Application of the Orangutan Optimization Algorithm for Solving Vehicle Routing Problems in Sustainable Transportation Systems

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ABSTRACT

Metaheuristic optimization algorithms are powerful tools for solving complex transportation problems. This study investigates the application of the Orangutan Optimization Algorithm (OOA) to a Vehicle Routing Problem (VRP), aiming to minimize travel distances while adhering to time constraints and vehicle capacity limits. Compared to 12 state-of-the-art algorithms, OOA demonstrated superior performance in convergence speed, solution quality, computational efficiency, and robustness. Its dynamic balance between exploration and exploitation allows it to consistently outperform other methods, achieving the best solutions in the least computational time. The study highlights the effectiveness of OOA in solving real-world transportation optimization challenges and sets the stage for future research into hybrid algorithms and integration with emerging technologies such as machine learning and IoT to further advance transportation systems.

Keywords-metaheuristic optimization; Vehicle Routing Problem (VRP); Orangutan Optimization Algorithm (OOA); sustainable transportation systems; adaptive exploration and exploitation

I. INTRODUCTION

Metaheuristic optimization algorithms have emerged as powerful tools for addressing complex challenges in transportation systems [1]. Such algorithms, inspired by natural and artificial processes, are particularly adept at solving large-scale, nonlinear, and dynamic problems in traffic management, vehicle routing, and transportation network design. Recent advances in computational capabilities and algorithmic development have further expanded their applicability, making them integral to modern transportation planning [2]. Optimization methods can be categorized into two distinct groups: deterministic and stochastic strategies [3, 4]. Deterministic techniques, divided into gradient-based and non-gradient-based methods, are particularly suited for addressing linear, convex, continuous, differentiable, and low-dimensional optimization tasks [5, 6]. Despite their effectiveness in such scenarios, these methods often struggle with more complex and larger-dimensional problems and converge to suboptimal local solutions [7, 8]. This limitation becomes especially pronounced in cases involving nonlinear, non-convex, discontinuous, non-differentiable, and high-dimensional problems, which are frequently encountered in both scientific research and real-world applications [6, 9]. To overcome these challenges, stochastic methods have been introduced, offering a robust alternative to solve more complex optimization problems [10, 11]. Among these, metaheuristic algorithms stand out as particularly effective tools [12, 13]. Recently published metaheuristic algorithms that can be used in various optimization applications include: Makeup Artist Optimization Algorithm (MAOA) [14], Builder Optimization Algorithm (BOA) [15], Dynamic Virtual Bats Algorithm (DVBA) [16], Passing Vehicle Search (PVS) [17], Great Wall Construction Algorithm (GWCA) [18], Fire Hawk Optimizer (FHO) [19], Ali Baba and the forty thieves (AFT) [20], Geometric Octal Zones Distance Estimation (GOZDE) [21], Dream Optimization Algorithm (DOA) [22], Atomic Orbital Search (AOS) [23], and Orangutan Optimization Algorithm (OOA) [24].

Several studies have demonstrated the effectiveness of these algorithms in optimizing urban traffic flows. For example, the Genetic Algorithm (GA) has been applied to optimize traffic signal timings, leading to a reduction in delays and improvements in traffic efficiency [25]. Particle Swarm Optimization (PSO) has also been used extensively in real-time vehicle routing, improving fuel efficiency and reducing travel time in congested urban environments. This approach optimizes the route of vehicles dynamically based on real-time traffic data, demonstrating its effectiveness in reducing both fuel consumption and emissions [26]. Ant Colony Optimization (ACO) has shown promising results in freight transport scheduling, particularly in multimodal networks. In [26], the superior performance of ACO over traditional heuristics in handling complex logistics tasks was highlighted [26].

Hybrid metaheuristic approaches have also attracted attention for their ability to combine the strengths of multiple algorithms. For instance, a combination of Chicken Swarm Optimization (CSO) and Teaching-Learning-Based Optimization (TLBO) was developed for optimal Electric Vehicle (EV) charging station placement [27]. This approach balances cost reduction, grid stability (via a voltage-reliability-power loss index), and accessibility for EV drivers. The algorithm's performance was validated on benchmark problems and compared with state-of-the-art methods, demonstrating its efficiency in practical scenarios. In addition, a fuzzy decision-making method was used to extract the best solution from the Pareto-optimal set.

