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Integrated Inventory Routing Problem for Cold Chain Logistics Considering Carbon Emission

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Abstract
The integrated inventory routing problem (IRP) in cold chain logistics has gained significant attention due to its potential to optimize both inventory management and transportation decisions. In addition to traditional objectives such as cost minimization, the consideration of carbon emissions has become crucial in sustainable logistics operations. This study proposed a solution approach based on the integration of genetic algorithms and simulated annealing to address the IRP while considering carbon emissions. The study begins by formulating the IRP as a mathematical model that incorporates inventory management, vehicle routing, and carbon emissions as key decision variables. Genetic algorithms are employed to explore the search space and generate diverse solutions, while simulated annealing is utilized to enhance solution quality by allowing for local search and optimization. The project demonstrates the effectiveness of the genetic simulated annealing (GSA) approach in solving the problem and the results indicate significant improvements in both cost minimization and carbon emissions reduction. The study highlights the importance of considering carbon emissions in decision-making processes and provides valuable insights for practitioners and decision-makers in the field of cold chain logistics. The results demonstrate the potential for significant cost savings and environmental benefits through the integration of inventory management and vehicle routing while considering carbon emissions.

Keywords: Inventory routing problem; cold chain logistics; carbon emissions; genetic simulated annealing

1.0 Introduction

The e-commerce industry in Malaysia has witnessed substantial growth, driven by digitally literate consumers and increasing retail spending on cold chain products (Marcom,2020). The cold chain market has experienced significant growth, fuelled by government investments, consumer demand, and the expanding pharmaceuticals industry. However, there is still room for improvement in cold chain services especially in addressing temperature breakdown issues and meeting the demand for controlled temperature logistics in the Halal industry (Khanna & Tyagi, 2022),.

Cold chain logistics (CCL) involves the transportation and storage of temperature-sensitive goods to maintain their quality and safety. Temperature fluctuations during transportation and storage can have adverse effects on perishable foods, pharmaceuticals, and medical supplies. Inadequate cold chain management leads to spoilage and financial losses (Refrigeration, 2021). The COVID-19 pandemic has further highlighted the importance of CCL for vaccine storage.

Insufficient cold chain management contributes to food waste and environmental impact. Inefficient transportation, such as refrigerated trucks, results in higher energy consumption and increased carbon dioxide emissions. With climate change and increased demand for 24/7 product availability, the complexity of the cold chain industry grows. Higher ambient temperatures require more refrigeration, leading to increased energy consumption and carbon dioxide emissions.

To mitigate climate change, carbon cap policies have been implemented globally. These policies aim to reduce greenhouse gas emissions, including carbon dioxide, through measures like carbon caps, carbon taxes, and carbon trading (Konur & Schaefer, 2014). This research paper focuses on the implementation of carbon cap policies in the context of cold chain logistics.

Cold chain products require careful temperature control during transportation, and carbon emissions need to be reduced. Efficient inventory routing planning is crucial for preserving product quality, minimizing distribution costs, and addressing environmental concerns. The challenge lies in finding optimal routes for delivery vehicles based on customer locations and demand data while ensuring proper temperature management and reducing carbon emissions. The objective of this research is to develop an integrated inventory routing planning model for cold chain logistics considering carbon emissions. The model aims to optimize delivery routes, minimize temperature excursions, reduce distribution costs, and meet carbon emission targets. By integrating inventory management and routing decisions, this research intends to contribute to the improvement of cold chain services in terms of efficiency, product quality, and environmental sustainability.

2. Literature Review

2.1 Cold Chain Logistics

Researchers have recognized the need to reduce carbon dioxide emissions in the transportation sector, leading to the development of modified models of the Inventory Routing Problem (IRP) that consider carbon emissions. One early study introduced the IBM Carbon Analyzer (CARBAN) tool, which helps companies calculate and reduce their carbon emissions in logistics (Sourirajan et al., 2009). Cold chain logistics, which rely on refrigeration, incur high costs, energy usage, and carbon emissions. Therefore, further research is needed to optimize cold chain operations, considering both cost reduction and sustainability factors. A study proposed a new inventory model that incorporates costs and emissions associated with temperature-controlled items, aiming to find the balance between cost and emissions in decision-making (Bozorgi, Pazour, & Nazzal, 2014) Another study utilized a GSA algorithm to solve the IRP while considering carbon emissions (Li, Yang, & Qin, 2019).

