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Supply Chain Optimization Encompasses Integrated Forward and Reverse Logistics using Memetic Algorithm

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Abstract Distribution allocation is one of the main problems in the logistics network models, particularly during the attempt to enable quick and efficient decision making strategically in the industrial context. Once the examination has been done in inspection centre, the recycled materials are assumed to be of the same quality as the raw materials in general. As not every recycled material will always be of high quality so we have created a recycle center node with a novelty to determine the quality of the products that were collected. Another point that we discussed about was how materials move with relevant assessment in the inspection system, which resulted in informed decisions on recycling, reusable/remanufacturing, or disposal in the reverse logistic system. This not only enables a clear picture of the resources that have been collected, but it also guarantees that the needs of the raw materials remain balanced; that the demand is met. Our approach proposes a model of integrated forward and reverse logistics network to determine the actual transportation cost in two different cases, with or without the new node open so that the cost of inventory transportation is optimized. The model is implemented by use of optimization software and the results of the simulation are compared by use of a numerical example.

Keywords Recycle Center; Inspection Mechanism; Integrated Forward and Reverse Logistics; Quality–Based Path; Optimization.

AMS 2010 subject classifications 90C59, 90C27, 68T20, 49M37.

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1. Introduction

In recent decades, promoting sustainability in industrial operations, which is driven by conservation efforts and increasing demand for eco-friendly practices, has been a tough task through Green Supply Chain Management (GSCM). The industrial decision-makers are facing many challenges to the logistics network, such as (i) visibility of the limited supply chain constraints (ii) manual operations (iii) inadequate labor, etc. Nowadays, modern techniques support to reduce the above issues through interdisciplinary and data-driven approaches to enhance real-world adaptability.

1.1. Reverse Logistics and Closed Loop Supply Chain

Govindan et al. [1] presented the state-of-the-art for RL/CLSC problems. Hu et al. [2] created a post-disaster debris reverse logistics. Costs related to logistics, risk, and psychology are reduced. Additionally, a growing marginal function of waiting time is used to quantify the psychological cost. A reliable stochastic optimization model for reverse logistics in closed-loop supply chains was created by Shahparvari et al. [3]. Chance Constrained Robust

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Stochastic Programming (CCRSP) is used to determine the optimal flow of products, highlighting how variations in the price of carbon credits affect the number of plant openings. Both forward and reverse flows are engaged, and two production options are taken into account: either directly producing new goods at manufacturing facilities or remanufacturing returned goods under new conditions. In order to integrate remanufacturing as a recovery option into the tactical planning process, Subulan et al. [4] developed a mathematical programming model and tried to optimize each successive step in the closed-loop supply chain. Behmanesh et al. [14] conveyed the cyclic seven-stage logistics network problem as a NP hard mixed integer linear programming model. Behmanesh et al. [15] presented an integrated supply chain model that is flexible in the delivery path. Katsoras et al. [25] provided a system dynamics-based analysis for tragedy events on the operation of CLSCs to study the system response and observed the dynamics at a manufacturer, parts producer, collector, and disassembly center level by providing control mechanisms for resilient CLSCs in disaster effects. A genetic algorithm and a nonlinear mixed-integer programming model were presented by Min et al. [30] to address the reverse logistics problem linking the product returns.

1.2. Facility Location with Cost Minimization and Time Window

Wang et al. [7] offered a Cycle Evolutionary Genetic Algorithm to solve the model. Meanwhile, actual data are used with CEGA to carry out numerical experiments to deliberate deviations of distribution routes with different carbon emissions under different carbon taxes and their effect on the total distribution cost. Takeyasu et al. [13] extended it to the system, which reflects a reduced cost for the volume of loads. Here, a reduced cost by the discount of volume is also taken into account when multiple loads are transported using the similar type of transport. A methodology for solving a multi-objective vehicle routing problem with soft time-window constraints that demand the earliest and latest client arrival times was presented by Yan et al. [19]. Kulakova and Jalaei et al. [22, 23] suggested mathematical models of logistics networks based on GIS. Ho et al. [27] discussed optimization for space logistics using time expanded networks with dynamic modeling. Liu et al. [29] offered nonlinear models. A genetic algorithm is implemented to solve the models, where a Monte Carlo simulation-based technique is intended to deal with the travel time ambiguity.

1.3. Cold Chain Sustainability and Green Logistics

Chen et al. [6] discussed the cold chain logistics of front granaries, and a TDGVRP is offered from the view of low-carbon economy. In order to challenge the tactical optimization of fresh food distribution networks, Bortolini et al. [8] proposed a three-objective delivery planner with goals for operational cost, carbon footprint, and delivery time. Additionally, the expert system he created outperforms the frequently utilized methods that are primarily concerned with cost minimization. Lu et al. [9] utilize a grey wolf optimization approach that combines memory-showed location apprise equations, dynamic adaptive inertia weights, and good point sets. Adenso-Díaz et al. [17] studied the effect of integrating the environmental effect with logistics network design models, relating the results found as a cost minimization only. Mahapatra et al. [20] streamlined the crude oil transportation and minimized carbon emissions to achieve green logistics. Aljohani [21] discussed Logistics network models to optimize travel distance. Halvorsen et al. [26] discussed optimizing environmental and economic aspects of collaborative transportation logistics..

1.4. Integrated Forward/Reverse Logistics and Efficient Vechile Routing

Pishvaee et al. [5] offers a memetic algorithm for scheming included forward and reverse logistics networks. The model instantaneously minimizes cost and environmental impact, refining efficiency and sustainability in logistics network planning. Ping, et al. [10] investigates the use of AI large models to optimize logistics transportation routes. It proposes intelligent route planning techniques that analyse traffic, distance, and demand data to improve efficiency, diminish transportation costs, and improve decision-making in current logistics systems. Danchuk et al. [11] developed cargo delivery through dynamic route optimization in smart logistics systems. Behmanesh et al. [15] discussed integrated logistics networks, they used memetic algorithm with chromosomal encoding and Taguchi analysis that was unique.

1.5. Multi-objective Optimization and Uncertanity

Billal et al. [16] combined metaheuristics, fuzzy logic and stochastic programming. Ghazvinian et al. [18] explained the health care sector through multi-objective optimization using machine learning. Prorok [28] examined uncertain networks with the help of robust robot assignment.

1.6. Research Gap

Generally, the people believe that all recycled materials are of the same quality. This simplistic assumption ignores the variation in the quality of recycled goods. These significant results can lead improper resource allocation and poor decision-making. Moreover, most existing models do not have specific inspection mechanisms to check the quality of recycled materials before processing or disposal. Additionally, the integration of inspection-driven decision points within closed-loop logistics systems, which include both forward and reverse logistical flows, has not received much attention. As the resource allocation problem is a combinatorial NP-hard problem, a memetic algorithm is used to obtain the efficient optimal solution.

1.7. Motivations

- The research is motivated by the increasing need for efficient and sustainable supply chain operations in modern logistics environments.
- The growing practical importance of integrating forward and reverse logistics networks necessitates more comprehensive analytical models.
- Reducing waste generation and transit costs has become critical for improving both economic and environmental performance.
- Existing studies often lack holistic models that simultaneously address cost efficiency, material quality, and sustainability objectives.
- There is a strong demand for advanced optimization-based decision-support tools to manage complex closed-loop logistics systems.

1.8. Objectives

- The study aims to optimize resource allocation in closed-loop supply chains through the application of an adaptive dynamic-path routing framework.
- It seeks to integrate forward and reverse logistics operations to enhance overall network efficiency and coordination.
- The proposed model is designed to minimize total inventory and transportation costs across selected facilities.
- Another objective is to maintain and improve the quality management of recycled materials within the closed-loop system.
- The research intends to develop a flexible and scalable optimization framework capable of addressing complex logistics decision variables.

