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Original Article

Reverse Logistics of Waste Plastic Model Optimization Using Genetic Algorithm

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Abstract - *Plastic waste management is critical on a global scale because of the widespread environmental and economic consequences. Businesses are confronted with increasing cost challenges, forcing an increasing number of them to investigate alternatives for more cost-effective product returns and recycling solutions. Several studies have investigated the challenges of reverse logistics for various waste materials such as C&D wastes, iron, and aluminium; there exists a significant gap in research addressing the holistic incorporation of reverse logistics for plastic waste. This research aims to fill this gap by proposing a comprehensive model that not only minimizes the total reverse logistics cost but also determines the optimal number of recycling plants. The proposed waste plastic recycling model introduces a distinctive two-stage modelling approach, integrating collection centres before recycling plants. This novelty is crucial for minimizing transportation costs from municipalities to recycling plants, given that plastic is a low-density material and is often mixed with non-plastic substances like dirt, iron, and aluminium. To address this issue effectively, the proposed model employs a mixed-integer linear programming deterministic model, solved using the Genetic Algorithm (GA). The model's effectiveness is validated through practical applications involving illustrative examples that demonstrate its applicability to the complexities of reverse logistics in the waste plastic management field.*

Keywords - *Plastic recycling, Reverse logistics, Waste management, Genetic algorithm, Mixed integer linear programming.*

1. Introduction

Plastics are extremely versatile industrial materials with wide application in different sectors of the economy due to their low density and easily mouldable in nature leading to a 4% annual output growth in plastic production forecasted by 2030 [1]. Plastics are non-biodegradable, thus causing a great impact on the environment and climate change also recycling rate of waste plastics is approx. 14% as compared to some other metals whose recycling rate is as high as 90% [2]. Over the past few decades, plastic has accumulated in large quantities in aquatic and terrestrial ecosystems as well as landfills around the world due to an increase in the amount of plastic manufactured, inappropriate waste management techniques, impulsive human behaviour, and negligence [3]. Thus, waste reduction and recycling of waste plastic have become important areas for plastic industry activities due to the shrinking of landfill lands particularly in urban areas.

Reverse logistics, as defined by Fleischmann [4], involves the strategic planning, implementation, and monitoring of a smooth entering flow and storage of subordinate products and their related information. This method is used in the reverse direction of the traditional supply chain, aiming towards reclaiming value and ensuring appropriate disposal. Reverse logistics is distinct from conventional forward logistics, which involves the production and sale of new materials or parts to customers. The complexity of recovery routes and the limited number of recovery centres pose challenges in forecasting the time or quantity of returns in reverse logistics. These uncertainties arise from factors such as the period of product use and the conditions of recovered items. The waste plastic reverse logistics route comprises a range of tasks such as gathering, organizing, stockpiling, moving, compressing or compacting, shredding, and liaising with customers alongside the retro manufacturing process. [5].

Utilizing reverse logistics, especially for handling product returns, offers several advantages. It not only enhances customer reliability and potential sales but also contributes to the reduction of waste disposal costs, transportation expenses, and inventory holding costs associated with returned goods [6]. When contemplating the logistics network, a critical decision revolves around whether to outsource or maintain an in-house fleet. This decision is paramount, given that transportation typically represents the most significant cost component of reverse logistics operations [7]. Careful consideration of transportation options is vital for optimizing the efficiency and cost-effectiveness of the reverse logistics network.

Barros et al. [8] introduced a Mixed-Integer Linear Programming (MILP) model that addresses a multilevel capacitated warehouse location problem concerning sand recycling. The proposed model was optimized by implementing heuristic techniques. Within the sand recycling process, the study effectively pinpointed the optimal quantity, capacity, and locations for both depots and cleaning facilities. Another MILP model, as presented by Kirkke et al. [9], focused on a multilevel incapacitated depot position model. This particular model was applied to a case study revolving around a network of reverse logistics dealing with the collection, processing, and return of abandoned copiers. The investigation successfully determined the optimal locations and capacities of recovery facilities, along with transportation connections linking various points, thereby enhancing the overall logistics of copier return processes. Multi-objective optimization problems, which involve the simultaneous optimization of multiple objective functions, are extensively used across various domains, including management, economics, and engineering. Several ideas and solutions have emerged to handle the complexity and diversity of multi-objective problems. Since conflicting objective functions often arise, prioritizing one parameter may entail sacrificing others. Decision-makers must consider their preferences when determining which parameters to prioritize or sacrifice in the process of addressing a multi-objective problem [10]. Given that logistics network design problems are NP-hard, researchers have developed novel heuristics, meta-heuristics, and Lagrangian Relaxation (LR)-based approaches to solve these problems. Pishvaee and Torabi [11] noted that these methods have proven effective, particularly since exact techniques are impractical for addressing real-size problems associated with multi-objective mixed-integer programming (mo-MIP).

