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Optimizing Transportation Costs with a Hybrid Northwest Corner and Genetic Algorithm Strategy

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Abstract

Transportation problems are used in many real-world applications to determine the best way to ship products from supply to demand. Delivering certain goods from the supply to the demand is the subject of the transportation problem. The initial basic feasible solution is an essential step in solving the transportation problem's least total cost. Still, the current initial basic feasible solution techniques don't always offer an effective feasible solution that may reduce down the number of iterations needed to obtain the optimal solution. As a result, creating an improved initial basic feasible solution approach remains difficult. This study uses a two-stage solution strategy to solve the classical transportation problem. In order to provide an estimate for the transportation cost, the Northwest Corner Method is first applied to produce a feasible initially solution. In order to reduce the overall cost of transportation, a Genetic Algorithm is then used to enhance the initial solution. The hybrid approach makes use of the Genetic Algorithm's search capabilities for solution enhancing and the Northwest Corner Method's simple use and effectiveness for initialization. According to experimental data, the suggested approach converges to near-optimal solutions in an acceptable computational time and successfully lowers transportation costs when compared to conventional initial solutions.

Keywords: Transportation Problems; Genetic Algorithm; Northwest Corner Method; Least Cost Cell Method; Vogel's Approximation Method; Optimization.

1 | Introduction

The process of looking for the best solution among a finite or countably infinite set of possible solutions is known as discrete optimization or combinatorial optimization. The optimal scenario is defined in relation to a fit-ness function or an objective function that should be maximized or minimized. Combinatorial structures like sequences, arrangements, product choices, assignments, network routes, etc., might be the solutions. The two methods deterministic and stochastic are typically used to get these results. Only objective functions or constraints that are continuous or differentiable in solution space can be used with deterministic techniques, which are mostly gradient-based approaches. Although they are not always the best, stochastic approaches use probabilistic transition rules rather than deterministic ones to obtain good results. And this frequently led



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to enormous computational efforts, which may not succeed as the problem's complexity rises. Heuristic or meta-heuristic approaches have been developed to address these problems, and their low computing complexity, simplicity of usage, and very small number of parameters have made them increasingly popular [1, 2].

The goal of transportation problems (TPs) is to satisfy all supply and demand requirements while minimizing the cost of transporting products from sources to destinations. It includes reducing transportation costs while allocating resources as efficiently as possible. The base of it is the objective function. In the optimization process, an objective function is one whose value we aim to maximize the profit or minimize the travel time, expenses, etc. Transport responsibilities include finding out the best way to move similar products from producers to consumers while lowering the overall cost of delivery [3].

1.1 | Basic Transportation Problem

Delivering particular products from the source to the destination at the lowest possible total cost while meeting supply and demand limitations is known as the TP [4, 5]. As an ideal solution, TP aims to have the lowest possible total cost. Since many businesses spend millions of dollars transporting goods from supply to demand, transportation costs constitute a significant factor for many of them. [6] In order to move their product from supply to demand, businesses must plan carefully. [7] The concept of successful item transportation is increasing in interest. TP is a subset of the following: the mixed integer linear programming, the mixed integer nonlinear programming [8], the nonlinear programming [9, 10], the linear programming [9], and a specific type of network optimization problems [7].

Table 1 typically displays TP. Finding the variable x_{ij} that can affect the minimal total cost of TP is the aim of TP. The following is a mathematical formulation of the TP goal as a linear programming problem:

$$\text{Minimize Cost} = \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij}$$

s. t

$$\text{supply}_i = \sum_{j=1}^n x_{ij} \quad \text{for } i \text{ from } 1 \text{ to } m$$

$$\text{demand}_j = \sum_{i=1}^m x_{ij} \quad \text{for } j \text{ from } 1 \text{ to } n$$

$$x_{ij} \geq 0 \quad \text{for all } i \text{ and } j$$

Where

m Supplies total number

n Demands total number

c_{ij} Unit transportation cost from supply i to demand j

x_{ij} Unit number that needed to be transported from supply i to demand j

Table1. Transportation problem.

	Destination ₁	Destination ₂		Destination _n	Supply
Source ₁	$c_{11}x_{11}$	$c_{12}x_{12}$		$c_{1n}x_{1n}$	Supply ₁
Source ₂	$c_{21}x_{21}$	$c_{22}x_{22}$		$c_{2n}x_{2n}$	Supply ₂
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
Source _m	$c_{m1}x_{m1}$	$c_{m2}x_{m2}$		$c_{mn}x_{mn}$	Supply _m
Demand	Demand ₁	Demand ₂		Demand _n	

Shortly, there are two steps involved in finding the optimal TP solution. Since it is a fundamental solution for finding the minimal total cost, the Initial Basic Feasible Solution (IBFS) is the first step in discovering an initial solution of TP [11]. The second step is to use stepping stone or modified distribution (MODI) to choose the best IBFS solution [12]. It is crucial to begin with IBFS in order to obtain the optimal solution of TP, since many researchers have investigated this method to do so directly without the use of stepping stone or MODI [13]. A better IBFS approach is necessary and desirable since the IBFS value influences the best solution [11]. According to [12], the value may be closer or equivalent to the optimal solution. The well-known current techniques for obtaining IBFS include the least cost cell (LCM), Northwest Corner Method (NWCN), and Vogel's Approximation Method (VAM) [14].

1.1.1 | Northwest Corner Method (NWCN)

NWCN is an approach for solving the TP. The goal of this method is to simply satisfy demand at the initial location while ignoring transportation costs [15]. If there is still supply at the source, distribute as much of the product as you can to the initial destination. Then passed on to the following request; if not, the subsequent source will be assigned. It is a rapid fix because it doesn't include transportation costs, making it appropriate for identifying a first solution [16]. It also is the most straightforward method for producing the initial feasible solution. The steps are listed as follows:

1. Choose the box on the far left of the first row and allocate as much as you can.
2. Revise demand and supply.
3. In the modified table, allocate now either in the first row's extreme left box or, if applicable, in the second row's extreme left box.
4. Continue till the last distribution.
5. Choose any in the situation of a tie [17].

1.1.2 | Least cost cell Method (LCM)

LCM depends on a greedy method of allocation. Kruskal's minimum spanning tree approach is similar in that it selects the edge with the least weight until a spanning tree is produced. LCM looks for the cell with the lowest cost in the entire matrix and assigns the greatest value, the lowest of the supply and demand values, to that specific cell. Random selection is used when dealing with non-unique least cost cells. Although it is one of the most straightforward heuristic methods, it takes a lot of time because it is difficult to search for the least expensive cell across the full matrix each time. [18, 19]. Figure 1 represents the flowchart of the LCM.

