International Journal of Basic and Applied Sciences, 14 (8) (2025) 9-14

SPC

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/amjh9c26
Research paper

A Hybrid K-Means, MST, and DFS Approach for Solving The Capacitated Routing Problem

Soro Wongniga Seydou [1] *, Diaby Moustapha [2], Goore Bi Tra [1]

[1] LASDIA, Institut National Polytechnique Félix Houphouët-Boigny (INPHB); Côte d'Ivoire, BP 1093 Yamoussoukro
[2] LASTIC, École Supérieure Africaine des TIC (ESATIC); Côte d'Ivoire, 18 BP 1501 Abidjan 18
**Corresponding author E-mail: wongnigaseydous@gmail.com*

Received: September 30, 2025, Accepted: November 21, 2025, Published: December 4, 2025

Abstract

The Routing Problem (VRP) is a central challenge in logistics, where optimizing costs and adhering to operational constraints are critical for efficient distribution networks. These challenges include minimizing distances traveled, reducing transportation costs, and limiting computation times for real-time applications. This paper proposes a hybrid approach combining K-Means clustering, Minimum Spanning Tree (MST), and Depth-First Search (DFS) to efficiently solve the Capacitated Routing Problem (CVRP). Using the Solomon datasets as a benchmark, we evaluate the method's performance. The results demonstrate a significant reduction in total distance traveled while maintaining low computation times, making this approach competitive with traditional heuristics.

Keywords: *DFS; Means; MST; VRP.*

1. Introduction

The rise of e-commerce, the expansion of distribution networks, and the growing demand for rapid deliveries have heightened the importance of the Routing Problem (VRP) in modern logistics, particularly in Côte d'Ivoire, where logistical challenges such as variable road infrastructure and urban constraints in Abidjan require efficient solutions. Introduced by Dantzig and Ramser (1959), the VRP involves planning optimal routes for starting from one or more depots to serve geographically dispersed customers while minimizing transportation costs.

The VRP has several variants, including:

- Capacitated VRP (CVRP): Each has a limited capacity.
- VRP with Time Windows (VRPTW): Incorporates temporal constraints.
- Multi-Depot VRP: Includes multiple starting and ending points.

As an NP-hard problem (Laporte, 2009), exact methods become impractical for large instances, leading to the development of heuristics (e.g., Clarke & Wright, 1964) and metaheuristics (e.g., Tabu Search or genetic algorithms; Gendreau et al., 1994). These approaches provide near-optimal solutions within reasonable timeframes but involve trade-offs: speed versus solution quality or high computational complexity. To address these challenges, hybrid approaches combining multiple techniques have emerged. This paper proposes a novel method integrating K-Means clustering to reduce spatial complexity, Minimum Spanning Tree (MST) to minimize intra-cluster distances, and Depth-First Search (DFS) to generate efficient routes. This approach aims to balance simplicity, speed, and solution quality, drawing inspiration from recent advances in combinatorial optimization (Wu et al., 2025; Sharma & Lau, 2025).

1.1. Originality and contribution

Although clustering techniques (such as K-Means) and graph-based approaches (such as MST or DFS) have been used separately in the literature to address the VRP (Amarouche et al., 2018; Mohamed & El-Shaikh, 2009), their integration into a hybrid framework for the CVRP remains underexplored. This study stands out due to its structured approach and practical application, particularly in logistical contexts such as urban distribution in Abidjan or rural delivery in Côte d'Ivoire, where capacity constraints and tight deadlines are critical.

The main contributions of this work are:

1) Innovative Hybridization: The integration of K-Means, MST, and DFS in a unified framework enables efficient customer partitioning, construction of minimal intra-cluster connections, and generation of feasible routes with reduced computational cost, unlike traditional approaches that focus on a single technique (Clarke & Wright, 1964).
2) Scalability and Temporal Efficiency: The proposed approach executes in seconds, even on complex instances, making it suitable for near-real-time operational scenarios, unlike exact methods (Laporte, 2009) or complex metaheuristics (Gendreau et al., 1994).

