Multi-Objective Optimization of Truck Assignments Using Heuristic and Metaheuristic Methods

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Abstract

In this paper, We developed an optimization methodology based on multi-objective and multi-criteria approaches. The research includes the mathematical modeling of transport orders covering problem, and the implementation of heuristic and metaheuristic methods to create an automated optimization process. Our approach aims to improve the quality of transport order-truck allocations, increasing loaded travel, better adherence to priorities and delivery deadlines, and reducing penalties. This optimization methodology is designed to enhance Numilog Algeria's operational efficiency and reduce transport costs.

Keywords: Transport Optimization, Heuristic, Metaheuristic, Multi-Criteria Analysis, Allocation of Transport Orders, Covering Problem

1 Introduction

The transportation sector is crucial for the modern economy, ensuring the efficient movement of goods. With increasingly complex supply chains, optimizing costs and delivery times is a significant challenge for transport companies. Inefficiencies in truck-to-order assignments, such as delays and non-optimal routes, can severely impact customer satisfaction and profitability. Addressing these issues requires robust mathematical modeling and effective resolution methods to enhance planning and flow management processes.

This paper focuses on optimizing the assignment of trucks to transport orders, using Numilog as a case study. We develop a comprehensive mathematical model to represent the problem and propose a resolution method that combines heuristic and metaheuristic techniques. The initial heuristic provides a feasible solution, which is further refined through metaheuristic methods to enhance overall efficiency.

2 Related Works

Several recent studies have explored various approaches to solving covering and assignment problems, as well as multi-objective optimization problems using heuristic and metaheuristic methods.

Lai and Tong [1] tackled the vehicle routing problem with simultaneous pickups and deliveries and time window constraints (VRP-SPDTW) by developing a mixed integer programming model and a hybrid metaheuristic approach. Their solution integrates improved ant colony optimization (IACO) for minimizing the number of vehicles and improved Tabu search for reducing travel costs. The proposed method effectively optimized both vehicle count and travel expenses, demonstrating significant improvements over traditional methods. This work provides a strong foundation for addressing complex logistical challenges using advanced metaheuristic techniques.

Wu et al. [2] developed a deep reinforcement learning framework to address routing problems, focusing on the Travelling Salesman Problem (TSP) and Capacitated Vehicle Routing Problem (CVRP). Their method, leveraging self-attention based policy networks, learns improvement heuristics to iteratively refine solutions. This approach demonstrated superior performance over traditional and state-of-the-art deep learning methods, effectively optimizing route planning and showcasing strong generalization across different problem sizes and real-world datasets. This framework offers a novel strategy for enhancing routing efficiency through learned heuristics, relevant to our multi-objective truck assignment optimization.

Costa et al. [3] introduced a deep reinforcement learning framework for solving the Traveling Salesman Problem (TSP) and the Capacitated Vehicle Routing Problem (CVRP). Their approach employs a policy gradient algorithm combined with a pointer attention mechanism to learn effective 2-opt improvement heuristics. The

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framework significantly enhances solution quality over traditional heuristics and other deep learning methods, demonstrating robust generalization across various problem instances.

The article "Genetic Algorithm with Pareto Front Selection for Multi-Criteria Optimization of Multi-Depots and Multi-Vehicle Pickup and Delivery Problems with Time Windows" by E. Ben Alaia, I. Harbaoui Dridi, H. Bouchriha, and P. Borne [4] focuses on solving the multi-depot and multi-vehicle pickup and delivery problem with time windows (m-MDPDPTW). The approach involves a multi-objective genetic algorithm that uses Pareto dominance for optimization. The genetic algorithm is designed to minimize three key objectives: total travel distance, total tardiness time, and the number of vehicles used. The algorithm employs an elitist selection strategy and a new chromosome path representation to ensure an efficient search for optimal solutions that satisfy the constraints of the m-MDPDPTW problem.

Sabba and Chikhi. [5] enhanced the genetic algorithm for solving the Traveling Salesman Problem (TSP) by integrating a local optimization heuristic called the Best 2-opt method. This hybrid approach improved the genetic algorithm's ability to find optimal solutions while reducing execution time. Tested on instances from 29 to 246 cities, the method demonstrated significant improvements in both solution quality and runtime, showcasing its effectiveness for combinatorial optimization problems.

