Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Hybrid ICA–Local Search for the Multi-Depot Vehicle Routing Problem

Rafiatun Ferdous Khan Lubaba

rafiatun.lubabakhan@gmail.com

North South University https://orcid.org/0009-0002-0498-4783

Research Article

Keywords: multi-depot vehicle routing problem, imperialist competitive algorithm, local search, metaheuristics, combinatorial optimization

Posted Date: August 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10780277/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Hybrid ICA–Local Search for the Multi-Depot Vehicle Routing Problem

Abstract

The Multi-Depot Vehicle Routing Problem (MDVRP) is an NP-hard combinatorial optimization problem that requires simultaneously assigning customers to depots and constructing capacity-feasible vehicle routes to minimize the total travelled distance. This paper proposes a two-layer hybrid method that combines the Imperialist Competitive Algorithm (ICA) with a local-search router. The outer ICA layer searches over customer-to-depot assignments, while the inner layer constructs routes by cheapest insertion and improves them through a local search over the 2-opt, relocate, and swap neighbourhoods; the two layers are coupled through the routing distance, which serves as the fitness of the assignment. The method further employs nearest-depot seeding and an assignment-level local search that refines the best solution by reassigning customers across depot boundaries. The method is evaluated on the capacity-constrained Cordeau benchmark instances and compared against the best-known solutions. It attains gaps within approximately two percent on several small and medium instances, with a smallest gap of 1.16 percent, while maintaining low variability across independent runs.

Index Terms

multi-depot vehicle routing problem, imperialist competitive algorithm, local search, metaheuristics, combinatorial optimization

I. Introduction

The Vehicle Routing Problem (VRP), introduced by Dantzig and Ramser (1959), seeks a set of minimum-cost routes for a fleet of vehicles serving geographically dispersed customers from a single depot (Toth and Vigo 2002). In many real distribution systems, goods are dispatched from several depots rather than one. The Multi-Depot Vehicle Routing Problem (MDVRP) generalizes the VRP to this setting: customers with known demands must be served by capacitated vehicles operating from multiple depots, where every route begins and ends at the same depot, every customer is visited exactly once, and the total travelled distance is minimized (Cordeau et al. 1997). The MDVRP is NP-hard and is harder than the single-depot VRP because it couples two interdependent decisions—the assignment of customers to depots and the construction of routes within each depot (Montoya-Torres et al. 2015).

Since exact methods do not scale to realistic instance sizes (Laporte 1992), heuristic and metaheuristic approaches dominate. A recurring and effective design pattern is a two-stage decomposition, in which customers are first partitioned among depots and a single-depot routing problem is then solved for each depot. This paper follows that decomposition, proposing a two-layer hybrid in which the Imperialist Competitive Algorithm (ICA), a population-based metaheuristic (Atashpaz-Gargari and Lucas 2007), searches over customer-to-depot assignments, while a local-search router constructs and optimizes routes within each depot. The two layers are coupled through the routing distance, which serves as the ICA fitness. The proposed method is evaluated on the Cordeau benchmark instances (Cordeau et al. 1997) and compared against best-known solutions.

The remainder of this paper is organized as follows. Section II reviews related work; Section III presents the proposed method; Section IV describes the results and analysis; and Section V concludes.

II. Literature Review

The MDVRP dates back to early multi-terminal dispatching studies (Wren and Holliday 1972; Gillett and Johnson 1976), and comprehensive overviews are given by Montoya-Torres et al. (2015) and, for the broader VRP, by Toth and Vigo (2002) and Golden et al. (2008). Because the problem is NP-hard, research has focused on heuristic and metaheuristic methods, surveyed for the MDVRP by Karakatič and Podgorelec (2015) and Samsuddin et al. (2018).

Trajectory-based methods have been widely applied. Simulated annealing (Kirkpatrick et al. 1983) and tabu search (Gendreau et al. 1994) are classical local-search metaheuristics, and tabu search in particular has proven effective for the MDVRP, notably in the works of Renaud et al. (1996) and Cordeau et al. (1997), the latter also providing the standard benchmark instances. Variable neighborhood search has likewise been applied to the problem (Imran 2013).