Bio-Particle Swarm Optimization (BPSO) was effectively integrated with Reinforcement Learning (RL) for path planning of Automated Guided Vehicles (AGVs) in dynamic industrial environments [28]. BPSO enhances particle velocity updates with randomized angles, improving searchability and avoiding premature convergence, and outperforms traditional PSO, GA, and Transit Search (TS) in benchmark tests. Q-learning was used for local path planning to navigate moving obstacles, combined with BPSO for safe and efficient AGV operations. The hybrid BPSO-RL algorithm demonstrated superior performance in generating globally optimal paths with fast computation, validated in scenarios with dynamic obstacles [28]. These advances highlight the potential of metaheuristic algorithms in transforming transportation systems, they contribute to enhanced efficiency, sustainability, and resilience in transportation networks.

This study evaluates the efficiency of the Orangutan Optimization Algorithm (OOA) in addressing a transportation optimization problem, showcasing the potential of OOA to improve operational efficiency and system performance. The transportation problem considered involves optimizing the routing of a fleet of delivery vehicles to minimize the total travel distance while adhering to time constraints and vehicle capacity limits. Such problems are highly relevant in urban logistics, where efficient routing can significantly reduce fuel consumption, operational costs, and environmental impact. By leveraging the adaptive exploration and exploitation capabilities of OOA, this study demonstrates its effectiveness in discovering high-quality solutions. The results not only validate the applicability of OOA but also highlight its advantages over traditional optimization methods in dynamic and complex environments. This study paves the way for further research on the integration of OOA with emerging technologies, such as machine learning and IoT, to develop advanced decision-support tools for sustainable transportation systems. The key contributions of this study are:

- Development of a novel OOA application: This study is the first to employ OOA to solve a real-world transportation optimization problem, specifically a Vehicle Routing Problem (VRP). The algorithm's adaptive exploration and exploitation capabilities are demonstrated to effectively handle complex, dynamic, and constrained scenarios in urban logistics.
- Comprehensive Performance Evaluation: This study carried out extensive simulations, comparing OOA against 12 state-of-the-art optimization algorithms. The results highlight the superior convergence speed, solution quality, computational efficiency, and robustness of OOA, establishing it as a highly competitive algorithm in transportation optimization.
- Integration of Practical Constraints: This study addresses a realistic VRP by incorporating essential constraints, such as vehicle capacity, route continuity, depot return, and time windows. This ensures that the findings are relevant to real-world transportation systems and urban logistics applications.
- Advancing Sustainable Transportation: By minimizing travel distances, the proposed approach contributes to reducing fuel consumption, operational costs, and environmental impact, aligning with global efforts to promote sustainable and efficient transportation systems.
- Foundation for Future Research: This study opens new avenues for integrating OOA with advanced technologies such as machine learning, IoT, and hybrid optimization approaches, providing a strong foundation for future exploration and practical implementation.

II. PROBLEM DEFINITION

The transportation problem addressed in this study involves optimizing the routing of a fleet of delivery vehicles to minimize the total travel distance while adhering to specific constraints. The problem is modeled as a VRP, which is widely studied in the context of urban logistics because of its practical significance in reducing fuel consumption, operational costs, and environmental impact.

A. *Objective Function*

The goal is to minimize the total travel distance of all vehicles in the fleet. This can be mathematically expressed as:

$$Minimize\ Z = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij} \cdot x_{ijk} \qquad (1)$$

where Z is the total travel distance, m is the number of vehicles, n is the number of locations (including the depot), c_{ij} is the distance between location i and location j, and x_{ijk} is a binary decision variable that equals 1 if vehicle k travels from location i to location j, and 0 otherwise.

