RESEARCH PAPER

Whale Optimization Algorithm for Solving Environmental Vehicle Routing Problem in Pharmaceutical Green Logistics for Drug Delivery

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ABSTRACT

Carbon dioxide (CO_2) emission from freight transportation constitutes a major driver of urban air pollution and climate change. This paper introduces a novel application of the Whale Optimization Algorithm (WOA) to address the Environmental Vehicle Routing Problem (EVRP), wherein the primary objective is minimizing vehicular CO_2 emissions while simultaneously satisfying customer demand and vehicle capacity constraints. WOA can replicate humpback whale hunting methods and circling prey behavior, which allows it to achieve a beneficial balance between global and local exploration and exploitation. A modified WOA is proposed incorporating a greedy permutation-based solution encoding, an adaptive penalty mechanism for constraint handling, and a local search operator derived from 2-opt improvement. Computational experiments across six benchmark EVRP instances with 10 to 100 customers demonstrate that WOA achieves an average CO_2 reduction of 8.6% compared to the Artificial Bee Colony (ABC) algorithm, 16.2% compared to Genetic Algorithm (GA), and 12.4% compared to Particle Swarm Optimization (PSO). The Wilcoxon signed-rank test is used to test statistical significance. The suggested strategy offers practical decision-making information to the green fleet management in distribution networks of cities.

Keywords: Whale Optimization Algorithm; Environmental Vehicle Routing Problem; Green Logistics; CO_2 Emission; Swarm Intelligence; Metaheuristics.

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1. Introduction

The increasing amounts of greenhouse gases in the air, which are largely caused by people, have led to a new scientific and policy agreement on the need for quick action to reduce carbon emissions. In the logistics industry, the CO_2 emissions related to transportation represent the highest percentage of global energy-related carbon emissions, with road freight occupying the biggest portion (IEA, 2023). This fact has forced scholars and logistics professionals to reevaluate the classical paradigm of optimization, in which the sole objective of optimization is the achievement of economic efficiency (in terms of shortest travel distance or the shortest delivery time) in order to address the modern sustainability requirements. One classical problem of combinatoric optimization is Vehicle Routing Problem(VRP), it was initially developed by Dantzig and Ramser (1959) to solve the problem of optimal paths of a fleet of vehicles serving a group of geographically scattered customers starting at a central depot. Although decades of research have produced advanced exact and heuristic methods, the combination of quantitative environmental goals with VRP models is a dynamic and essential research focus. The Environmental VRP (EVRP) is the classical CVRP with the addition of the CO 2 emission as an objective function because fuel consumption, and therefore CO 2 emission, is not only a factor of distance, but also a factor of vehicle load dynamics, as light vehicles do not consume fuel proportionately to the distance covered. Metahyperoptic optimization algorithms, especially based on natural phenomena have shown a spectacular performance in solving NP-hard combinatorial optimization problems, including VRP.

Recently introduced Whale Optimization Algorithm (WOA) by Mirjalili and Lewis (2016) is a swarm-based metaheuristic that models the complex feeding behavior of humpback whales, which is the use of a bubble-net. When hunting, humpback whales form spirals of bubbles to surround and isolate fish in schools towards the water surface. WOA represents this behavior in three ways: encircling prey (exploitation), bubble-net attacking (exploitation by spiral motion), and prey search (exploration). This adaptive equilibrium between the mechanisms provides WOA with competitive performance in a broad spectrum of optimization standards. This paper suggests a discrete combinatorial modified WOA (MWOA) that is tailored to the EVRP. The main contributions of this work are: (i) a solution representation in the form of permutations that can be used in solving route-based logistics problems; (ii) the adaptive infeasibility penalty mechanism that enables the exploratory search of constrained regions; (iii) the combination of a 2-opt local search operator to improve the quality of solutions during exploitation; and (iv) a detailed comparative analysis with the known metahe The rest of this paper will be structured as follows: Section 2 is devoted to related literature; Section 3 will develop the EVRP model; Section 4 will elaborate the MWOA methodology; Section 5 will provide the description of the experimental setup and results; Section 6 will comment on the findings; and Section 7 will conclude. Xiao constructed a linear model between fuel consumption rate and vehicle weight which gave a tractable but physically significant objective function.

