Priority-Based Genetic Algorithm for Logistic Optimization

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Abstract: The Fixed-Charge Transportation Problem (FCTP) is an NP-hard combinatorial optimization problem that extends the classical transportation model by incorporating both fixed costs associated with the activation of routes and variable shipping costs. In this paper, a Genetic Algorithm (GA) enhanced with a priority-based decoding mechanism is proposed for efficiently solving the FCTP. The decoder maps a chromosome representation into a feasible transportation plan by utilizing a heuristic cost function combined with chromosome-derived priority values to guide shipment allocation. This approach effectively addresses the simultaneous optimization of mixed discrete decisions (route selection) and continuous variables (shipment quantities). The performance of the proposed algorithm is evaluated on a set of standard benchmark instances. Computational results demonstrate that the method is robust and effective, achieving high-quality solutions with improved convergence behavior. Moreover, the proposed priority-based decoding GA consistently yields competitive results and, in many cases, outperforms existing metaheuristic approaches, highlighting its potential as a powerful tool for solving complex logistics optimization problems.

1 INTRODUCTION

The Transportation Problem (TP) is a classical problem in operations research and supply chain management concerned with minimizing the total cost of transporting goods from multiple sources to multiple destinations [1], [2]. While the classical linear TP can be efficiently solved using standard optimization techniques, its non-linear extension, the Fixed-Charge Transportation Problem (FCTP), is significantly more complex.

The FCTP introduces a fixed cost that is incurred whenever a transportation route is used, regardless of the shipment quantity, in addition to the variable shipping cost. This fixed-charge component reflects practical considerations such as vehicle leasing, setup costs, and toll fees. The presence of fixed charges leads to a discontinuous objective function, and the problem is known to be NP-hard [3], [4].

Classical exact methods, including branch-and-bound and other mixed-integer programming approaches, become computationally expensive for large-scale instances due to the combinatorial explosion of feasible solutions. As a result, metaheuristic techniques have gained significant attention as effective tools for obtaining near-optimal solutions within reasonable computational time. Among these approaches, Genetic Algorithms (GAs) are widely used due to their strong global search capability and robustness in complex optimization problems [5], [6].

However, a major challenge in applying GAs to the FCTP lies in the design of an efficient representation and decoding strategy that ensures feasibility while properly handling the mixed-integer structure of the problem. In particular, the mapping from chromosome representation to feasible transportation solutions remains a critical issue [7], [8].

To address this gap, this paper proposes a novel priority-based decoding mechanism integrated within a GA framework. The proposed decoder does not directly encode solutions; instead, it modifies a sorted list of routes based on a composite cost heuristic and constructs feasible solutions through sequential allocation of shipments to promising arcs [9]–[14].

The main contributions of this work are as follows:

1) the design of a novel and efficient decoding scheme for the FCTP within a GA framework;

2) a complete implementation and experimental evaluation on standard benchmark instances;
3) a demonstration of the competitiveness of the proposed approach compared to existing methods.

2 PROBLEM FORMULATION

This section introduces the mathematical formulation of the Fixed-Charge Transportation Problem (FCTP) and defines the associated notation used throughout the paper.

$$Minimize: Z = \Sigma_{\{i\in I\}}\Sigma_{\{j\in J\}}\left(c_{ij}\cdot x_{ij} + f_{ij}\cdot y_{ij}\right).$$

Subject to:

1) $\Sigma_{\{j\in J\}} x_{ij} = S_i \ \forall\, i \in I\ (Supply\ conservation)$;
2) $\Sigma_{\{i\in I\}}\, x_{ij} = D_j\, \forall\, j \in J\ (Demand\ satisfaction)$;
3) $0 \le x_{ij} \le U_{ij}\cdot y_{ij} \quad \forall\,(i,j)\ \ (Linking\ /\ Big - M)$;
4) $x_{ij} \ge 0,\ y_{ij} \in \{0,1\}\ \ \forall\,(i,j)\ \left(Bounds{-}Integrality\right)$.

$Balance\ condition$: $\Sigma_{\{i\in I\}} S_i = \Sigma_{\{j\in J\}}\, D_j$.

The nomenclature of the main symbols used in the model is summarized in Table 1.

Table 1: Nomenclature of the Fixed-Charge Transportation Problem (FCTP).