Gunawan and Iryanto.[6] addressed the Traveling Salesman Problem (TSP) by developing a hybrid algorithm that integrates Simulated Annealing (SA) with the 2-opt local search method. This approach enhances the SA algorithm by incorporating both outer and inner loop iterations and applying the 2-opt heuristic to refine the solutions. Their method demonstrated superior performance in finding optimal solutions and reducing computational time across various TSP benchmark instances, outperforming traditional SA and other hybrid algorithms

"Parameter tuning for meta-heuristics" by Susheel Kumar Joshi and Jagdish Chand Bansal [7], published in Knowledge-Based Systems, focuses on optimizing the performance of meta-heuristic algorithms through effective parameter tuning. this approach introduces a parameter tuning framework called PTGSA (Parameter Tuning Gravitational Search Algorithm) that can be used to fine-tune the parameter α of the Gravitational Search Algorithm (GSA), which influences the gravitational coefficient G and hence the convergence behavior of GSA.

The article "Approche de résolution du problème d'affectation sous contraintes de compétences et préférences" was written by Raoudha Mkaouar Hachicha, El Mouloudi Dafaoui, Abderrahman El Mhamedi from MGSI – IUT DE MONTREUIL [8] proposes a global approach for solving the personnel assignment problem with consideration of both competencies and preferences. The key points are: The approach consists of three steps: 1) Evaluating the acquired and required competencies using a 2-tuple linguistic representation model, 2) Comparing the preference degree of each resource to a reference satisfaction degree, and 3) Formulating an optimization model to minimize the total assignment cost, including penalty costs for unsatisfied preferences

Hao, Galinier, and Habib (1999) [9] provide an extensive overview of metaheuristics for combinatorial optimization and constraint satisfaction problems. They categorize these methods into neighborhood search, evolutionary algorithms, and hybrids, and offer practical guidelines and insights into their limitations. The paper emphasizes the flexibility of metaheuristics in solving complex optimization problems and highlights their effectiveness in providing approximate solutions when exact methods are impractical.

Boumedyen presents the PROMETHEE method as a tool for multicriteria decision-making [10] . The article outlines the principles of the PROMETHEE I and II methods, which provide partial and complete rankings of alternatives based on preference flows. This method, developed at the Université de Bruxelles by Jean Pierre Brans, is part of the outranking methods family. It is particularly useful for incorporating both qualitative and quantitative criteria in decision-making processes, offering a structured approach to handle complex problems with multiple conflicting criteria.

Brans and Mareschal provide a comprehensive overview of the PROMETHEE-GAIA methodology for multicriteria decision analysis (MCDA) [11]. They discuss the history and development of PROMETHEE methods, starting from PROMETHEE I and II for partial and complete ranking to more advanced versions like PROMETHEE V for multiple selections under constraints and PROMETHEE VI for sensitivity analysis. The methodology is noted for its clarity in defining preferences and weights, and its user-friendly implementation through the DECISION LAB software. The paper highlights various applications of PROMETHEE in fields such as banking, healthcare, and environmental management, emphasizing its robustness and adaptability in handling complex decision-making problems.

Pentico provides a comprehensive survey of the variations of the assignment problem that have emerged since Kuhn's seminal 1955 paper on the Hungarian method. The article [12] categorizes these variations, including the classic assignment problem, bottleneck assignment problem, and quadratic assignment problem, among others. It aims to help researchers identify relevant models for specific applications and highlights the developments and practical applications of assignment problems over the past fifty years.

Gunantara reviews various methods and applications of multi-objective optimization (MOO)[13], focusing on the Pareto and scalarization methods. The Pareto method identifies non-dominated solutions to generate a Pareto optimal front, while the scalarization method transforms multiple objectives into a single solution using weighted sums. The paper discusses applications in fields such as economics, finance, politics, and engineering, highlighting the versatility and effectiveness of MOO techniques in addressing complex decision-making problems.

Pacheco and Martí present a tabu search approach for solving a multi-objective school bus routing problem [14], aiming to minimize both the number of buses and the maximum travel time for students. The method integrates a path relinking strategy to enhance solution quality. Computational experiments with real data demonstrate that the proposed approach outperforms existing methods, providing a set of efficient solutions that balance operational cost and service level.

