

Sustainable Supply Chain Optimization Using CRCTP and MCLP

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Abstract: The 21st century has seen a growing divide between urban and rural areas driven by urban development and migration from rural regions to cities. This shift, along with rising demand, has resulted in complex and unsustainable supply chains that significantly contribute to climate change. In response, many companies are prioritizing the development of more sustainable supply chains to meet customer demand. This paper aims to optimize supply chain logistics by selecting the best meeting points, locations, and vehicle capacities for various query points while fulfilling basic needs to deliver products to retailers at minimal cost. The study will utilize Collective Travel Planning alongside the Maximal Covering Location Problem (MCLP) to create a function capable of computing the most efficient route. This approach differs from previous methods by incorporating both product categories and vehicle capacities, factors that better reflect real-world conditions, including the dynamic fluctuations in supply and demand from both retailers and customers. The proposed function will be evaluated through experiments using synthetic data designed to model realistic-scale problems. The results of these evaluations will help assess the practical applicability and effectiveness of the developed function in optimizing supply chain routes, offering a more sustainable solution for supply chain management in the face of modern challenges.

Keywords: *Collective Travel Planning, Maximal Coverage Location Problem, Query Point, Meeting Point.*

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I. INTRODUCTION

The twenty-first century has seen a significant escalation in the divide between urban and rural areas due to urban development and migration from rural regions to cities. This divide has led to complex and inefficient supply chains, which are highly unsustainable and contribute to environmental degradation. Climate change has manifested globally, with record-breaking temperatures, extreme natural disasters, and worsening air and noise pollution. In 2021, the frequency of natural disasters was three times higher than it was 50 years ago causing increasing damage worldwide. As global temperatures approach the critical 1.5°C threshold, addressing sustainability has become one of the most urgent issues. Minimizing environmental impact and emissions is now crucial to prevent irreversible damage. The supply chain sector, responsible for up to 90% of a company's emissions, is particularly unsustainable, especially with its rapid growth worldwide, such as Japan's sixfold increase in sales over the last decade. Therefore, improving sustainability in supply chains is essential.

While optimizing supply chains for efficiency has been advocated for years, this paper aims to propose a network

design that maximizes profitability while considering environmental and social costs. The supply chain industry is complex, making it difficult to pinpoint specific emission sources, but key contributors include air and noise pollution, excessive fuel use, and delayed transportation times. Reducing these costs is possible without sacrificing efficiency or increasing expenses.

One potential solution is Collective Travel Planning (CTP), which minimizes travel costs by setting optimal meeting points for collective goods transportation. However, this method does not account for vehicle capacity or the nature of the goods being transported. To address this, Resource Capacitated Collective Travel Planning (RCCTP) incorporates vehicle capacity, but it still lacks the ability to classify goods, which is crucial for ensuring safe transport and accommodating fluctuating demand.

To further optimize meeting point locations, the Maximal Covering Location Problem (MCLP) will be used to determine the optimal points that cover the largest area.

This paper's contributions include: (1) defining a problem that considers environmental impact, carbon

emissions, and real-world business needs; (2) proposing a system based on MCLP, CTP, and RCCTP to reduce costs and optimize capacity; and (3) introducing new methods like a modified MCLP for efficiency and CRCTP for product categorization.

In Chapter 2, I introduce related works on MCLP, CTP, and RCCTP; in Chapter 3, we present the proposed system with examples; in Chapter 4, we evaluate these methods; and in Chapter 5, we conclude and suggest future research directions.

II. BACKGROUND

➤ Notations

This section contains various notations from MCLP, CTP, RCCTP. The notations are introduced in the Table.1 below.

Table 1 Notations used in Paper

Notation	Description
q_i	Query point
Q	Set of q_i
m_j	Meeting point (vehicle?)
M	Set of m_j
r	Radius of coverage
$\min\text{Dist}(A,B)$	minimum distance of A and B
c	category
C	Set of c
$\text{dist}(A, B)$	Euclidean distance between two points between points a and b
X_i	$\{0, 1\}$. A binary value that is assigned a value of 1 if q_i is covered and is assigned a value of 0 if not.
Y	Vehicle capacity

➤ MCLP

The Maximal Covering Location Problem (MCLP) is a problem that seeks to determine the optimal location of a set number of facilities in order to maximize the coverage of demand nodes. The paper proposes a function that aims to maximize the number of demand nodes covered by a fixed number of facilities.

coverage status of each node and facility. All facilities are assumed to have the same coverage radius, denoted as r . In this example, two facilities are activated, covering a total of 22 nodes. By selecting facilities 1 and 4, the coverage is maximized. Alternatively, selecting facilities 3 and 4 results in a coverage of 19 nodes. Since the combination of facilities 1 and 4 covers more nodes, this pair is selected as the optimal solution.

➤ Collective Travel Planning (CTP)

Collective Travel Planning (CTP) is a method designed to minimize the total travel cost for individuals by establishing a meeting point to share the travel burden. Each query point is allocated to the nearest meeting point, and this allocation is computed once and stored.