2. Literature Review

Bing et al. [12], after analyzing various scenarios, have developed a model for predicting future events and established a Mixed-Integer Linear Programming (MILP) scheme aimed at enhancing plastic recycling processes. Their aim was twofold: to minimize the environmental impact of plastic recycling and minimize transportation costs. Pati et al. [13], on the other hand, tackled paper recycling by adopting a Mixed-Integer Goal Programming (MIGP) approach. This model examined the complex interaction of different goals within the recycled paper distribution network, encompassing aspects like cost, quality improvement, and recovery benefits. Shulman [14] contributed to the discourse with a MILP model featuring multiple facility types with finite capacities. This model tackled the strategic placement of facilities within open plants to determine plant capacities over a planned horizon and also addressed the location problem of a capacitated dynamic plant by employing a Lagrangian relaxation technique. Dat et al. [15] ventured into the world of electrical and electronic devices and developed a strategy for cost minimization across multiple nodes of reverse logistics, including collection centres, disassembly centres, and treatment facilities. Their approach called for the development of a multi-objective genetic algorithm capable of effectively coping with large-scale challenges [16]. The Genetic Algorithm (GA), as a part of Evolutionary Computation (EC) approaches, has garnered significant attention and success in solving combinatorial optimization problems [17]. With its foundation in the principles of natural selection and genetics, the GA is a stochastic search technique known for its versatility and effectiveness, particularly in scenarios with vast search spaces and minimal prior information on problem solutions [18]. As a member of heuristic optimization techniques, GAs, alongside evolutionary algorithms, Tabu search, and Simulated Annealing (SA), have proven remarkably successful in providing optimal or near-optimal solutions for a diverse range of complex problems.

Bautista and Pereira [19] tackled the challenge of identifying optimal waste collection point locations in Barcelona by formulating a set coverage problem and devised a genetic algorithm to effectively address this problem, demonstrating a strategic approach to waste management. Gonzalez-Torre and Adenso-Diaz [20] developed a two-step objective programming model to optimize the distribution of recycling containers specifically for glass recycling. Their primary objectives were to maximize the quantity of material collected and minimize logistics expenses. The first stage involved determining bin distribution, while the subsequent stage focused on planning the most efficient routes. These studies concentrate on the tactical and operational levels, emphasizing the importance of determining optimal collection point locations and efficient routes for waste management. Recognizing the need to incorporate dynamic elements like lead times and inventory placements, Lieckens and Vandaele [21] expanded on a conventional model framed as a Mixed-Integer Linear Programming (MILP) with the integration of a queuing model and addressed the complexities of a dynamic system, considering factors such as unpredictability in determining optimal plant locations and lowering costs throughout the reverse supply chain. Their comprehensive approach highlights the importance of adapting waste management strategies to dynamic and uncertain conditions for enhanced efficiency and cost-effectiveness. Giri and Sharma [22] examined the relationships between the producer, retailer, collector, and raw material source by deciphering the intricacies of the closed-loop supply chain. Their contribution lies in proposing algorithms for sequential and global optimization, with a unique focus on considering product quality and introducing a threshold above which goods are earmarked for remanufacturing, showcasing the successful implementation of their suggested methods. This approach demonstrates a nuanced understanding of closed-loop supply chain dynamics. Alshamsi and Diabat [23] made significant strides by formulating a Mixed-Integer Linear Programming (MILP) model, and it not only determined optimal locations and capacity for crucial processes but also placed emphasis on transportation decisions and explored the choice between in-house and outsourced vehicles, building decisions on cost-effectiveness. Their contribution to the development of a robust Genetic Algorithm (GA) capable of quickly tackling large-scale problems in a very short period of time. The GA code devised led to a substantial reduction in the number of variables and constraints by 92% and 86%, respectively, showcasing an innovative approach to streamline and optimize the modelling process.