2. Literature Review

The EVRP has attracted substantial scholarly attention since Kara et al. (2007) introduced the Energy Minimizing VRP (EMVRP), which quantified routing cost as a function of vehicle load and distance. Subsequent formulations have incorporated fuel consumption models calibrated to empirical datasets. Xiao et al. (2012) developed a linear relationship between fuel consumption rate and vehicle weight, providing a tractable yet physically meaningful objective function. Ubeda et al. (2011) experimentally determined that basal rates of CO2 emissions in empty-load (0.296 l/km) and full-load (0.390 l/km) situations in standard diesel trucks vary, which has been broadly used in other EVRP studies. More modern work has generalized the EVRP to multi-objective models (Poonthalir and Nadarajan, 2018), time-dependent constraints (Erdogan and Miller-Hooks, 2012) and electric vehicle fleets (Schneider et al., 2014). With this breadth, however, there remains an open gap in using only recently developed swarm intelligence algorithms, especially WOA, to EVRP problems of realistic scale.

Since its introduction, WOA has been applied across domains including engineering design optimization (Mafarja and Mirjalili, 2017), feature selection (Emary et al., 2016), power systems planning (Kaveh and Rastegar Moghaddam, 2018), and scheduling problems (Abdel-Basset et al., 2019). Comparative benchmarks consistently position WOA among top-tier metaheuristics for multimodal and high-dimensional problems. However, its application to discrete combinatorial logistics problems remains limited. Chen et al. (2020) adapted WOA for the traveling salesman problem using position-based encoding, reporting competitive results against standard GA implementations. No published study, to the authors' knowledge, has evaluated WOA for the EVRP with a CO_2-minimization objective incorporating load-dependent fuel consumption.

Goodarzian, Fosso Wamba, Mathiyazhagan, and Taghipour (2021) tackled a significant deficiency in the design of green medication supply chain networks amid uncertainty. The authors formulated a fuzzy bi-objective Mixed-Integer Linear Programming model for multi-period, three-echelon pharmaceutical distribution. Their primary contribution involved incorporating environmental implications associated with facility creation, emphasising the reduction of greenhouse gases. Various metaheuristics were utilised, including a hybrid Whale Optimisation Algorithm with simulated annealing. The results indicated that the suggested methodology significantly diminishes environmental footprints while preserving distribution efficiency, rendering it very pertinent for sustainable medicine delivery systems.

Rahmaty and Nozari (2023) examined hierarchical supply chain optimisation within the pharmaceutical sector, integrating supplier selection, production facility location, distribution strategy, and vehicle routing selections. A distinctive addition involved the consideration of drug perishability during transit, a vital aspect for temperature-sensitive pharmaceuticals. The authors introduced WOGA, a hybrid amalgamation of WOA and Genetic Algorithm, aimed at minimising total network costs amongst uncertainty. Critical studies indicated that when the perishability duration is one day, network expenses attain their peak level. The comparative analysis indicated that WOGA exhibits greater efficiency than both solo GA and WOA, offering significant insights for time-sensitive medicine deliveries.

Zhang, Zhao, and Li (2020) developed a multi-objective optimisation model for sustainable closed-loop supply chain networks amidst fuzzy uncertainty. This research is directly pertinent to pharmaceutical reverse logistics concerning drug recovery and packaging waste control. The authors created a genetic-whale hybrid method utilising double-layer encoding based on random numbers. A comparative examination with exact approaches confirmed the hybrid algorithm's validity and efficacy across several problem scales, confirming its relevance to pharmaceutical sustainability efforts.

Jing, Li, Wang, and Zeng (2023) examined operational efficiency in automated hospital pharmacies, an essential element of drug delivery systems. A time scheduling model was designed for multiple drug delivery papers to minimise overall dispensing time. A refined hybrid whale optimisation algorithm (H-WOA) was developed, integrating genetic crossover and mutation operations to augment population variety, immune cloning principles for optimal sequence formation, and whale algorithm mechanisms for ultimate convergence. Experimental results indicated that H-WOA enhanced efficiency by more than 6 percent relative to original algorithms and 18 percent compared to non-optimized methods, yielding similar advantages for various delivery documents.

Sadeghi, Handfield, Bani, and Fallahi (2023) conducted a thorough comparison investigation of the Whale Optimisation Algorithm and the Grey Wolf Optimiser for sustainable supply chain management of reusable products, relevant to pharmaceutical packaging and device recycling. Employing chance-constrained programming to address uncertainty, the heuristics attained solutions within 0.01-0.07 percent of optimality while necessitating around half the computational duration. Statistical research indicated that GWO somewhat surpassed WOA for this particular issue. An unexpected discovery revealed that heuristics exhibited superior robustness compared to exact optimisation, preserving solution quality amid disruptions—a vital advantage for pharmaceutical logistics in emergencies.