• Example 2. Consider Fig.2

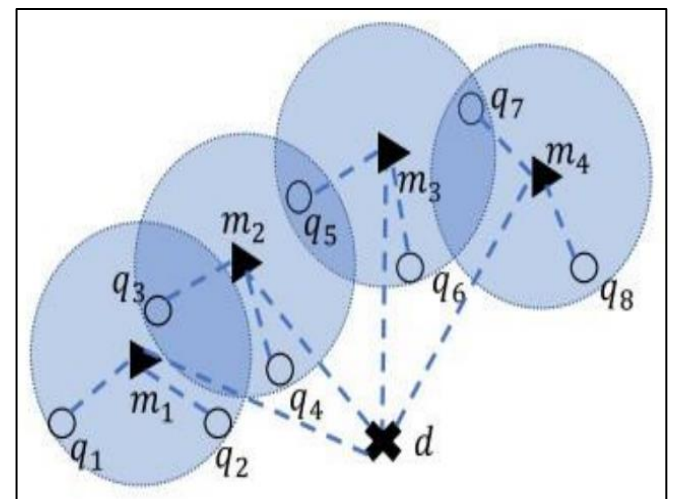


Fig 2 Meeting Point Optimization in CTP

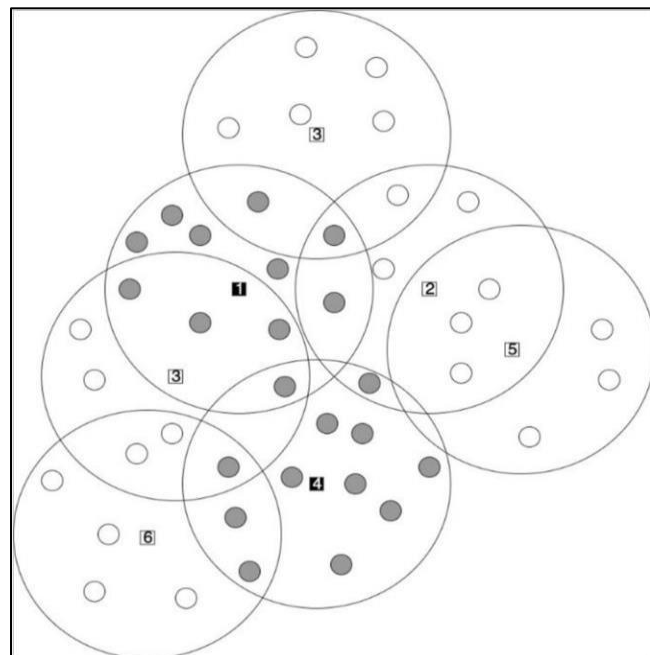


Fig 1 Facility Coverage Example in MCLP

• Example 1. Consider Fig 1.

In Fig.1, the squares represent the locations of the facilities, which determine whether the surrounding circles (demand nodes) are covered. The shading indicates the

In Fig.2, the triangles represent cost-effective meeting points, while the dotted lines indicate the nearest connection between each query point and the meeting points. The proposed destination is denoted by an "X". The total travel cost in Collective Travel Planning (CTP) is calculated using the following formula:

The first component of the formula computes the minimum distance between each query point and its corresponding nearest meeting point, summing the individual travel costs. The second part of the formula calculates the distance from the meeting points to the final

destination, denoted as "x."

For instance, consider a scenario with $n=8$ query points and no predefined meeting point. When CTP is applied, the optimization of travel distances can be observed. The application of CTP significantly reduces the total travel distance by nearly half, demonstrating its effectiveness in minimizing the overall travel cost.

➤ *RCCTP (Resource Capacitated Collective Travel Planning)*

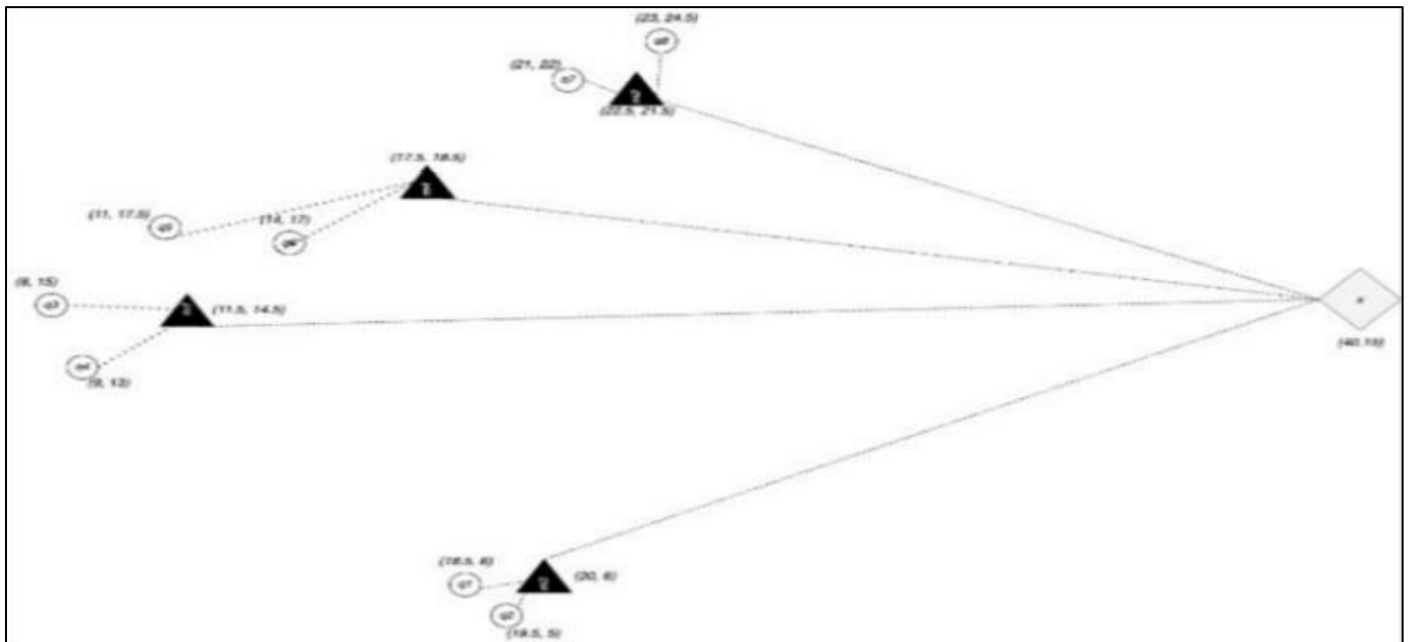


Fig 3 Vehicle Capacity Allocation

RCCTP (Resource Capacitated Collective Travel Planning) is an extension of CTP that incorporates the capacity of the service vehicle along with the selection of the optimal meeting point. **Fig.3** illustrates the RCCTP diagram, assuming the vehicle has a capacity of 2, and shows the optimal meeting points for all queries.