2.2 Carbon Cap

A carbon cap policy sets a limit on the total amount of greenhouse gas emissions that can be emitted by companies or sectors within a specific timeframe. Its aim is to reduce emissions and mitigate the negative impacts of climate change. Carbon cap policies are widely used to address greenhouse gas emissions. The effectiveness of such policies is influenced by various factors, including the level of the cap. A higher cap allows for more flexibility and lower costs but may lead to fewer emissions reductions. Conversely, a lower cap can result in greater emissions reductions but may pose challenges for companies and potentially higher costs.

2.3 Inventory Routing

The Inventory Routing Problem (IRP) is a critical aspect of supply chain management, involving the optimization of inventory replenishment and delivery scheduling while adhering to constraints (Coelho, Cordeau, & Laporte, 2015). Early studies on the IRP were adaptations of Vehicle Routing Problem (VRP) models, with heuristics developed to incorporate inventory (Bell et al., 1983). The basic version of the IRP involves the distribution of a product from a depot to customers using a specific number of vehicles, with each vehicle commencing and ending its route at the depot, while adhering to capacity limitations (Shaabani, 2022). The objective function chosen in the IRP plays a crucial role in determining the optimal solution. Depending on the focus, whether it is minimizing transportation costs or inventory costs, the optimal solution may involve infrequent transportation with highly loaded vehicles or frequent transportation to minimize inventory costs. When a decision-maker is responsible for all cost components, minimizing the sum of inventory and transportation costs becomes a more suitable objective. In the IRP, a single supplier must determine the optimal timing of customer visits, the quantity to deliver, and how to consolidate these visits into routes within each time period. The scenarios in IRP can vary based on deterministic or stochastic demands, the number of customers considered, the variety of products delivered, the planning horizon, and the inclusion of different constraints. This paper focuses on a specific IRP problem within a two-echelon supply chain, consisting of a supplier and multiple retailers. According to Ballou (1989), traditional approaches to modeling supply chain and logistics problems include simulation, optimization using exact algorithms, and various types of heuristics, such as classical heuristics and metaheuristics.

2.4 Classical Heuristics

Classical heuristics for the routing problem can be categorized into merging existing routes using a savings criterion and gradually assigning vertices to vehicle routes using an insertion cost (Laporte, Gendreau, Potvin, & Semet, 2000). The Clarke and Wright Savings Algorithm is a widely used classic heuristic for its simplicity and effectiveness (Bard, Huang, Jaillet, & Dror, 1998).

2.5 Metaheuristics

Metaheuristics, on the other hand, are more adaptable and efficient than classic heuristics and can be applied to a wide range of optimization problems. They explore the search space to find "good enough" solutions and can be easily parallelized. Genetic Algorithms (GA) are a type of metaheuristic that operates on a population of potential solutions and evolves them through fitness-based selection and recombination. Simulated Annealing (SA) is a metaheuristic inspired by the annealing process in metallurgy, preventing getting stuck in local minima by allowing for the acceptance of suboptimal solutions. Genetic Simulated Annealing Algorithm (GSA) combines elements of GA and SA to guide the search towards promising areas of the solution space while escaping local optima. These approaches have been applied to the Inventory Routing Problem (IRP) with varying degrees of success, offering efficient and effective solutions for optimizing supply chain logistics.

3.0 Methodology

This study is using GSA algorithm to solve IRP with considering carbon emission and is solved by using PyCharm with Python 3.11 programming language. The parameters for the model for the IRP are set as below:

V'	set of nodes representing retailers
V_0	the node representing supplier
T	set of time periods
h_i	the inventory holding cost of retailer i for storing per unit product
I_{it}	the inventory level of retailer i at the beginning of the period t
q_{it}	the demand of retailer i in period t
P	the price of unit product
ϑ	the spoilage rate of the product
t_s	the time duration of a period
p_o	the empty load fuel consumption rate (e.g., L/km)
$p*$	the full load fuel consumption rate (e.g., L/km)

f_k	the fixed cost of vehicle k
u	the price of unit fuel consumption
Q	the weight capacity of refrigerated vehicle
C_i	the largest inventor capacity of retailer i
d_{ij}	the distance between retailer i and j
e_0	the carbon emissions generated by unit fuel consumption
Q_c	the total carbon emissions generated during the planning horizon
Q_q	the carbon cap allocated by the government
C_p	the carbon price
g	the carbon emissions generated by per kWh electricity
p_s	the energy consumption generated by storing unit product in one period
Q_{ijkt}	the load carried by vehicle k from retailer i to j in period t
D_{it}	the amount of product delivered to retailer i in period t
Y_{kt}	1 if vehicle k is used to deliver products; 0 otherwise
x_{ijkt}	1 if vehicle k travels from retailer i to j; 0 otherwise