1.9. Limitations

- The study provides limited discussion on the interrelationships among forward and reverse logistics, metaheuristic approaches, and sustainability considerations.
- The absence of real-world case studies and implementation details reduces the practical validation of the proposed framework.
- The model is evaluated primarily under specific scenarios, which may limit its scalability to larger and more complex logistics networks.
- Key sources of uncertainty—such as weather conditions, traffic variability, and demand fluctuations—are not incorporated into the model.
- Certain simplifying assumptions may restrict the direct applicability of the proposed approach to real-life logistics environments.

1.10. Structure of the paper

The rest of the article is sorted as follows: Section 2 discusses the proposed model and its mathematical formulation. Section 3 analyses the integrated forward & reverse logistics network model using MILP and provides description of the proposed algorithm. Section 4 discusses the computational and experimental setup. Section 5 provides a numerical example and Section 6 gives the conclusion and future research work.

2. Problem Description

Formulate a supply chain network model aimed at minimizing the total transportation and operational costs within a dynamic reverse logistics network. The goal is to determine the optimal capacity of each node and the most efficient distribution strategy. Let $G = (N, E)$ be a directed graph, where 'N' denotes the set of nodes and 'E' represents the set of directed edges. The cost structure in this model includes two main components:

1. A fixed cost c_i incurred for operating node $i \in N$, and
2. A unit transportation cost $c_{ij}$for transferring goods along edge $(i, j) \in E$.

The mathematical formulation can be represented as follows:

$$Min\, z = c_{ij}^T x_{ij} + c_i^T y_i$$

subject to

$$a^T x_{ij} + b^T y_i \leq \phi,$$

where z –objective function, a,b – constraint matrices, y – Integer decision variables

2.1. Proposed Model

The suggested model operates on deterministic circumstances along with limited facilities and well-known customer demand. We simplified the logistics assumption of the perfect transportation and the deficiency of agent steps with all predetermined cost parameters. The importance of this model is the behavior of the product returns. Through the assessment centers, (i) recyclable products are returned to the production center at the same time as the (ii) non-recyclable products are sent to the disposal unit. Therefore, we inferred that the origin of the product and recycled materials are considered equivalent raw material quality. In this connection we are satisfying the customer demand and professionally managing invalidated products, because the objective of the proposed model is to minimize the overall cost, facility operation, and transportation cost. We extend [15] by introducing one recycle node to check the actual quality of the product that were collected by whether that node is open or not. Figure 1 describes the integrated forward and reverse logistics of the proposed model.
Consider $G = (N, E)$ as a directed graph, where 'N' be the set of nodes, 'E' be the set of edges. Let fixed cost for node $i \in N$ denoted by c_i, unit transportation cost on edge (i,j) belongs to E denoted by c_{ij} and$x_{ij} \in N$, and a_i & b_i known vector coefficients for the involved constraints.

The set of nodes is defined in $N = S \cup P \cup D_c \cup R \cup C \cup C_0 \cup R_c \cup D_i$. There may be multiple edges between facilities within the same stage of the supply chain. The forward flow ensures complete delivery of products, while the reverse flow is represents returned products by a simple graph structure.

$E = (S * P) \cup (P * D_c) \cup (P * R) \cup (P * C) \cup (D_c * R) \cup (D_c * C) \cup (C * C_0) \cup (C_0 * D_i) \cup (C_0 * R_c) \cup (R_c * P) \cup (R_c * D_i)$

In the proposed model, customer demands are deterministic that must be fully satisfied. Each stage in the supply chain has a limited number of facilities with a specified capacity. All cost parameters, including fixed and variable costs, are assumed to be known in advance. Transportation operates under ideal conditions, with perfect transfer

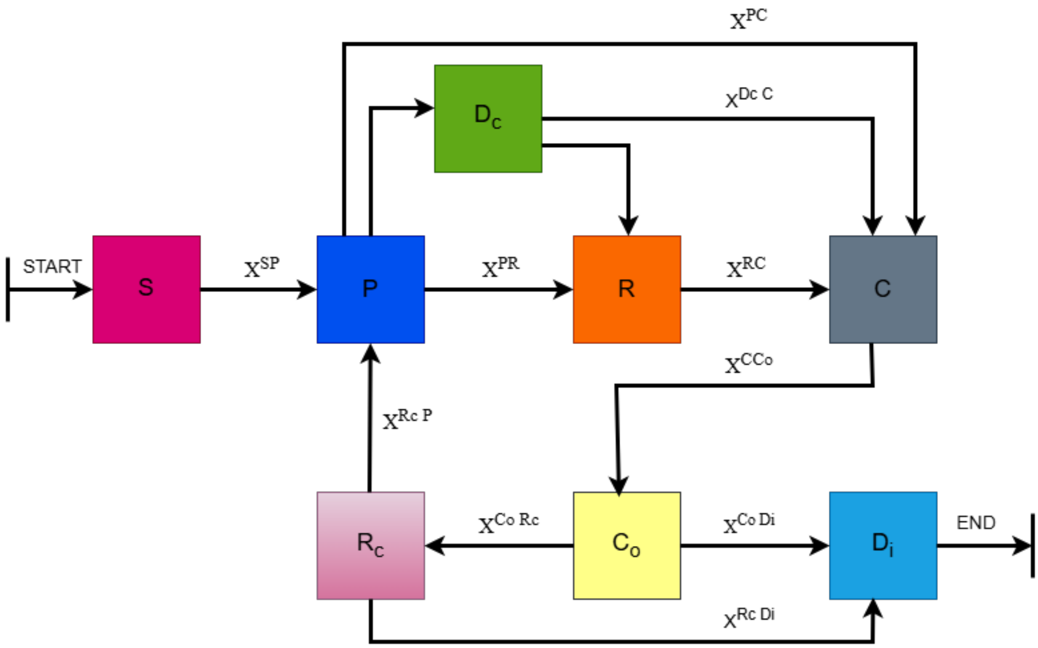

Figure 1. Schematic Diagram of the Proposed Model

rates and no additional stages involved. The return process is characterized by fixed rates such that, return rate p_m, disposal rate p_n, and recovery rate $(1 - p_n)$. Similarly, in the proposed model P_n, P_p, 1–P_p denotes return rate, disposal rate and the recovery rate. All returned products from customers must be collected. The inspection cost for returned items is incorporated into the overall collection cost. Returned products which cannot be recycled are sent to disposal centers, while the remaining items are returned to the original plant for recovery. The recycled materials are assumed to be of the same quality as the raw materials supplied by external vendors in the initial stage. Hence, plants prefer sourcing materials from collection or inspection centers over external suppliers. The uniform customer disbursement can be considered, even if you give no priority to the specific facilities, it means that all service point's prices remain constant. So, the total model can be described as

Total Cost = Transportation Cost + Fixed Opening Cost.

2.2. Mathematical Formulation

The objective of this model is to minimize the total cost of the proposed supply chain.

(i) Model indices

i – Index of supplier, $i = 1, 2....I$
j – Index of plant, $j = 1, 2....J$
k – Index of distribution center, $k = 1, 2....K$
l – Index of retailer, $l = 1, 2....L$
m – Index of customer, $m = 1, 2....M$
n – Index of inspection/collection center, $n = 1, 2....N$
o – Index of disposal center, $o = 1, 2....O$
p – Index of recovery/recycle center, $p = 1, 2....P$

(ii) Model Parameters

I – Number of suppliers
J – Number of plants
K – Number of distribution centers
L – Number of retailers
M – Number of Customers
N – Number of inspection/collection centers
O – Number of disposal centers
P – Number of Recycle centers
$\overline{S_i}$ – Number of products supplied by supplier 'i'
$\overline{P_j}$ – Number of products produce by plant 'j'
$\overline{D_{c_k}}$ – Capacity of distribution center 'k'
$\overline{R_l}$ – Capacity of retailer 'l'
$\overline{D_m}$ – Demand of customer 'm'
$\overline{C_{o_n}}$ – Capacity of collection/inspection center 'n'
$\overline{D_{i_o}}$ – Capacity of disposal center 'o'
$\overline{R_{c_p}}$ – Capacity of recycle center 'p'
p_m^C – Return percentage of customer 'm'
$p_n^{C_0}$ – Disposal percentage of collection/inspection center 'n'
$1 - p_n^{C_0}$ – Recovery percentage of collection center 'n'
P_n –Return percentage of collection/inspection center 'n'
$P_p^{R_c}$ – Disposal percentage of recycle center 'p'
$1 - P_p^{R_c}$ – Recovery percentage of recycle center 'p'

