5	4	1	16	20	16
2	207	476	249	2	3	3	5	2	11	15	10
3	400	493	475	3	3	3	3	3	19	15	12
4	302	214	432	4	4	4	5	4	16	13	13
5	359	421	440	5	5	3	4	5	13	19	19
6	223	459	249	6	5	4	4	6	15	14	10
7	155	339	337	7	3	4	5	7	14	11	10
8	290	454	449	8	4	5	4	8	10	18	11
9	245	478	474	9	4	5	3	9	12	14	17
10	416	320	368	10	4	3	3	10	11	12	18
11	412	392	182	11	4	5	5	11	12	14	17
12	368	331	362	12	4	3	3	12	12	11	14
13	153	110	128	13	3	4	3	13	14	11	16
14	108	279	263	14	4	4	4	14	10	20	13
15	324	359	367	15	3	5	5	15	19	20	18

Table 4: Travel time

t_{ij}	Buyer														
Buyer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Depo
1	0	11	26	11	26	11	29	14	10	11	21	17	14	26	20	19
2	11	0	24	24	14	19	6	6	18	25	29	8	19	17	5	13
3	26	24	0	18	9	20	11	22	22	24	16	7	10	28	8	26
4	11	24	18	0	7	30	5	25	26	27	7	15	11	25	16	28
5	26	14	9	7	0	20	19	8	27	21	14	18	15	6	11	8
6	11	19	20	30	29	0	17	17	13	28	14	7	25	15	11	15
7	29	6	11	5	19	17	0	14	26	5	6	9	21	24	21	16
8	14	6	22	25	8	17	14	0	25	7	29	25	17	16	16	12
9	10	18	22	26	27	13	26	25	0	29	27	19	21	20	10	12
10	11	25	24	27	21	28	5	7	29	0	16	9	28	30	16	7
11	21	29	16	7	14	14	6	29	27	16	0	18	7	11	25	5
12	17	8	7	15	18	7	9	25	19	9	18	0	22	15	14	30
13	14	19	10	11	15	25	21	17	21	28	7	22	0	25	23	28
14	26	17	28	25	6	15	24	16	20	30	11	15	25	0	9	11
15	20	5	8	16	11	11	21	16	10	16	25	14	23	9	0	26
Depo	19	13	26	28	8	15	16	12	12	7	5	30	28	11	26	0

Table 5: Earliest time, latest time and maximum capacity of buyers

	Buyer														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
e_i	19	13	15	14	6	8	5	11	12	8	10	13	9	4	7
l_i	190	133	150	140	60	80	52	111	120	82	103	135	90	46	70
F_i^B	96687	90548	74227	87838	70852	98590	99399	93208	69444	72737	62334	89221	94142	95686	77914

Table 6: Products information

	Product		
	1	**2**	**3**
D_p	41842	43883	45095
R_p	42277	44223	45314
A_{vp}	2000	1500	2500
C_p^V	15	20	10
h_{vp}	0.2	0.15	0.25
V_p	3	1	2

Table 7: Maximum capacity, longest permitted route time, and fix cost of each transportation time

	machine		
	1	**2**	**3**
q_k	50000	45000	55000
τ_k	100	90	110
ct	2	4	3

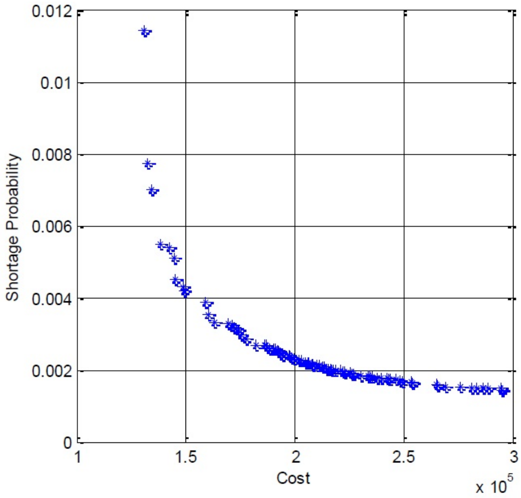

Figure 3: Pareto front of NSGA-II.