In this scenario, even though meeting point m4 is not the nearest neighbor for query points q5 and q6, these points should still be covered by m4(the second nearest neighbor), because the capacity of the original nearest neighbor, m1, is full (capacity = 2). This adjustment ensures that the system accommodates the vehicle's capacity while still optimizing the meeting points for coverage.

III. METHOD FOR SOLUTION

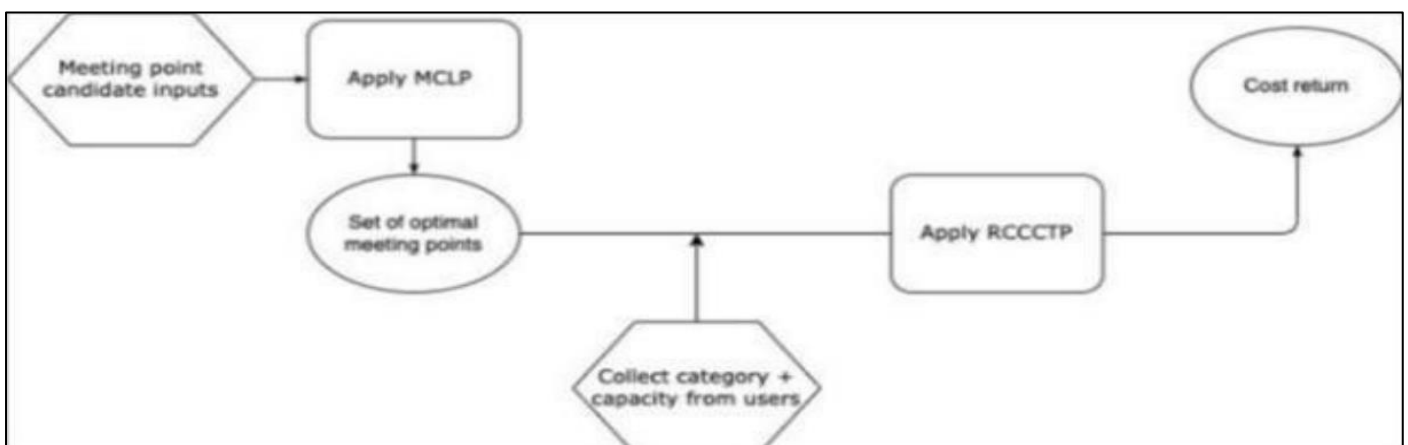


Fig 4 System Workflow for CRCTP

The process of the proposed system is illustrated in **Fig.4**. In the diagram, the hexagons represent the input values, the rectangles represent the various processes, and the ellipses represent the output values. The system begins with the user inputting a set of potential meeting point candidates. The MCLP function is then applied, determining the optimal number of meeting points. Following this, the user's selected vehicle capacity and product category are incorporated into the database. The CRCCTP is subsequently applied, calculating and returning the total cost.

➤ *CRCTP (Categorized Resource Capacitated Collective Travel Planning)*

Is an advanced method derived from RCCTP, which

incorporates the category of goods being transported and allocates them according to the user's requirements. This approach is essential for the supply chain industry to respond to market fluctuations, meet user demand, and comply with regulations. By considering product categories, supply chains can effectively adapt to varying customer needs, such as seasonal goods or food trends. For instance, in August, a delivery point may require a parcel of milk to meet the demand for shaved ice in a particular region, but by October, the demand could shift to a maximum of two units due to changing seasonal preferences. One of the key functions of CRCTP is its ability to set category-specific boundaries, allowing the user to establish minimum and maximum limits based on the nature of the goods being transported.