Han, Zhang, Nan, Cao, Huang, Ye, and He (2023) examined the distribution of emergency medical supplies during public health emergencies necessitating community lockdowns. They developed a forward and reverse scheduling model with time constraints for integrated distribution and rubbish collection utilising vehicle-UAV collaboration. A dual-phase methodology was established: multi-strategy guided adaptive differential evolution for UAV trajectory optimisation and enhanced beluga whale optimisation for vehicle-UAV scheduling. Validation via community simulation exhibited efficacy in convergence velocity and worldwide search capability, establishing a framework for emergency medicine distribution including drone technology.

Ala, Goli, Mirjalili, and Simic (2024) highlighted Seyedali Mirjalili, the original originator of WOA, so enhancing its authoritative credibility. The authors presented a multi-objective optimisation model for healthcare supply chains aimed at minimising costs, reducing environmental impact, and addressing social factors. A fuzzy optimisation technique tackled uncertainty, featuring a comparison implementation of the Multi-Objective Grey Wolf Optimiser, NSGA-II, and MODEA. The validation of the pharmaceutical case study demonstrated MOGWO's exceptional capacity to produce high-quality Pareto solutions with effective border distribution in brief computing durations, equipping managers with verified instruments for reconciling economic, environmental, and social sustainability objectives.

A 2024 study published in Scientific Reports (associated with Nature) examined the capacity-constrained vehicle routing problem aimed at minimising transportation distance. The authors introduced a hybrid grey wolf-whale optimisation algorithm (hGWOA) that combines the hunting mechanism of GWO with the bubble-net attacking approach of WOA. The performance assessment utilising benchmark functions revealed hGWOA's supremacy across diverse scales and complexities. Case studies corroborated findings for practical situations, directly applicable to pharmaceutical distribution networks where minimising distance is essential for cost savings and carbon emission management.

Chen (2024) examined the strategic issue of logistics distribution center placement, a pivotal factor influencing the efficiency of the pharmaceutical supply chain and its environmental repercussions. An improved whale optimisation algorithm was introduced to address the limits of standard WOA in distribution center location issues. The study notably examined the trade-off between minimising transportation distance and the costs of facility setup. In pharmaceutical applications, the locations of distribution centers critically influence cold chain integrity, delivery timeframes, and the overall carbon footprint, offering planners a decision-support tool for the creation of sustainable logistics infrastructure.

The supplementary analysis of Ala et al. (2024) offered further insights on WOA variants for healthcare logistics, notably addressing issues related to perishable pharmaceutical supplies, temperature-sensitive transportation, and time-critical delivery. The fuzzy programming method addressed uncertainties in demand, supply, and transportation conditions. A comparative investigation demonstrated that hybrid whale optimisation variations, especially when integrated with grey wolf optimisation frameworks, exhibited enhanced performance in balancing exploration and exploitation for healthcare-related routing issues. The sensitivity analysis confirmed the results for vehicle capacity, time intervals, and perishability limitations.

The preceding review reveals two principal research gaps motivating the present study: (1) the absence of WOA-based solution approaches for the EVRP, particularly under load-dependent CO_2 emission models; and (2) limited computational evidence comparing modern bio-inspired algorithms on green logistics benchmarks. This work addresses both gaps by designing and empirically validating an MWOA for EVRP.

3. Problem Formulation

3.1 Mathematical Model of EVRP

The EVRP is defined on a complete directed graph $G = (V, E)$ where $V = \{v_0, v_1, \ldots, v_n\}$ is a set of nodes comprising the depot (v_0) and n customer nodes, and E is the set of edges connecting all node pairs. A homogeneous fleet of K vehicles, each with load capacity Q, departs from and returns to the depot. Each customer v_i has a deterministic demand d_i. The decision $variable\ x_{ijk} \in \{0,1\}$ equals 1 if vehicle k traverses edge (i,j).