3) Competitiveness with Classical Heuristics: Experiments on Solomon instances show that our method outperforms the Clarke & Wright heuristic (1964) in terms of total distance while maintaining comparable or better computation times.
4) Flexibility and Extensibility: The modular framework allows for the integration of local optimization techniques (e.g., 2-opt, 3-opt; Gendreau et al., 1994) and adaptation to VRP variants, such as VRPTW or multi-depot VRP (Purba & Meta, 2021), offering a versatile solution for diverse logistical contexts.

Thus, this work presents a lightweight yet effective heuristic, bridging the gap between simple heuristics and complex metaheuristics, with potential applications in real-world settings, such as logistics in Côte d'Ivoire.

2. Literature Review

2.1. Foundational works

Dantzig and Ramser (1959) [1] laid the foundation for the VRP by formulating the truck dispatching problem. Solomon (1987) introduced standardized datasets, which have become benchmarks for evaluating VRP algorithms, particularly for VRPTW.

2.2. Classical heuristics

Methods like the Clarke & Wright heuristic (1964) or the Sweep algorithm are valued for their simplicity and speed. However, they lose effectiveness for complex or large instances, where solution quality degrades (Laporte, 2009).

2.3. Metaheuristics

Approaches such as Tabu Search, genetic algorithms, and ant colony optimization efficiently explore the solution space (Gendreau et al., 1994). They offer high-quality results but require fine parameter tuning and significant computation time. For instance, Wu et al. (2025) proposed a hybrid framework combining an enhanced Clarke & Wright heuristic with knowledge transfer strategies to optimize CVRP.

2.4. Hybrid and clustering approaches

Recent works, such as those by Amarouche et al. (2018) and Purba and Meta (2021), demonstrate that hybrid approaches combining clustering and local optimizations improve performance. Mohamed and El-Shaikh (2009) showed the effectiveness of heuristics leveraging the spatial structure of customers to reduce costs. More recently, Sharma and Lau (2025) explored reinforcement learning to dynamically adjust parameters in solvers based on augmented Lagrangian methods.

2.5. Limitations of existing approaches

Current approaches face several limitations:

- Sensitivity to parameters (e.g., number of clusters or their initialization).
- High computation times for large instances (Laporte, 2009).
- Lack of consideration for real-world constraints, such as traffic or road conditions (Wang et al., 2025).
- Challenges in handling scenarios where demand exceeds available capacity (Wang et al., 2025).

These gaps justify exploring new methods combining simplicity and efficiency, as proposed in this paper.

3. Problem Description

3.1 Overview of CVRP

The Capacitated Routing Problem (CVRP) involves planning routes from a single depot to serve (n) geographically dispersed customers. Each customer (i) has a demand d_i , and each has a maximum capacity (Q). The objective is to minimize the total distance traveled while satisfying:

- Capacity constraint: The sum of demands in each route must not exceed (Q).
- Complete coverage: Each customer is visited exactly once.
- Mandatory return: Each must return to the depot.

In real-world contexts, such as food or goods distribution in urban settings, CVRP reduces logistical costs and CO_2 emissions (Wu et al., 2025).

3.2. Mathematical formulation

Consider a complete graph G = (V, E) , where:

- V={0,1,2,…,n}V = \{0, 1, 2, \dots, n\}V = {0, 1, 2, …, n} represents vertices (0 being the depot).
- (E) is the set of edges connecting vertices.
- cijc_{ij}cij is the distance between vertices (i) and (j).
- did_idi is the demand of customer (i).

Decision Variables:

x_{ij} = 1 if edge ((i,j)) is used, and 0 otherwise.

Objective Function:

$$\min Z = \sum_{i \in V} \sum_{j \in V} CijXij$$

Constraints:

1) Each customer is visited exactly once:

$$\sum_{j\in V} Xij = 1 , \forall i \in V\backslash\{0\}$$

2) Flow conservation:

$$\sum_{i\in V} Xij = \sum_{i\in V} Xji , \forall j \in V$$

3) Capacity:

$$\sum_{i\in S} di \leq Q, \forall S \subset V$$

4) Binary variables:

$X_{ij} \in \{0,1\}$

3.2. Solomon datasets

The Solomon datasets (C1, C2, R1, R2) are standard benchmarks for testing VRP algorithms (Solomon, 1987). They include customer coordinates ((X, Y)), demands, and sometimes time windows. This study uses a capacity of Q = 200, focusing on capacity constraints.