Giagkiozis, Purshouse, and Fleming present an extensive overview of prominent population-based algorithms and their extensions for multi-objective optimization [15]. The paper discusses the adaptability of these techniques for real-world applications, highlighting their ability to escape local optima and handle both linear and nonlinear constraints. It categorizes these algorithms into families such as Genetic Algorithms, Ant Colony Optimization, Particle Swarm Optimization, Differential Evolution, and others, providing a critique of their capabilities and applications in various fields.

3 Case Study

In this section, we present an optimization methodology designed to improve operational efficiency and reduce costs. First, we describe the specific problem context and the logistical challenges faced by Numilog. Following this, we provide a detailed mathematical formulation of the optimization problem. Finally, we discuss the heuristic and metaheuristic approaches used to achieve significant improvements.

Numilog Algeria faces significant challenges in optimizing the allocation of transport orders, including issues such as delays, non-optimal routes, and excessive costs. Addressing these challenges requires an effective optimization methodology that considers multiple technical constraints and operational criteria to enhance the overall efficiency and cost-effectiveness.

3.1 Problem statement

Directional Movement: Trucks only move in one direction, from their current location to the transport order they are assigned to cover. Empty returns, which refer to the practice of returning to a depot or point of origin after making a delivery, are not allowed.

Homogeneous Fleet: All available trucks are homogeneous in terms of capacity and speed.

Fixed Service and Travel Times: The service times for Orders and the travel times between Orders are assumed to be fixed and known in advance. This means that the time required to complete an Order is not affected by external factors such as traffic congestion or weather conditions.

No Precedence Constraints: There are no specific precedence constraints among the Orders, meaning that there is no particular order in which Orders must be completed. The model is free to assign Orders to trucks in any order that minimizes the total coverage cost. However, there is a priority among certain Orders, which is calculated using multi-criteria analysis methods.

3.2 Mathematical formulation

3.2.1 Sets

O: Set of transport orders.

K: Set of trucks.

3.2.2 Parameters

o: Index of the transport order.

k: Index of the truck.

$[e_o, l_o]$*: Time window for order o.*

f_o*: Priority of order o.*

t_o*: Service time of order o.*

d_k*: Duration of truck k, duration between its availability time and the driver's rest day.*

H_k*: Availability time of truck k.*

t_{ok}*: Travel time between order o and the depot of truck k.*

t_{ko}*: Travel time between truck k and order o.*

$t_{oo'}$*: Travel time between the positions of orders o and o'.*

3.2.3 Variables

$$x_{ok} = \begin{cases} 1 & \text{If truck } k \text{ is assigned to order } o \\ 0 & \text{Otherwise} \end{cases}$$

$$p_{ok} = \begin{cases} 1 & \text{If the availability duration of truck } k \text{ is not respected if assigned to order } o \\ 0 & \text{Otherwise} \end{cases}$$

T_{ok} = Service start time of order o by truck k.

3.2.4 Constraints

$$\sum_{k \in K} x_{ok} \leq 1, \quad \forall o \in O \tag{1.1}$$

Every order must be covered by at most one truck.

$$T_{ok} \geq e_o - (1 - x_{ok})M, \quad \forall o \in O, \forall k \in K; M >> 0 \tag{1.2}$$

$$T_{ok} \leq l_o + (1 - x_{ok})M, \quad \forall o \in O, \forall k \in K; M >> 0 \tag{1.3}$$

The service start time of each order o must lie within the assigned time window.

$$T_{ok} x_{ok} \leq 24, \quad \forall o \in O, \forall k \in K \tag{1.4}$$

The service start time of each order o must occur before midnight.

$$T_{ok} x_{ok} = \max \left\{ \max_{\substack{o' \in O \\ o' \neq o}} \{(T_{o'k} + t_{o'} + t_{o'o}) x_{o'k}\}, (H_k + t_{ko}) x_{ok} \right\} x_{ok} \quad \forall o \in O, \forall k \in K \tag{1.5}$$

The service start time of a new order o must account for the travel and service times of previous orders.

$$(T_{ok} + t_o + t_{ok} - d_k) x_{ok} \geq (1 - p_{ok})(1 - M) x_{ok} \quad \forall o \in O, \forall k \in K; M >> 0 \tag{1.6}$$

$$(T_{ok} + t_o + t_{ok} - d_k) x_{ok} \leq M p_{ok} x_{ok} \quad \forall o \in O, \forall k \in K; M >> 0 \tag{1.7}$$

Constraints (3.6) and (3.7) ensure penalties are applied for violating the truck availability duration constraints.