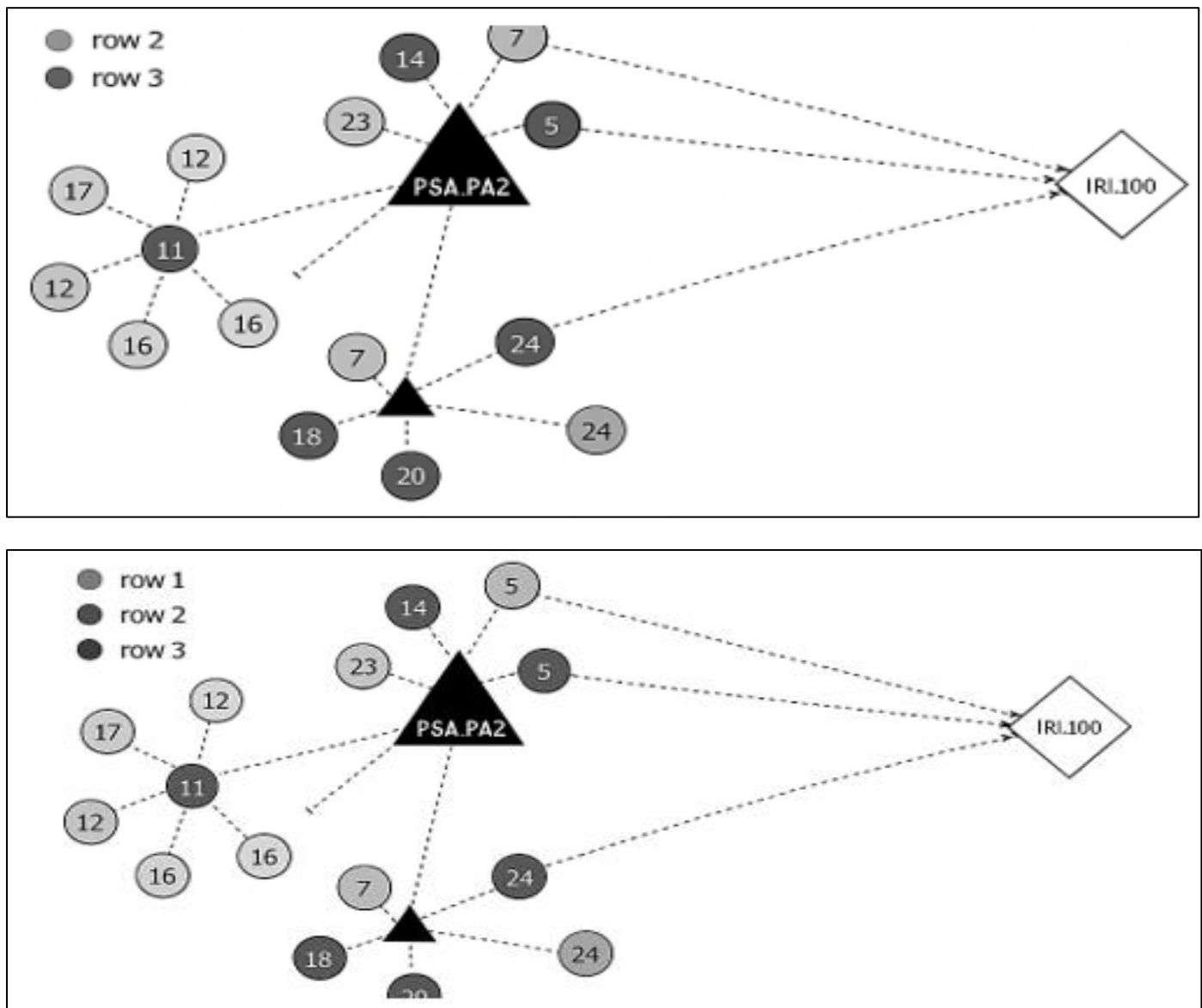


Fig 5 Category-Based Query Allocation

Fig.5 illustrates this concept: the upper figure shows a scenario without category-specific boundaries, where each vehicle has a capacity of 7 and four meeting points are selected. The lower figure demonstrates how boundaries are applied in CRCTP, with limits set for each category, such as

a maximum of two Category A queries per meeting point, a minimum of two Category B queries, and a minimum of one Category C query. As shown, the query points are adjusted based on the user-defined category boundaries.

➤ Modified MCLP

In the context of this study, the primary objective is to minimize total distance. Therefore, the brute force MCLP algorithm can be enhanced by pruning candidates based on a distance upper bound. Consider a meeting point m_k and candidate meeting points m_i and m_j . The score of meeting point m_l is represented as $C(m_l)$, and the total distance $D(m_l)$ is the sum of the distance from the query points covered by m_l to m_l , plus the distance from m_l to the destination d . The system will not compute the score for m_k

if the distance from m_k to the destination exceeds the maximum of $D(m_i)$ and $D(m_j)$, even if $C(m_k)$ is greater than $C(m_i)$ or $C(m_j)$.

• Example 3.

Consider Fig.6 and the following Table.2 below. Table.2 shows the distances between each meeting point and the destination. Let the range $r = 1$