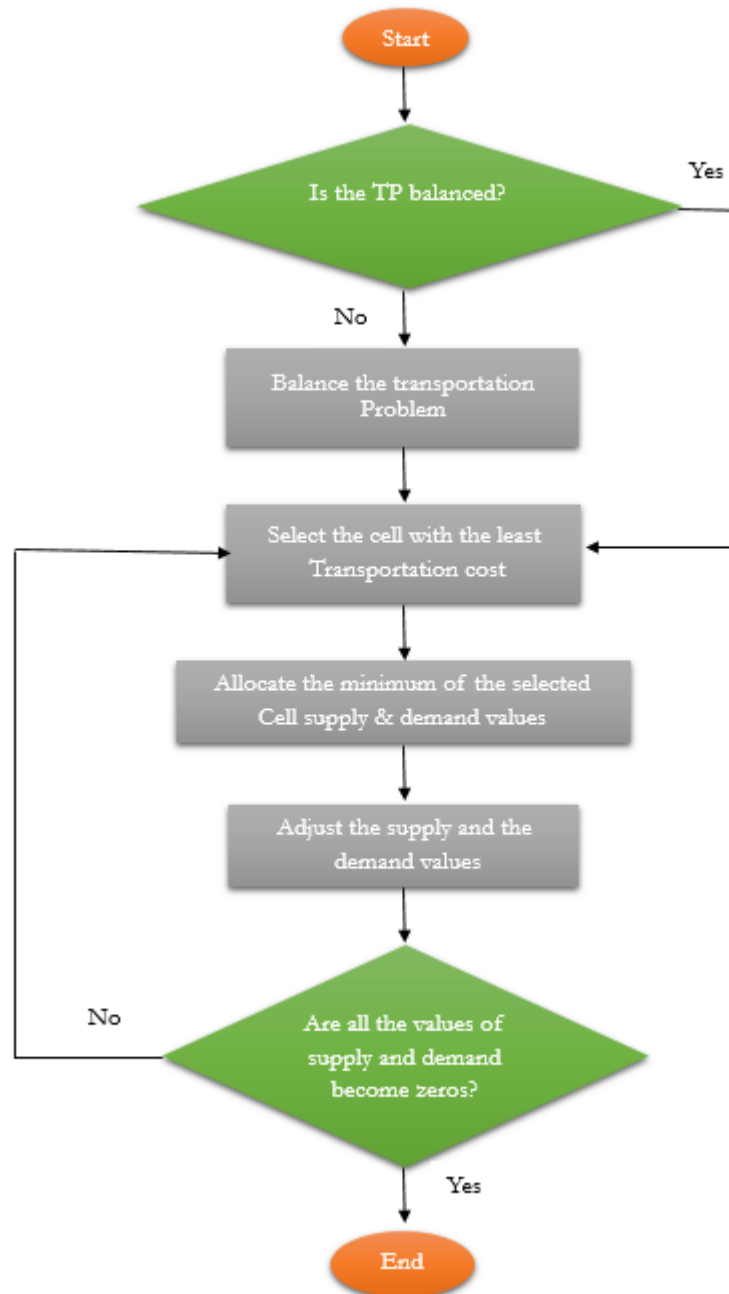


Figure 1. LCM flowchart.

1.1.3 | Vogel's Approximation Method (VAM)

This approach is not as straightforward as computational processes like LCM. However, this approach usually results in higher IBFS [20]. This method's solution process is broken down step-by-step below.

Step1: Determine which cells in each row have the lowest and next-to-lowest transportation costs, then record the difference (penalty) against the appropriate row down the table's side.

Step2: Determine which cells in each column have the lowest and next-to-lowest transportation costs, then record the difference (penalty) against the appropriate column on the table's side.

Step3: Determine the maximum penalty in step three. Give the cell with the lowest transportation cost in that row the maximum allocation if it is along the table's edge. Make the maximum allocation to the cell with the lowest transportation cost in that column if it is below the table.

Step4: Choose the top row and the leftmost position if the penalties for two or more rows or columns are equal.

Step5: The row or column that is satisfied doesn't need any more thought. Only one of the two should be deleted if both the row and the columns are met at the same time, and the remaining row and the column will be given zero supply (or demand).

Step6: As in step 1, compute a new penalty for the remaining submatrix and distribute it in accordance with the previous step's protocol. Until every row and column is satisfied, keep going.

Step7: Lastly, the sum of the cost and the associated supply/demand value is used to get the total minimal cost. The total cost $= \sum_{i=1}^m \sum_{j=1}^n c_{ij}x_{ij}$ [21, 22].

This study presents a hybrid approach to solve the classical TP. The NWCM is used to develop the initial solution, and the GA is used for optimization in order to minimize the overall cost of transportation.

1.2 | Genetic Algorithms (GAs)

In general, GAs are search-based algorithms built on the principles of natural selection. GA is a branch of the much larger field of computational science known as evolutionary computation. In GAs, there are various and diverse solutions for a given problem [23]. Also, it makes use of the survival of fittest theory [24]. Iteratively applying genetic operators to existing population members creates new populations. The main components of GA are the representation of the chromosomes, selection, crossover, mutation, and calculation of the fitness function. The GA process is as follows:

A random initialization is made for a population y of n chromosomes. Each chromosome's fitness in Y is calculated. Based on the fitness value, two chromosomes, $C1$ and $C2$, are chosen from the population y . $C1$ and $C2$ are subjected to the single-point crossover operator with crossover probability in order to generate an offspring, let's say O . The generated offspring with mutation probability is then subjected to a uniform mutation operator to produce $\hat{O}$ [25]. GA simplifies and speeds up computation by utilizing crossover, mutations, and natural selection procedures. Because of these factors, it is a more valuable, effective, and efficient algorithm than others [26-28]. The following is the mathematical analysis of GA:

With the use of crossover and mutation probabilities, GA dynamically modifies the search process until it finds an optimal solution. The encoded genes can be edited by GA. GA is able to assess numerous people and generate several ideal solutions. As a result, GA offers superior worldwide search capabilities. It is likely that the offspring created by parent chromosome crossover will eliminate the excellent genetic patterns. The crossover formula and parent chromosomes are as follows:

$$R = \frac{(G + 2\sqrt{g})}{3G} \quad (1)$$

where G is the total number of evolutionary generations determined by population, and g is the number of generations. Equation 1 shows that R changes dynamically and increases as the number of evolutionary generations increases. In the early phases of GA, similarities exist between individuals are low. To guarantee that the new population won't delete the exceptional genetic architecture of individuals, the value of R should be minimal. Individuals are quite like one another at the conclusion of evolution, and R should also be high [24]. The Schema theorem states that a modified schema must be used in place of the original template. The new schema preserves the original population during the early stages of evolution in order to preserve population variety. When evolution is complete, the right schema will be created to avoid any modification to the excellent genetic schema [29]. GA process is explained in Figure 2.