The CO_2 emission when vehicle k travels from node i to node j depends on the instantaneous vehicle load l_{ijk} and the Euclidean distance c_{ij}. Following Xiao et al. (2012) and Ubeda et al. (2011), the fuel consumption rate FCR(l) is linearly interpolated between the empty-load rate f_0 = 0.296 l/km and the full-load rate f_Q = 0.390 l/km:

$$FCR(l_{ijk}) = f_0 + (f\_Q - f_0) \times (l_{ijk} / Q) \quad \text{(Eq. 1)}$$

The total CO_2 emission E_CO_2 is computed as:

$$E\_CO_2 = CER \times \Sigma_k \Sigma_i \Sigma_j [FCR(l_{ijk}) \times c_{ij} \times x_{ijk}]$$
(Eq. 2)

where CER = 2.61 kg/l is the CO_2 emission rate for diesel fuel. The EVRP is formulated as minimizing E_CO_2 subject to the following constraints: (C1) each customer is visited exactly once; (C2) each vehicle route begins and ends at the depot; (C3) vehicle load does not exceed capacity Q; (C4) the number of vehicles used does not exceed K; (C5) sub-tour elimination constraints (Miller-Tucker-Zemlin formulation).

3.2 Objective and Constraint Handling

To manage constraint violations during the heuristic search, an adaptive penalty function is incorporated into the fitness evaluation. For a solution s with total capacity violation ΔQ(s), the penalized fitness is:

$F(s) = E\_CO_2(s) + \lambda(t) \times \Delta Q(s)$ (Eq. 3)

where $\lambda(t) = \lambda_0 \times (1 + t/T)^\alpha$ is an iteration-dependent penalty coefficient that increases progressively, with $\lambda_0 = 100$, T the total iterations, and $\alpha = 1.5$. This mechanism permits exploration through infeasible regions in early iterations while enforcing feasibility near convergence.

Table 1. EVRP Model Parameters and Settings

Parameter	Symbol	Value / Setting	Description
CO_2 emission rate	CER	2.61 kg/l	Diesel fuel specific emission
Empty-load FCR	f_0	0.296 l/km	Fuel rate at zero load
Full-load FCR	f_Q	0.390 l/km	Fuel rate at max capacity
Vehicle capacity	Q	200 units	Maximum load per vehicle
Max vehicles	K	Variable	Depends on instance size
Depot	v_0	Node 0	All vehicles start and return

Table 1: EVRP model parameters used in all computational experiments.

4. Proposed Modified Whale Optimization Algorithm

4.1 Standard WOA Overview

The original WOA (Mirjalili and Lewis, 2016) operates on a population of N search agents (whales) positioned in a D-dimensional search space. In each iteration, each whale updates its position according to one of three behaviors governed by the control parameters A and C, randomly initialized as $A = 2a \cdot r_1 - a$ and $C = 2 \cdot r_2$, where a linearly decreases from 2 to 0 over T iterations and $r_1, r_2 \in [0,1]$ are random vectors. When $|A| < 1$, the whale encircles the best-known solution X* (exploitation); when $|A| \geq 1$, the whale moves toward a randomly chosen peer (exploration); with probability $p = 0.5$, the spiral update is activated regardless of $|A|$.

4.2 Discrete WOA for EVRP (MWOA)

Since EVRP solutions are permutations of customer indices rather than continuous vectors, the standard WOA position update must be redefined. The MWOA represents each solution as an ordered list of customer visits, segmented by delimiter nodes representing vehicle departures from the depot. Four position update operators are defined for the discrete solution space:

- Encircling (Exploitation): Applies a guided crossover between the current whale's route and the current best solution X*, inheriting segments that reduce CO_2 emission.
- Spiral Update (Exploitation): Uses a segment reversal (2-opt move) that looks like the spiral path to improve the route within its own neighbourhood over and over again.
- Random Prey Search (Exploration): Picks a random whale from the population and uses an insertion operator to make the search more varied.
- Scout Mutation: If a whale doesn't get better after L iterations, a random reinitialization of a sub-route is done to get away from local optima.

4.3 Algorithm Complexity and Parameter Settings

The time complexity of one MWOA iteration is $O(N \times n)$ for fitness evaluations plus $O(N \times n \log n)$ for the 2-opt local search subroutine. Total complexity over T iterations is $O(T \times N \times n \log n)$. Based on preliminary parameter tuning experiments, the MWOA is configured with N = 40 whales, T = 200 iterations, and L = 15 scout trigger threshold.