(ii) Cost Model Parameters

The following parameters are considered as transportation cost per unit:
C_{ij}^{SP} – From supplier to plant
$C_{jk}^{PD_c}$ – From plant to distribution center
$C_{kl}^{D_cR}$ – From DC to retailer
C_{lm}^{RC} – From retailer to customer
$C_{mn}^{CC_o}$ – From customer to collection/inspection center
$C_{no}^{C_oD_i}$ – From collection/inspection center to disposal center
$C^{C_oR_C}_{np}$ – From collection/inspection center to recycle center
$C_{pj}^{R_CP}$ – From recycle center to plant
$C_{po}^{R_CD_i}$ – From recycle center to disposal center
C_{jl}^{PR} – From plant to retailer
C_{jm}^{PC} – From plant to customer
$C_{km}^{D_cC}$ – From distribution center to customer
The following parameters are considered as fixed cost of each node:
C_j^P – For operating plant 'j'
$C_k^{D_c}$ – For distribution center 'k'
C_l^R – For retailer 'l'
$C_n^{c_o}$ – For collection/inspection center 'n'
$C_o^{D_i}$ – For disposal center 'o'
$C_p^{R_c}$ – For recycle center 'p'

(iii) Decision Variables

The following variables are considered as number of products transported:
X_{ij}^{SP} – From supplier i to plant j
$X_{jk}^{PD_c}$ – From plant j to DC 'k'
$X_{kl}^{D_cR}$ – From DC k to retailer l
X_{lm}^{RC} – From Retailer 'l' to customer 'm'
$X_{mn}^{CC_0}$ – From customer 'm' to collection/Inspection center 'n'
$X_{no}^{C_oD_i}$ – From collection/inspection center 'n' to disposal center 'o'
$X_{np}^{C_oR_c}$ – From collection/inspection center 'n' to recycle center 'p'
$X_{pj}^{R_cP}$ – From Recycle center 'p' to plant 'j'
$X_{po}^{R_cD_i}$ – From Recycle center 'p' to disposal center 'o'

(iv) Binary Relations about the Proposed Model

$$X_j^P = \begin{cases} 1, & \text{if plant 'j' is used for production and remanufacturing,} \\ 0, & \text{otherwise.} \end{cases}$$
$$X_k^{D_c} = \begin{cases} 1, & \text{if distribution center 'k' is used for distribution,} \\ 0, & \text{otherwise.} \end{cases}$$
$$X_l^R = \begin{cases} 1, & \text{if retailer 'l' is used for distribution,} \\ 0, & \text{otherwise.} \end{cases}$$
$$X_n^{C_o} = \begin{cases} 1, & \text{if collection/inspection center 'n' is used for collecting/inspecting,} \\ 0, & \text{otherwise.} \end{cases}$$
$$X_o^{D_i} = \begin{cases} 1, & \text{if disposal center 'o' is used for safe disposal,} \\ 0, & \text{otherwise.} \end{cases}$$
$$X_p^{R_c} = \begin{cases} 1, & \text{if recycle center 'p' is used for recycle,} \\ 0, & \text{otherwise.} \end{cases}$$

To construct the cost function, some components are obtained by multiplying the unit transportation cost by the quantity transported from each origin to its corresponding destination, the remaining components of the cost function accounts for the fixed operating cost associated with each facility in the logistics and manufacturing network.
The mathematical formulation of the cost:
$Min\ Z = \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{SP} * X_{ij}^{SP} + \sum_{j=1}^{J}\sum_{k=1}^{K} C_{jk}^{PD_c} * X_{jk}^{PD_c} + \sum_{k=1}^{k}\sum_{l=1}^{L} C_{kl}^{D_cR} * X_{kl}^{D_cR} + \sum_{l=1}^{L}\sum_{m=1}^{M} C_{lm}^{RC} * X_{lm}^{RC} + \sum_{m=1}^{M}\sum_{n=1}^{N} C_{mn}^{CC_0} * X_{mn}^{CC_0} + \sum_{n=1}^{N}\sum_{o=1}^{O} C_{no}^{C_0D_i} * X_{no}^{C_0D_i} + \sum_{j=1}^{J}\sum_{l=1}^{L} C_{jl}^{PR} * X_{jl}^{PR} + \sum_{j=1}^{J}\sum_{m=1}^{M} C_{jm}^{PC} * X_{jm}^{PC} + \sum_{k=1}^{K}\sum_{m=1}^{M} C_{km}^{D_cC} * X_{km}^{D_cC} + \sum_{n=1}^{N}\sum_{p=1}^{P} C_{np}^{C_0R_c} * X_{np}^{C_0R_c} + \sum_{p=1}^{P}\sum_{j=1}^{J} C_{pj}^{R_cP} * X_{pj}^{R_cP} + \sum_{p=1}^{P}\sum_{o=1}^{O} C_{po}^{R_cD_i} * X_{po}^{R_cD_i} + \sum_{j=1}^{J} C_j^p * X_j^p + \sum_{k=1}^{K} C_k^{D_c} * X_k^{D_c} + \sum_{l=1}^{L} C_l^R * X_l^R + \sum_{n=1}^{N} C_n^{c_0} * X_n^{c_0} + \sum_{o=1}^{O} C_o^{D_i} * X_o^{D_i} + \sum_{p=1}^{P} C_p^{R_c} * X_p^{R_c}$

Since the capacities are deterministic, the following constraints described the limitations of suppliers, manufacturing plants, distribution centers, and retailers in the forward logistics flow then collection/inspection centers, disposal centers, and recycling centers pertain to the reverse logistics flow.

$$\sum_{j=1}^{J} X_{ij}^{SP} \leq \overline{S_i},\ \forall i \in I \tag{1}$$

$$\sum_{k=1}^{K} X_{jk}^{PD_c} + \sum_{l=1}^{L} X_{jl}^{PR} + \sum_{m=1}^{M} X_{jm}^{PC} \leq X_j^P \overline{P}_j, \ \forall j \in J \tag{2}$$

$$\sum_{l=1}^{L} X_{kl}^{D_cR} + \sum_{m=1}^{M} X_{km}^{D_cC} \leq X_k^{D_c} \ \overline{D_{c_k}}, \ \forall k \in K \tag{3}$$

$$\sum_{m=1}^{M} X_{lm}^{RC} \leq X_l^R \ \overline{R_l}, \ \forall l \in L \tag{4}$$

$$\sum_{p=1}^{P} X_{np}^{C_oR_c} + \sum_{o=1}^{O} X_{no}^{C_oD_i} \leq X_n^{C_0} \ \overline{C}_{0_n}, \ \forall n \in N \tag{5}$$

$$\sum_{j=1}^{J} X_{pj}^{R_cP} + \sum_{0=1}^{O} X_{po}^{R_cD_i} \leq X_p^{R_c} \ \overline{R}_{c_p}, \ \forall p \in P \tag{6}$$

$$\sum_{n=1}^{N} X_{no}^{C_oD_i} + \sum_{p=1}^{P} X_{po}^{R_cD_i} \leq X_o^{D_i} \ \overline{D_{i_0}}, \ \forall o \in O \tag{7}$$

In the aforementioned constraints, constraint (1) represents the maximum capacity of suppliers supplied by supplier ‘i’, (2) represents the maximum capacity of plants produced by plant ‘j’, (3) represents the maximum capacity of distribution centers ‘k’ and (4) represents the maximum capacity of retailers ‘l’. Equation (5) represents the maximum capacity of collection center ‘n’. Equation (6) represent the maximum capacity of recycle center ‘p’. Equation (7) represents the maximum capacity of disposal centers ‘o’.