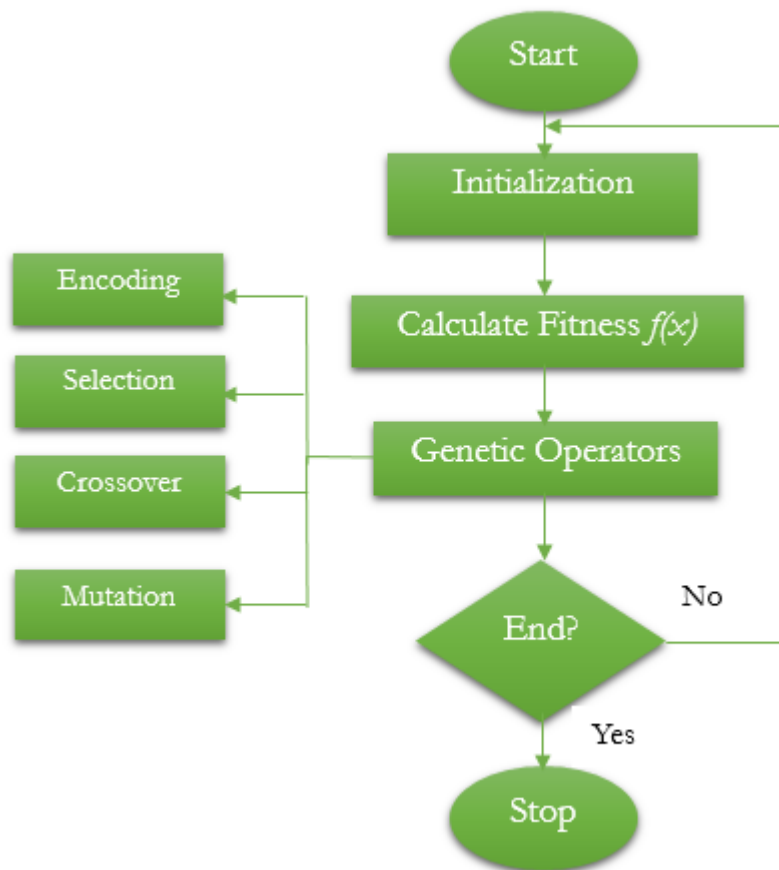


Figure 2. Genetic algorithm flowchart.

The most common applications of the GA are in optimized problems where we must employ a given set of conditions to either maximize or decrease a specified objective function value. Such a method will address an optimization-related issue. The optimization presents problems with minimizing or optimizing variables with several factors, which are usually restricted by fairness and inequality. This is crucial to operations related to manufacturing, marketing, and research. Industrial engineering architecture presents a number of complex problems that are difficult to solve with conventional optimization techniques. GA's prospects as an innovative optimization technique has attracted a lot of attention in recent years. It has been widely used to address a range of problems due to its convenience, simplicity of use, minimal requirements, and simultaneous and global perspective [30]. Knapsack problem, traveling salesman problem (TSP), and real-parameter optimization are just a few of the many issues that GA has been effectively used as an optimization algorithm to solve [31].

2 | GA for a Classical Transportation Problem

2.1 | Problem Statement

Consider the TP cost matrix in Table 2 below, in which each cell entry shows the cost of transportation between sources and destinations, as well as the supply S_i at each source and the demand D_j at each destination.

Table 2. Used TP cost matrix.

	D₁	D₂	D₃	D₄	D₅	S_i
S₁	68	35	4	74	15	18
S₂	57	88	91	3	8	17
S₃	91	60	75	45	60	19
S₄	52	53	24	7	82	13
S₅	51	18	82	13	7	15
D_j	16	18	20	14	14	

According to the table above, There is no need for dummy rows or columns because all inputs are deterministic and meet the balanced criterion, which states that total supply equals total demand. Because of this, using the NWCM as a first step to produce a feasible solution was simple. The approach works well for balanced problems and offers a rapid means of filling the transportation table while meeting all constraints. The obtained IBFS is in table 3 with a transportation cost of 4284.

Table 3. NWCM IBFS.

	D₁	D₂	D₃	D₄	D₅	S_i
S₁	16	2	0	0	0	18
S₂	0	16	1	0	0	17
S₃	0	0	19	0	0	19
S₄	0	0	0	13	0	13
S₅	0	0	0	1	14	15
D_j	16	18	20	14	14	

According to Figure 3, the movement of goods and related expenses is illustrated by showing a transportation network that links five sources from S1 to S5 with five destinations from D1 to D5. A distinct directional flow is produced by the vertical arrangement of the sources and destinations on the left and right sides, respectively. Curved edges, whose thickness varies with the amount transmitted, link the nodes, eliminating visual noise and identifying overlapping paths. In order to give quick insight into the logistics volume and financial impact, each edge is annotated with comprehensive numerical data that includes the quantity transported, unit transportation cost, and total cost per route e.g., $16\text{units} \times 68\$ = 1088\$$. The network highlights cost-effective large transports as well as routes with high per-unit prices, showing differences in shipment quantities and costs. The visualization is a useful tool for enhancing the productivity and economy of the transportation system since it allows stakeholders to prioritize optimization efforts and identify expensive routes.