3.3. Customer classification

In our approach, customers are grouped into clusters using K-Means, with each cluster representing a service zone. This segmentation treats each cluster as a sub-VRP, reducing overall complexity and route interactions (Amarouche et al., 2018).

4. Methodology

4.1. Exact methods

Exact methods, such as Branch & Bound or Mixed Integer Linear Programming (MILP), efficiently solve small instances (n < 50) (Laporte, 2009). However, their computation time grows exponentially with problem size, making them unsuitable for industrial cases.

4.2. Description of methods used

To solve the CVRP, our hybrid approach combines three complementary methods, each with a specific role and inherent limitations:

- K-Means: This clustering method partitions customers into groups based on their geographic coordinates to reduce spatial complexity. Main Limitation: Its sensitivity to centroid initialization and the choice of the number of clusters can affect partition quality (Amarouche et al., 2018).
- To initialize the number of vehicles (k), we compute the theoretical lower bound using the floor of the total demand divided by the vehicle capacity:

$$\text{kt} \approx [\frac{\sum_i di}{Q}]$$

With ∑di=3200 and Q=200, this yields kt=16

However, we deliberately start with kinit=5, a value significantly below this bound, in a deliberately aggressive strategy. Far from arbitrary, this choice aims to force maximum geographic compression of clusters from the outset. By severely limiting the number of routes, the algorithm is constrained to group customers into highly dense zones, minimizing overlaps and promoting naturally compact route structures. This low initialization leverages the spatial dispersion of customers to induce an implicit geometric regularization, avoiding the fragmented solutions typical of initializing at kt. A controlled iterative search then incrementally adjusts (k) (by +1 upon each capacity or time window violation), ensuring feasibility while preserving the high-quality initial structure.

- Minimum Spanning Tree (MST): Prim's algorithm constructs an MST for each cluster, minimizing distances between customers within the same group. Main Limitation: The MST does not guarantee an optimal visit sequence for routes, as it does not account for capacity constraints or depot return (Clarke & Wright, 1964).
- Depth-First Search (DFS): This method generates a visit sequence by traversing the MST, forming a route for each cluster. Main Limitation: DFS can produce suboptimal sequences in terms of total distance, as it follows a systematic exploration without local optimizations (Sharma & Lau, 2025).

4.3. Hybrid k-means–MST–DFS approach

The proposed approach combines three steps:

Step 1: K-Means Clustering

- Customers are partitioned into (k) groups based on their geographic coordinates.
- Clusters are adjusted to respect the capacity (Q). If a cluster's total demand exceeds (Q), it is split into sub-clusters (Amarouche et al., 2018).

Step 2: MST Construction

- For each cluster, a Minimum Spanning Tree is constructed using Prim's algorithm, minimizing distances between customers within the cluster (Clarke & Wright, 1964).

Step 3: DFS Traversal

- A Depth-First Search (DFS) traversal of the MST generates a visit sequence.
- The depot is added at the start and end of each sequence to form a complete route.

Pseudocode:

```
Algorithm: Hybrid K-Means–MST–DFS
Input: Customers, Demands, Capacity Q, k_init
1. Clusters = KMeans(Customers, k_init)
2. For each cluster in Clusters:
 If sum(Demands) > Q:
 cluster = SubCluster(cluster)
 MST = Prim(cluster)
 Path = DFS(MST)
 Add depot at start and end
3. Return a set of routes, total distance
```

5. Experiments

5.1. Experimental setup

Tests were conducted on an Intel Core i7 PC with 16 GB RAM, using Python 3.11 with pandas, scikit-learn, networkx, and matplotlib libraries. Tested instances are from the Solomon datasets (C1_2_X, C2_2_X, R1_2_X, C1_6_X) with a capacity of Q = 200. K-Means parameters were set to k_{init} = 5 and random_state = 42. Evaluated metrics include total distance, number of s used, and computation time.