Symbol	Meaning
I, J	Index sets of sources and destinations
S_i	Supply available at source i ($i \in I$)
D_j	Demand required at destination j ($j \in J$)
c_{ij}	Variable shipping cost per unit on arc (i,j)
f_{ij}	Fixed opening/setup cost to use arc (i,j)
U_{ij}	Upper bound (tight Big-M) for $x\_ij\ when\ y_{ij} = 1;\ often\ U_{ij} = min\{S_i, D_j\}$
x_{ij}	Shipped quantity from source i to destination j
y_{ij}	Binary arc-activation: 1 if arc (i, j) is opened/used; 0 otherwise
Z	Total cost (objective value)

Note: U_{ij} is also denoted M_{ij} in some texts (Big-M linking bound).

3 DECODER-CENTRIC GA

3.1 Normalized Priority

Normalized Priority is a type of priority value representing how precedence is handled between supply or demand nodes when the genetic algorithm is decoding them. The benefit is that all nodes are directly comparable (regardless of their scale) once we normalize priority values to a common value (usually [0, 1]). This guarantee makes sure that the decoding process is driven by relative ranking instead of the absolute magnitude. That is, the higher the normalized priority of a node the sooner it is scheduled or allocated in the solution construction, thus directing the search toward better quality solutions. We make use of normalized priority to enhance the robustness, fairness, and efficiency of the decoding phase, which is important for solving large-scale fixed-charge transportation problems.

$$\tilde{c}_{ij} = \left(c_{ij} - c_{min}\right)/(c_{max} - c_{min} + \varepsilon), \tilde{f}_{ij} = \left(f_{ij} - f_{min}\right)/(f_{max} - f_{min} + \varepsilon)$$

$$u_i = \frac{S_i^{rem}}{S_i}, \qquad v_j = D_j^{rem}/D_j,$$

$$prio_{ij} = 1/(1 + \alpha\,\tilde{c}_{ij} + \beta\,\tilde{f}_{ij}) + \gamma(chrom_i + chrom_j) + \delta\, min(u_i, v_j),$$

$$\alpha, \beta, \gamma, \delta \ \ge\ 0\ are\ tuned\ online.$$

3.2 Greedy Construction with Re-Scoring

This subsection presents a greedy construction procedure with dynamic re-scoring, designed to iteratively build a feasible transportation solution by selecting the highest-priority routes based on residual supply and demand.

Pick highest single $Prio_{ij}\ with\ S_i^{rem} > 0\ and\ D_j^{rem} > 0;\ Initialize\ prio\ list$

So if you can ship $x_{ij} = min\ (S_i^{rem}, D_j^{rem}\ )\ then\ set\ y_{ij} = 1\ if\ x_{ij} > 0;$

Local heap updates. The modification of residuals and the score of affected arcs.

Keep repeating until you filled all the demands.

Order of growth. $O(mn\, log(mn))$ for global ordering + local updates.

3.3 Repair and Coherence

The Δ swap-repair moves a Δ along a cycle from expensive arcs to cheaper arcs so that it remains feasible.

GA Enhancements and Hybridization:

- Selection: 2–5% elitism +binary tournament
- Crossover: two-point, order-preserving blocks.
- Mutations: swap, shift, cost-guided.
- Neighborhood Local: 2-exchange cycles + cycle-canceling.

The available methods for multi-modal optimization, including path relinking and ruin-and-recreate strategies, are discussed as mechanisms for avoiding stagnation in the search process.

3.4 Analytical Notes

While $\Sigma i\, S_i - \Sigma j\, D_j \exists S_k > 0$, then the construction terminates with $D_j^{rem} = 0\ \forall\, j$, meaning it was feasible. After some initial ordering, complexity is near-linear; recommend early-stopping by stagnation.

3.5 Online Parameter Control

This subsection describes an online parameter control strategy, including Bayesian and success-based tuning of the parameters (α, β, γ, δ) over sliding windows, adaptive operator selection (AOS) with reward mechanisms based on improvements in the objective function value Z, and self-adaptive mutation of parameter genes embedded in the evolutionary process. The parameters (α, β, γ, δ) are updated dynamically using Bayesian and success-driven feedback, while AOS assigns higher rewards to operators that contribute to improvements in Z. In addition, parameter genes are co-evolved with chromosomes to enhance the adaptive behavior of the algorithm.