3. Problem Description

Illustrated in Figure 1 is the strategic-level waste plastic reverse logistics network formulated in this study. The configuration outlines fixed locations for municipalities, collection centres, and landfills. The comprehensive network is segmented into four integral components: municipalities (sources), collection centres, recycling plants, and landfills. A critical aspect necessitates an in-depth exploration of the location allocation problem, specifically pertaining to recycling plants for waste plastic. The overarching objective is cost minimization, entailing considerations of fixed costs, transportation costs, sorting costs, processing costs, and disposal costs. This analysis aims to optimize the spatial distribution of recycling plants to achieve efficiency and economize on various associated costs within the waste plastic reverse logistics network.

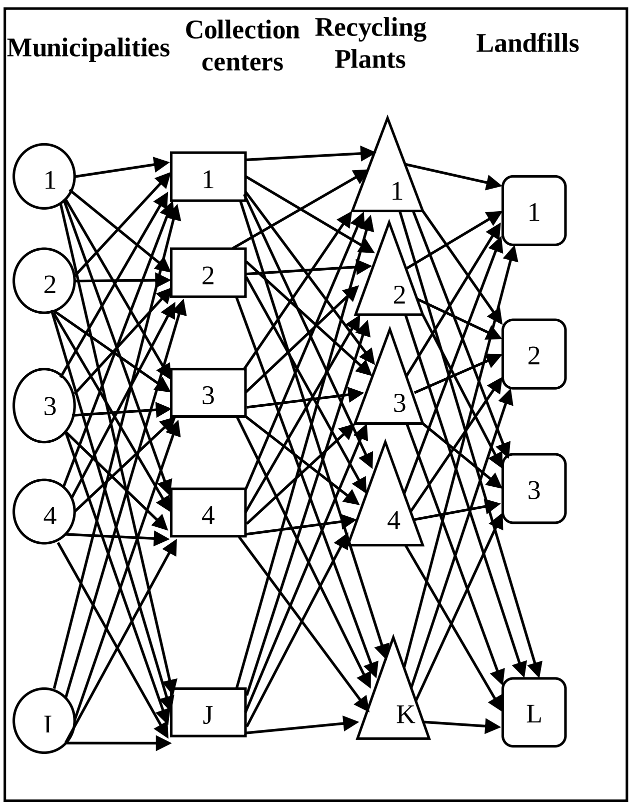

Fig. 1 Reverse logistics network of waste plastic recycling

There are I municipalities considered in the city of Patna: J collection centres, K recycling plants and L landfills. Waste plastic is collected from different households in a municipality, either in the form of dry garbage or wet garbage. In the collection centers, the plastic collected is segregated, and its density is increased by crushing to minimize transportation costs. Though some sorting and segregation of plastic waste are done at collection centres, bulk sorting and segregation are done at the recycling plants, after which processing and retromanufacturing are carried out. The residual waste, if any, is sent to the landfills.

Formulating the waste plastic reverse logistics network problem involves considering various parameters. With information on potential locations and capacities of collection centres and recycling plants, along with the total plastic waste generated by each municipality, transportation costs, fixed costs, sorting costs, processing costs, and disposal costs associated with waste plastic, the developed model aims to determine optimal solutions. Specifically, the model seeks to identify which potential waste plastic recycling facilities should be established and how the flow of waste plastic should be directed to these recycling plants. The ultimate goal is to design a reverse logistics network that minimizes overall costs, addressing the complex interplay of variables to achieve efficiency and economic viability in managing waste plastic.

3.1. Model Formulation

The anticipated model introduces a mixed-integer linear programming framework, incorporating both conventional continuous variables and integer variables. Key information, including the potential locations of recycling plants, cost structures for various processes in the reverse logistics of plastic waste (such as transportation, sorting, processing, and disposal), and the capacities of recycling plants and collection centres, is known. The primary goal of the proposed model is to strategically pinpoint the best locations for building recycling plants in the city of Patna. This overarching goal is designed to minimize the overall reverse logistics cost associated with waste plastic recycling, highlighting an effective and cost-effective approach to addressing the various aspects of waste plastic recycling. Index sets and parameters used in the MILP problem:

$i \in I$ - Set of sources or Municipalities
$j \in J$ - Set of collection centres
$k \in K$ - Set of recycling plants
$l \in L$ - Set of landfills

q_k = A binary value, either 0 or 1, indicates whether the recycling plant is open or closed.
D_k = Fixed cost of opening a recycling plant
a_{ij} = Total transportation costs from source i to collection centres j
v_{ij} = amount of waste plastic transported from source i to collection centers j
b_{jk} = Total transportation costs from collection centres j to recycling plants k

w_{jk} = amount of waste plastic transported from collection centres j to recycling plants k
c_k = Total sorting cost at recycling plants k
x_{jk} = amount of waste plastic sent from collection centres j to recycling plants k
d_k = Total processing cost at recycling plant
y_{jk} = amount of waste plastic sent from collection centres j to recycling plants k
e_{kl} = Total transportation costs from recycling plants k to landfill l
z_{kl} = amount of waste plastic sent from recycling plants to landfill l
S_j = Capacity of collection centres j
R_k = capacity of recycling plants k

Objective Function: -
Minimize (∑ Fixed cost + ∑ Transportation cost + ∑ Sorting cost + ∑ Processing cost +
∑ Disposal cost)

Minimise

$$\left(\sum_{k=1}^{K} D_k\, q_k + \sum_{i=1}^{I}\sum_{j=1}^{J} a_{ij}\, v_{ij} + \sum_{j=1}^{J}\sum_{k=1}^{K} b_{jk}\, w_{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} c_k\, x_{jk} + \sum_{j=1}^{J}\sum_{k=1}^{K} d_k\, y_{jk} + \sum_{k=1}^{K}\sum_{l=1}^{L} e_{kl}\, z_{kl} \right)$$

Subject to: -

$$\sum_{i=1}^{I} v_{ij} \le S_i \quad \forall \quad i \in I \tag{1}$$

$$\sum_{j=1}^{J} x_{jk} \le R_i \quad \forall \quad j \in J \tag{2}$$

$$\sum_{k=1}^{K} x_{jk} = \sum_{j=1}^{J} x_{ij} + \sum_{l=1}^{L} z_{kl} \quad \forall \quad k \in K \tag{3}$$

q_k= 0 or 1 where
q_k = 1 if recycling plant is open
q_k= 0 if recycling plant is not open

i = 1,2,3,4…………………. I

j = 1,2,3,4…………………. J

k = 1,2,3,4………………...K

$v_{ij}, w_{jk}, x_{jk}, y_{jk}, z_{kl} \geq 0$

The first term refers to the fixed cost associated with the establishment of the recycling plant. The second term refers to the transportation expenses involved in transporting waste plastic from its sources to the collection centres. The third term refers to the transportation costs from collection centres to the recycling plant. The fourth term refers to the sorting involved in the waste plastic recycling process. The fifth term refers to the processing costs, while the sixth term refers to the costs associated with transferring waste from the recycling plant to landfills. The first constraint (1) represents that the supply of waste plastic from sources to collection centres should be less than the capacity of the collection centres. The second constraint (2) states that the transfer of waste plastic from collection centres to the recycling plant must not exceed the capacity of the recycling plant. The third constraint (3), or balancing constraint, is based on the fact that the recycling plant neither produces nor consumes any material, thus acting as a pivotal balancing factor. These constraints collectively guide the optimization process, ensuring the model adheres to practical limitations and balances the flow of waste plastic within the reverse logistics network effectively.

4. Genetic Algorithm

Commonly known as a stochastic solution search technique, a genetic algorithm employs the principles of evolutionary computation to address combinatorial problems. This involves simulating the processes of natural selection and biological reproduction observed in animal species [24].