5.2. Performance evaluation

For each instance, clusters were adjusted to meet the capacity constraint, MSTs were generated, followed by DFS to create routes. Results were compared to three existing methods: the Clarke & Wright heuristic (1964), Tabu Search (Gendreau et al., 1994), and a genetic algorithm inspired by Li and Zhang (2023). Key values (shortest distances, fastest computation times, and minimum number of s) are highlighted (in bold) to facilitate comparison.

Table 1: Performance Comparison on Solomon Instances

Instance	K-Means–MST–DFS (Proposed)			Clarke & Wright			Tabu Search			Algorithme Génétique		
	Time (s)	Distance	Vehicles	Time (s)	Distance	Vehicles	Time (s)	Distance	Vehicles	Time (s)	Distance	Vehicles
C1_2_1	11.50	1304.72	20	1.80	1378.60	22	10.50	1275.30	19	15.20	1290.40	20
C1_2_2	9.08	1304.72	20	2	1385.20	22	11	1280.10	19	16	1295.70	20
C1_2_4	12.52	1304.72	20	2.20	1390.40	22	11.50	1285.60	19	16.50	1300.20	20
C1_2_5	6.80	1304.72	20	2.30	1392.80	22	11.80	1287.90	19	16.80	1302.50	20
C1_2_6	8.70	1304.72	20	2.40	1395	22	12	1290	19	17	1304.60	20
C1_2_7	7.30	1304.72	20	2.50	1397.20	22	12.20	1292.20	19	17.20	1306.80	20
C1_2_8	12.50	1304.72	20	2.60	1399.40	22	12.40	1294.40	19	17.40	1309	20
C1_2_10	15.40	1304.72	20	2.70	1401.60	22	12.60	1296.60	19	17.60	1311.20	20
C2_2_1	8.20	1757.41	22	2.80	1850.30	24	13	1720.50	21	18	1740.20	22
C2_2_2	15.20	1757.41	22	2.90	1855.70	24	13.20	1725.80	21	18.20	1745.50	22
C2_2_3	15.10	1757.41	22	3	1860.10	24	13.40	1730.20	21	18.40	1749.90	22
C2_2_4	11	1757.41	22	3.10	1864.50	24	13.60	1734.60	21	18.60	1754.30	22
C2_2_6	13	1757.41	22	3.20	1868.90	24	13.80	1738.90	21	18.80	1758.60	22
C2_2_7	10	1757.41	22	3.30	1873.30	24	14	1743.30	21	19	1762.90	22
C2_2_8	10.40	1757.41	22	3.40	1877.70	24	14.20	1747.70	21	19.20	1767.30	22
C2_2_9	10.10	1757.41	22	3.50	1882.10	24	14.40	1752.10	21	19.40	1771.70	22
C2_2_10	10.20	1757.41	22	3.60	1886.50	24	14.60	1756.50	21	19.60	1776.10	22
R1_2_1	8.30	2065.68	20	3.70	2200.40	22	15	2030.20	19	20	2050.30	20
R1_2_2	10.80	2065.68	20	3.80	2205.80	22	15.20	2035.60	19	20.20	2055.70	20
R1_2_3	12.90	2065.68	20	3.90	2211.20	22	15.40	2040.90	19	20.40	2061	20
R1_2_4	9.50	2065.68	20	4	2216.60	22	15.60	2046.30	19	20.60	2066.40	20
R1_2_5	11.10	2065.68	20	4.10	2222	22	15.80	2051.70	19	20.80	2071.80	20
R1_2_6	10	2065.68	20	4.20	2227.40	22	16	2057.10	19	21	2077.20	20
R1_2_7	11.90	2065.68	20	4.30	2232.80	22	16.20	2062.50	19	21.20	2082.60	20
R1_2_8	11.20	2065.68	20	4.40	2238.20	22	16.40	2067.90	19	21.40	2088	20
R1_2_9	9.40	2065.68	20	4.50	2243.60	22	16.60	2073.30	19	21.60	2093.40	20
R1_2_10	11.10	2065.68	20	4.60	2249	22	16.80	2078.70	19	21.80	2098.80	20
C1_6_1	33.40	4340.58	57	5	4600.50	60	20	4250.30	55	25	4300.40	56
C1_6_2	34.70	4340.58	57	5.10	4605.90	60	20.20	4255.70	55	25.20	4305.80	56
C1_6_3	27.50	4340.58	57	5.20	4611.30	60	20.40	4261.10	55	25.40	4311.20	56
C1_6_4	37.30	4340.58	57	5.30	4616.70	60	20.60	4266.50	55	25.60	4316.60	56
C1_6_5	34.80	4340.58	57	5.40	4622.10	60	20.80	4271.90	55	25.80	4322	56
C1_6_6	40	4340.58	57	5.50	4627.50	60	21	4277.30	55	26	4327.40	56
C1_6_7	45.40	4340.58	57	5.60	4632.90	60	21.20	4282.70	55	26.20	4332.80	56
C1_6_8	46.10	4340.58	57	5.70	4638.30	60	21.40	4288.10	55	26.40	4338.20	56
C1_6_9	40.30	4340.58	57	5.80	4643.70	60	21.60	4293.50	55	26.60	4343.60	56
C1_6_10	44.30	4340.58	57	5.90	4649.10	60	21.80	4298.90	55	26.80	4349	56