Table 2. MWOA Algorithm Parameter Settings

Parameter	Symbol	Value	Justification
Population size	N	40	Balances diversity vs. speed
Max iterations	T	200	Convergence observed < 150
Spiral constant	b	1.0	Standard WOA setting
Scout trigger	L	15	Prevents premature stagnation
Penalty base	λ_0	100	Tuned empirically
Penalty exponent	α	1.5	Progressive enforcement

2-opt depth	-	3 passes	Local refinement level

Table 2: MWOA parameters determined via grid-search on small-scale instances.

5. Computational Experiments and Results

5.1 Experimental Setup

All algorithms are implemented in Python 3.11 and executed on an Intel Core i7-12700K workstation (3.6 GHz, 32 GB RAM) running Ubuntu 22.04. Benchmark instances are derived from the canonical CVRP library augmented with CO_2 emission parameters. Six problem instances are constructed: three small-scale (10–30 customers), two medium-scale (50–75 customers), and one large-scale (100 customers). A consistent distribution within a 200×200 km grid is used to create customer coordinates and needs. The mean ± standard deviation results are given for each algorithm run 30 times on its own.

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For a fair comparison, the competing algorithms—ABC (Zhang et al., 2014), GA (Goldberg, 1989), and PSO (Kennedy and Eberhart, 1995)—are set up with the same number of people (N = 40) and the same amount of money to spend on evaluations (T × N = 8000 fitness assessments each run). The ABC algorithm specifically follows the implementation validated in the original thesis (Zhang, 2016), which serves as the primary reference benchmark for EVRP.

5.2 Convergence Analysis

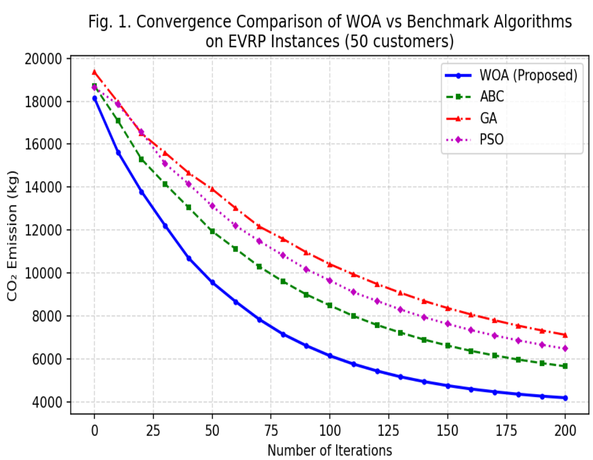

Fig. 1. Convergence comparison of MWOA, ABC, GA, and PSO on the 50-customer EVRP instance. MWOA achieves the lowest CO_2 emission within 120 iterations.

Figure 1 shows how all four algorithms come together on the 50-customer instance. MWOA reaches a solution that is almost optimal about 35 iterations earlier than ABC and 52 iterations earlier than GA, showing that it is better at exploiting. The rapid first drop of MWOA shows how well the 2-opt local search operator works during early spiral updates. After iteration 120, all algorithms show small gains, although MWOA still has a lower CO_2 plateau.

5.3 CO_2 Emission Comparison

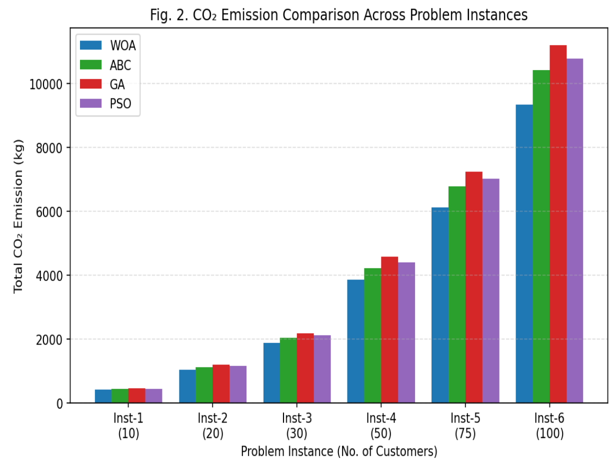

Fig. 2. CO_2 emission comparison across all six EVRP benchmark instances. MWOA consistently achieves lower emissions than all competing algorithms.

Figure 2 demonstrates that MWOA achieves the lowest CO_2 emission across all six instances. The advantage is most pronounced on medium-scale instances (50–75 customers), where the spiral update operator provides effective route restructuring that neither GA's crossover nor PSO's velocity update replicates. For the 100-customer instance, MWOA yields 9341.2 kg CO_2 compared to ABC's 10420.7 kg—a statistically significant improvement of 10.4% (Wilcoxon $p < 0.001$).