Here, the supply chain network is designed to be conservative, meaning that customer demands must be fully met without any shortages.

$$\sum_{j=1}^{J} X_{jm}^{PC} + \sum_{k=1}^{K} X_{km}^{D_cC} + \sum_{l=1}^{L} X_{lm}^{RC} = \ D_m, \ \forall m \in M \tag{8}$$

Based on the assumption, only a fraction p_m items are returned by customers, fraction p_n items to be disposed of and fraction $(1 - p_n)$ items should be recovered/recycled in existing model. Similarly, P_n, P_p and $1 - P_p$ denotes returned items by collection center, items to be disposed and items to be recycled respectively. In the supply chain, the inflow and outflow at each node must be balanced, to ensure the flow of conservation throughout the network.

$$\sum_{i=1}^{I} X_{ij}^{SP} + \sum_{p=1}^{P} X_{pj}^{R_cP} = \sum_{k=1}^{K} X_{jk}^{PD_c} + \sum_{l=1}^{L} X_{jl}^{PR} + \sum_{m=1}^{M} X_{jm}^{PC}, \ \forall j \in J \tag{9}$$

$$\sum_{j=1}^{J} X_{jk}^{PD_c} = \sum_{l=1}^{L} X_{kl}^{D_cR} + \sum_{m=1}^{M} X_{km}^{D_cC}, \ \forall k \in K \tag{10}$$

$$\sum_{j=1}^{J} X_{jl}^{PR} + \sum_{l=1}^{L} X_{kl}^{D_cR} = \sum_{m=1}^{M} X_{lm}^{RC}, \ \forall l \in L \tag{11}$$

$$p_m^c \left(\sum_{j=1}^{J} X_{jm}^{PC} + \sum_{k=1}^{K} X_{km}^{D_cC} + \sum_{l=1}^{L} X_{lm}^{RC} \right) = \sum_{n=1}^{N} X_{mn}^{CC_o}, \ \forall m \in M \tag{12}$$

$$\left(1 - p_n^{C_o}\right) \left(\sum_{n=1}^{N} X_{mn}^{CC_0} \right) = \sum_{p=1}^{P} X_{np}^{C_0R_c}, \ \forall n \in N \tag{13}$$

$$(1 - P_p^{R_c}\ ) \sum_{n=1}^{N} X_{np}^{C_0 R_c} = \sum_{j=1}^{J} X_{pj}^{R_c P},\ \forall p \in P \tag{14}$$

$$\sum_{o=1}^{O} X_{no}^{C_0 D_i} = P_n^{C_o} \sum_{m=1}^{M} X_{mn}^{CC_0},\ \forall n \in N \tag{15}$$

$$\sum_{o=1}^{O} X_{po}^{R_c D_i} = P_p^{R_c} \sum_{n=1}^{N} X_{np}^{C_0 R_c},\ \forall p \in P \tag{16}$$

The above equations (9)-(16) described the sum of the items from the plant to distribution centers,retailers and customers is equal to the sum of the total recyclable items from collection/inspection centers. Here all the decision variables to be non-negative or binary respectively. Memetic algorithm is used to obtain the optimal solution for a non-deterministic polynomial problem which provide the approximation to the respective solution.

3. Solution Approach

In general, probabilistic algorithms, approximation algorithms, and metaheuristic algorithms are used to solve non-deterministic polynomial problems. Although the aforementioned evolutionary algorithms are widely employed, they usually lack adequate search intensification, mostly depending on their goal in multidirectional search capabilities. The memetic algorithm, which was first presented by Moscato and Norman in 1992, improves the genetic algorithm by adding local search strategies to raise the search strength level. A population-based heuristic optimization technique that blends local exploitation with global exploration is the memetic algorithm. Wand and Hsu developed the two important algorithms (i) genetic operators (ii) Chromosome representation. The chromosome must encode all essential information required to solve the optimization problem. But the chromosome structure plays a critical role in the efficiency of the metaheuristic algorithms. Initially, they were using an evolutionary algorithm such as MA, particularly to design the structure of the chromosome and provides the potential solution.
Figure 2 denotes the integrated forward & reverse transportation network Model. We analyzed the above model such as
(i) Forward Logistics procedure
Suppliers (S_1,S_2) to Plants (P_1, P_2) to Distribution Centers (D_1, D_2) to Retailers (R_1,R_2) to Customers (C_1,C_2).
(ii) Reverse Logistics procedure
Products return from the customer (C_1, C_2) to Collection Centers (CC_1,CC_2) to Recycling Center (R_{c_1}) or Disposal Center (D_{S_1}). After Recycling the customer demand will be satisfied through as usual forward process. Figure 3 denotes the block diagram of the proposed model.

3.1. Description of the proposed algorithm

Memetic Algorithms (MA) is very useful in the optimization of logistics because it is a hybrid algorithm which combines evolutionary algorithms that handle the global search with local search algorithms that help in refining. The MA consider important logistics parameters, including the distance/cost matrix, vehicle capacity, customer demand, time windows, fleet size, and depot locations and incorporate them into the optimization process. As an example, the distance matrix can assess the cost of routes, whereas vehicle capacity can be used to find feasible solutions. The algorithm starts with the initiation of a population of feasible solutions, and then parent solutions are selected, by the use of such methods as tournament selection. Crossover involves the combination of parents to give birth to offspring and maintain good traits whereas mutation brings diversity by small random mutations. Local search, e.g. 2-opt optimization is used to refine offspring in order to enhance the quality of the solution. Finally, replacement eliminates the worst in the population to improve the offspring and guarantees that there is a continuous evolution. Stopping criteria are used to efficiently terminate the algorithm - there are maximum generation,

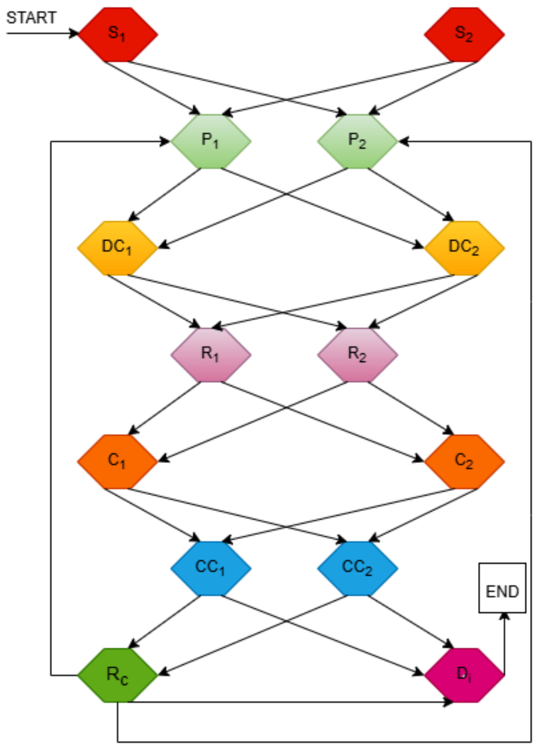

Figure 2. Integrated Transportation Network Model

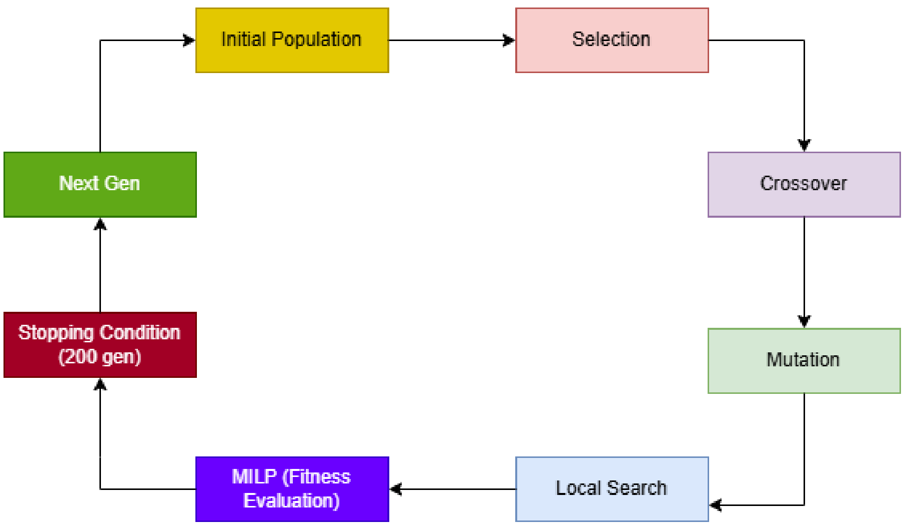

Figure 3. Block Diagram of the proposed Model

convergence, fitness, or time limits - and to trade off the cost of the solution and efficiency. This systematic solution makes MA an effective solver of difficult logistics issues such as vehicle routing. Chromosomes represent the capture of the vector flow of the retailer allocation capacity transversely and the potential conveniences. After the mutation, the local search will be activated with the low probability to obtain the nearest values by improving the efficient solution, and each solution will be evaluated through MILP to obtain the optimal route allocation. The integration of GA with the local search ensures the local refinement, leading to the high-quality solutions.