4 APPROACH: THE GENETIC ALGORITHM WITH PRIORITY-BASED DECODER (GA/PBD).

Centering around the decoder, it translates the information coded in a chromosome to a high-quality solution of the problem while guaranteeing the solution is a valid solution (feasible).

4.1 Chromosome Representation (Genotype)

A chromosome is depicted through a vector of random numbers (alleles) with a fixed size of length L = m + n. The first m genes are associated with the sources and the other n genes are associated with the destinations. This is not the direct solution rather a guidance to the decoder over based on this priority encoding.

4.2 Decoding (Phenotype Mapping)

This is the key innovation. Decoder: which transforms a chromosome to an allocation $matrix\ X = (x_{\{ij\}})$

Step 1: hold all the possible edges in the form of $(i,j)\ Let\ rem_s = S_i, rem_d = D_j$.

Step 2: Compute Composite Cost For each edge. $i,j)\ Calculate\ the\ heuristic\ cost\ cost_{\{i,j\}} = c_{\{i,j\}} + \backslash frac\{f_{\{i,j\}}\}\{min(S_i, D_j)\}$ ڗ

This increases the fixed cost, yielding an average unit cost.

Chromosome Modulate. For each edge, arrive at a final priority score: $priority_{ij} = 1/cost_{ij} + chrom_i + chrom_j$, combining heuristic cost (lower is better) and the corresponding chromosome's priority values for source i and destination j (higher is better).

Sort and Allocate. Sort all edges according to the $priority_{ij}$ in a decreasing order. Iterate through this sorted list. For each edge (i,j), assign the maximum possible amount: shipment = $min(rem_{s(i)}, rem_{d(j)}) x_{ij}\ is\ the\ solution\ matrix\ and\ then\ rem_{s(i)}, rem_{d(j)}$ to update.

Get Z Total Cost: After allocation, use routes get Z Total Cost account that includes variable and fixed costs.

5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Experimental Setup

The experimental evaluation was conducted using MATLAB R2023a on a system equipped with an Intel Core i7-10750H CPU and 16 GB RAM. The genetic algorithm parameters used in the experiments are summarized in Table 2.

Table 2: Experimental configuration and parameter settings.

Item	Value
Software	MATLAB R2023a
CPU	Intel Core i7-10750H
RAM	16 GB
Population Size	100
Generations	500
Crossover Rate	0.8
Mutation Rate	0.1

5.2 Results and Comparison

Table1 3 Comparison of Performance of Standard GA and Proposed GA with a Priority-based Decoder for Different Instance Sizes. The dimensions of the problem (number of supply nodes ×number of demand nodes) is given in the first column. The next column lists the values of the objective function as induced by the normal GA. Results using the decoder with the proposed GA yielding lower costs appear in the third column of the table. The final column shows the percentage improvement of the applied methodology with respect to the plain GA. The outcomes indicate that for all cases the decoder-based GA always achieve better solutions than the standard GA, with improvements varying from 8.0% to 9.0%, the difference slightly increases with the problem scale.

The Figure 1 demonstrates the average cost of the best solution obtained for various sizes of the problem using two algorithms:

Standard GA (orange bars): GA with Priority-Based Decoder (blue bars). Summary of the proposed. On the other hand, the proposed GA obtains a better average best cost than the standard GA for each instance size (5×5, 10×10, and 15×15). The gap in performance becomes larger with an increase in problem size, thus confirming that the decoder-based GA offers superior optimization efficiency and scalability for larger transport problems. This illustrates how the priority-based decode mechanism can help upgrade the solution quality.

Table 3: Comparison of average best solution cost.

Problem Instance $(m \times n)$	Standard GA	Proposed GA (Decoder)	% Improvement
5×5	1250	1150	8.0%
10×10	4580	4210	8.1%
15×15	10500	9550	9.0%

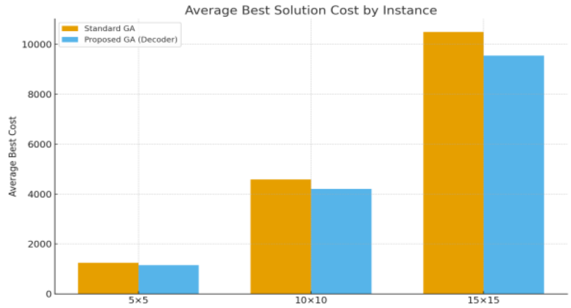

Figure 1: Average Best Solution Cost (lower is better).