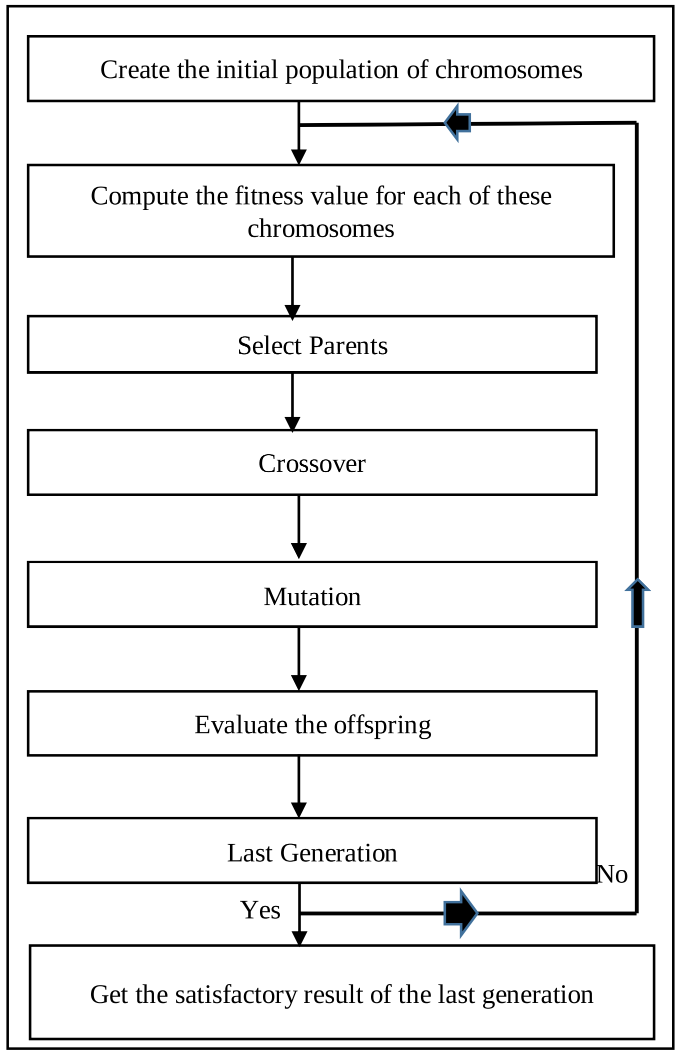

Fig. 2 Flow chart of the proposed GA

Significant research efforts have been dedicated to genetic algorithms, leading to the development of diverse encoding methods custom-made to specific problem domains over the past decade. The adaptability and effectiveness of genetic algorithms make them a widely explored and applied approach for solving complex combinatorial problems across various disciplines. Algorithm (GA) involves the careful design of a suitable chromosome. This chromosome, being subjected to a probabilistic transition rule, generates a population of chromosomes that competes fairly for the optimal solution. Within the context of this research, numerical value variables such as v_{ij}, w_{jk}, x_{jk}, and y_{jk} are employed alongside logical value variables denoted as q_k. The initial step in the successful implementation of a Genetic Algorithm (GA) involves the careful planning of a suitable chromosome. This chromosome, being subjected to a probabilistic transition rule, generates a population of chromosomes that competes fairly for the optimal solution. Within the context of this research, numerical value variables such as v_{ij}, w_{jk}, x_{jk}, and y_{jk} are employed alongside binary value variables denoted as q_k.

The method used in this research to define chromosomes is a hybrid encoding technique that mixes binary and floating-point representations. The format of these chromosomes is single-dimensional arrays with binary variables. These binary variables pertain to decision variables associated with municipalities, collection centres, recycling plants, and landfills. Concurrently, floating-point values within the chromosomes represent the transportation of waste plastic, delineating flows from source i to collection centres j, from collection centres j to recycling plants k, and from recycling plants k to landfills l. This hybrid encoding rule enhances the representation of chromosomes, providing a comprehensive framework for the optimization process within the genetic algorithm.

4.1. Evaluation

The evaluation procedure is essential because it assigns each member of the population a fitness value that represents their specific degree of fitness. Comparing an individual with others in the population is an important stage in this process. The fitness function that is applied is important since it needs to determine the desirability of the qualities that the chromosomes specify. Not only should this function be proficient at evaluating each solution, but it should also demonstrate computational efficiency, considering its repetitive use throughout the optimization process.

In instances where certain solutions within the population prove impractical, surpassing capacity limits for collection centres or recycling plants, the incorporation of a penalty function becomes imperative. The penalty function is designed to set a significantly higher penalty value in comparison to any potential objective value associated with the existing population of individuals. Mathematically expressed as "Fitness" in the developed algorithm, this penalty function is intended to address and discourage impractical solutions that deviate from the defined constraints.

$$\text{Fitness} = \{\text{Cmax} - f(X),\ \textit{if}\quad f(X) < C_{max}\ ; \quad 0,\ \textit{if}\quad f(X) \geq C_{max}$$