3.2. Objective Function

Min Z = Forward Logistics Cost + Reverse Logistics Cost + Fixed Cost

Memetic Algorithm Based Computational Experiment
Solution Representation:
Each Chromosome the shipment quantities across the supply chain network:

$$X = [x_{sp}, x_{pd_c}, x_{d_c r}, x_{cc_o}, x_{c_o d_i}]$$

Where x_{sp} – Supplier to plant shipment, x_{pd_c}- Plant to Distribution center, $x_{d_c r}$ – Distribution center to Retailer , x_{cc_o} – Return flow to collection, $x_{c_o d_i}$ – Collection to Disposal.
Therefore,

$$MinZ = C_f + C_t + C_r,$$

where
$C_f = \sum c_{sp}x_{sp} + \sum c_{pd_c}x_{pd_c} + \sum c_{d_c r}x_{d_c r}$ (Forward Logistics)
$C_r = \sum c_{cc_o}x_{cc_o} + \sum c_{c_o d_i}x_{c_o d_i}$ (Reverse Logistics)
$C_t = F_p + F_{d_c} + F_{r_c}$.

Here, forward shipment cost analyses through the respective parameters such as: suppliers to plants to distribution centers to retailers to customers. Reverse flow costs consider as (returns, recycling, disposal and remanufacturing). Figure 4 represents the flow chart for optimal solution.

3.3. Description of the Solution procedure of Memetic Algorithm

The importance of this algorithm is that it developed the genetic algorithm; it combines the global and local search.
Step 1: Encoding Problem

- Define the chromosome representation.
- X – represents the solution of vector shipment quantities and inventory model.

Step 2: Initial Populations

- Make a random sufficient solution; it will satisfy the flow constraints, capacity, and demand.
- Improve the starting population through greedy heuristics (i.e., nearest cost allocation),

Step 3: Evaluation of Fitness

- Using the objective function, find the total cost.
- Rewarded and random sufficient solutions, like those equal to the lower cost value, to better solutions.
- Infeasible solution gets a penalty.

Step: 4 Selections

- Select parent solution to using vehicle routing selection.

Step 5: Genetic Operators:

- Crossover Exchange shipment flow.
- Shifting Units between the DCs or retailers.

Step 6: Memetic Component.

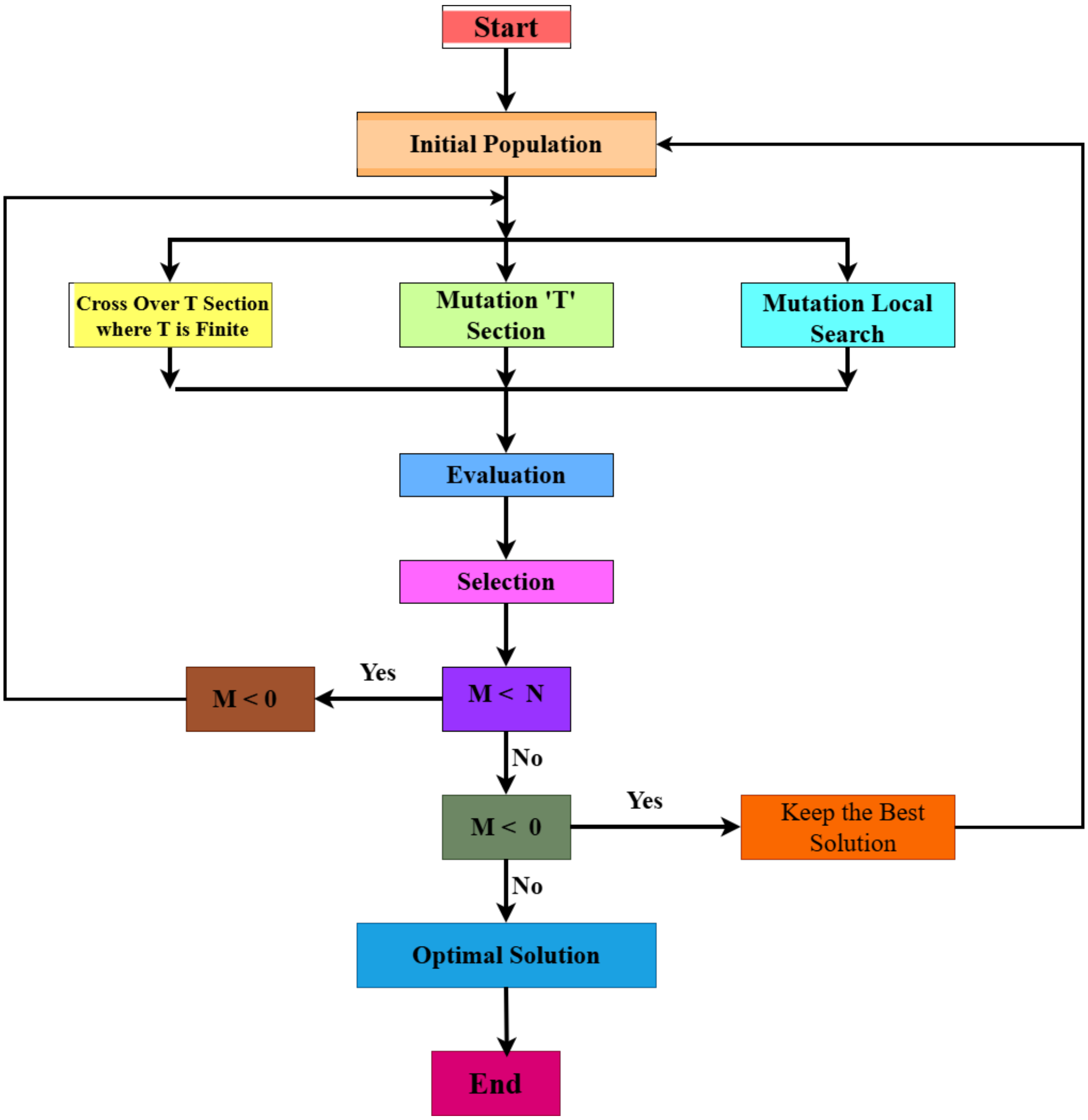

Figure 4. Flow Chart for Optimal Solution

- Use Variable Neighborhood Descent Method.
- Adjust shipment to nearest cheapest facility.
- Minimize the unnecessary routing returns.
- Cost savings for disposal units.

Step 7: Restrictedness

- Keep the unchanged best solution in the next generation.

Step 8: Iteration Process

- Repeat Selection to Cross Over.
- Cross Over to Mutation.
- Mutation to local search.

- Local Search to selectiveness.

If the convergence has been attained in the maximum iteration, then the result is unchanged. (constant).
Step 9: Result Output

- Best Solution = Inventory plan with minimum cost + shipment plan.
- The sum of the reverse logistics plan and present optimal forward value is the output of this model.