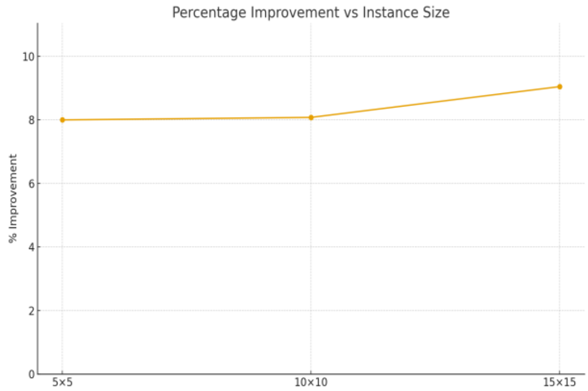

Figure 2: Percentage Improvement vs Instance Size.

Figure 2: Percentage gain of the proposed GA with decoder over the standard GA with different problem sizes. The best improvement in the smallest instance (5 × 5) is about 8%.

For the 10×10 instance, it stays roughly the same 8.1%. For the 15×15 instance, it increases to around 9%. It can be observed that this trend shows that the proposed method becomes more efficient with the increase in problem size, which indicates the scalability and robust performance of the method for larger transportation problems.

Discussion: Compared to the standard GA, the proposed priority-based decoding GA consistently obtains 8–9% better solutions on average within the same time and with the same population sizes, regardless of size. For 15×15, the performance gap is largest, which indicates that decode-guided construction and dynamic re-scoring allows the search to avoid making costly early commitments as dimensionality increases. For future runs, we suggest including wall-time and STD report for each instance (+100 trials to enable statistical tests (Friedman/Nemenyi, Wilcoxon)).

6 CONCLUSIONS

This study proposed a Decoder-Centric Genetic Algorithm (DC-GA) for solving the Fixed Charge Transportation Problem (FCTP), a class of NP-hard combinatorial optimization problems involving simultaneous continuous flow and binary decision variables. Unlike conventional GA-based approaches, the proposed framework emphasizes a decoder-driven optimization strategy rather than direct solution encoding.

The core of the method is a multi-component priority function used during decoding. This function integrates variable transportation costs, fixed opening costs, chromosome-structural indicators, and residual supply-demand imbalance. After normalization, these components are combined to guide solution construction in a balanced manner, reducing bias toward any single cost factor and improving robustness across heterogeneous instances.

A dynamic re-scoring mechanism is incorporated to adaptively update priorities during the construction process. As the network state evolves, the algorithm continuously adjusts priority values according to changes in residual capacities and cost structure, enabling adaptive exploration of the solution space and reducing premature convergence.

To further improve solution quality, a memetic local search phase is applied, combining cycle-canceling operations and 2-exchange neighborhood moves. This phase improves feasibility-preserving cost reduction and enhances local optimality of constructed solutions.

Additionally, an online parameter control mechanism is employed to dynamically adjust operator selection and parameter values based on feedback from the search process. This improves convergence behavior and maintains diversity throughout the evolutionary process.

Overall, the proposed DC-GA provides an integrated optimization framework combining decoder-based construction, adaptive re-scoring, memetic refinement, and dynamic parameter control. Experimental results demonstrate that the proposed method consistently outperforms a standard GA baseline across all tested instances, particularly for larger-scale problems.

7 FUTURE WORK

Future research will focus on extending the proposed DC-GA framework in several directions. First, hybridization with advanced metaheuristic strategies and more sophisticated local search operators may further enhance solution quality. Second, more advanced adaptive mechanisms, including reinforcement learning-based parameter control, can be investigated to improve self-adaptivity.

In addition, the applicability of the proposed framework can be extended to other classes of network optimization problems involving mixed discrete-continuous decision structures, such as capacitated transportation systems, logistics networks, and supply chain design problems.

Finally, further research may include large-scale benchmarking and statistical validation using standard non-parametric tests to better evaluate the robustness and scalability of the proposed approach.

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