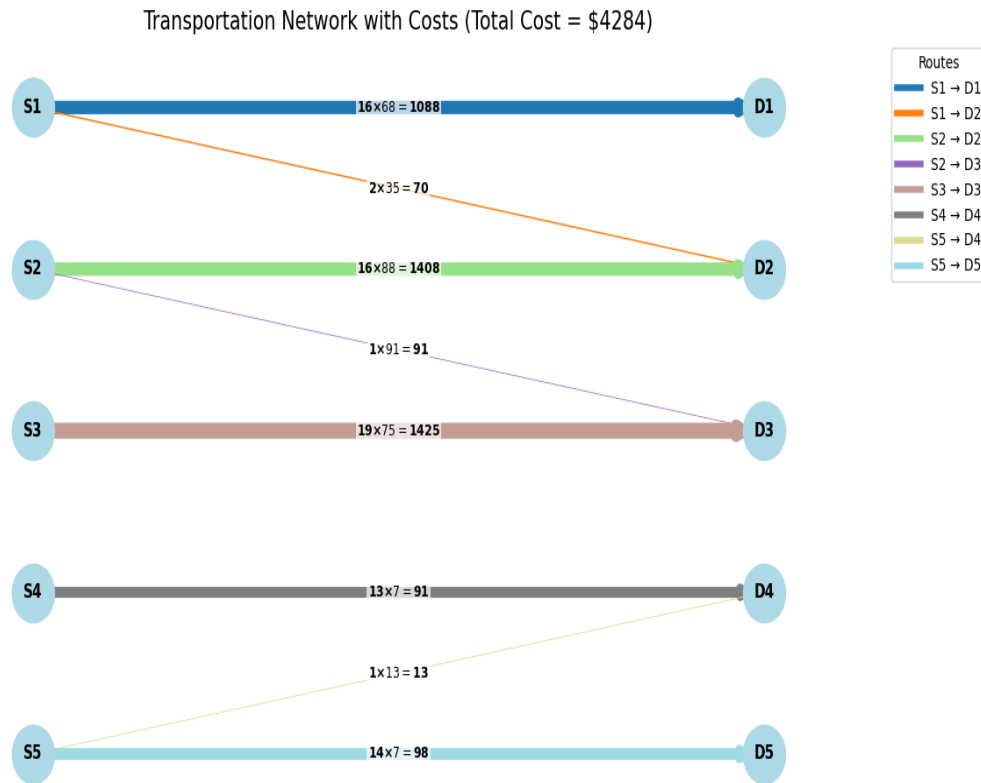


Figure 3. NWCM transportation network.

2.2 | Methodology

It is essential to remember that while the previously illustrated transportation network offers an acceptable solution that meets demand at every destination and supply at every source, it might not be the best option in terms of overall transportation costs. A number of observations obtained from the graphical representation suggest possible inefficiencies, including the usage of low-volume, high-cost connections, routes with significantly higher unit prices, and an unequal distribution of products throughout the network. These factors can greatly increase the overall cost and decrease the system's efficiency, even while they meet the fundamental limitations of the transportation problem. To generate an initial feasible solution, conventional techniques like the LCM or the NWCM are frequently employed. These approaches, however, frequently overlook the cost matrix's global structure and could result in less-than-ideal allocations. Furthermore, the search space for potential solutions gets too big to be managed efficiently by precise or greedy methods as the problem's size and complexity increase.

This paper suggests using a GA as an optimization method to get over these restrictions. Natural selection and genetics serve as the inspiration for a class of evolutionary algorithms known as genetic algorithms. They work by using mechanisms including crossover (recombination), mutation, and selection to develop a population of potential solutions over several generations. The main benefit of GAs is their capacity to investigate a large and complicated solution space without becoming caught in local optima, which is a frequent flaw in conventional improvement techniques. The GA can iteratively enhance the initial solution by creating a fitness function based on the overall transportation cost and recording potential transportation plans as chromosomes. The algorithm chooses the most fit people in each generation, recombines their features to create new offspring, and provides miniature, random mutations to preserve diversity. This evolutionary process tends to converge over time toward high-quality, optimal or nearly ideal solutions.

The GA will be utilized in this study to find a transportation strategy that respects supply and demand restrictions while minimizing overall costs. With the focus on cost reduction and allocation balance, the

algorithm's performance will be assessed in relation to the starting solution obtained using heuristic allocation. This method not only improves the quality of the solution but also shows how soft computing approaches can be used to solve practical supply chain management (SCM) and logistics optimization challenges. Algorithm 1 explains the utilized strategy as follows:

ALGORITHM 1: Initialization of GA with NWCM

Parameters: sources $i = 1, \dots, m$; destinations $j = 1, \dots, n$; population size POP_SIZE; generations number G

- 1 Using NWCM to produce IBFS
 Initial solution (X) = NWCM (supply, demand)
 Initial cost (C) = Calculate (X)
 - 2 Initialize population as
 Population $\leftarrow$ GenerateRandomSolutions (supply, demand, POP_SIZE)
 - 3 **for** $g = 1$ to G **do**
 for each individual Y in population do
 Evaluate cost
 end for
 Sort population of cost in ascending order
 Next generation $\leftarrow$ top 10
 While Next generation < POP_SIZE **do**
 Select parent 1, parent 2 from top 30
 Child $\leftarrow$ Crossover (parent 1, parent 2)
 if random() < mutation rate **then**
 Child $\leftarrow$ mutate (child)
 End if
 Add child to Next generation
 End While
 Update population $\leftarrow$ Next generation
 End for
 - 4 Get the best solution
 $X^* = \text{GetBestSolution}(\text{population})$
 - 5 Calculate the final cost
 $C^* = \text{CalculateCost}(X^*)$
 - 6 **Return** the initial solution (X), the initial cost (C), the optimized solution (X^*), and the optimized cost (C^*)
-

A detailed illustration of the GA convergence behavior in relation to the proposed TP can be found in figure 4. The algorithm's ability to reduce the overall cost of transportation across subsequent generations is seen from the convergence curve. Early in the algorithm's execution, particularly in the first 10 to 20 generations, there is a rapid decrease in cost. This significant early increase points to an exploration phase in which the algorithm actively seeks a wide range of solution spaces and gains from substantial genetic variety. Crossover and mutation operators efficiently recombine and modify solutions during this stage, resulting in the rapid identification of improved individuals.