3.4. Complete Description of the Proposed Memetic Algorithm

3.4.1. Problem Representation: Let $I = \{1, 2, ..., m\}$ be the set of retailers.
$J = \{1, 2, ..., n\}$ be the set of candidate distribution centers.
Parameters:
F_j : Fixed opening cost of facility 'j'
C_{ij} : Transportation cost per unit
d_i : Demand of retailer 'i'
U_j : Capacity of facility 'j'

(i) Chromosome Encoding
Each chromosome is represented as concatenated vector:
Chromosome = $\{Y_1, Y_2, ..., Y_n \;/\; X_{11}, X_{12}, ..., X_{mn}\}$
Interpretation: (a) Facility 1 is opened; Facility 2 is closed (b) Retailer 1 receives 50 units from facility 1 (c) Retailer 2 receives 30 units from facility 1 (d) No flow from closed facility.
This representation ensures that:

$$\sum_j X_{ij} = d_i, \ \forall i$$
$$\sum_i X_{ij} = U_j d_i, \ \forall j$$

(ii) Fitness Evaluation:
The fitness function is the total supply chain cost computed directly from the chromosome:
Fitness = $\sum_{j=1}^{n} F_j Y_j + \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} X_{ij}$
No MILP is solved during evaluation. The chromosome itself determines facility decision and flow allocation. Feasibility is ensured through repair mechanisms.
(iv) Genetic Operators:
A two part crossover operator is employed and the genetic operators employed in the Memetic algorithm.

1. Binary Segment (Facility Decisions): Uniform crossover is applied, where each gene Y_i is inherited from their parent with probability 0.5.
2. Flow segment (Shipment Quantities): Arithmetic crossover is applied as $X_{ij}^{*} = \alpha X_{ij}^{1} + (1 - \alpha) X_{ij}^{2}$, where $\alpha \in [0, 1]$.

(i) Crossover Operator
Let parents be p^1 and p^2.
Select crossover points $k_1 < k_2$.
Offspring generations: $O = p^1[1 : k_1] \cup p^2[k_1 + 1 : k_2] \cup p^1[k_2 + 1 : end]$.
(ii) Capacity and demand violations are repaired after crossover.
Pseudo Code:
Input: p^1 and p^2.
Select k_1, k_2 randomly
Offspring= concatenate
 $(p^1[1 : k_1]$
 $p^2[k_1 + 1 : k_2]$
 $p^1[k_2 + 1 : end])$

Repair infeasibility
Return Offspring

(iii) Mutation
Mutation is also defined in two stages:

- Binary Mutation: bit–flip with probability p_m.
- Flow mutation: small perturbation defined as $X_{ij}^{*} = X_{ij} + \delta$, where $\delta \sim U(- \in, \in)$.

Constraint repair mechanisms (Demand Satisfaction, Capacity Compliance and Non – negative Constraints) are applied to ensure feasibility after genetic operations.

3.5. Local Search: Variable Neighbourhood Descent (VND)

To intensify high quality solutions, a deterministic VND procedure is integrated.
Define three neighbourhood structures as follows:
(i) Facility Toggle Move: Open or close one facility. (ii) Flow Reallocation Move: Shift small shipment quantities between facilities.
(iii) Swap Move: Exchange allocation patterns between two facilities.
The local search process operate as:

Input: Solution S
$K = 1$
While $k = 3$
  Generate neighbour S' in N_k
  If Fitness (S') < Fitness (S)
  $S = S'$
  $K = 1$
Else
$K = k + 1$
Return S

The local search is applied to the top 20% elite offspring in each generation. The search systematically explores neighbourhoods sequentially. If improvements is found, the process restarts from the first neighbourhoods; otherwise, it proceeds to the next. The search terminates when no neighbourhood yields further improvement.

3.6. Fitness Evaluation Mechanism

The evaluation procedure operates as follows:

- The binary segment determines open facilities.
- Given fixed facility decision, the shipment allocation sub-problem becomes a linear programming problem.
- The LP is solved efficiently using a polynomial time transportation solver.
- The total cost(facility + transportation cost) constitutes the fitness value

The MA avoids solving the MILP repeatedly and significantly reduces computational complexity. The MILP solver is used only for small benchmark validation, not during evolutionary evaluation.

3.7. Algorithm Structure: Pseudo Code

Initialize population P
Evaluate fitness for each chromosome
While stopping criterion not met do

Select parents
Apply crossover
Apply nutation
Repair infeasible solutions
Evaluate offspring fitness
Apply VND to elite individuals
Update population
End while
Return best solution found

4. Computational Study and Experimental Setup

The experimental framework based on benchmark instances of varying sizes, systematic parameter, generation, exact MILP validation and comparative Metaheuristic analysis.
Benchmark Instance Design:
To assess scalability and computational efficiency, three categories of benchmark instances (small, medium and large) were constructed. These instances differ in the number of suppliers, plants, distribution centers, retailers, customers, inspection centers and recycling centers. The network structure reflects realistic closed loop supply chain configurations encountered in industrial logistics systems.

Small scale instances were designed for solvable to optimality using exact MILP solvers, enabling validation of the proposed Metaheuristic, Medium and large scale instances reflect real world problems sizes where exact optimization becomes computationally intractable.

The benchmark sizes are summarized conceptually as follows:
(i) Small instances: Limited facilities and customers, used for exact validation.
(ii) Medium instances: moderate network size, used assess convergence behaviour.
(iii) Large Instances: High-dimensional networks, used to scalability and superiority.

4.1. Notations and Decision Variables

Let the closed loop supply chain be represented as a directed graph $G = (N, E)$, where N-denotes the set of facilities and 'E' denotes the set of transportation links.
Indices:
$i \in I$ – Suppliers
$j \in J$ – Plants
$k \in K$ – Distribution centers
$l \in L$ – Retailers
$m \in M$ – Customers
$n \in N$ – Inspection/Collection centers
$p \in P$ – Recycling Centers
$o \in O$ – Disposal centers
Decision Variables:
$X_{i,j}^{SP}$ – Quantity shipped from supplier 'i' to plant 'j'.
$X_{j,k}^{PD}$ – Quantity shipped from plant 'j' to distribution center 'k'.
$X_{k,l}^{DR}$ – Quantity shipped from distribution center 'k' to retailer 'l'.
$X_{l,m}^{RC}$ – Quantity shipped from retailer 'l' to customer 'm'.
$X_{no}^{C_0 D_i}$ – Quantity sent from inspection 'n' to disposal center 'i'.
$X_{m,n}^{CC_0}$ – Returned quantity from customer 'm' to inspection center 'n'.
$X_{n,p}^{C_0 R_c}$ – Quantity sent from inspection 'n' to recycling center 'p'.

Binary variables determine whether facilities are opened or not.

4.2. Parameter Generation and Justification:

Transportation costs were generated using a discrete based model $c_{ij} = \alpha \times d_{ij}$, where d_{ij} is the Euclidean distance between nodes 'i' to 'j', and α is a transportation cost coefficient selected from the interval and it reflecting fuel, labor and handling costs commonly used in logistics studies. Facility capacities were generated within realistic industrial ranges, ensuring feasibility across all echelon. Customer demand values were uniformly distributed within predefined bounds to simulate market variability,
Reverse logistics parameters were defined as follows:
Return state: $\rho \in [0.1, 0.3]$
Recycling fraction: $\beta \in [0.5, 0.9]$
Disposal fraction: $1 - \beta$
These values reflect typical product return and recovery behavior observed in closed loop supply chains.

4.3. Experimental Setup:

All experiments were conducted in MATLAB on a standard computing environment. The proposed MA, Genetic Algorithm and simulated Annealing (SA) were implemented using identical stopping criteria to ensure fairness.

Algorithm Parameters
(i) Population Size: 200
(ii) Crossover Probability: 0.9
(iii) Mutation Probability: 0.02
(iv) Local Search: Variable Neighbourhood Descent (VND)
(v) Maximum iterations: 200
(vi) Number of independent runs: 10
The MA integrates a local improvement phase within each generation, allowing intensification around promising solution while maintaining global exploration through evolutionary operators.