Population-based methods form the other major stream. Genetic algorithms have been used extensively for the MDVRP (Surekha and Sumathi 2011), and hybrid genetic methods combining evolutionary search with local improvement have produced state-of-the-art results (Vidal et al. 2012). Related work has also addressed problem variants such as split delivery (Gulczynski et al. 2011).

The Imperialist Competitive Algorithm (Atashpaz-Gargari and Lucas 2007) has been applied to several routing problems; for instance, Rezaei et al. (2023) combined a multi-population ICA with genetic local search for the capacitated VRP. Most relevant to this work, Dzalbs and Kalganova (2020) proposed a two-stage hybrid in which the ICA assigns customers to depots

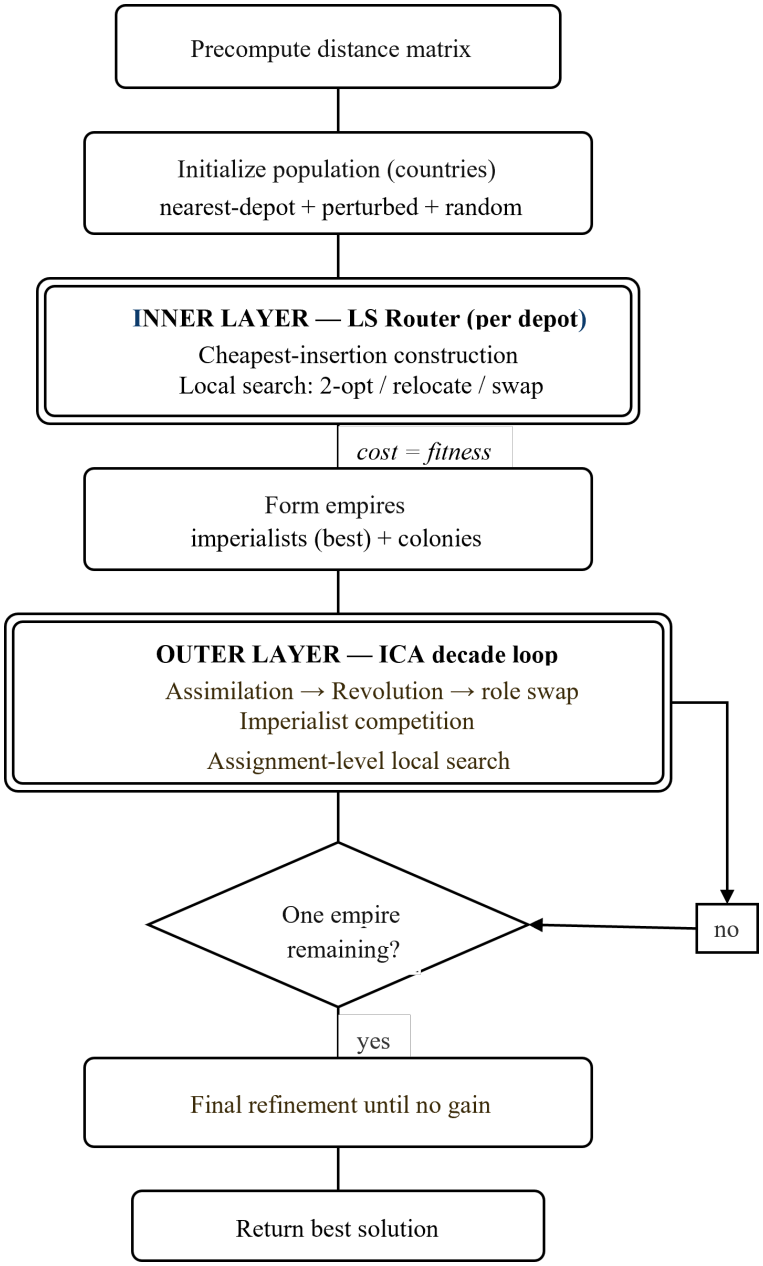


Fig. 1: Overall framework of the proposed hybrid ICA–LS method.

and ant colony optimization sequences the routes. The present work adopts the same assignment–routing separation but differs by employing a local-search router and an assignment-level local search that directly refines the customer-to-depot assignment. Since customer assignment is the main challenge in the MDVRP, this improves solution quality.