3.1 Model Formulation with Carbon Cap Policy

The objective function for the model of the IRP while considering carbon emission are as below:

$$
\begin{aligned}
Min\, Z_{cc} = \quad & C_1 + C_2 + C_3 + C_4 \\
= \quad & \sum_{t\in T}\sum_{i\in V'}\left(h_i + p\left(1-e^{-\vartheta t_s}\right)\right)\left(I_{it} - \frac{1}{2}q_{it}\right) + \sum_{t\in T}\sum_{i\in V'} f_k Y_{kt} \\
& + \sum_{t\in T}\sum_{k\in K'}\sum_{i,j\in V'} u(p_0 + \frac{p* - p_0}{Q} Q_{ijkt}) x_{ijkt} d_{ij}
\end{aligned} \tag{1}
$$

where

$$C_1 = \sum_{t\in T}\sum_{i\in V'} h_i(I_{it} - \frac{1}{2}q_{it}) \tag{2}$$

$$C_2 = \sum_{t\in T}\sum_{i\in V'} p(I_{it} - \frac{1}{2}q_{it})(1 - e^{-\vartheta t_s}) \tag{3}$$

$$C_3 = \sum_{t\in T}\sum_{i\in V'} f_k Y_{kt} \tag{4}$$

$$C_4 = \sum_{t\in T}\sum_{k\in K'}\sum_{i,j\in V'} u(p_0 + \frac{p* - p_0}{Q} Q_{ijkt}) x_{ijkt} d_{ij} \tag{5}$$

$$Q_c = \sum_{t\in T}\sum_{k\in K'}\sum_{i,j\in V'} e_0(p_0 + \frac{p* - p_0}{Q} Q_{ijkt}) x_{ijkt} d_{ij} + \sum_{t\in T}\sum_{i\in V'} g * p_s(I_{it} - \frac{1}{2}q_{it}) \tag{6}$$

subject to

$$I_{i,t+1} - D_{it} = I_{it} - q_{it} - (I_{it} - \frac{1}{2}q_{it})(1 - e^{-\vartheta t_s}) \tag{7}$$

$$\sum_{k\in K}\sum_{j\in V'} x_{ijkt} = 1, \forall i \in V, \forall t \in T \tag{8}$$

$$\sum_{i\in V'} D_{it}y_{ikt} \leq Q\ ,\forall k \in K, \forall t \in T \tag{9}$$

$$\sum_{k\in K} y_{ikt} = \begin{cases} 1, i \in V' \\ K, i = 0 \end{cases} \tag{10}$$

$$\sum_{j\in V'} x_{ijkt} = \sum_{j\in V'} x_{ijkt} \leq 1, i = 0, k \in K \tag{11}$$

$$\sum_{j\in V'} \sum_{k\in K} x_{ijkt} \leq K, i = 0 \tag{12}$$

$$x_{ijkt} + x_{jikt} \leq 1, \qquad \forall i,j \in V', \qquad \forall k \in K, \forall t \in T \tag{13}$$

$$x_{ijkt}, Y_{kt}, D_{it} \geq 0 \tag{14}$$

$$I_{it} - q_{it} - \left(I_{it} - \frac{1}{2}q_{it}\right)\left(1 - e^{-\vartheta t_s}\right) \geq 0 \tag{15}$$

$$\sum_{t\in T} \sum_{k\in K'} \sum_{i,j\in V'} e_0\left(p_0 + \frac{p * - p_0}{Q} Q_{ijkt}\right) x_{ijkt} d_{ij} + \sum_{t\in T} \sum_{i\in V'} g * p_s\left(I_{it} - \frac{1}{2}q_{it}\right) \leq Q_q \tag{16}$$

Equation (1) is the objective function of the model that minimizes the total costs of the cold chain IRP. Equation (2) refers to inventory holding cost and it is costs associated with storing inventory or materials. These costs can include expenses such as rent or lease payments for warehouse or storage space, insurance, utilities, and labor costs for inventory management. Equation (3) is damage cost. The damage cost of the products needs to be carefully calculated and incorporated in the model due to the perishability of the cold products. This paper assumes that the products are damaged at the exponential rate when they are stored in the retailer's warehouse. Equation (4) represents the vehicle fixed cost. Vehicle fixed costs are the expenses associated with owning and operating a vehicle that do not vary based on the number of miles driven. The vehicle fixed cost is generated once a refrigerated truck is dispatched to carry out a distribution task. It includes the driver salary, road maintenance fee, the depreciation expense of the vehicle during use and onboard refrigeration equipment, and so on. Equation (5) is the fuel consumption cost during delivery process. Equation (6) is the calculation for carbon emission during the transportation stage.