4.4. MILP Validation for small Instance:

Small scale benchmark instances were solved using an exact mixed integer linear programming formulation implemented through MATLAB. The solver was configured with a strict optimality tolerance of 10^6 and a maximum time limit of one hour.
The objective values obtained by the MA were compared against MILP optimal solutions.
Results: Demonstrate that the MA consistently achieves near optimal solutions, with an average optimality gap below 0.3%, while requiring significantly lower computation time. This confirms the correctness of the mathematical formulation and validates the effectiveness of the MA.

4.5. Metaheuristic Comparison for Medium and Large Instances:

For medium and large scale instances, the MILP solver failed to converge within the prescribed time limit due to the exponential growth of decision variables. Therefore, performance comparison was conducted among MA, GA and SA.
The evaluation metrics include:
(i) Best objective value (ii) Average objective value (iii) Standard deviation across runs (iv) Computational time (v) Convergence speed.

The MA consistently outperformed GA and SA, achieving 2-4% lower total cost and demonstrating faster convergence due to its hybrid global local search mechanism.

Convergence Analysis:
Convergence behavior was analyzed by plotting objective values versus iteration count. The MA exhibits rapid initial improvement followed by stable refinement, indicating effective exploitation. In contrast, GA shows slower convergence while SA exhibits higher variance and less stability. The reduced variance and faster convergence of the MA confirm the advantage of incorporating local search into the evolutionary framework.

4.6. Parameter Generation

Step 1: Realistic Transportation modeling: Each node is assigned random coordinates as $(x_i, y_j) \approx U(0, 100)$ for all facilities and customers.

Distance computation: For every arc (i,j), compute Euclidean distance $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

Step 2: Transportation Cost Generation:
Transportation cost per unit $c_{ij} = \alpha * d_{ij}$, linear distance model is widely used in supply chain optimization.

Step 3: Demand Generation
Customer demand is generated as: $D_m \sim U(D_{min}, D_{max})$, where (i) small $D_m \sim U(10, 40)$, (ii) medium $D_m \sim U(20, 80)$, and (iii) large $D_m \sim U(50, 150)$.
Total demand: $D^{Total} = \sum_{m=1}^{M} D_m$.

Step 4: Facility Capacity Assignment:
Supplier capacity: $S_i = y_s * \frac{D^{Total}}{|I|}$, where $y_s \in [1.1, 1.3]$. This ensures suppliers can meet total demand.
Plant Capacity: $Cap_j^P = \gamma_p * \frac{D^{Total}}{|J|}$.
Distribution Center Capacity: $Cap_j^P = \gamma_p * \frac{D^{Total}}{|K|}$.
Step 5: Retailer Capacity: $Cap_j^P = \gamma_p * \frac{D^{Total}}{|L|}$. All scaling factors $y \in> 1$ ensure feasibility.
Step 6: Return Rate Modeling (Reverse Flow)
Define return fraction: $\rho \sim U(0.1, 0.3)$ and $R_m = \rho R_m$.

Step 7: Recycling and Disposal Fraction:
Define recycling fraction: $\beta \sim U(0.5, 0.9)$, Recycled = βR_m and Disposed = $(1 - \beta)R_m$
Fixed Cost Generation: Facility fixed costs scaled proportionally to capacity: $F_j^P = \delta_p Cap_j^P$, where $\delta_p \in [5, 15]$.
Similarly for DC, recycling and disposal centers. This avoids unrealistic fixed cost distortions.

Step 8: Feasibility Check: (i) $\sum_i S_i \geq D^{Total}$, (ii) $\sum_j Cap_j^P \geq D^{Total}$

5. Numerical Example

Experimental Setup:

To validate efficiency of the proposed optimization framework a computational experiment based on the Memetic Algorithm is conducted on the developed forward reverse supply chain network. The consider network structure consists of suppliers, manufacturing plants, distribution centers, retailers, customers and reverse logistics facilities such as collection centers, recycling centers and disposal centers. The objective of the model is to minimize the total operational cost, which includes forward transportation cost, reverse logistics cost and fixed facility operating cost.

Network parameter followed as
Forward Logistics Flow: $s \to p \to d_c \to r \to c$
Reverse Logistics Flow: $c \to c_o \to (d_i/r_c)$.
$(s_1, s_2) = (60, 50)\,, d_c = (70, 60)$.
Retailer Demand: $(r_1, r_2) = (30, 40)$.

Return and Recycling Parameter:
Customer Return Rate: 20%
Return Quantity: 70 x 0.2 = 14.
Recycling Rate: $\alpha = 0.7$, Disposal Fraction: $\beta = 0.3$
Recycled Units = Recycling Rate $\times$ Returned Quantity = 0.7 x 14 = 9.8 = 10.
Disposal Units: 14 – 10 = 4 units.

The transportation cost is given in Table 1.

Table 1. Transportation Cost

Route	Cost	Route	Cost
$s_1 \to p_1$	3	$d_{c_2} \to r_2$	2
$s_2 \to p_1$	2	$r_1 \to c_1$	1
$p_1 \to d_{c_1}$	4	$r_2 \to c_2$	1
$p_1 \to d_{c_2}$	5	$c \to c_0$	2
$d_{c_1} \to r_1$	2	$c_0 \to r_c$	3
$d_{c_1} \to r_2$	3	$c_0 \to d_i$	4
$d_{c_2} \to r_1$	4		

Fixed cost: (Plant, Distribution Center, Recover Center) = (1000, 500, 300)
Forward Cost Calculation:
(i) $S \to P$
$s_1 \to p_1 = 40$ and $s_2 \to p_1 = 30$.
Therefore: (40 x 3) + (30 x 2) = 180.
(ii) $P \to DC$

$$p_1 \to d_{c_1} = 40, p_1 \to d_{c_2} = 30.$$

Therefore: (40 x 4) + (30 x 5) = 310.
(iii) $D_c \to R$
$d_{c_1} \to r_1 = 30$ and $d_{c_2} \to r_2 = 40$.
Therefore: (30 x 2) + (40 x 2) = 140.
(iv) $r \to c$: ((30+40) x 1) = 70.
Total Forward Logistic Transportation Cost = 180+310+140+70 = 700.
Return Quantity = 14.

Case (i) Recycle Center Closed (All returns go to disposal)
Customer to Collection Center = 14 x 2 = 28.
Collection Center to Disposal = 14 x 4 = 56.
Reverse Cost = 28 + 56 = 84.
Fixed Cost(Plant + d_c) = 1500 units.

Therefore Total Cost = 700 + 84 + 1500 = 2284.

Case (ii) Recycle Center is open
Returned Units = 14, To be recycled = 10, Disposal = 4.
Customer to Collection Center = 14 x 2 = 28.
Collection Center to Recycle Center = 10 x 3 =30.
Collection Center to Disposal = 4 x 4 = 16.
Total Reverse Cost = 74.
Fixed Cost: (Plant + DC + Recycle) = 1800 units.
Total Cost: 700 + 74 + 1800 = 2574.

The comparison of recycle center is open and closed in Table 2.

Table 2. Comparison of Recycle center is open and closed

Recycle Center	Forward Cost	Reverse Cost	Fixed Cost	Total Cost
Closed	700	84	1500	2284
open	700	74	1800	2574

Table 2 discussed the transportation cost comparison in two cases such as (i) recycle center is open (ii) recycle center is closed. We concluded that even though the total transportation cost is greater while recycle center is open it leads to reduce the number of quantities to be disposed and reduce manufacturing cost, raw material purchase cost which improves the efficient resource usage and also helps to meet actual demand level with enhanced customer satisfaction level. We applied the conventional method to find the total cost which is highly complex for large instances. Using the memetic algorithm, we find transportation costs with local search to refine the obtained solutions very effectively and efficiently.