4.2. Selection Operator

The selection operator plays a vital role in enhancing the general quality of the population by preferring chromosomes of higher quality, thus increasing their chances of being copied into the next generation. There are various distinct selection techniques, each determining the reproduction opportunities for individual parents in the population. These techniques comprise random selection, roulette wheel selection, tournament selection, rank selection, and elitist selection, providing diverse approaches to parent selection [24]. In this study, the roulette wheel selection approach is employed as the method of selection. Using this method, two parents are chosen at random from each generation's solutions based on a probability value that represents the individual fitness to population fitness ratio. By use of this roulette wheel selection process, individuals are selected to advance into the following generation, improving the average population's overall quality. This approach ensures that high-quality chromosomes are granted a higher probability of being replicated in the upcoming generation, fostering the evolution of the population towards more favourable characteristics following equations (10)-(24), the proposed fuzzy reverse logistics network model can be completely translated into a corresponding crisp α-parametric model. Subsequently, this transformed model can be efficiently addressed as a mixed-integer linear programming problem.

5. Model Applications and Results

For the reduction of total reverse logistics cost associated with waste plastic recycling, the developed model is subjected to a numerical trial, specifically applied to evaluate the optimal number of waste plastic recycling plants required in the city of Patna, India. Given the scarcity of information regarding potential sources of waste plastics and demand points for recycled plastics in the Patna region, a systematic approach is employed. This involves the identification of 15 major sources of waste plastics, 20 significant collection centres, 30 major fixed-type recycling plants, and 5 landfills. The information is sourced from representatives of the Municipal Corporation of Patna, and the on-site reconnaissance is conducted to validate the relevant details. To identify potential locations for recycling plants, the assessment considers factors such as land availability and current land use, prioritizing waste or barren lands and existing waste dumping areas. These identified locations are graphically represented in Figure 3. The primary objective of this model is to build a reverse logistics network for waste plastic recycling and strategically select ideal locations. The lack of data to explore more intricate elements of the network design gives rise to this strategic focus.

In the city of Patna, where the practice of recycling waste plastic is not widespread, pertinent data has been gathered from waste plastic recycling plants situated in Indore, acclaimed as the cleanest city in India. This acquisition of data involved a combination of reconnaissance efforts and a structured questionnaire survey. Also, some of the relevant data was sourced from the Centre for Science and Environment (CSE) 2021 and the Central Pollution Control Board (CPCB) 2021 [25]. The fixed cost associated with setting up the recycling plants is US$ 60979, which includes initial land and machinery investment. The collection cost, including the cost of purchasing unsegregated waste plastic, is US$ 43830 every year. The sorting cost done manually to segregate different types of waste plastic is US$ 46740. The processing cost cumulative of electricity cost and cost of processing the sorted and shredded waste plastic is US$ 28630.

The transportation cost is US$ 36.59 per ton, which is included in the collection cost. The disposal cost or tipping charges is the cost of disposal of waste plastics or materials after processing is US$ 12.20 per ton. The processing capacity of recycling plants is 2850 tons/ year. The handling capacity and storage capacity are 2850 tons/year and 550 tons /year, respectively. The cost related to the environment has been incorporated into the disposal costs. To solve the deterministic model, the genetic algorithm is employed with the following parameters: a population size of 400, a maximum of 500 generations, a crossover rate of 0.9, and a mutation rate ranging from 5% to 10%, adjusting as the number of generations is increased. The execution of the genetic algorithm solution procedure is conducted on the MATLAB 2020b system, featuring 4GB RAM and 500GB memory. This configuration ensures a robust application of the genetic algorithm for optimizing the given model.

Table 1. Data used to implement the model

Description	Value
Total supply of waste plastic in Patna region	32,850 tons/year
Total demand for waste plastic	7673 tons/year
Capacity of plastic waste recycling plants for processing	2850 tons/year
Capacity of plastic waste recycling plants for management	2850 tons/year
Capacity of plastic waste recycling plants for storage	550 tons/year
Fixed cost for establishing a recycling plant	US$ 60979
Transportation cost	US$ 36.59 per ton per km
Sorting cost	US$116.85 per ton/year
Processing cost	US$ 71.57 per ton/year

The subsequent assumptions are also needed for the application of the developed reverse logistics network of waste plastic.