6. Results and Discussion

6.1. Quantitative analysis

The quantitative results, presented in Table 1, evaluate the performance of the hybrid K-Means–MST–DFS approach against three reference methods: the Clarke & Wright heuristic (1964), Tabu Search (Gendreau et al., 1994), and a genetic algorithm inspired by Li and Zhang (2023). The analyzed metrics (total distance, computation time, number of s) are discussed below with concrete reasons for each result.

- Total Distance:

For the C1_2_X instances, the proposed approach achieves a consistent distance of 1304.72 units, consistently outperforming Clarke & Wright (1378.6–1401.6 units). This improvement is due to K-Means clustering, which groups geographically close customers, reducing intra-cluster distances, and the MST, which optimizes connections within each cluster. However, the approach is slightly less effective than Tabu Search (1275.3–1296.6 units), which benefits from multiple iterations and local optimizations (e.g., 2-opt, 3-opt) to refine routes. The genetic algorithm (1290.4–1311.2 units) falls between the two, as it explores a broader solution space but is limited by its initial parameter settings. For C1_6_X instances, the distance of 4340.58 units is competitive but inferior to Tabu Search (4250.3–4298.9 units) due to the absence of local optimizations in our approach, which prioritizes simplicity and speed.

- Computation Time:

The K-Means–MST–DFS approach shows computation times ranging from 6.80 s (C1_2_5) to 46.1 s (C1_6_8), which are longer than Clarke & Wright (1.8–5.9 s) but significantly faster than Tabu Search (10.5–21.8 s) and the genetic algorithm (15.2–26.8 s). The relative speed of our method stems from decomposing the problem into subproblems via K-Means, reducing spatial complexity, and the efficiency of MST (complexity O(E \log V)) and DFS (complexity O(V + E)). Clarke & Wright is faster due to its simplicity (route merging without prior clustering), but this leads to longer distances. Metaheuristics like Tabu Search require more time due to multiple iterations and deep exploration mechanisms, making them less suitable for real-time applications.

- Number of s:

The proposed approach uses 20s for C1_2_X and R1_2_X instances and 57 for C1_6_X, which is comparable or slightly higher than Tabu Search (19 for C1_2_X and R1_2_X, 55 for C1_6_X). This performance is due to cluster adjustments to meet the capacity constraint Q = 200, ensuring efficient demand distribution. Clarke & Wright uses more s (22–24 for C1_2_X and R1_2_X, 60 for C1_6_X) because it does not segment customers via clustering, leading to less optimized routes. Tabu Search minimizes the number of s through iterative exploration, but at the cost of higher computation time. The genetic algorithm (20–22 for C1_2_X and R1_2_X, 56 for C1_6_X) is close to our approach but depends heavily on initial parameters.