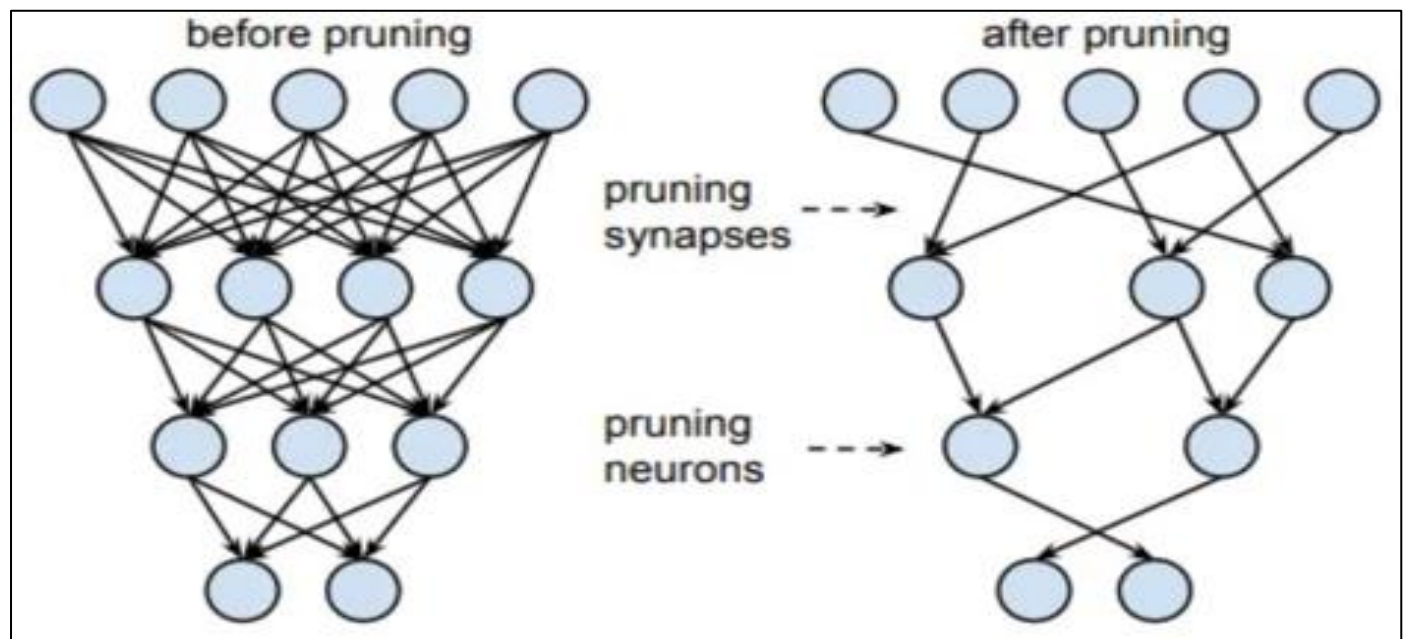


Fig 6 Distance-Based Pruning

Table 2 Distance Matrix

m1	10	m3	13	m5	21	m7	25	m9	29
m2	11	m4	17	m6	22	m8	24		

- **Iteration 1.** Candidate set: $[m1, m2]$ $C(m1) = 3$, $C(m2) = 4$ $D(m1) < 13$, $D(m2) < 15$, $\max[D(m1), D(m2)] \leq 15 =$ previous max total dist (PMTD)
- **Iteration 2.** current target = $m3$ Previous candidate set: $[m1, m2]$ $\text{Dist}(m3, d) = 13$, $C(m3) = 6$ Val: $\text{PMTD} = 15 > \text{Dist}(m3, d) = 13 \Rightarrow$ no pruning Check: $C(m3) > C(m1) \Rightarrow$ change Current candidate set: $[m3, m2]$ $D(m3) < 19$, $D(m2) < 15$, $\max[D(m3), D(m2)] \leq 19 = \text{PMTD}$
- **Iteration 3.** current target = $m4$ Previous candidate set: $[m3, m2]$ $\text{Dist}(m4, d) = 17$, $C(m4) = 7$ Val: $\text{PMTD} = 19 > \text{Dist}(m4, d) = 17 \Rightarrow$ no pruning Check: $C(m4) > C(m2) \Rightarrow$ change Current candidate set: $[m3, m4]$ $D(m4) < 24$, $D(m2) < 15$, $\max[D(m3), D(m2)] \leq 19 = \text{PMTD}$
- **Iteration 4.** current target = $m5$ Previous candidate set: $[m3, m4]$ $\text{Dist}(m5, d) = 21$, $C(m4) = 7$ Val: $\text{PMTD} = 19 < \text{Dist}(m5, d) = 21 \Rightarrow$ **pruning** No additional computations

Since the rest of the meeting points have a bigger distance value than the PMTD (which will not change), they all occur during pruning. In this case, only half of the meeting points are involved in the computations. Which decreases the time complexity.

IV. EXPERIMENTAL RESULTS

➤ Dataset and Environment.

The methods are evaluated in python, i7-10gen processor. In this research, built-in or open libraries are not used. The data used are all synthetic and distributed uniformly. Table.3 shows parameter variance. The number of the query points varies from 300 to 1000; the ratio is fixed at 1:4. The ratio of the query points and the meeting points varies from 1:3 to 1:9, and the number of the query points is fixed at 500. Three evaluations were conducted. First, I evaluated the comparison of time complexity between the brute force MCLP and the modified MCLP. Second, the total cost in the case of no CTP, CTP, and RCCTP. Finally, the total cost and the time complexity in the case of RCCTP and CRCTP.

Table 3 Experimental Parameters

Number of the Query Points	300	400 500 600	700
	800 900 1000		
Ration of the Query Points and The Meeting Points	1:3 4, 5, 6, 7, 8, 9		
Evaluated Methods	Brute Force		vs
	MCLP		vs
	modified MCLP		
	no	CTP vs	CTP
	RCCTP		
	RCCTP vs CRCTP		

- Comparison of Time Complexity between the Brute Force MCLP and the Modified MCLP