Table 8: Results of NSGA-II algorithm

	TIME	DIVERSITY	SPACING	NOS	MID
NSGA-II	85.23	1.6613E+05	1.0015E+03	100	2.1197E+05

Furthermore, Fig. 3 showcases the optimal Pareto front obtained through the implementation of NSGA-II. This visualization offers a graphical representation of the trade-offs between competing objectives, clearly depicting the Pareto-optimal solutions generated by the algorithm. By examining the Pareto front, researchers can discern the relationships between different objectives and make informed decisions regarding the selection of solutions that best align with their preferences and constraints.

5 Conclusion

In this paper, we have delved into the complexities of a single vendor-multi buyer bi-objective inventory model within the realm of supply chain management (SCM). Our primary objectives were to minimize the cost of SCM and maximize the service level provided to buyers. Given this model's non-linear integer programming nature and its classification as NP-hard, we employed the NSGA-II algorithm to tackle the optimization challenge effectively.

The proposed model has been formulated with the aim of minimizing the total expected cost associated with various facets of the supply chain, including production, inventory management, transportation, and lead time reduction. By optimizing production, inventory, and routing decisions while simultaneously ensuring the satisfaction of buyer service level constraints, we strive to enhance the overall efficiency and performance of the supply chain system.

Several avenues for further studies present themselves. Firstly, alternative multi-objective optimization algorithms, such as multi-objective particle swarm optimization (MOPSO), could be investigated to compare their efficacy and performance against NSGA-II. Additionally, the scope of research could be broadened to encompass more complex supply chain scenarios, such as multi-vendor-multi-buyer models, which would introduce additional layers of complexity and challenge to the optimization problem.

By continuing to push the boundaries of research in supply chain optimization, exploring new methodologies, and addressing increasingly complex real-world scenarios, we can strive towards developing robust and adaptive supply chain strategies capable of navigating the evolving landscape of global commerce with agility and resilience.

References

[1] T.F. Abdelmaguid and M.M. Dessouky, *A genetic algorithm approach to the integrated inventory-distribution problem*, Int. J. Prod. Res. **44** (2006), no. 21, 4445–4464.

[2] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, *A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II*, Parallel Problem Solving from Nature PPSN VI: 6th Int. Conf. Paris, France, Proc., Springer Berlin Heidelberg, Vol. 6, 2000, pp. 849–858.

[3] S.K. Goyal, *An integrated inventory model for a single supplier-single customer problem*, Int. J. Prod. Res. **15** (1976), no. 1, 107–111.

[4] S.K. Goyal, *A joint economic-lot-size model for purchaser and vendor: A comment*, Decision Sci. **19** (1988), no. 1, 236–241.

[5] F. Hosseinzadeh Lotfi, T. Allahviranloo, M. Shafiee, and H. Saleh, *Supply chain management*, Supply chain performance evaluation, Studies in Big Data, Springer, Cham, 2023.

[6] J.K. Jha and K. Shanker, *An integrated inventory problem with transportation in a divergent supply chain under service level constraint*, J. Manufact. Syst. **33** (2014), no. 4, 462–475.

[7] W. Lee, *A joint economic lot size model for raw material ordering, manufacturing setup, and finished goods delivery*, Omega-Int. J. Manag. Sci. **33** (2005), no. 2, 163–174.

[8] Y.J. Lin, *An integrated vendor–buyer inventory model with backorder price discount and effective investment to reduce ordering cost*, Comput. Ind. Eng. **56** (2009), no. 4, 1597–1606.

[9] L. Lu, *A one-vendor multi-buyer integrated inventory model*, Eur. J. Oper. Res. **81** (1995), no. 2, 312–323.

[10] H. Mahmoudi, M. Sharifi, M.R. Shahriari, and M.A. Shafiee, *Solving a reverse logistic model for multilevel supply chain using genetic algorithm*, Int. J. Ind. Math. **12** (2020), no. 2, 177–188.

[11] V. Mohagheghi, S.M. Mousavi, B. Vahdani, and M.R. Shahriari, *R&D project evaluation and project portfolio selection by a new interval type-2 fuzzy optimization approach*, Neural Comput. Appl. **28** (2017), no. 12, 3869–3888.