III. Proposed Hybrid ICA–LS Method

The proposed method is organized in two coupled layers: an Imperialist Competitive Algorithm (ICA) that assigns customers to depots, and a local-search (LS) router that constructs and optimizes the routes within each depot. The two are coupled through the total routing distance, used as the ICA fitness. The overall procedure is shown in Fig. 1 and summarized in Algorithm 2.

A. Solution Representation

A solution is encoded as an assignment vector $A = [a_1, a_2, \ldots, a_n]$, where n is the number of customers and $a_i \in \{1, \ldots, m\}$ denotes the depot serving customer i, with m the number of depots. For a given assignment vector, the LS router produces, for each depot, a set of capacity-feasible routes. The representation separates the customer-to-depot assignment from the routing

Algorithm 1 LS Router (single depot)

Require: depot d, assigned customers C_d, capacity Q
Ensure: routes and total distance for depot d
if $C_d = \emptyset$ **then**
  return $\emptyset,\ 0$
end if
Build initial routes for C_d by cheapest insertion, respecting Q
$best \leftarrow$ current routes; $no_improve \leftarrow 0$
while $no_improve < N_{\max}$ **do**
  Select a neighbourhood at random from {2-opt, relocate, swap}
  Generate its best-improving, capacity-feasible move
  if the move reduces total distance **then**
    apply the move; remove any empty route
    update $best$; $no_improve \leftarrow 0$
  else
    $no_improve \leftarrow no_improve + 1$
  end if
end while
return $best$ and its total distance

process: the ICA handles the assignment, while the LS algorithm determines the routes. To reduce computation time, the distances between all customers and depots are computed once and stored in a distance matrix, which the algorithm looks up during the search rather than recomputing.

B. Route Construction

For each depot, an initial set of routes is created using the cheapest-insertion heuristic. A route starts with the customer closest to the depot. Customers are then added one by one at the position that causes the smallest increase in travel distance while satisfying the vehicle-capacity limit. If no more customers can be added without exceeding capacity, a new route is started. The process continues until all customers assigned to the depot are routed.

C. Local-Search Router

The initial routes are improved using a local search with three operators: 2-opt, relocate, and swap. The relocate and swap operators can make changes within the same route or between different routes. In each iteration, one operator is selected at random and its best feasible move is applied. Vehicle capacity is checked before every move, and any empty route is removed. A move is accepted if it reduces the total travel distance. The search stops after a fixed number of consecutive iterations without improvement. For depots with many customers, the swap operator is disabled to reduce computation time, and only the 2-opt and relocate operators are used. The routing procedure is summarized in Algorithm 1.

D. Imperialist Competitive Algorithm

The ICA improves the customer-to-depot assignment using a population of candidate solutions, called countries. The initial population includes one nearest-depot assignment, several slightly modified versions of it, and a number of random assignments. Each country is evaluated using the LS router, and the countries are ranked by total travel distance. The best countries become imperialists, while the remaining countries become colonies assigned to the imperialists to form empires.

The algorithm runs for a number of iterations, called decades. In each decade, every colony moves closer to its imperialist by copying some of its customer-to-depot assignments. With a small probability, a colony undergoes revolution, where some assignments are changed randomly to maintain diversity. If a colony becomes better than its imperialist, they exchange roles. During imperialist competition, the weakest colony of the weakest empire is transferred to the strongest empire, and any empire with no colonies is removed. The best solution found is always retained.

E. Assignment-Level Local Search

To further improve the solution, an assignment-level local search is applied to the best solution at the end of each decade. Each customer is temporarily assigned to every other depot, one at a time, and the reassignment giving the largest reduction in total travel distance is accepted; this continues until no further improvement is possible. To save computation time, only the two depots affected by a reassignment are re-routed, while the routes of the other depots remain unchanged. When only one empire is left, this refinement is repeated until no additional improvement can be found.