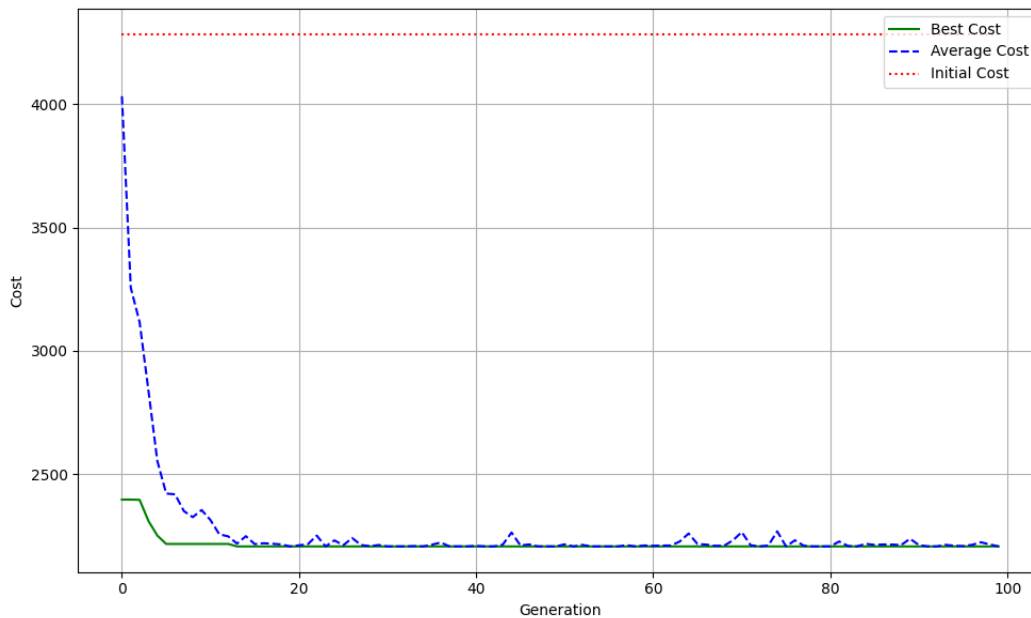


Figure 4. Convergence of GA and comparison with IBFS generated by NWCM.

The curve progressively decreases as the algorithm runs. This indicates that population convergence is near. The algorithm has probably reached a near-optimal or global optimum when the best cost line becomes stable, making further advancements less important. The best cost line is getting closer to the average cost line at the same time. This indicates a concentration of people around the best solutions and a decline in population variety. This trend, which shows that the algorithm has moved from global exploration to local exploitation, is a typical indication of convergence in evolutionary algorithms. This graphic highlights the notable difference in cost between the GA's final optimized solution and the first feasible solution. The first solution, which was probably derived using the NWCM, is not the best; rather, it just demonstrates that a solution is feasible. By simulating natural selection, the GA on the other hand, is designed to progressively enhance solution quality. The whole cost as depicted in table 4 is reduced by 48.51%, from 4284 to 2206. This demonstrates how the algorithm can result in significant cost savings in difficult transportation networks. Additionally, the convergence curve demonstrates the GA's stability and dependability. The GA discovers high-quality solutions rapidly. Because of this, it works especially well for solving big or nonlinear TPs that conventional approaches would find challenging.

Table 4. NWCM IBs vs GA optimized solutions.

	Initial Solutions with C = 4284					S_i	Optimized Solutions with C = 2206				
	16	2	0	0	0	18	0	0	18	0	0
	0	16	1	0	0	17	0	0	0	14	3
	0	0	19	0	0	19	3	16	0	0	0
	0	0	0	13	0	13	11	0	2	0	0
	0	0	0	1	14	15	2	2	0	0	11
D_j	16	18	20	14	14						

The significant reduction in the average cost over the early generations is the most noticeable feature of figure 5 and figure 6. The difference between generations 0 and 15 is particularly apparent. This pattern indicates that the algorithm performs excellently during the exploration stage. It rapidly finds and utilizes high-quality regions in the solution space. Both the minimum and optimum costs have decreased in parallel with the significant reduction in the average cost. This indicates that both top solutions and the overall population are improving.

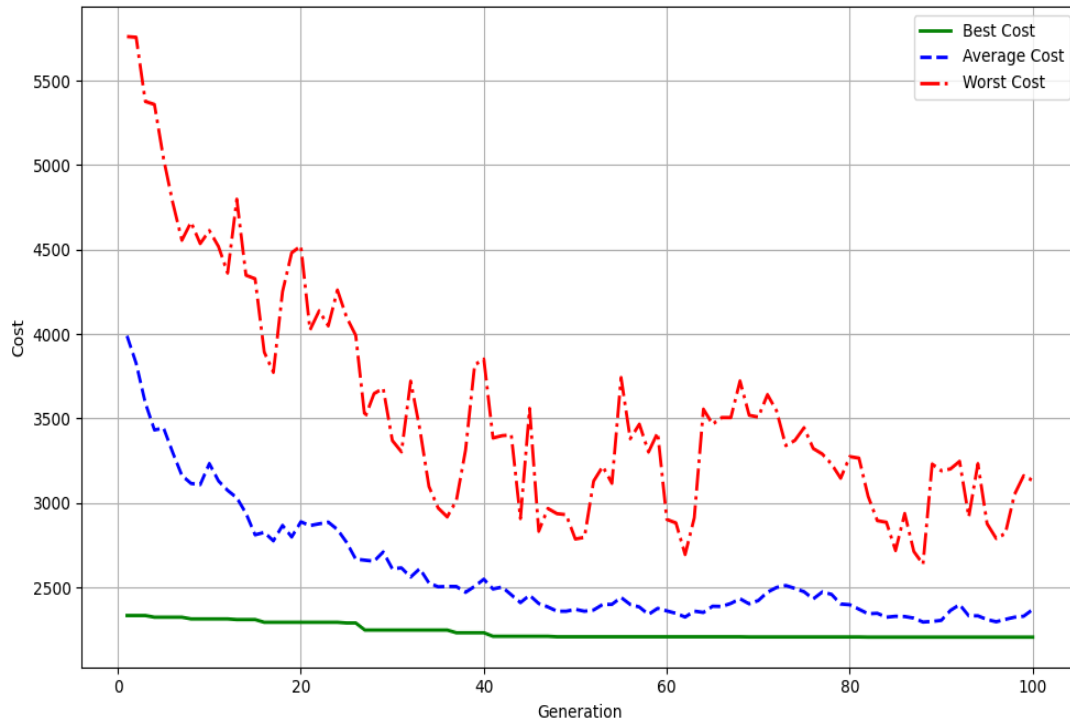


Figure 5. Cost comparison per generations.