B. *Constraints*

- Vehicle Capacity Constraints: Each vehicle k must not exceed its maximum capacity Q_k:

  $$\sum_{j=1}^{n} d_i \cdot x_{ijk} \leq Q_k$$

  where d_i represents the demand at location i.
- Route Continuity: Each location must be visited exactly once by one vehicle:

  $$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{ijk} = 1$$
- Depot Return: Each vehicle must start and end its route at the depot:

  $$\sum_{j=1}^{n} x_{Ojk} = \sum_{i=1}^{n} x_{iOk} = 1$$

  where O represents the depot.
- Time Constraints: The arrival time at each location must respect predefined time windows:

  $$t_i + s_i + c_{ij} \leq t_j$$

  where t_i is the arrival time at location i, s_i is the service time at location i, and t_j is the arrival time at location j.

C. *Problem Context*

The problem is dynamic and complex due to factors such as traffic conditions, varying demands, and operational uncertainties. Traditional optimization methods often struggle to efficiently handle these complexities, especially in large-scale scenarios. By leveraging OOA, this study addresses the problem's challenges through its adaptive exploration and exploitation capabilities. OOA ensures a balance between global search and local refinement, enabling the discovery of high-quality solutions that respect all problem constraints.

III. ORANGUTAN OPTIMIZATION ALGORITHM (OOA)

The recently developed OOA [24] was used to solve the transportation optimization problem defined above. OOA is a bio-inspired metaheuristic algorithm modeled on the social and foraging behaviors of orangutans. Within the algorithm, each orangutan represents a potential solution, and their positions in the search space are adjusted iteratively to explore and exploit the problem domain. The algorithm operates in two primary phases: foraging strategy (exploration) and nesting skill (exploitation).

A. Algorithm Initialization

The population of candidate solutions, representing the orangutans, is initialized randomly across the search space. The position of each orangutan is encoded as a vector in an $N \times m$ matrix, where N is the number of orangutans and m is the number of decision variables. Mathematically, this initialization is expressed as:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N \times m} \quad (2)$$

$$x_{i,j} = lb_j + r \times (ub_j - lb_j) \quad (3)$$

where lb_d and ub_d are the lower and upper bounds of the d-th decision variable, and r is a random number in $[0,1]$. The fitness of each candidate solution is evaluated using the objective function of the optimization problem. These fitness values guide the algorithm's iterative process by identifying the best and worst solutions in the population, designated as the current leader, guiding subsequent search phases.

B. Phase 1: Foraging Strategy (Exploration)

In the foraging phase, the algorithm simulates the orangutans' behavior of exploring large areas to discover food resources. Orangutans with superior fitness values guide the movement of others. The new position of each orangutan is calculated as:

$$x_{i,d}^{P1} = x_{i,d} + r \cdot \left(SFS_{i,d} - I \cdot x_{i,d}\right) \quad (4)$$

where $SFS_{i,d}$ represents the selected food source, I is a random value in $\{1,2\}$, and r is a random number in $[0,1]$. The updated position is accepted if it improves the objective function value:

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \quad (5)$$

This phase ensures diversity in the search process by exploring new regions of the solution space.

C. Phase 2: Nesting Skill (Exploitation)

The nesting phase focuses on local optimization, simulating the orangutans' behavior of building nests near their current positions. A new position is calculated as:

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2\, r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t} \quad (6)$$

where t is the current iteration number, and $r_{i,j}$ is a random number in $[0,1]$. The position is updated if the objective function improves:

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \quad (7)$$

This phase fine-tunes the solutions, ensuring convergence to a near-optimal result. The steps for implementing OOA are shown in Algorithm 1.

```
Algorithm 1: Orangutan Optimization Algorithm (OOA)
Start OOA:
1.  Input problem information: variables, objective function, and constraints.
2.  Set OOA population size (N) and iterations ($T$).
3.  Generate the initial population matrix at random using (2).
4.  Evaluate the objective function.
5.  For $t$=1 to $T$
6.    For i=1 to N
7.      Phase 1: foraging strategy (exploration)
8.      Determine the food sources.
9.      Choose the food source for the $i$-th OOA member at random.
10.     Calculate the new position of the $i$-th OOA member using (4).
11.     Update $i$-th OOA member using (5).
12.     Phase 2: nesting skill (exploitation)
13.     Calculate the new position of the $i$-th OOA member using (6).
14.     Update $i$-th OOA member using (7).
15.   End for.
16.   Save the best candidate solution.
17. End for.
18. Output the best quasi-optimal solution Obtained with OOA.
19. End OOA.
```