Constraint (7) is the inventory balance equation for each retailer. Constraint (8) imposes that each retailer is only served by one refrigerated vehicle. Constraint (9) represents that the load that is carried by one vehicle cannot exceed the vehicle capacity. Constraint (10) represents that the depot has K vehicles in total and each customer is served by only one truck. Constraint (11) imposes the notion that the path route of each vehicle is a closed loop. Constraint (12) shows that the number of routes cannot exceed the quantity of vehicle that is owned by the depot. Constraint (13) is introduced to eliminate the sub-loops. Constraint (14) ensures that the decision variables are non-negative. Constraint (15) represents that stockouts are not permitted. Constraint (16) represents that the carbon emissions that are generated cannot exceed the carbon cap.

3.2 Chromosome Representation and Encoding

With employing GSA to solve the problem, each chromosome is an individual or a solution to the problem. This study utilizes a chromosome representation and encoding technique to capture delivery and routing information for each retailer. This information is represented in a two-dimensional matrix, where each row corresponds to a period. The first 20 columns represent delivery amounts, while the remaining columns encode routing details. The delivery amounts for each retailer in each period. These amounts are randomly generated within specified limits, calculated based on inventory levels and demand. These limits ensure inventory constraints are met and prevent stockouts. Equations (17) and (18) in the research paper are used to determine the delivery amount limits.

$$L_{it} \quad = q_{it} - \left[I_{it-1} - q_{it-1} - (I_{it-1} - \frac{1}{2}q_{it-1})(1 - e^{-\delta t_s})\right] \ \forall\, i \neq 0 \tag{17}$$

$$U_{it} \quad = C_i - \left[I_{it-1} - q_{it-1} - (I_{it-1} - \frac{1}{2}q_{it-1})(1 - e^{-\delta t_s})\right] \ \forall\, i \neq 0 \tag{18}$$

Finally, the routes of each vehicle are generated using the Nearest Neighbour_Search_(NNS) heuristic. The NNS heuristic starts at the depot and finds the non-visited retailer that is closest to the last visited retailer. The specific steps of the NNS heuristic are as follows:

1. Set the starting point in first period $(t = 1)$.
2. Visit the closest retailer and add it to the current vehicle's route
3. Repeat step 2 until all retailers have been visited
4. Move to the next period $(t = t + 1)$ and repeat steps 2-4 until all periods have been considered $(t \leq T)$.

3.3 Initialization and fitness evaluation

Generate 100 individuals based on the random method. Then the fitness value of every individual is calculated as the reciprocal of the objective function value and the formula is as below:

$$F_i = \frac{10000}{Z_i} \tag{19}$$

3.4 Genetic Simulated Annealing

The selection operator used in this research paper is the tournament selection strategy. The crossover operator involved the steps of randomly select two individuals as parents, generate two cut-points indicating the retailers for crossover in the delivery and route genes, perform the crossover operation by swapping the respective genes of the parents, and obtain two new offspring. The mutation involves two procedures: the delivery exchange procedure and the retailer swap procedure. The specific delivery exchange procedure are as follows:

1. Randomly chose a period t
2. If the last period is chosen, let t = $t - 1$
3. Select the vehicle l with the highest remaining capacity.
4. Randomly chose a retailer i who is included in the path vehicle l among those dispatched for deliver in time t
5. If $RC_{kt} \geq D_{it+1}$ let $D_{it} = D_{it} + D_{it+1}$else, $RC_{kt} < D_{it+1}$let $D_{it} = D_{it} + RC_{kt}$, $D_{it+1} = D_{it+1} + RC_{kt}$

while the retailer swap procedure are as follows:

1. Randomly chose a period t
2. Choose two retailers (each is served by different vehicle) in period t randomly.
3. Exchange the service vehicles of two retailers.