Algorithm 2 Hybrid ICA–LS for the MDVRP

Require: customers C, depots D, capacity Q, decades T
Ensure: best assignment S^*, its routes, and total distance

```
Precompute the distance matrix over C ∪ D
Generate initial assignments: nearest-depot, perturbed-nearest, random
Evaluate each assignment with the LS router (Algorithm 1)
Sort assignments by cost; form empires (imperialists, colonies)
S* ← best assignment
for t = 1 to T do
    for all empires do
        for all colonies do
            colony ← Assimilate(colony, imperialist)
            with probability p_r: colony ← Revolve(colony)
            if cost(colony) < cost(imperialist) then
                swap roles of colony and imperialist
            end if
        end for
    end for
    Perform imperialist competition; absorb any empire with no colonies
    S* ← min(S*, best empire)
    S* ← AssignmentLocalSearch(S*)
    if only one empire remains then
        repeat AssignmentLocalSearch(S*) until no improvement
        break
    end if
end for
return S*, its routes, and total distance
```

IV. Results and Analysis

This section presents the performance of the proposed hybrid ICA–LS algorithm on the capacity-constrained Cordeau benchmark instances, evaluated in terms of solution quality, stability, and convergence. Each instance was solved five times using different random seeds; the best, average, and standard deviation of the total travel distance are reported. The percentage gap between the best solution and the best-known solution (BKS) is

$$\text{Gap} = \frac{\text{Best} - \text{BKS}}{\text{BKS}} \times 100\%. \tag{1}$$

The results are summarized in Table I, where n denotes the number of customers, t the number of depots, and Q the vehicle capacity.

TABLE I: Results of the proposed method on the Cordeau MDVRP benchmark instances

Inst.	n	t	Q	BKS	Best	Avg.	Std	Gap(%)
p01	50	4	80	576.87	589.38	598.45	6.37	2.17
p02	50	4	160	473.53	483.91	485.85	2.97	2.19
p03	75	5	140	641.19	648.61	661.20	9.98	1.16
p04	100	2	100	1001.59	1064.38	1082.03	20.40	6.27
p05	100	2	200	750.03	786.47	812.21	15.22	4.86
p07	100	4	100	885.80	903.94	910.02	3.91	2.05
p12	80	2	60	1318.95	1375.74	1454.95	43.28	4.31
p15	160	4	60	2505.42	2842.57	2875.75	22.33	13.46

A. Solution Quality

As shown in Table I, the method obtains solutions close to the best-known values on the small and medium instances. The smallest gap, 1.16%, is achieved on p03, and gaps of about 2% are obtained on p01, p02, and p07—instances with several depots, which give the outer ICA layer a meaningful assignment to optimize. The performance also depends on the number of depots and the problem size. For the two-depot instances (p04, p05, and p12), the gap increases to 4.31%–6.27%, because there is less opportunity to improve the customer-to-depot assignment, so most of the improvement must come from route

optimization under vehicle-capacity constraints. The largest gap, 13.46%, is observed for p15, the largest instance, where the problem size limits the depth of the local search.

B. Stability

The standard deviations in Table I show that the method is stable across runs. For several instances, such as p02 (2.97) and p07 (3.91), the standard deviation is very small, indicating consistent results regardless of the random seed. Larger standard deviations are observed for the two-depot instances, especially p12 (43.28), showing that these instances are more difficult to solve consistently.

C. Convergence Behaviour

Fig. 2 shows representative results for four instances: (a) p01, (b) p03, (c) p04, and (d) p15. For each, the best route map and its convergence curve are presented. In the route maps, depots are shown as squares and customers assigned to the same depot share a colour, with routes drawn as closed tours. In all cases, customers are grouped into clear depot regions with compact routes, indicating effective assignments.

The convergence curves show how the best travel distance changes over the decades. For the largest instance, p15, the distance gradually decreases from about 3035 to the final best of 2842.57 before stabilizing. For the smaller instances, the best solution is reached within the first few decades and then remains almost unchanged, showing that most of the improvement occurs early in the search while later iterations provide only small additional gains.