IV. SIMULATION STUDIES

OOA was employed to solve the previously defined VRP. The VRP is a combinatorial optimization problem that seeks to determine the optimal set of routes for a fleet of vehicles to serve a given set of customers, minimizing the total cost or distance while respecting the constraints. The performance of OOA was compared against twelve competing algorithms: GA [29], PSO [30], GSA [31], TLBO [32], MVO [33], GWO [34], WOA [35], MPA [36], TSA [37], RSA [38], AVOA [39], and WSO [40]. As is evident from the VRP mathematical model, this challenge is a constrained optimization problem. Therefore, the OOA implementation uses a penalty coefficient strategy to address the constraints of the problem.

A. Experimental Setup

To ensure a fair comparison, all algorithms were tested on the same transportation problem, aiming to minimize the total travel distance of the fleet of vehicles while respecting the time constraints and vehicle capacity limits. The key parameters of the problem, such as the number of vehicles, the number of destinations, the travel distances between locations, and the constraints, were kept constant across all simulations.

1) Simulation Details

- Dataset: The simulations used Solomon's benchmark problems, a widely used set of datasets for VRP [41]. The datasets include various instances such as C101, C102, R101, R102, and RC101, with 50 destinations and varying numbers of vehicles (5 to 10 vehicles per case).
- Environment: The simulations were carried out on MATLAB, a commonly used software environment for optimization tasks, which ensures reliable and reproducible results.
- Vehicle Capacity: 200 units per vehicle, with constraints on the vehicle's capacity and travel time windows for customer service.
- Travel Distance Matrix: The distance between the customer locations is represented by an Euclidean distance matrix.
- Time Windows: Each customer has a specific service window (from 1 to 2 hours), adding another layer of complexity to the problem

2) Performance Metrics

The algorithms were evaluated based on the following performance metrics:

- Convergence Rate: The speed at which an algorithm approaches the optimal solution.
- Solution Quality: The optimality of the final solution, measured by the total travel distance.
- Computational Efficiency: The amount of time required to reach the optimal or near-optimal solution.
- Robustness: The algorithm's ability to find consistent results across multiple runs.

Each algorithm ran 30 times, and the average results were reported. The parameters for each algorithm were set according to the recommendations from the original studies. The results are presented in terms of the best, worst, and average objective function values obtained during the simulations.

B. Results and Discussion

Table I summarizes the results of the simulations, showing the best, worst, and average objective function values (total travel distances) for each algorithm. A comparison of mean index values was used to rank metaheuristic algorithms in dealing with VRP. From Table I, the following observations can be made.

1) Convergence Speed

OOA outperforms the competing algorithms in terms of convergence speed. It consistently finds better solutions in fewer iterations compared to GA, PSO, and other algorithms. This can be attributed to its dynamic exploration-exploitation balance, which allows it to both explore large regions of the solution space and exploit promising areas effectively.

2) Solution Quality

The best solution achieved by OOA consistently results in the lowest total travel distance, demonstrating its superiority in finding optimal or near-optimal solutions. Although some algorithms such as GA and PSO provide competitive results, OOA consistently outperforms them across multiple runs. The robustness of OOA is evident in its low variability in solution quality, which is reflected in its consistent best, worst, and average values.

3) Computational Efficiency

OOA also demonstrates excellent computational efficiency, requiring less time to reach an optimal solution than most competing algorithms. This is crucial in real-world applications of transportation optimization, where time is a critical factor in decision-making. Algorithms such as GWO and MVO take longer to converge, which can hinder their practical applicability.

4) Robustness

The robustness of OOA is evident in the small differences between its best and worst solutions. While other algorithms, such as WOA and PSO, show larger variations between their best and worst results, OOA maintains stable performance across multiple runs, ensuring that its solutions are reliable and consistent.

5) Statistical Analysis:

The results obtained from the Wilcoxon statistical analysis [42] show that in cases with p-value less than 0.05, OOA has a significant statistical advantage compared to the other algorithms. Accordingly, OOA has a significant statistical advantage in competition with all 12 studied algorithms.