4. Using NNS heuristics to regenerate vehicle routes.

Then the simulated annealing operator is carried out after the mutation operator and the procedure are as follows:

1. The adjusted new solution is $newsolu$, the objective function value is $newobjv$, and Δf is used to represent the increment of the objective function, $\Delta f = newobjv - objv$.Then according to the Metropolis criterion:

$$p = \begin{cases} exp\left(-\frac{\Delta f}{T_i}\right), \Delta f \geq 0 \\ 1,, \Delta f \leq 0 \end{cases} \tag{20}$$

2. Do cooling operation according to the cooling coefficient $r, T_{i+1} = T_i \times r$;
3. If $T_i < T_{end}$, then turn to step 4; Otherwise, turn to step 2.
4. Output the current solution $solu$.

4.0 Results and Discussion

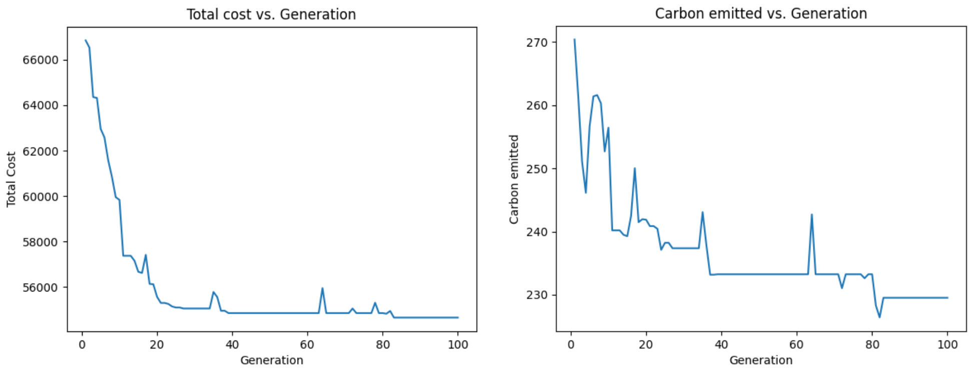
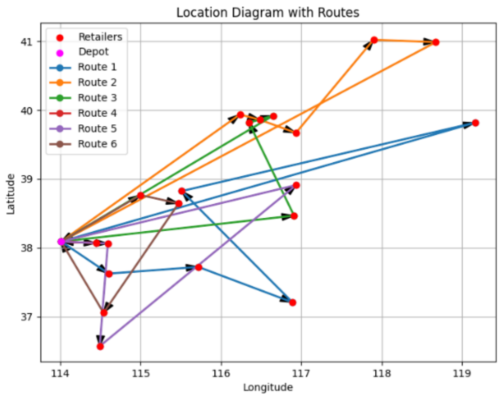


Figure 1 Total cost and carbon emmited throughout generations

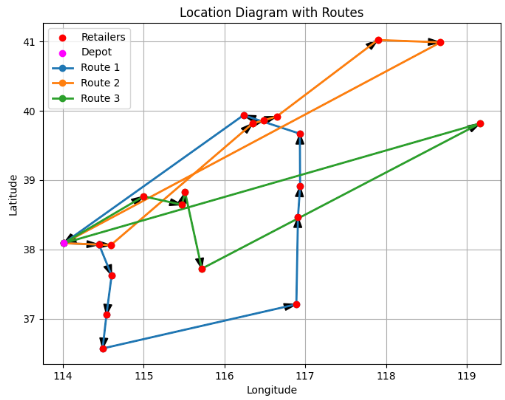
The GSA algorithm was run with a population size of 100 and 100 number of generations to optimize the fitness function representing total cost. The results analysis focused on examining the fitness values throughout the generations. The plotted graph indicated convergence towards an optimal solution, with the fitness values stabilizing after Generation 20, suggesting a near-optimal solution. The slope of the plot showed a significant improvement in total cost from Generation 1 to Generation 20.

Fluctuations in the total cost were observed in the plot, which could be attributed to the influence of the SA operator introducing mutations for exploration. These mutations temporarily increased the total cost, causing fluctuations. However, the exploration ability of the SA operator aided in finding a better solution after Generation 80 when the optimal solution remained unchanged.