V. Conclusion

This paper proposed a two-layer hybrid algorithm for the MDVRP by combining the Imperialist Competitive Algorithm (ICA) with a local-search (LS) routing method. The ICA determines the customer-to-depot assignments, while the LS algorithm builds and improves the routes using cheapest-insertion construction and the 2-opt, relocate, and swap operators. The best solution is further improved using an assignment-level local search.

The method was tested on the capacity-constrained Cordeau benchmark instances. It achieved results close to the best-known solutions on small and medium instances, with gaps of around 2% for several cases and a minimum gap of 1.16%, and showed consistent performance across runs. Larger gaps were observed for the two-depot instances, where there is less opportunity to improve customer assignments, and for the largest instance, where the problem size limits the effectiveness of the local search. Overall, the approach performs well, especially when the customer-to-depot assignment significantly impacts solution quality.

References

[1] Atashpaz-Gargari, E. and Lucas, C., Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, *Proceedings of the IEEE Congress on Evolutionary Computation*, pp. 4661–4667, Singapore, September 25–28, 2007.

[2] Cordeau, J.-F., Gendreau, M. and Laporte, G., A tabu search heuristic for periodic and multi-depot vehicle routing problems, *Networks*, vol. 30, no. 2, pp. 105–119, 1997.

[3] Dantzig, G. B. and Ramser, J. H., The truck dispatching problem, *Management Science*, vol. 6, no. 1, pp. 80–91, 1959.

[4] Dzalbs, I. and Kalganova, T., Hybrid 2-stage imperialist competitive algorithm with ant colony optimization for solving multi-depot vehicle routing problem, *arXiv preprint arXiv:2005.04157*, 2020.

[5] Gendreau, M., Hertz, A. and Laporte, G., A tabu search heuristic for the vehicle routing problem, *Management Science*, vol. 40, no. 10, pp. 1276–1290, 1994.

[6] Gillett, B. E. and Johnson, J. G., Multi-terminal vehicle-dispatch algorithm, *Omega*, vol. 4, no. 6, pp. 711–718, 1976.

[7] Golden, B. L., Raghavan, S. and Wasil, E. A., *The Vehicle Routing Problem: Latest Advances and New Challenges*, Springer, New York, 2008.

[8] Gulczynski, D., Golden, B. and Wasil, E., The multi-depot split delivery vehicle routing problem: an integer programming-based heuristic, new test problems, and computational results, *Computers & Industrial Engineering*, vol. 61, no. 3, pp. 794–804, 2011.

[9] Imran, A., A variable neighborhood search-based heuristic for the multi-depot vehicle routing problem, *Jurnal Teknik Industri*, vol. 15, no. 2, pp. 95–102, 2013.

[10] Karakatič, S. and Podgorelec, V., A survey of genetic algorithms for solving multi depot vehicle routing problem, *Applied Soft Computing*, vol. 27, pp. 519–532, 2015.

[11] Kirkpatrick, S., Gelatt, C. D. and Vecchi, M. P., Optimization by simulated annealing, *Science*, vol. 220, no. 4598, pp. 671–680, 1983.

[12] Laporte, G., The vehicle routing problem: an overview of exact and approximate algorithms, *European Journal of Operational Research*, vol. 59, no. 3, pp. 345–358, 1992.

[13] Montoya-Torres, J. R., López Franco, J., Nieto Isaza, S., Felizzola Jiménez, H. and Herazo-Padilla, N., A literature review on the vehicle routing problem with multiple depots, *Computers & Industrial Engineering*, vol. 79, pp. 115–129, 2015.

[14] Renaud, J., Laporte, G. and Boctor, F. F., A tabu search heuristic for the multi-depot vehicle routing problem, *Computers & Operations Research*, vol. 23, no. 3, pp. 229–235, 1996.

[15] Rezaei, B., Guimarães, F. G., Enayatifar, R. and Haddow, P. C., Combining genetic local search into a multi-population imperialist competitive algorithm for the capacitated vehicle routing problem, *Applied Soft Computing*, vol. 142, art. 110309, 2023.