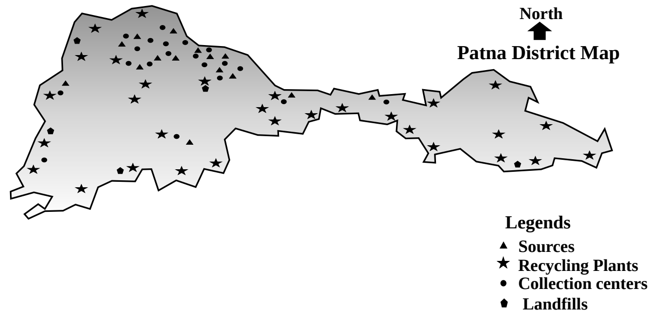

Fig. 3 Potential reverse logistics network for the deterministic model

- Mechanical efficiency remains consistent across similar types of facilities, such as collection centres and recycling plants.
- Municipalities are the city's primary suppliers of waste plastics. All the waste is collected from different households and collection points located in that particular municipality from where it is transported to the collection centres where all the different plastics and non-plastic materials are separated and shredded based on the type of plastics. In the final stage, the waste products reach the recycling plants, and subsequently, the residual waste from these recycling plants is disposed of in landfills.
- The waste belonging to the non-plastic categories like dirt, moisture, aluminium, and iron are not sorted to maintain mechanical efficiency, and this disposal happens only in collection centres.
- The network considers eight types of products, encompassing non-plastic, PET, HDPE, V, LDPE, PP, PS, and other resins, along with layered multi-material.

6. Sensitivity Analysis

Sensitivity investigation of the developed deterministic MILP model was done with variations in transportation cost, GA parameters, demand and supply. The results of optimization after varying transportation costs associated with waste plastic recycling are shown in Table 2. The location of the optimized recycling plant network in the city of Patna is shown in Figure 4.

Table 2. Results of optimization after varying transportation cost

Condition	Transportation Cost (US$)	Total Cost (US$)	No. of Plants Required
Base	43670	184,436	23
10% reduction	39302	172,575	23
20% reduction	34936	160,713	23
10% increase	48037	196,297	23
20% increase	52404	208,158	23

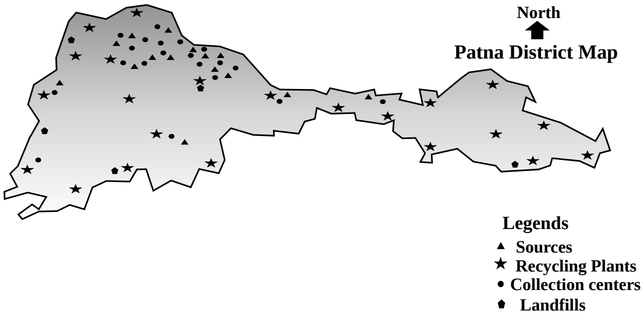

Fig. 4 Location of optimized recycling plants

Table 3. Results of the model with variation in the GA parameters

Generation	Population	No. of Recycling Plants	Total Cost (US$)
100	400	23	220,436
200	400	23	210,208
300	400	23	190,500
400	400	23	184,436
500	400	23	184,750
200	300	23	184,145
300	300	23	178,208
400	300	23	173,650
500	300	23	180,317

Variations in supply and demand for the reverse logistics network of waste plastics recycling are done, and optimized results are also shown in Figures 5 and 6. The number of recycling plants needed to be opened with variations in supply and demand of waste plastic is also shown. The results of the model with varying GA parameters are shown in Table 3.

The fitness value steadily decreased to a relatively constant level of 184,500 at the 400th generation. The application of the genetic algorithm to the model is not aimed at obtaining the most precise results but rather at achieving a satisfactory solution with high efficiency. The obtained optimal solution is 184,436, indicating the need to open 23 recycling plants. Remarkably, nine different combinations of genetic algorithm parameters produced results that were either identical or very similar. This implies that variations in population size or the maximum number of generations for the genetic algorithm have minimal impact on the model's solution. Such robustness suggests that the proposed genetic algorithm solution method exhibits resilience to adjustments in its parameters.

7. Conclusion and Future Scope

This research paper addresses the problem of designing a reverse logistics network specifically for recycling waste plastic. The suggested mixed-integer linear programming model aims to recognize the ideal number of recycling facilities required in Patna city while also curtailing the overall total cost of the reverse logistics network.