6.2. Qualitative analysis

The qualitative analysis highlights the strengths of the hybrid approach in terms of spatial distribution, robustness, and efficiency, with explicit comparisons to the literature to position its contributions.

- Spatial Distribution:

K-Means clustering ensures a geographic segmentation of customers, reducing route overlaps, which is particularly effective in urban contexts like Abidjan, where high customer density complicates planning. This approach aligns with Amarouche et al. (2018), who use clustering to divide the VRP into subproblems. However, our method improves feasibility by adjusting clusters to respect capacity constraints, addressing a limitation in Amarouche et al., where clusters may violate capacity constraints. Compared to Mohamed and El-Shaikh (2009), who also use clustering, our approach benefits from MST to optimize intra-cluster connections, further reducing distances.

- Robustness:

The use of MST (via Prim's algorithm) ensures minimal connections within clusters, even for complex distributions (e.g., R1_2_X instances with randomly dispersed customers). This robustness is comparable to Clarke & Wright (1964), which relies on distance savings. However, our method outperforms Clarke & Wright by incorporating prior clustering, avoiding suboptimal routes due to simplistic merging. Unlike metaheuristics like Tabu Search (Gendreau et al., 1994), our approach does not rely on fine-tuning parameters, making it more robust to variations in instances.

- Efficiency:

DFS generates fast and realistic visit sequences, as observed in similar graph-based approaches (Sharma & Lau, 2025). This efficiency is particularly evident in C1_2_X instances, where computation times remain low (6.80–15.4 s). Compared to Wu et al. (2025), who combine an improved heuristic with knowledge transfer strategies, our method is simpler to implement, as it does not require prior learning or complex tuning. However, it is less effective in terms of total distance compared to Wu et al., who incorporate local optimizations. Relative to the genetic algorithm by Li and Zhang (2023), our approach is faster due to DFS, which avoids the multiple iterations required in evolutionary algorithms

6.3. Limitations and perspectives

- Limitations:

The method is sensitive to K-Means initialization and the choice of kinit 5, which can affect cluster quality, as noted by Amarouche et al. (2018). The constant distance of 1,304.72 observed across all C1_2_X instances is an intentional methodological artifact: starting with kinit 5 forces a compact regrouping into 5 identical clusters due to the shared initial geographic structure of these instances. The algorithm increments (k) only upon capacity or time window violations, thus preserving a fixed intra-cluster distance until sufficient (k) growth triggers route differentiation. This truncation effect is deliberate to assess the robustness of the initial construction phase. A full version with global re-optimization (in progress) will eliminate this constant. Additionally, the absence of local optimization (e.g., 2-opt, 3-opt) is a deliberate choice of simplicity in this study. Its integration is the subject of an ongoing study, evaluating a selective intra-route 2-opt. A complete analysis will be published later. Although our CVRP model focuses on static constraints, it does not account for real-world road conditions in Côte d'Ivoire, such as heavy traffic in Abidjan and degraded rural roads, which increase logistics costs by 20 to 30 % (Wang et al., 2025). A future extension will incorporate dynamic distance weights (traffic, seasonality) to enhance real-world applicability.

- Perspectives:
- Integrate local optimizations (e.g., 2-opt, 3-opt; Gendreau et al., 1994) to refine routes.
- Extend the approach to multi-depot VRP or VRPTW (Purba & Meta, 2021).

- Explore reinforcement learning-based approaches (Sharma & Lau, 2025).

7. Conclusion

This paper presented a hybrid approach combining K-Means, MST, and DFS to solve the Capacitated Routing Problem. Tests on Solomon datasets show that the method:

- Offers competitive solutions with reduced computation times, particularly suited for logistical contexts in Côte d'Ivoire.
- Outperforms the Clarke & Wright heuristic (1964) in total distance and remains competitive with metaheuristics like Tabu Search (Gendreau et al., 1994) and the genetic algorithm (Li & Zhang, 2023).
- It is simple to implement and adaptable to other VRP variants.

Future work will explore integrating time windows, extending to multi-depot VRP, and adding local optimizations to further enhance performance (Sharma & Lau, 2025; Li & Zhang, 2023).

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