3.2.5 *Objective Functions*

$$\min \sum_{k \in K} \max \left\{ \left(\max_{o \in O} (T_{ok} + t_o) x_{ok} \right) - H_k x_{ok} - \sum_{o \in O} t_o x_{ok} \right\} \tag{1.8}$$

This function aims to minimize the travel time of empty trucks, considering the time between truck availability and the service start time of the first order plus the travel time between orders.

$$\max \sum_{k \in K} \sum_{o \in O} f_o x_{ok} \tag{1.9}$$

This function aims to maximize the priority of covered orders.

$$\min \sum_{k \in K} \sum_{o \in O} p_{ok} x_{ok} \tag{1.10}$$

This function aims to minimize penalties associated with violations of truck availability constraints.

3.3 *Resolution*

We opted for approximate methods, which are carried out in several steps:

Multi-Criteria Analysis: To optimize the management of transport orders and establish a clear priority order, a multi-criteria analysis evaluates each Order based on three main criteria: Order destination, client priority, and revenue. Weights of these criteria are calculated using the AHP method, and the PROMETHEE II method is used to calculate the net flow of each OT, indicating its relative priority.

Heuristic: The heuristic used to propose an initial assignment follows an iterative approach guided by a fitness function that combines three objectives: minimizing travel time, rest day penalties, and maximizing Orders net flows to evaluate and choose the best Order-truck assignment at each step.

Metaheuristic: The heuristic produces an initial solution, which is then improved by a metaheuristic composed of two steps: The first step uses the Sonar algorithm to evaluate and execute possible permutations between transport orders assigned to different trucks, aiming to reduce empty mileage and rest day penalties. The second step uses 2-opt and Tabu Search metaheuristics to explore new neighborhoods from the solutions generated by Sonar, integrating uncovered OTs.

3.3.1 *Calculus of priorities by the Multi-Criteria Analysis*

The multi-criteria analysis aims to optimize the management of transport orders and establish a clear priority order for them. This is achieved using the PROMETHEE II method, which calculates the net flow for each Order, indicating its priority relative to others. The steps involved are as follows:

Criteria Definition

Three main criteria are identified to evaluate each Order:

- Destination of the Order: Importance of minimizing empty mileage and the attractiveness of a destination.
- Client Priority: Reflects the frequency of orders and the relationship with the client.
- Revenue: Influences the priority based on the economic impact of the Order.

Weight Calculation Using AHP

The Analytic Hierarchy Process (AHP) is used to calculate the weights of the criteria. A comparison matrix is constructed to assess the relative importance of each criterion. The weights are determined using the Saaty scale, resulting in the following weights:

- Destination: 0.7230
- Client Priority: 0.2157
- Revenue: 0.0612

Priority Evaluation
The priority of the cities and clients is evaluated using comparison matrices. Cities are categorized into four categories based on their importance, and each city receives a score. The AHP method calculates scores for each category of city and client, reflecting their importance.

Net Flow Calculation Using PROMETHEE II
Each Order is evaluated against the three criteria using the PROMETHEE II method. This method calculates the net flow , which is the difference between positive and negative flows relative to other Orders. The positive flow indicates how much an Order outranks others, while the negative flow indicates how much it is outranked by others. The net flow is used to rank the Orders.

The calculated net flows are integrated into the decision-making process for selecting and assigning Orders. This improves decision efficiency and Order allocation by directly incorporating the priorities.

3.3.2 Heuristic approach for an initial solution

The proposed heuristic relies on an iterative approach guided by a fitness function that combines three objectives to evaluate and select the best Order-truck assignment at each step. The algorithm can be explain as follows:

1. Initialization: All Orders and trucks are marked as unassigned, and all trucks are marked as available.
2. Assignment Cost Calculation: For each pair of available truck and unassigned Order, the algorithm calculates the associated assignment cost. The assignment cost takes into account:

   Travel Time: Calculated based on the distance between the truck's current location and the Order's departure city, using the distance matrix.