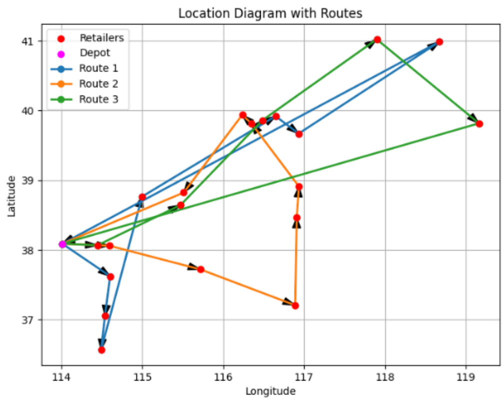
Regarding carbon emissions, the graph shows a general decrease in carbon emissions during the delivery process across generations. Although fluctuations are present, the optimization process focuses on minimizing total costs rather than explicitly targeting carbon emissions. As the optimization progresses and total costs decrease, it indirectly leads to a reduction in carbon emissions by minimizing factors such as inventory volume and fuel consumption. The decrease in carbon emissions is primarily driven by lower inventory levels, which reduce electrical energy consumption, and decreased fuel consumption, resulting in lower emissions from burning fuel.



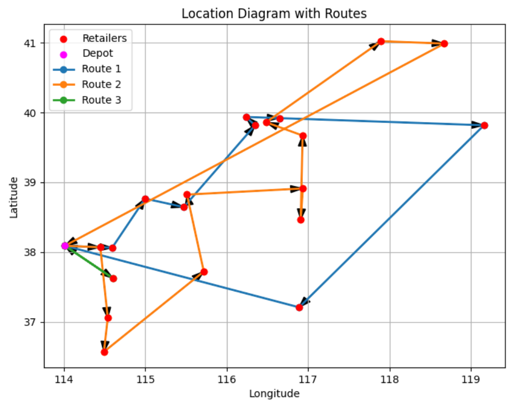
Period 1



Period 2



Period 3



Period 4

Figure 2 Location of the depot and retailers with routes of every vehicles connecting to the nodes for every period.

The plot depicts the retailer locations and the connecting routes for time period 1, showing that all retailers are connected by vehicle routes. A notable observation from the data is that during time period 1, six vehicles are utilized, while in the subsequent periods, only three vehicles are used. This difference can be attributed to the initial zero inventory levels at the retailers, which necessitate more deliveries to meet the demand. As the retailers establish their inventory store flow system, the frequency of deliveries decreases, resulting in a lower requirement for vehicles. In summary, the number of vehicles used is highest in time period 1 due to the initial demand, but decreases in subsequent periods as the inventory system becomes more efficient.

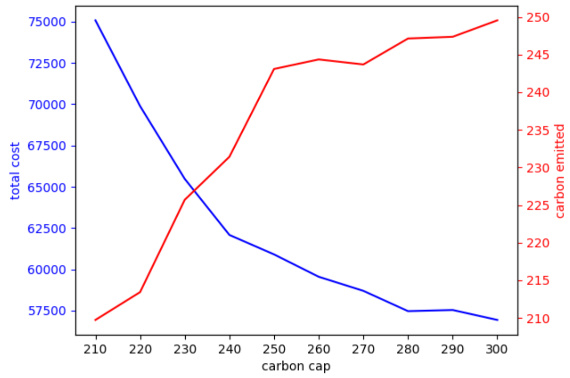


Figure 3 Plot of total cost and carbon emitted over carbon cap

Increasing the carbon cap leads to a decrease in cost, indicating a negative correlation between the two variables. When the carbon cap is too low, it becomes impossible to meet the emission constraint. Higher carbon caps offer more flexibility in emission management strategies, resulting in cost savings. Initially, emissions increase with the carbon cap, but they plateau around 250, suggesting that further increases in the carbon cap have limited impact on emissions. The primary objective, based on the data, is to save costs while maintaining reasonable emission control. The decreasing cost trend with higher carbon caps supports this objective, as organizations can effectively reduce costs without compromising emission control by increasing the carbon cap.

Conclusion

This study successfully achieved its objectives by optimizing the delivery process in a cold chain logistics system. The utilization of the GSA algorithm resulted in improved resource utilization and reduced total cost. By considering various cost components and minimizing total distribution costs, the algorithm effectively optimized the cold chain integrated IRP. Additionally, the research incorporated carbon emissions as a factor to be minimized, providing insights into the trade-offs between cost optimization and environmental sustainability. The outcomes offer a comprehensive framework for routing and inventory management in cold chain logistics, contributing to enhanced decision-making, resource utilization, and cost reduction in the integrated IRP.

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