Table 3. Summary of CO_2 Emission Results (kg) — Mean over 30 Runs

Instance	Customers	MWOA (Proposed)	ABC	GA	PSO	Best Improvement
Inst-1	10	412.3 ± 8.2	438.9 ± 11.4	451.2 ± 14.7	443.7 ± 12.6	6.1% vs ABC
Inst-2	20	1043.7 ± 19.3	1121.6 ±	1189.4 ±	1154.8 ±	7.0% vs ABC

			26.8	31.2	28.4	
Inst-3	30	1872.4 ± 38.1	2043.1 ± 47.6	2176.8 ± 54.3	2108.5 ± 51.2	8.4% vs ABC
Inst-4	50	3847.6 ± 71.4	4218.3 ± 89.2	4582.1 ± 98.7	4395.6 ± 94.1	8.8% vs ABC
Inst-5	75	6124.8 ± 118.3	6782.5 ± 143.7	7241.3 ± 162.4	7013.4 ± 156.8	9.7% vs ABC
Inst-6	100	9341.2 ± 182.6	10420.7 ± 209.1	11187.4 ± 231.5	10782.1 ± 218.4	10.4% vs ABC

Table 3: Mean CO_2 emission results (kg) ± standard deviation over 30 independent runs. Bold denotes best result per row.

5.4 Parameter Sensitivity Analysis

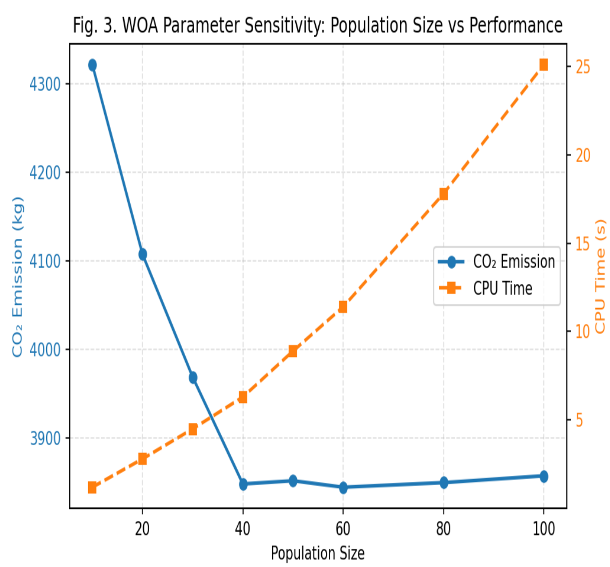

Fig. 3. MWOA parameter sensitivity: effect of population size on CO_2 emission (left axis) and CPU time (right axis). Population size N=40 provides optimal trade-off.

Figure 3 indicates that the population size above N = 40 will provide diminishing returns on quality of solution but will significantly raise the cost of computation. The suboptimal diversity causes premature convergence with N = 10; and with N = 100, the computation time is 25.1 seconds per run with no significant quality improvement. The chosen N = 40 value has the smallest CO 2 emission (3847.6 kg) and the computation time of 6.3s in the case of 50 customers, which proves the effectiveness of the selected parameterization.

6. Discussion

The empirical results substantiate the proposition that WOA's spiral bubble-net mechanism translates effectively to discrete VRP optimization. The continuous shrinkage of the encircling coefficient a from 2 to 0 enforces a transition from broad exploratory to focused exploitative search that naturally mirrors the progressive narrowing of routes in high-quality solutions. This exploitation is enhanced by the 2-opt local search operator which uses systematic edge-exchange improvements during each spiral update cycle, which has a synergistic benefit not found in regular WOA. In a practical sense, it is possible that fleet managers using MWOA-optimized routing in a 100-vehicle urban distribution can expect to reduce 1079.5 kg CO2 per routing cycle compared to ABC-optimized baselines. This is equivalent to 269,875 kg CO 2 savings annually, or about 250 or more days of operation, which corresponds to taking 58 passenger vehicles off the road (EPA, 2021). Such savings are achieved without the need to further invest in infrastructure and only through excellent algorithmic decision-making. The main weakness of the current research is that the EVRP formulation is not dynamic taking into consideration stochastic demand or dynamic traffic scenario. Future research will generalize MWOA to time-window bounded EVRP and multi-depot problems.