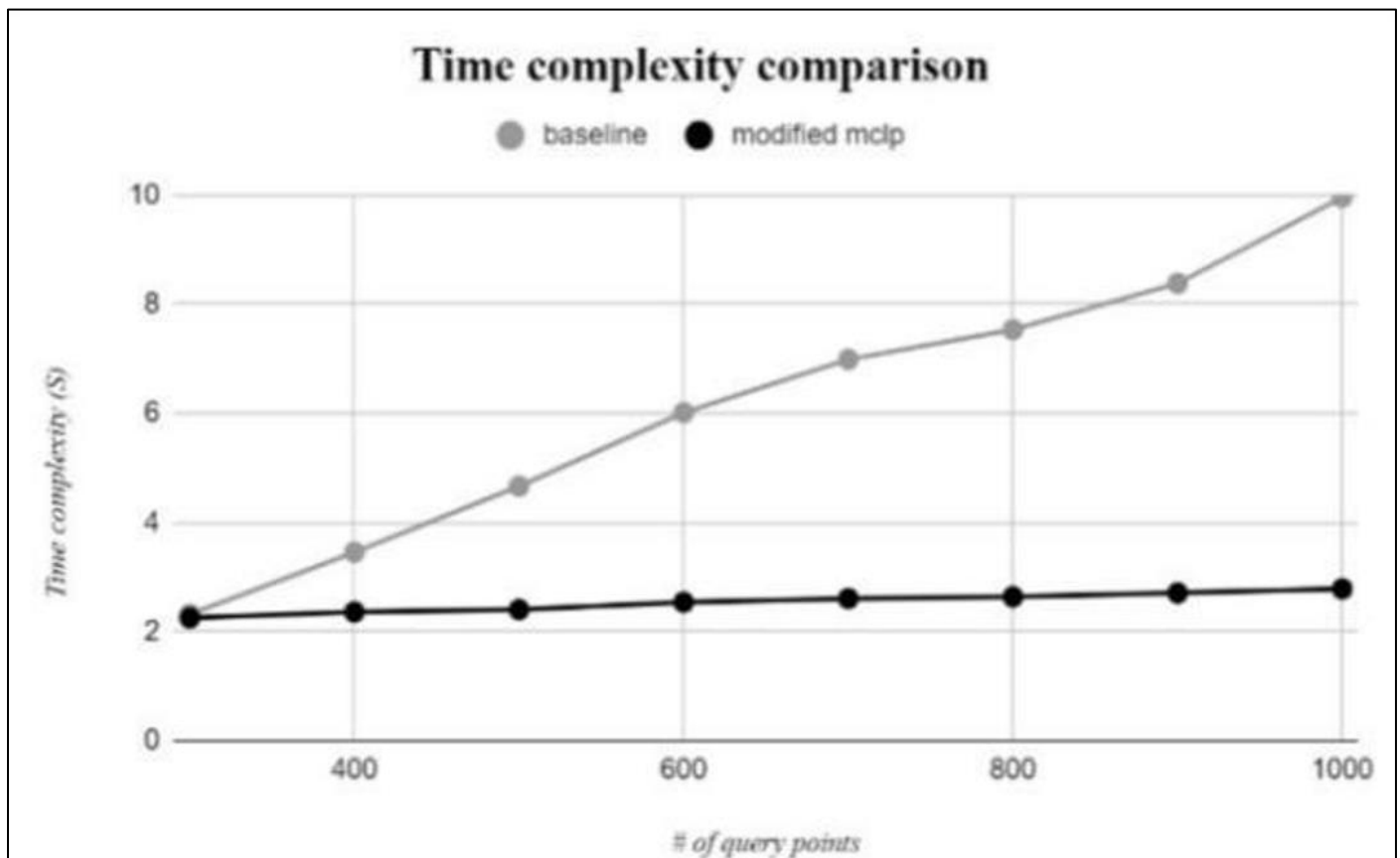


Fig 7 Time Complexity

In Fig.7, the gray line represents brute force MCLP as a baseline algorithm, and the black line represents the modified MCLP as the proposed algorithm with a pruning technique. As observed, the baseline increases linearly but sharply while the proposed method stays constant. Since it stops the computation when it comes to a certain distance difference.

➤ Results

- The Total Cost and the Time Complexity in the case of no CTP, CTP and RCCTP

In Fig.8 and Fig.9, blue is considered as no CTP, red as CTP, and yellow as RCCTP.

In the total cost comparison varying the number of the query points in Fig.8, the result of the total cost increases exponentially without CTP. However, the increment barely shows when it comes to CTP and RCCTP. The total cost of RCCTP is slightly lower than CTP because there is a limit to capacity. The capacity is a fixed value.