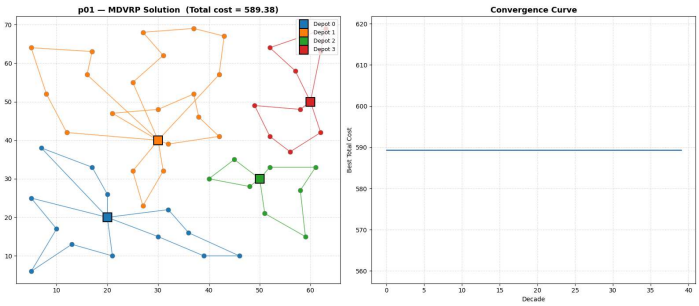
[16] Samsuddin, S., Othman, M. S. and Yusuf, L. M., A review of single and population-based metaheuristic algorithms solving multi depot vehicle routing problem, *International Journal of Software Engineering and Computer Systems*, vol. 4, no. 2, pp. 80–93, 2018.

[17] Surekha, P. and Sumathi, S., Solution to multi-depot vehicle routing problem using genetic algorithms, *World Applied Programming*, vol. 1, no. 3, pp. 118–131, 2011.

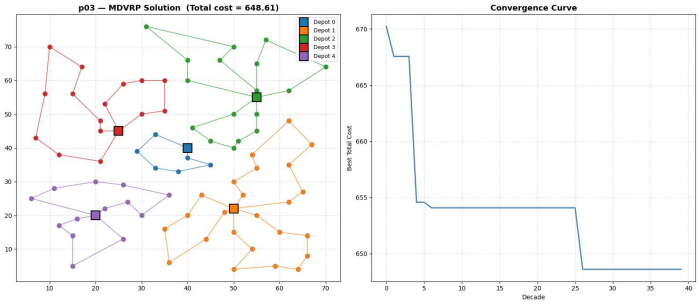
[18] Toth, P. and Vigo, D., *The Vehicle Routing Problem*, Society for Industrial and Applied Mathematics, Philadelphia, 2002.

[19] Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N. and Rei, W., A hybrid genetic algorithm for multidepot and periodic vehicle routing problems, *Operations Research*, vol. 60, no. 3, pp. 611–624, 2012.

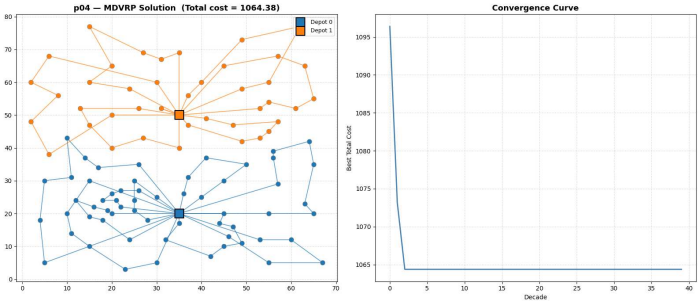
[20] Wren, A. and Holliday, A., Computer scheduling of vehicles from one or more depots to a number of delivery points, *Operational Research Quarterly*, vol. 23, no. 3, pp. 333–344, 1972.



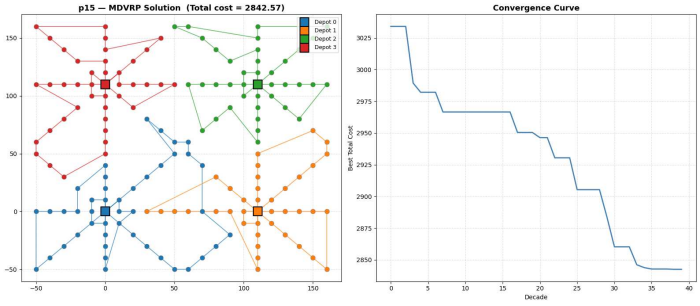
(a) p01



(b) p03



(c) p04



(d) p15

Fig. 2: Best-found solutions and convergence curves for representative instances: (a) p01, (b) p03, (c) p04, (d) p15. In each route map, depots are shown as squares and customers assigned to the same depot share a colour; the adjacent curve shows the best total distance versus decade.