[12] S.P. Nachiappan, A. Gunasekaran, and N. Jawahar, *Knowledge management system for operating parameters in two-echelon VMI supply chains*, Int. J. Prod. Res. **45** (2007), no. 11, 2479–2505.

[13] M.A. Nayebi, M. Sharifi, M.R. Shahriari, and O. Zarabadipour, *Fuzzy-chance constrained multi-objective programming applications for inventory control model*, Appl. Math. Sci. **6** (2012), no. 5, 209–228.

[14] S. Nourali, N. Imanipour, and M.R. Shahriari, *A mathematical model for integrated process planning and scheduling in flexible assembly job shop environment with sequence dependent setup times*, Int. J. Math. Anal. **6** (2012), no. 41–44, 2117–2132.

[15] C.H.J. Pan and J.S. Yang, *A study of an integrated inventory with controllable lead time*, Int. J. Prod. Res. **40** (2002), no. 5, 1263–1273.

[16] H. Rahimi Sheikh, M. Sharifi, and M.R. Shahriari, *Designing a resiliense supply chain model (case study: the welfare organization of Iran)*, J. Ind. Manag. Persp. **7** (2017), no. 3, 127–150.

[17] H.I.L.D.A. Saleh, F. Hosseinzadeh Lotfi, M. Rostmay-Malkhalifeh, and M. Shafiee, *Provide a mathematical model for selecting suppliers in the supply chain based on profit efficiency calculations*, J. New Res. Math. **7** (2021), no. 32, 177–186.

[18] M.R. Shahriari, *A cultural algorithm for data clustering*, Int. J. Ind. Math. **8** (2016), no. 2.

[19] M.R. Shahriari, *Set a bi-objective redundancy allocation model to optimize the reliability and cost of the Series-parallel systems using NSGA II problem*, Int. J. Ind. Math. **8** (2016), no. 3, 171–176.

[20] M. Shahriari, *Multi-objective optimization of discrete time–cost tradeoff problem in project networks using non-dominated sorting genetic algorithm*, J. Ind. Eng. Int. **12** (2016), no. 2, 159–169.

[21] M.R. Shahriari, *Soft computing based on a modified MCDM approach under intuitionistic fuzzy sets*, Iran. J. Fuzzy Syst. **14** (2017), no. 1, 23–41.

[22] M.R. Shahriari, *Using genetic algorithm to optimize a system with repairable components and multi-vacations for repairmen*, Int. J. Nonlinear Anal. Appl. **13** (2022), no. 2, 3139–3144.

[23] M.R. Shahriari, *Redundancy allocation optimization based on the fuzzy universal generating function approach in the series-parallel systems*, Int. J. Ind. Math. **15** (2023), no. 1, 69–77.

[24] M.R. Shahriari and N. Pilevari, *Agile supplier selection in sanitation supply chain using fuzzy VIKOR method*, J. Optim. Ind. Eng. **21** (2017), 19–28.

[25] M. Sharifi, P. Pourkarim Guilani, and M. Shahriari, *Using NSGA II algorithm for a three objectives redundancy allocation problem with k-out-of-n sub-systems*, J. Optim. Ind. Eng. **9** (2016), no. 19, 87–96.

[26] M. Sharifi, M.R. Shahriari, and A. Zaretalab, *The effects of technical and organizational activities on redundancy allocation problem with choice of selecting redundancy strategies using the memetic algorithm*, Int. J. Ind. Math. **11** (2019), no. 3, 165–176.

[27] N. Srinivas and K. Deb, *Muiltiobjective optimization using nondominated sorting in genetic algorithms*, Evol. Comput. **2** (1994), no. 3, 221–248.

[28] B. Vahdani, S.S. Behzadi, S.M. Mousavi, and M.R. Shahriari, *A dynamic virtual air hub location problem with balancing requirements via robust optimization: Mathematical modeling and solution methods*, J. Intell. Fuzzy Syst. **31** (2016), no. 3, 1521-1534.

[29] A. Zaretalab, V. Hajipour, M. Sharifi, and M.R. Shahriari, *A knowledge-based archive multi-objective simulated annealing algorithm to optimize series–parallel system with choice of redundancy strategies*, Comput. Ind. Eng. **80** (2015), 33–44.