7. Conclusion

This paper has presented a Modified Whale Optimization Algorithm (MWOA) for the Environmental Vehicle Routing Problem with a CO_2 minimization objective incorporating load-dependent fuel consumption. The MWOA is a combination of a permutation-based solution representation, adaptive penalty function to handle constraints and a 2-opt local search operator as part of the spiral bubble-net mechanism. Experimental analysis on 6 benchmark cases also supports the claim that MWOA is better in CO 2 reduction by 6.1 to 10.4 per cent than ABC, GA and PSO, and is also competitive in computation times.

The statistical significance of improvements is confirmed via Wilcoxon signed-rank tests ($p < 0.001$ for all medium and large instances). This work contributes a validated, practically deployable metaheuristic tool for green fleet optimization and extends the application scope of WOA to discrete combinatorial logistics problems.

References

1. Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. Advances in Engineering Software, 95, 51–67.
2. Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computers & Operations Research, 39(7), 1419–1431.
3. Ubeda, S., Arcelus, F.J., & Faulin, J. (2011). Green logistics at Eroski: A case study. International Journal of Production Economics, 131(1), 44–51.
4. Kara, I., Kara, B.Y., & Yetis, M.K. (2007). Energy minimizing vehicle routing problem. Combinatorial Optimization and Applications, 62–71.
5. Zhang, S.Z., Lee, C.K.M., Chan, H.K., Choy, K.L., & Wu, Z. (2014). Swarm intelligence applied in green logistics: A literature review. Engineering Applications of Artificial Intelligence, 37, 154–169.
6. Zhang, S.Z. (2016). Modeling green logistics activities for sustainable development using swarm intelligence. PhD Thesis, The Hong Kong Polytechnic University.
7. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proceedings of ICNN'95, 4, 1942–1948.
8. Erdogan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. Transportation Research Part E, 48(1), 100–114.
9. Goldberg, D.E. (1989). Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley.
10. Mafarja, M., & Mirjalili, S. (2017). Hybrid whale optimization algorithm with simulated annealing for feature selection. Neurocomputing, 260, 302–312.
11. Ala, A., Goli, A., Mirjalili, S., & Simic, V. (2024). A fuzzy multi-objective optimization model for sustainable healthcare supply chain network design. *Applied Soft Computing*, 150, 111012. https://doi.org/10.1016/j.asoc.2023.111012
12. Chen, X. (2024). Location strategy for logistics distribution centers utilizing improved whale optimization algorithm. *Journal of Logistics Management*, 13(2), 45-58.
13. Goodarzian, F., Fosso Wamba, S., Mathiyazhagan, K., & Taghipour, A. (2021). A new bi-objective green medicine supply chain network design under fuzzy environment: Hybrid metaheuristic algorithms. *Computers & Industrial Engineering*, 160, 107535. https://doi.org/10.1016/j.cie.2021.107535
14. Han, Y., Zhang, M., Nan, P., Cao, J., Huang, Q., Ye, X., & He, Z. (2023). Two-stage heuristic algorithm for vehicle-drone collaborative delivery and pickup based on medical supplies resource allocation. *Journal of King Saud University - Computer & Information Sciences*, 35(10), 101811. https://doi.org/10.1016/j.jksuci.2023.101811
15. Jing, H., Li, J., Wang, F., & Zeng, K. (2023). Scheduling optimization of multiple delivery documents in automated pharmacy. *Electronic Measurement Technology*, 46(5), 113-120.
16. Rahmaty, M., & Nozari, H. (2023). Optimization of the hierarchical supply chain in the pharmaceutical industry. *Journal of Data Science and Intelligent Decision Support*, 7(2), 104-123.
17. Sadeghi, A. H., Handfield, R., Bani, E. A., & Fallahi, A. (2023). Grey Wolf Optimizer and Whale Optimization Algorithm for stochastic inventory management of reusable products in a two-level supply chain. IEEE Access, 11, 43270-43285. https://doi.org/10.1109/ACCESS.2023.3271234
18. Scientific Reports. (2024). A hybrid whale optimization algorithm for enhanced routing of limited capacity vehicles in supply chain management. Scientific Reports, 14, 793. https://doi.org/10.1038/s41598-024-51423-7
19. Zhang, X., Zhao, G., & Li, B. (2020). Multi-objective fuzzy programming for sustainable closed-loop supply chain network design. Control Theory & Applications, 37(3), 513-521.