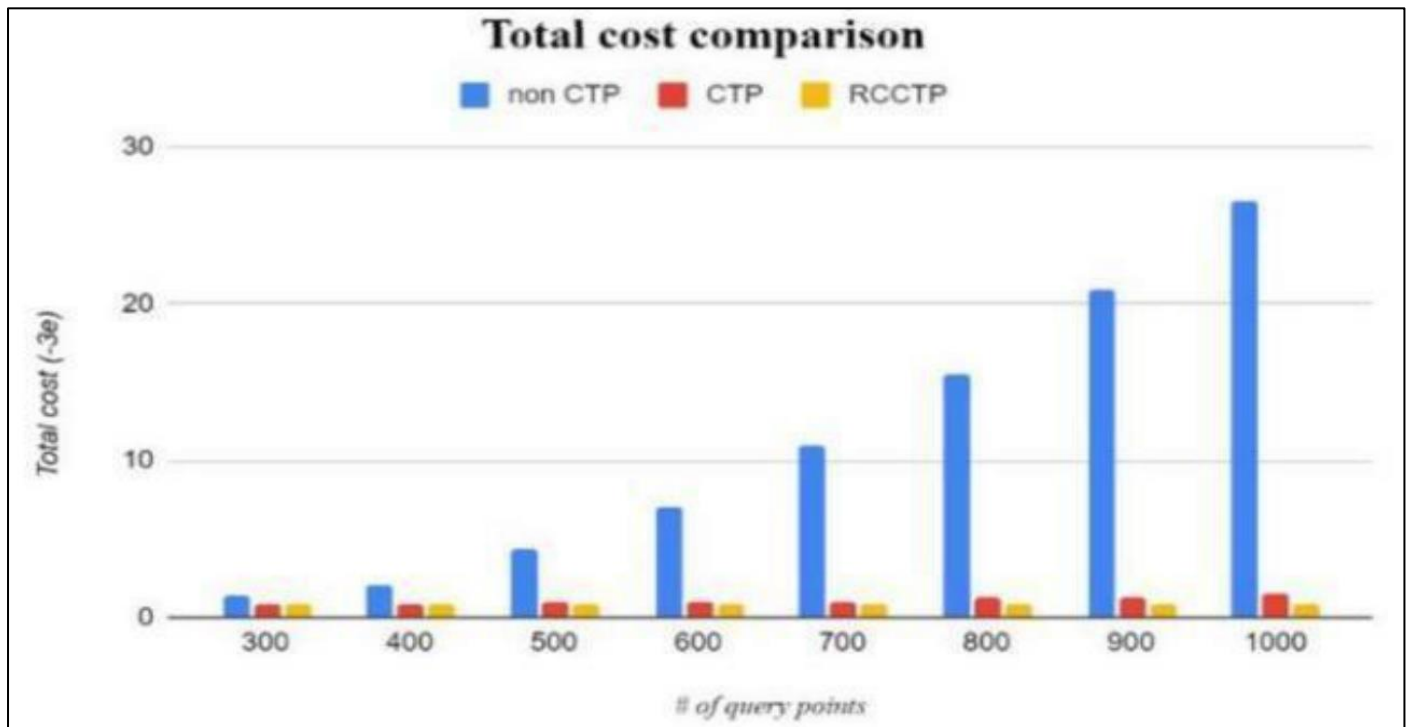


Fig 8 Cost Comparison by Query Count

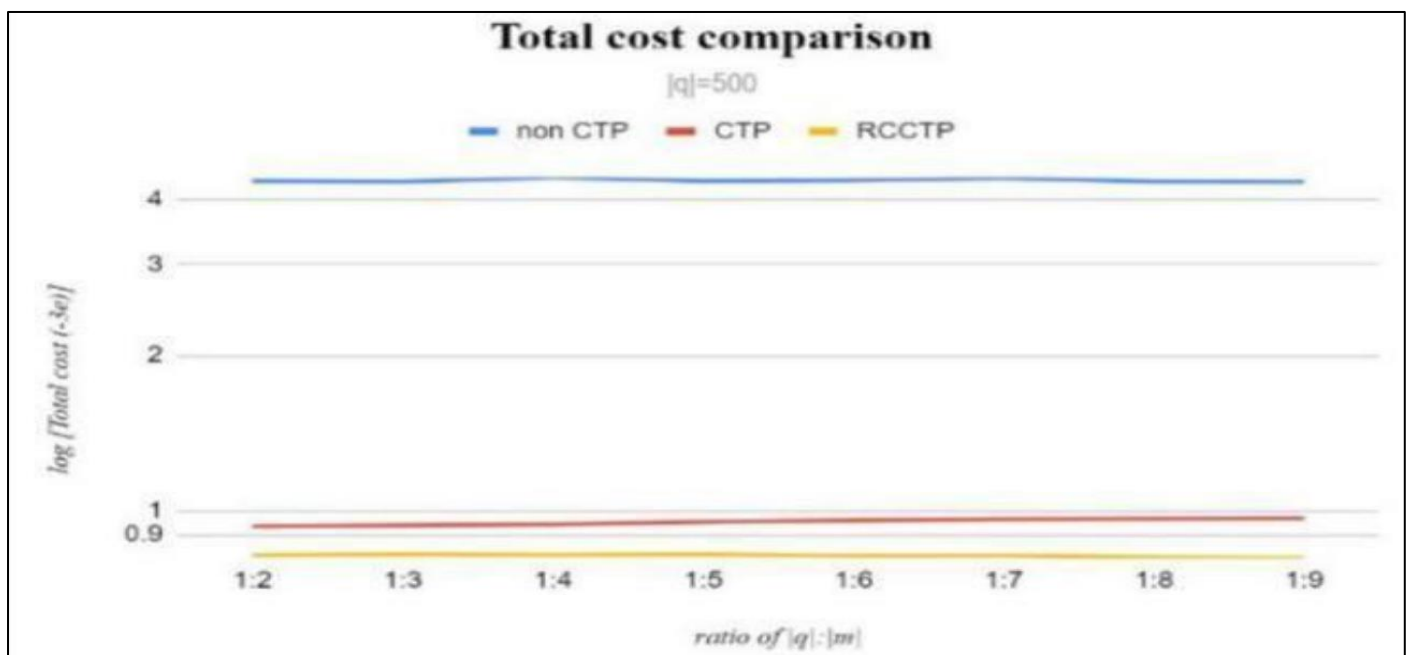


Fig 9 Cost Comparison by Query-Meeting Point Ratio

In the total cost comparison varying the ratio of the query points and the meeting points in Fig.9, the result of the total cost stays constant without CTP but with the highest value since this approach has nothing to do with meeting points. As the portion of the meeting points gets lower, the total cost slightly increases in CTP and RCCTP but very lower than without CTP.

➤ *The total cost and the Time Complexity in the case of no CTP, CTP and RCCTP*

In Fig.10, purple is CRCTP (the approach which considers the categories), and yellow is RCCTP.

In the total cost comparison varying the number of the query points in Fig.10, the result of the total cost increases exponentially at first, but soon the increasing ratio gets very low. Because CRCTP doesn't simply consider the capacity but more complex matching by the user demanded category, more far query points may match with the meeting points, which caused total cost than RCCTP.