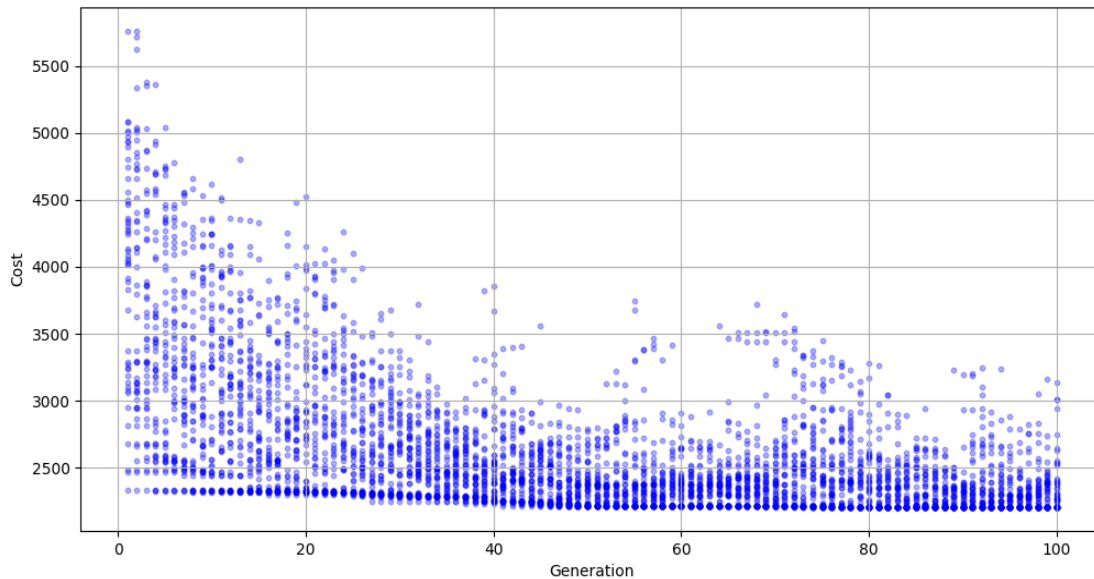


Figure 6. Solutions per generations.

On the other hand, during most of generations, the maximum cost red line remains unstable. This continuous variation indicates that the population contains weak individuals. They most likely survive due to diversity strategies like mutation or genetic modifications. These individuals are essential for maintaining diversity and preventing early convergence, even though they don't contribute as much to the greatest solutions. The algorithm's ability to efficiently identify superior solutions for reducing transportation costs is strongly shown by the final convergence of cost measures with the top-performing solutions. The supply and demand balance is clearly depicted in the Figures. The required supply and the actual supply from five different sources are contrasted in figure 7. With no under- or over-supply, each provider achieved a 100% completion rate by providing precisely what was requested. The required demand and the actual quantities received by five consumers are contrasted on figure 8. In this case as well, all demand points are fully satisfied because the actual quantities received correspond to the necessary demand for each customer. These findings

imply that the distribution network operates as efficiently as possible, minimizing waste and ensuring that resources are used efficiently.

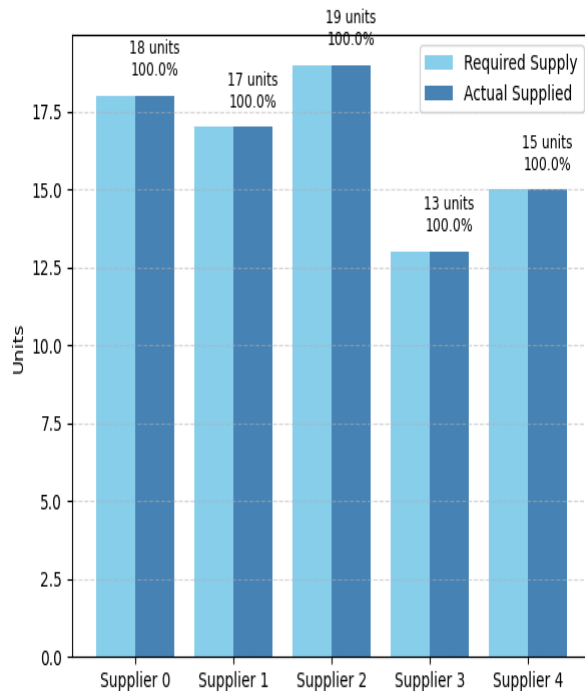


Figure 7. Supply: required vs actual.

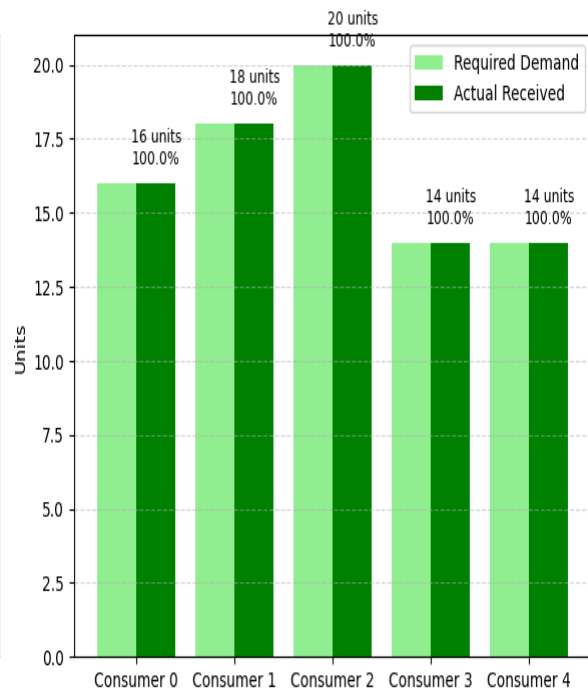


Figure 8. Demand: required vs actual.

3 | Results and Discussions

The NWCM was used as an initial technique. It offered an acceptable solution that satisfied supply and demand limitations without any optimization. The overall cost of transportation was 4284, and this number remained constant during several observations. Zero variance and zero standard deviation according to table 5 were the statistical measures that showed this. As a deterministic starting point, NWCM basically yields the same outcome no matter how many times it is used. Although helpful in producing a first initial solution, it is unable to explore more effective solutions. With a standard deviation of approximately 22, the results showed a moderate degree of variability, suggesting that although the solutions varied slightly between generations, they were always superior to NWCM. This adaptability is a strength rather than a problem. It demonstrates that the GA is actively searching the solution space rather than making a quick decision about a potentially less-than-ideal solution. The GA avoids local minima and looks for more effective allocations by incorporating controlled randomness through crossover and mutation.

Table 5. Statistical comparison.