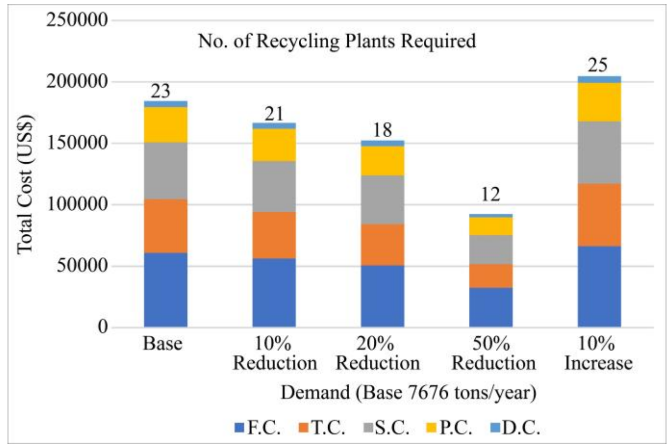

Fig. 5 Optimization results with variation in demand

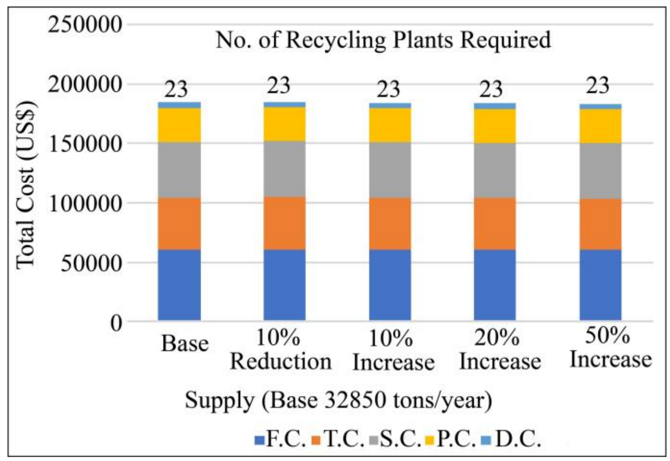

Fig. 6 Optimization results with variation in supply

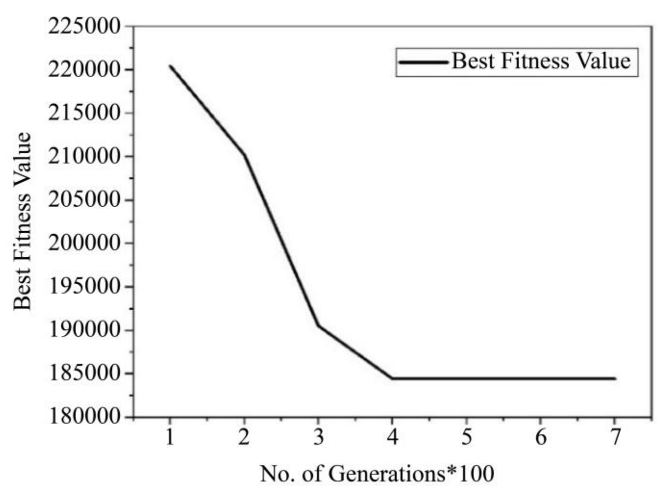

Fig. 7 Fitness value vs No. of generations of genetic algorithm

To enhance computational efficiency and obtain an acceptable solution, an evolutionary algorithm, specifically the genetic algorithm, is employed. The application of the genetic algorithm on practical-size problems involving 15 sources, 20 collection centres, 30 potential recycling plants, and 5 landfill sites demonstrates promising results. The model suggests the inclusion of collection centres before recycling plants to minimize transportation costs. This strategic placement is driven by the low density of plastic material and the impracticality of opening recycling plants in densely populated urban areas due to land and environmental constraints. The results of the numerical test show that the suggested strategy is more effective when used in tandem with the waste plastic reverse logistics model. They draw attention to increased efficiency, which is demonstrated by faster calculation and better optimization. Diverging from existing literature on reverse logistics for various materials, this paper pioneers the application of fundamental theories specifically to plastic waste. The primary objective is to improve the logic and effectiveness of the waste plastic return and recycling process, aiming to tackle a significant environmental issue prevalent in the contemporary world. While the proposed models and solution methods boast several merits, the paper also suggests avenues for future work in this evolving field:

1. By extending the model into a stochastic framework, the risks and uncertainties associated with establishing the reverse logistics network for waste plastic can be addressed. The changes in scenarios by varying different parameters can also be explored.
2. GA application in reverse logistics can also be compared to some newer algorithms like Ant Colony Optimization and Grey Wolf Optimization.
3. GA algorithm can also be combined with some other heuristics algorithms like Lagrangian relaxation, fuzzy logic and Tabu search methods.

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