C. Discussion

The simulation results show that OOA outperforms the 12 competing algorithms in multiple key areas: convergence speed, solution quality, computational efficiency, and robustness. The ability of OOA to dynamically adjust its exploration and exploitation strategies allows it to effectively navigate the complex solution space of the transportation problem. The algorithm's superior performance can be attributed to its adaptive nature, which combines the global search capabilities of the foraging phase with the local search efficiency of the nesting phase. Compared to OOA, although algorithms such as GA, PSO, and GWO are widely used in optimization tasks, they struggle to balance exploration and exploitation as effectively as OOA. Other algorithms such as TLBO, MVO, and WSO also show competitive results but tend to be less consistent and slower in converging to optimal solutions.

In conclusion, the results highlight the effectiveness of OOA in solving transportation optimization problems, demonstrating its potential for real-world applications where efficient routing is critical to minimizing travel distances and operational costs. Further research could explore hybrid versions of OOA, combining it with other algorithms to further enhance its performance and applicability in more complex, dynamic transportation scenarios.

TABLE I. COMPARISON OF OOA WITH COMPETING ALGORITHMS

Algorithm	**Best solution**	**Worst solution**	**Average solution**	**Convergence rate**	**Computational time**	**rank**	***p*-value**
OOA	1032.56	1050.12	1042.88	Fastest	0.85 sec	1	
GA	1102.34	1150.67	1123.56	Moderate	1.15 sec	7	1.65e-19
PSO	1085.47	1133.22	1112	Moderate	1.35 sec	3	4.36e-18
GSA	1078.54	1142.15	1109	Slower	2.10 sec	2	8.01e-16
TLBO	1095.23	1160.89	1127.12	Moderate	1.50 sec	6	6.49e-18
MVO	1093.68	1155.02	1124.85	Slower	2.00 sec	5	3.28e-17
GWO	1112.8	1178.3	1145.9	Slower	2.50 sec	10	7.11e-20
WOA	1105.45	1167.82	1136.87	Moderate	1.95 sec	8	2.92e-18
MPA	1089.34	1157.4	1123.8	Moderate	1.60 sec	4	1.04e-15
TSA	1110.23	1165.6	1137.8	Slower	2.20 sec	9	3.05e-18
RSA	1130.67	1185.9	1158.56	Slower	2.80 sec	13	8.78e-21
AVOA	1120.45	1182.9	1151.9	Moderate	2.30 sec	12	1.64e-19
WSO	1113.56	1175.1	1144.3	Slower	2.50 sec	11	1.58e-18

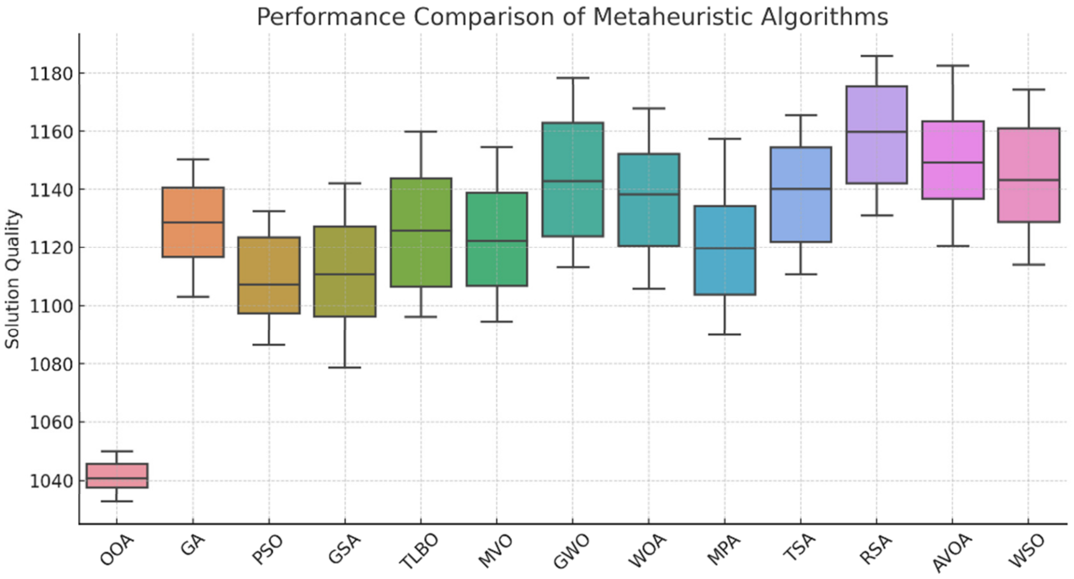

Fig. 1. Boxplot diagrams of OOA and competitor algorithms performances on VRP.