   Rest Day Penalties: Assessed by checking if assigning an Order prevents the truck from returning to its agency before the driver's rest day.

   Order Priority: Assigned based on the importance of the Order, with high-priority Orders having a lower assignment cost.
3. Order Selection: For each available truck and unassigned Order, the algorithm selects the Order associated with the lowest assignment cost that satisfies all constraints. An Order can only be assigned to a truck if the truck can reach the Order's departure city before the end of the client's time window.
4. Status Update: After each assignment, the Order is marked as assigned, and the truck's information is updated (current position and estimated availability time at the Order's arrival city).
5. Repetition: The procedure is repeated until all Orders are assigned or no trucks are available.

The details can be proceed as follows:

Algorithm 1 Heuristic Algorithm

Input: Orders file, Availability file, Distance matrix
Output: initial assignment
// fitness Fonction //
Function `Cost`(*truck, order*)**:**
    if *waiting_time(truck, order) == 0* **then**
        cost $\leftarrow \alpha \times$ travel_time(truck, order) $+ \beta \times$ penalty(truck, order) $- \gamma \times$ order$['netFlow']$
    else
        cost $\leftarrow \infty$
    end
    return cost
// Assignment Fonction //
Function `Assignment`(*truck, order*)**:**
    while *There is an unassigned order* **do**
        if *No truck is available* **then**
            break
        end
        for *Each available truck* **do**
            for *Each unassigned order* **do**
                `Cost`(*truck, order*) : Calculate assignment costs
                cost_min ←Find the minimum cost
                idx_ot_min ← Find the index of the order with the minimum cost
                if *cost_min* == ∞ **then**
                    break
                end
                idx_ot_min ← Assign
                truck ← Update the truck information
            end
        end
    end
    return initial assignment

3.3.3 Metaheuristic for improvement solution

In our approach, we propose a two-step method to improve the initial solution provided by the heuristic.

Step 1: Intensification using Sonar Metaheuristic

The objective of this first step is to minimize the empty travel distance of trucks and the penalties due to non-respect of driver rest days.

We begin by initializing the set of non-dominated solutions with the solution generated by the heuristic.

The Sonar algorithm is employed to evaluate possible permutations among the transport orders assigned to different trucks for each non-dominated solution.

Identify the permutation that yields the greatest reduction in empty travel distance.

When a promising permutation is identified, it is implemented.

The solution is then compared to the existing set of non-dominated solutions. If the new solution represents an improvement, it is incorporated into this set.

The intensification process continues until no further improvements can be made. This phase focuses solely on examining possible permutations among transport orders already considered in the initial solution, without introducing any new transport orders not covered by the initial solution.

Step 2: Diversification Using 2-opt and Tabu Search Metaheuristics

The second step aims to explore new solution neighborhoods generated by the Sonar algorithm using the 2-opt metaheuristic and Tabu Search. This exploration seeks to uncover additional solutions that were not examined during the intensification phase.

This phase extends the search to the entire solution space, without being restricted to the transport orders covered by the initial solution. It aims to integrate uncovered transport orders and reconsider all potential solutions.

For each non-dominated solution, the 2-opt algorithm is applied to permute between covered and uncovered transport orders. Tabu Search is utilized to prevent revisiting previously explored solutions by maintaining a Tabu list that records recently performed moves, thus promoting search diversification.

If a permutation improves the empty travel distance, reduces penalties, or enhances net flow, it is executed. Each newly generated solution is evaluated against the set of non-dominated solutions, and if it represents an improvement, it is added to this set. The ultimate goal is to iteratively refine this set towards the Pareto front.

The exploration process continues until no significant improvements can be achieved or the allocated search time is exhausted.