Metric	NWCM Initial Solution	Genetic Algorithm
Observations	100.0	100.0
Average	4284.0	2211.2
Mean	4284.0	2211.2
Variance	0.0	489.4
Standard Deviation	0.0	22.1

According to Figure 9, the GA is compared against the NWCM. The red dotted line depicts how the total cost of transportation, using the conventional NWCM, remains consistent across generations. In contrast, the green curve shows how the cost of the optimal solution produced by the GA evolves over 100 generations.

It is evident that the GA improved upon the original solution by continuously decreasing the shipping cost. This demonstrates, as opposed to the traditional method, the dramatically effectiveness of the algorithm to search the solution space and converge to with an optimal allocation scheme.

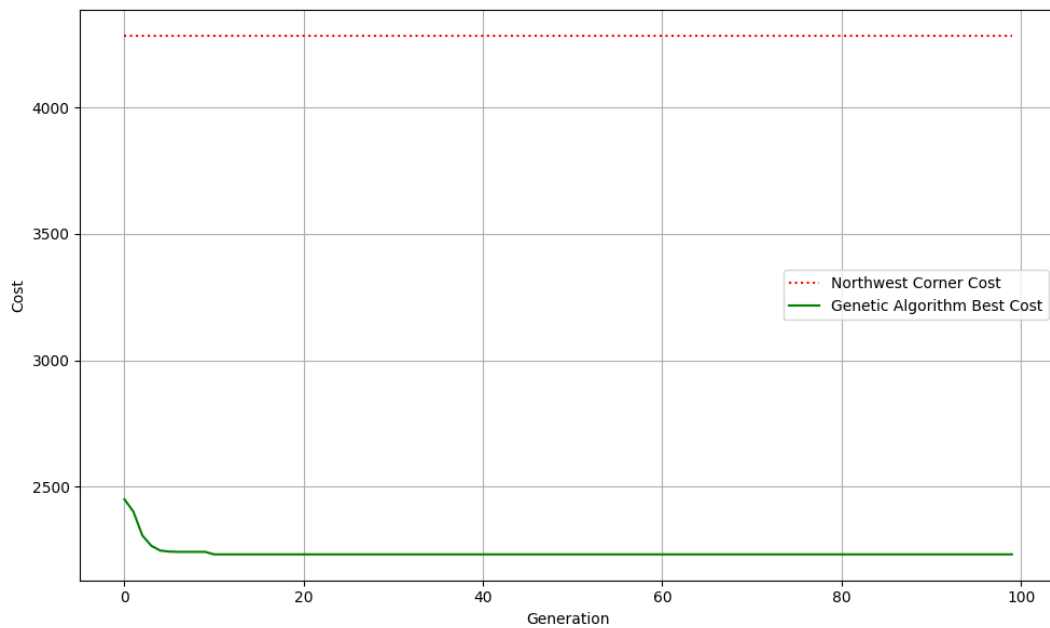


Figure 9. NWCM vs CA cost comparison.

There were observable and statistically significant improvements when the GA was used to solve the identical problem. The algorithm was able to lower the average overall cost from 4284 to about 2206 with an improvement rate of 48.51% over the course of 100 generations as illustrated in Figure 10.

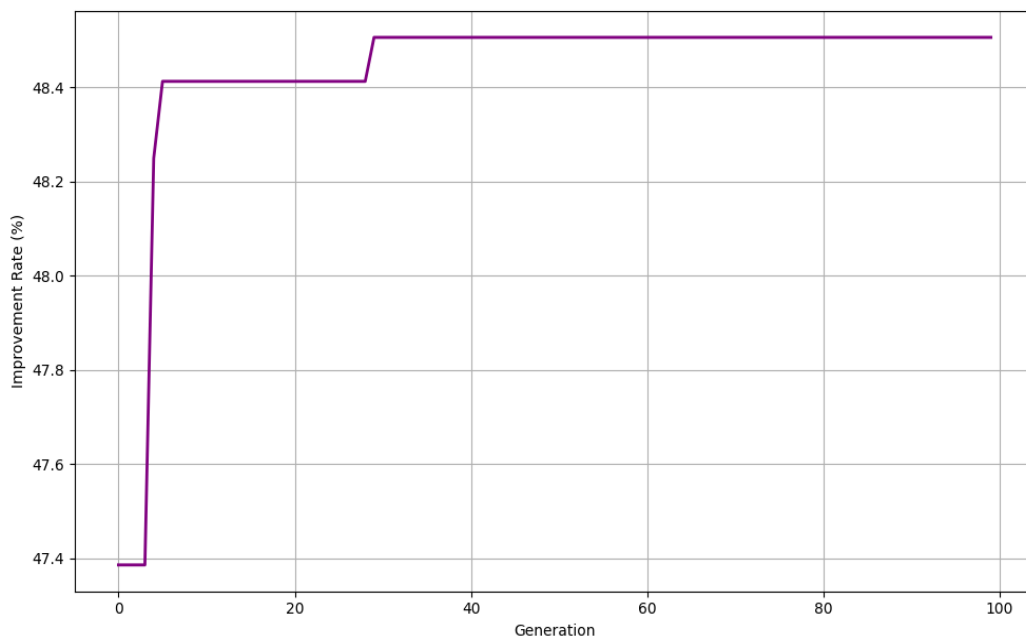


Figure 10. Improvement rate over generations.

The execution time required to complete each generation in the GA's optimization phase is displayed in figure 11. The generation number, which ranges from 1 to 100, is shown on the horizontal axis. The execution time in seconds for every generation is displayed on the vertical axis. With maxima of approximately 0.01 seconds, it is evident that the early generations compute a little more slowly generally. This is because setting up and evaluating different solutions in the initial population requires a lot of operations. We observe a general lower

trend in execution time as the generation's progress. This demonstrates that as better solutions occur and convergence begins, the algorithm is more effective. Random processes like crossover, mutation, and repair operations, which occasionally need more computing, still cause minor changes in subsequent generations. Whatever is considered, the figure demonstrates that the suggested GA maintains consistent and reasonable execution durations throughout all generations. This supports its applicability to more significant problem cases.