5.1. Memetic Algorithm Approach

The parameter values used in the computational experiment are defined according to the numerical example. The plant distributes products to two distribution centers, which continuously deliver goods to two retailers. Customer demand is assumed to be 30 units for the first retailer and 40 units for the second retailer. The return rate of used products is assumed to be 20% and the recycling efficiency is considered as: 70%

The Memetic Algorithm is implemented with a population size of 30 and a maximum of 50 iterations. The algorithm integrates global search operators such as selection, crossover and mutation with a local improvement strategy that refines candidate solution in the neighbourhood search space.

Iteration 1: Initial Population Generation

The algorithm randomly generates a feasible solution satisfying the network constraints
$x_{s_1p_1} + x_{s_2p_2} = 70$ (Supplier capacity constraints)
$x_{s_1p_1} = 35$, $x_{s_2p_2} = 35$ (Initial Allocation)
$x_{p_1dc_1} = 30,\ x_{p_2d_{c_2}} = 40$ (Plant to Distribution Centers)
$x_{d_{c_1}r_1} = 30,\ x_{d_{c_2}r_2} = 40$ (Distribution to retailers)
$x_{d_{c_1}R_1} + x_{d_{c_2}r_2} = 40$ (Customer Demand Constraints)
$x_{cc_o} = 0.2 \times 70 = 14$ (Return flow)
$x_{c_or_c} = 10, x_{c_0d_i} = 4$ (Recycling allocation)

(i) Cost allocation
Supplier to Plant: $C_{sp} = (35 \times 3) + (35 \times 2) = 175.$
Plant to DC: $C_{pd_c} = (30 \times 4) + (40 \times 5) = 320.$
DC to Retailer: $C_{d_cr} = (30 \times 2) + (40 \times 2) = 140.$

Retailer to customer : $70 \times 1 = 70$

(ii) **Forward cost**

$$C_f = 175 + 320 + 140 + 70 = 705.$$

(iii) **Reverse Cost**
Customer to Collection: $14 \times 2 = 28$
Collection to Recycle: $10 \times 3 = 30$
Collection to Disposal: $4 \times 4 = 16$ Therefore,

$$C_r = 28 + 30 + 16 = 74.$$

(iv) **Fixed Cost**

$$C_t = 1000 + 500 + 300 = 1800.$$

Total cost for First Iteration is: $Z^1 = 2580$.

Iteration 2: Crossover Operation

In second iteration, two candidate chromosome exchanged shipment quantities. The crossover improves transportation distribution.
New allocation: $x_{s_1p_1} = 38$, $x_{s_2p_1} = 32$.
Plant Distribution: $x_{p_1d_{c_1}} = 35$, $x_{p_1d_{c_2}} = 35$.
Retailer Allocation: $x_{d_{c_1}r_1} = 30$, $x_{d_{c_2}r_2} = 40$.

(i) **Cost allocation**
Supplier to Plant: $C_{sp} = (38 \times 3) + (32 \times 2) = 178$.
Plant to DC: $C_{pd_c} = (35 \times 4) + (35 \times 5) = 315$.
DC to Retailer: $C_{d_cr} = (30 \times 2) + (40 \times 2) = 140$.
Retailer to customer : $70 \times 1 = 70$.

(ii) **Forward cost**

$$C_f = 178 + 315 + 140 + 70 = 703.$$

(iii) **Reverse Cost**

$$C_r = 74$$

(iv) **Fixed Cost**

$$C_t = 1000 + 500 + 300 = 1800$$

Total cost for second iteration is: $Z^2 = 2577$.

Iteration 3: Mutation Operation

Mutation slightly modifies the shipment distribution to explore a new region of the search space.
Updated Shipment: $x_{s_1p_1} = 40$, $x_{s_2p_1} = 30$.
Plant Distribution: $x_{p_1d_{c_1}} = 40$, $x_{p_1d_{c_2}} = 30$.
Retailer Allocation: $x_{d_{c_1}r_1} = 30$, $x_{d_{c_1}r_2} = 40$.

(i) **Cost allocation**
Supplier to Plant: $C_{sp} = (40 \times 3) + (32 \times 2) = 180$.
Plant to DC: $C_{pd_c} = (40 \times 4) + (30 \times 5) = 310$.
DC to Retailer: $C_{d_cr} = (30 \times 2) + (40 \times 2) = 140$

Retailer to customer : $70 \times 1 = 70$.

(ii) **Forward cost**

$$C_f = 180 + 310 + 140 + 70 = 700.$$

(iii) **Reverse Cost**

$$C_r = 70.$$

(iv) **Fixed Cost**

$$C_t = 1000 + 500 + 300 = 1800$$

Total cost for third iteration is: $Z^3 = 2574$.

Iteration 4-24: Local Search (Memetic Improvement)
The memetic algorithm applied a local neighbourhood search to improve shipment distribution while maintaining feasibility constraints. The algorithm adjusts quantities within supplier capacity limits and recalculates cost.
The improvement rule is: $Z^{(k+1)} = Z^{(k)} - \Delta$, where Δrepresents cost reduction obtained through local search.
Through repeated refinement, the algorithm progressively reduces the total cost is:

$$Z^4 = 2555, Z^5 = 2550, ..., Z^9 = 2455, ..., Z^{14} = 2348, ..., Z^{19} = 2304, ..., Z^{24} = 2284$$

.

Iteration 25-49: Convergence Phase
After iteration 24, no further improvements is obtained. The solution stabilizes, indicating that the algorithm has reached the global optimum: $Z^{25} = Z^{26} = ...Z^{49} = 2284$.

Therefore, the optimal shipment plan obtained is: $x_{cc_o} = 14$, $x_{c_or_c} = 10$, $x_{c_or_i} = 4$.
Final Optimal Cost: $Z^* = 2284$. The convergence behavior determine that the Memetic Algorithm gradually improves the solution quality through evolutionary operations and local search modification. Initially, the algorithm starts with a moderately high cost value of 2580, which corresponds to a randomly produced feasible shipment allocation. A significant improvement ensures the first 20 iterations, our proposed algorithm will converges faster than the first 20 iterations on the local search space. After the 24^{th} iteration reaches the optimal cost value of 2284 and observed the remaining iteration have not further improvement. This mentioned that the proposed algorithm has converged to the global optimal solution under the given experimental setup.

To evaluate the performance of the proposed approach, the attained results are compared with some metaheuristic optimization techniques in Table 3.

Table 3. Comparison Analysis

Method	Total Cost
Genetic Algorithm	2410
Particle Swarm Optimization	2355
Simulated Annealing	2312
Memetic Algorithm	2284

The results demonstrate that the proposed work gets the lowest total cost among all compared methods. The improvement in solution quality occurs due to the fixed local search mechanism, which improves candidate solutions and checks precipitate convergence.
The percentage improvement compared with the genetic algorithm is almost: $\frac{2410-2284}{2410} \times 100 = 5.2.\%$
Similarly, the improvement compared with particle swarm optimization and the simulated annealing are approximately: 3% and 1.2% respectively.
So, these results confirmed that the proposed approach provides superior optimization capability for integrated forward reverse supply chain problems.

6. Conclusion

The proposed model develops an integrated forward and reverse supply chain optimization model using a memetic algorithm to minimize total transportation cost. It effectively incorporates forward distribution reverse logistics, recycling and disposal decisions within an integrated model. The proposed algorithm effectively satisfies supply, demand and capacity constraints while determining optimal shipment allocations. The convergence analysis confirms that the proposed model is faster than the traditional models and attains the global optimum within a limited number of iterations. The computational evaluation combined with local search, significantly improves the optimal cost. Also, the result comparison indicates that the proposed approach outperforms conventional metaheuristic methods such as Genetic Algorithm, PSO and SA in terms of cost minimization. The performance of the system is recognized to the integrated local search mechanism, which improves the solution.

Overall, the proposed method provides a strong and computationally efficient tool for solving complex supply chain optimization problem. Future, research may extend this work by integrating stochastic parameters, multi objective formulations and large scale real world applications for ensuring its practical applicability and reliability.

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