Algorithm 2 Metaheuristic Algorithm

Input: Initial Solution: Assignment dictionary
Time Limit: Time limit for tabu search in seconds
Tabu Size: Size of the tabu list
Output: Set of non-dominated solutions
// Intensification Phase //
  Initialize the set of NDS with the initial solution
  for *each pair of trucks* (i, j) **do**
    Calculate the mileage difference Δkm by evaluating the exchange of Orders
    Choose the highest value of Δkm
    if Δkm <= *0* **then**
      break
    end
    Exchange the Orders (i, j)
    Update the set of NDS
end
// Diversification Phase //
  Initialize the set of NDS with the solutions returned from the intensification phase
  Initialize *start time* with the current time ;
  for *each non-dominated solution* **do**
    for *each covered Order* **do**
      for *each uncovered Order* **do**
        if *the exchange is not in the tabu list* **then**
          Evaluate the exchange (Δkm, $\Delta flow$, $\Delta penalty$)
          if Δkm *or* $\Delta flow$ *or* $\Delta penalty$ *is improved* **then**
            Perform the exchange
            Add the exchange to the tabu list
            Update the set of NDS
            Update *last improvement time* with the current time
            if *last improvement time - start time* >= *Time limit* **then**
              break
            end
            Update *start time* with the current time
          end
        end
      end
    end
end

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4 RESULTS

4.1 Tuning Parameters for the Fitness Function

4.1.1 Presentation of Tuning Parameters

The cost function uses three tuning parameters:

- α: Controls the weight of travel time in the cost calculation.
- β: Controls the penalty weight associated with non-compliance with drivers' rest days.
- γ: Controls the weight of the net flow of the order to differentiate between orders with equal travel time and penalty.

4.1.2 Justification of Chosen Values

The values of the parameters α, β, and γ were selected through extensive testing to find the combination that provides the best results in terms of solution quality. All possible combinations of these parameters were tested under the constraint:

$$\alpha + \beta + \gamma = 1$$

with $\alpha \neq 0, \beta \neq 0, \gamma \neq 0$.

Possible values for each parameter: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8.

The optimal combination ($\alpha = 0.5, \beta = 0.2, \gamma = 0.3$) was found to provide the best compromise among the three objectives: Loaded travel percentage, Net flow, Penalty

4.2 Heuristic Results (Initial Solution)

We present the results obtained from the heuristic applied on March 27, 2024, compared to the results achieved by the company on the same day. These results were obtained after assigning 214 available trucks, allowing for the completion of 383 transport orders.

The heuristic achieved significant results for the three objective functions within an execution time of 20.67 seconds:

Loaded travel percentage: 85.28%

Net flow: 18.38

Penalty: 11

Indicators	Company	Heuristic	Improvement Rate
Loaded travel (%)	75.3	85.28	13.25%
Net flow	13.23	18.38	38.93%
Penalties	17	11	35.29%

Table 1: Comparison table of the company's results and the heuristic's results.

Given the large number of transport orders, detailed results are available in the table accessible via the following link: Detailed Results.

The heuristic significantly outperforms the company's current method in terms of loaded travel percentage, net flow, and penalties. Specifically, it achieved a 13.25% improvement in loaded travel, a 38.93% improvement in net flow, and a 35.29% reduction in penalties. These results demonstrate the heuristic's effectiveness in optimizing truck assignments and improving operational efficiency.

4.3 Metaheuristic Results

During the second phase of diversification, using a Tabu list of size 5 and a time limit between two non-dominated solutions of 120 seconds, the final results obtained are as follows:

Loaded travel percentage: 88.01%

Net flow: 27.81

Penalty: 11

The total execution time of the metaheuristic was 9 minutes and 84 seconds. This solution represents the best possible trade-offs between the three considered objectives: loaded travel percentage, net flow, and penalties.

Indicators	Company	Metaheuristic	Improvement Rate
Loaded travel (%)	75.3	88.01	16.88%
Net flow	13.23	27.81	110.2%
Penalties	17	11	35.29%

Table 2: Comparison table of the company's results and the metaheuristic's results.

The application of the metaheuristic demonstrated significant improvements in all performance indicators compared to the company's current results. These improvements translate to better resource utilization, more efficient selection of transport orders to fulfill, and a reduction in penalties.

Detailed results can be accessed via the following link: Detailed Results.

5 Conclusion

In this paper we presented a mathematical model for the covering problem of transport orders by available trucks, clearly defining the sets, parameters, variables, constraints, and objective functions. This served as the basis for the practical implementation and resolution of the problem. A structured approach was implemented to solve the Orders allocation problem, starting with multi-criteria analysis, followed by the application of a heuristic guided by a fitness function. This initial solution was further improved using metaheuristics such as the Sonar algorithm, 2-opt, and Tabu search.

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