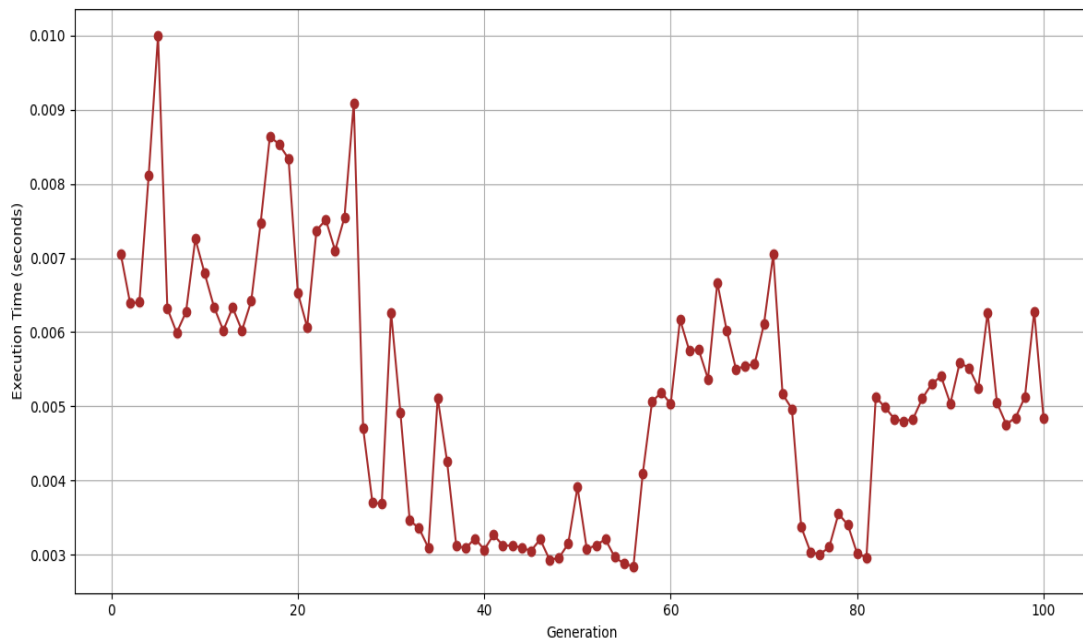


Figure 11. Execution time per generations.

The best solution generated by the GA is shown in Figure 12 as a heatmap. It displays the distribution of transportation loads between each supply and demand point. This simplifies the solution's interpretation and ensures that the final allocation conforms to all conditions while obtaining a much lower overall cost.

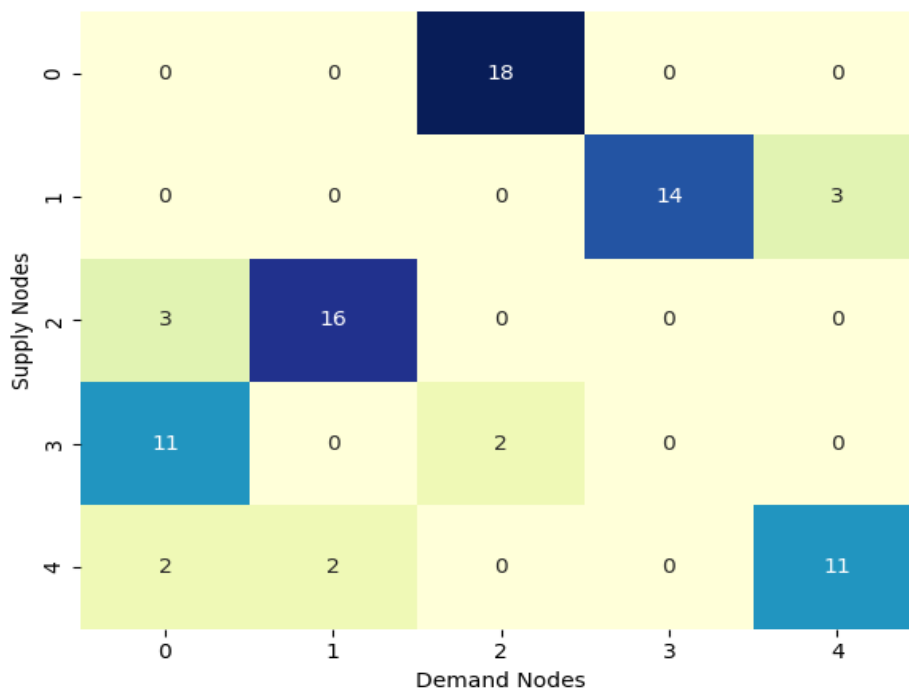


Figure 12. Final GA solutions heat map.

Practically, the GA performs better than NWCM in terms of cost reduction and flexibility. When it comes to real-world applications like logistics, production scheduling, and resource allocation, where operational conditions can change and flexibility is essential, the GA provides a range of effective solutions, allowing planners and decision-makers to select from several feasible options. It's important to remember that the GA's efficacy is greatly impacted by the configuration of its parameters; crossover probability, population size, number of generations, and mutation rate are all critical. The method may take longer to converge or may not find the best answer if it is not properly tuned. Therefore, adaptive parameter tuning techniques where these values automatically modify based on performance during runtime should be investigated in future studies.

Furthermore, contrasting GAs with other well-known metaheuristic approaches like simulated annealing, tabu search, ant colony optimization (ACO), and particle swarm optimization (PSO) may provide additional understanding of the advantages and disadvantages of each strategy in comparable situations. Combining the advantages of several algorithms could potentially be a good strategy for improving outcomes. The scalability and flexibility of GAs as practical solutions for modern optimization problems may also be demonstrated by extending this research to larger problem instances, real-world datasets, or dynamic environments where problem parameters vary over_time.

Overall, the results indicate that NWCM lacks optimization capabilities, despite being a quick and easy way to identify feasible transportation routes. On the other hand, the GA offers substantial cost reductions, more adaptability, and more reliable performance, which makes it an excellent choice for optimization challenges in the real world.

4 | Conclusions

The goal of the TP, a basic optimization problem in operations research, is to find the least costly way of distributing goods, given supply and demand restrictions, from multiple sources to multiple destinations. It is essential to resource allocation, supply chain management, and logistics, yet conventional heuristic approaches frequently fail to deliver the best answers in challenging situations. This study combined the NWCM with the GA to propose a hybrid solution to the classical TP. Although the heuristic approach provided a quick and acceptable initial solution, it was not optimized. Convergence plots and statistical analysis, on the other hand, showed that the GA greatly enhanced the quality of the solution by lowering the overall cost of transportation across generations. With a significant improvement rate over the baseline, the results validated the algorithm's capacity to produce improved solutions over time. For future works, Real-world limitations like vehicle capacity, time periods, and shifting supply or demand situations can be incorporated into the research. Furthermore, hybridizing GAs with approaches like simulated annealing, tabu search, ACO, and PSO may improve solution adaptability and convergence speed.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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