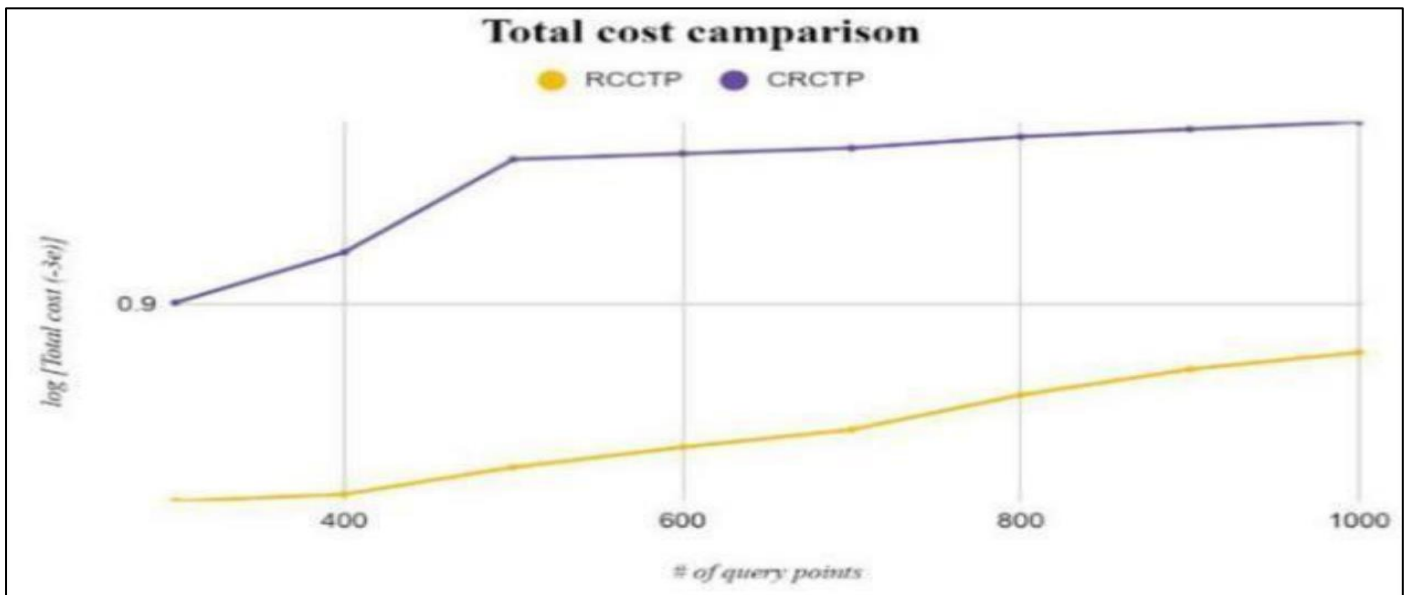


Fig 10 Total Cost Comparison

V. CONCLUSION AND FUTURE WORKS

In conclusion, this study introduces a novel problem framed within the context of business theory and environmental trends, particularly focusing on the issue of carbon emissions. A new system was proposed to address the defined problem, integrating Maximal Covering Location Problem (MCLP) and Collective Travel Planning (CTP) frameworks. In addition to these foundational approaches, two advanced algorithms were presented—modified MCLP and Categorized Resource Capacitated Collective Travel Planning (CRCTP)—both of which have been shown to be effective through experimental validation and theoretical analysis.

Despite the promising results, there remains potential for further refinement in developing more accurate and adaptable systems. First, incorporating algorithms that are more closely aligned with modern supply chain models could enhance the system's flexibility and relevance to current business needs. These algorithms could stem from both business management and informatics fields, such as geographic computations, which would not only improve system flexibility but also aid in generating synthetic datasets for testing and analysis. Second, collecting relevant data and implementing pattern recognition techniques for supply and demand dynamics—whether through locationbased data or numerical values—would contribute to predicting more accurate targets and optimizing decisionmaking in real-world applications. These future enhancements could provide a more robust and scalable solution for supply chain optimization in the face of evolving environmental and business challenges.

REFERENCES

- [1]. United Nations. (n.d.). Natural disasters occurring three times more often than 50 years ago: New FAO Report | UN News. United Nations. Retrieved from <https://news.un.org/en/story/2021/03/1087702>
- [2]. United Nations. (2022, May 9). Climate: World getting 'measurably closer' to 1.5-degree threshold | UN News. United Nations. Retrieved from <https://news.un.org/en/story/2022/05/1117842#:~:text=There%20is%20a%2050%3A50,published%20on%20Tuesday%20in%20Geneva>
- [3]. Timmermans, K. (2023, January 6). Supply chains key to unlocking net zero emissions. Accenture. Retrieved from <https://www.accenture.com/us/en/insights/supply-chain-operations/supply-chainskey-unlocking-net-zero-emissions>
- [4]. NFI Industries. (2021, March 30). Leverage the supply chain to improve customer experience. Retrieved from <https://www.nfiindustries.com/aboutnfi/insights/leverage-the-supply-chain-to-improvecustomer-experience/>
- [5]. Burgess, K., Singh, P.J., & Koroglu, R. (2006). Supply chain management: a structured literature review and implications for future research. *International Journal of Operations & Production Management*, 26(7), 703729. <https://doi.org/10.1108/01443570610672202>
- [6]. Onfleet, I. (2023, February 8). 7 ways to improve last mile logistics. Delivered Blog. Retrieved from <https://onfleet.com/blog/last-mile-logistics/> [Figures 2, 3] Lee, J., & Park, S. (2020).
- [7]. Resource Capacitated Collective Travel Planning in Spatial Databases. *IEEE Access*, 8, 135443-135457. <https://doi.org/10.1109/ACCESS.2020.3011528>
- [8]. Porras, C., Fajardo, J., Rosete, A., & Masegosa, A. D. (2021). Partial Evaluation and Efficient Discarding for the Maximal Covering Location Problem. *IEEE Access*, 9, 20542-20556. <https://doi.org/10.1109/ACCESS.2021.3055295>