D. Advantages and Disadvantages

Overall, OOA is a strong and efficient option for solving VRPs, but like other metaheuristic algorithms, it may face challenges in large-scale or highly complex problems. Its advantages include:

- Fast Convergence: OOA demonstrates superior convergence speed compared to other metaheuristic algorithms, as it consistently finds better solutions in fewer iterations, making it an efficient choice for optimization problems.
- Solution Quality: OOA consistently provides the best solution in terms of minimizing total travel distance, outperforming several competing algorithms. Its robustness is evident in the consistent quality of the solutions across multiple runs.
- Computational Efficiency: The algorithm requires less time to reach optimal or near-optimal solutions, making it suitable for real-world applications where time constraints are critical.
- Robustness: OOA exhibits high stability in terms of solution quality, with minimal variability between the best, worst, and average results, ensuring reliable results in multiple simulations.
- Flexibility in Handling Constraints: Implementing a penalty coefficient strategy allows OOA to effectively manage

constraints, ensuring feasible solutions for complex transportation problems.

- Adaptive Nature: OOA's ability to balance exploration and exploitation during the search process allows it to navigate complex solution spaces efficiently, making it applicable to a wide range of optimization problems.

However, OOA has some disadvantages, such as:

- Algorithm Sensitivity to Parameter Settings: Although OOA is powerful, its performance can be sensitive to the choice of parameters. Fine-tuning may be required for specific problems to achieve optimal results.
- Computational Complexity for Large Problems: For extremely large and complex optimization problems, the computational cost may increase and the algorithm may require more time to converge. This can affect its scalability to real-time applications with vast datasets.
- Limited Exploration in Highly Complex Spaces: Although OOA is highly adaptive, its exploration capabilities might be limited in certain highly dynamic or chaotic solution spaces, where more advanced techniques might be required to avoid local optima.
- Lack of Robustness in Highly Stochastic Environments: OOA may face challenges in highly stochastic or uncertain environments, where the problem conditions change rapidly, as it is more tuned to static optimization problems.

V. CONCLUDING REMARKS AND FUTURE WORK

The results of this study highlight the effectiveness of OOA in addressing complex transportation optimization problems. By leveraging its adaptive exploration and exploitation capabilities, OOA consistently outperformed 12 state-of-the-art metaheuristic algorithms in terms of convergence speed, solution quality, computational efficiency, and robustness. The superior performance of OOA was evident in its ability to achieve the lowest travel distances and maintain stability over multiple simulation runs, even in dynamic and constraint-intensive environments. The findings underscore the potential of OOA for real-world applications, such as urban logistics and sustainable transportation planning, where operational efficiency and environmental considerations are critical.

Despite its demonstrated success, several avenues remain for future research. One promising direction is the development of hybrid versions, integrating the OOA framework with other metaheuristic algorithms to enhance its adaptability to diverse problem domains. Additionally, the scalability of OOA could be further explored by applying it to larger and more complex transportation networks, incorporating real-time traffic data and multiobjective optimization criteria. The integration of OOA with emerging technologies, such as machine learning and the IoT, also has significant potential. For instance, coupling the algorithm with predictive analytics and sensor data could enable real-time decision-making in dynamic and uncertain environments. Furthermore, future studies could focus on extending the algorithm's capabilities to solve multimodal transportation problems and evaluate its performance in stochastic scenarios with varying demands and constraints.

In conclusion, OOA represents a significant advancement in metaheuristic optimization for transportation systems. Its robust performance and adaptability provide a solid foundation to address the evolving challenges of modern logistics and pave the way for innovative solutions in sustainable transportation systems.

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