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OPTIMIZING TRANSPORTATION COSTS: ENHANCING LOGISTICS EFFICIENCY AND RESOURCE UTILIZATION IN A DYNAMIC ENVIRONMENTS

Cao Ngoc Anh, Tran Bich Thao, Tran Ba Hung, Trinh Thu Huong, Nguyen Viet Hung. **Optimizing Transportation Costs: Enhancing Logistics Efficiency and Resource Utilization in a Dynamic Environments.**

Abstract. The increasing demand for goods transportation, driven by the expansion of global supply chains and rising customer expectations, underscores the critical need to optimize transportation costs to enhance logistics efficiency. In a rapidly evolving and competitive market, businesses face mounting challenges in managing complex transportation networks, minimizing operational costs, and meeting diverse customer requirements. To address these issues, this paper introduces a solution designed to reduce transportation expenses by optimizing the flow of goods and improving resource utilization. By leveraging advanced optimization techniques and data-driven strategies, the proposed solution identifies inefficiencies, streamlines decision-making, and enhances resource allocation. Initial results demonstrate that this approach not only significantly reduces operational costs but also strengthens the ability of businesses to respond quickly and effectively to fluctuating customer demands, ensuring both cost efficiency and customer satisfaction. However, as the logistics industry continues to grow and transaction volumes increase, transportation scenarios are expected to become more complex, and customer requirements more diverse. This evolving landscape demands further refinement and scalability of the proposed solution to address larger networks, more intricate logistics challenges, and a broader range of customer demands. Future research will prioritize the development of larger-scale models capable of incorporating more variables, improving computational efficiency, and delivering faster, more accurate decision-making to meet the increasing complexity of the logistics sector. Therefore, the proposed solution represents a significant advancement in optimizing transportation costs and improving logistics efficiency. Initial results indicate that this solution can cut down transportation costs by 19.02% to 29.65% and enhance computational efficiency in small- to medium-scale routing tasks (10-20 customers). Despite its potential, more research is required to justify scalability to larger datasets. Hence, our approach provides a solid foundation for logistics optimization, with clear prospects for expansion and adaptation in real-world contexts.

Keywords: vehicle routing problem (VRP), linear programming (LP), ant colony optimization (ACO), integer linear programming (ILP), DBSCAN, genetic algorithms (GA).

1. Introduction. The Vehicle Routing Problem (VRP) is one of the most prominent combinatorial optimization problems, with wide-ranging applications in logistics, supply chain management, and transportation [1–3]. The main objective of VRP is to determine the optimal routes for a fleet of vehicles to serve a group of customers while adhering to constraints such as vehicle capacity limits, ensuring each customer is visited once, and requiring vehicles to start and return to a depot. As an NP-hard problem, the complexity of VRP grows significantly with the problem size. This makes traditional optimization methods inefficient in terms of computational time and resources when addressing large-scale VRP instances [4, 5]. This paper mainly focuses on the optimization of transportation costs in large-scale VRP scenarios with extremely non-uniform customer spatial distributions and spatial outliers. Such unequal distributions are frequently too difficult for traditional VRP techniques to handle, which results in inefficient routing, greater transportation costs, and more computational burdens.

One of the major challenges in VRP lies in handling customer data that is unevenly distributed across large geographic areas. Traditional methods often struggle to optimize routes in such scenarios, leading to high transportation costs and extended computation times. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm has demonstrated outstanding performance in clustering data based on density, particularly in cases where customer distributions are non-uniform. A key advantage of DBSCAN is its ability to automatically determine the number of clusters without requiring pre-defined parameters, as is necessary for other clustering algorithms like K-Means [6–8]. Furthermore, DBSCAN can detect and process outliers – customers located far from densely populated clusters – thereby mitigating their potential negative impact on overall routing and cost optimization [9].

To address this issue, clustering techniques, such as the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, have been widely adopted. DBSCAN is particularly effective in identifying clusters of customers based on density while also detecting outliers [10–12]. However, while DBSCAN can isolate these outliers, their treatment remains a significant challenge in logistics optimization. If not managed properly, outliers can lead to disproportionately high transportation costs, as vehicles may need to travel long distances for a single delivery. Future advancements in VRP optimization must therefore incorporate robust strategies to address outliers, such as integrating heuristic or metaheuristic methods (e.g., Ant Colony Optimization or Genetic Algorithms) to design dedicated routes, or dynamically assigning outliers to neighboring clusters based on cost-impact analysis.

In this study, we propose a novel approach that combines DBSCAN and integer linear programming (ILP) models to address VRP effectively. The core idea involves using DBSCAN to cluster customers based on density and geographic proximity. This clustering process divides a large-scale VRP into smaller, more manageable sub-problems, significantly reducing computational complexity. After clustering, each customer group is treated as an independent VRP instance, which is solved using an ILP model. This approach enables cost optimization for each cluster while minimizing the overall computation time, especially in large-scale logistics systems [13–15].

The novelty of this method lies in its flexible integration of clustering and optimization. DBSCAN not only clusters customers effectively but also reduces the dependence on pre-defined parameters such as the number of clusters, making the method more adaptable to complex real-world situations. Moreover, by identifying and processing outliers separately, the approach ensures that route optimization is not adversely affected by customers located far from central areas. Once the clustering process is completed, the customer groups are fed into an ILP model to solve the VRP for each cluster, ensuring accurate and efficient solutions [16–18].

The methodology proposed in this study aims to enhance efficiency and flexibility in addressing the Vehicle Routing Problem (VRP), particularly in large-scale, real-world scenarios with non-uniform customer distributions. Unlike conventional approaches that treat the VRP as a single, monolithic problem, the proposed framework introduces a two-step process to reduce computational complexity and improve scalability. First, the DBSCAN clustering algorithm is employed to partition customers into distinct groups based on geographic proximity and density, transforming the VRP into smaller, independent sub-problems. Each sub-problem is then optimized using Integer Linear Programming (ILP) to minimize costs within individual clusters. To address the challenges posed by customer outliers, these are managed separately to minimize their impact on the overall solution. As illustrated in Figure 1(a), traditional approaches struggle with large-scale instances, uneven customer distributions, and outliers, leading to high computational costs and limited flexibility. In contrast, as shown in Figure 1(b), the proposed methodology leverages clustering and sub-problem optimization to significantly reduce computational demands, enhance cost efficiency, and demonstrate robust scalability, making it particularly well-suited for real-world logistics systems.

This approach not only reduces computational time by breaking down the problem into smaller parts but also opens up possibilities for integration with modern algorithms such as Genetic Algorithms (GA) or Ant Colony Optimization (ACO) to tackle larger or more complex VRP instances. Additionally, the approach can be extended to address VRP variations such as Multi-Depot VRP, VRP with Time Windows (VRPTW), or Green VRP, where environmental considerations are incorporated [7, 19, 20]. With these advantages, our approach promises to provide an effective and practical solution for addressing VRPs in modern logistics systems.

The remainder of this paper is organized as follows: In Section 2, the existing state-of-the-art methodologies are thoroughly reviewed and discussed. In Section 3, the proposed algorithm is introduced and its details are carefully elaborated upon. Following this, in Section 4, an evaluation of the algorithm is conducted using appropriate metrics and benchmarks. Finally, the conclusions of the study are summarized and presented in Section 5, where the key findings and implications of the research are highlighted.

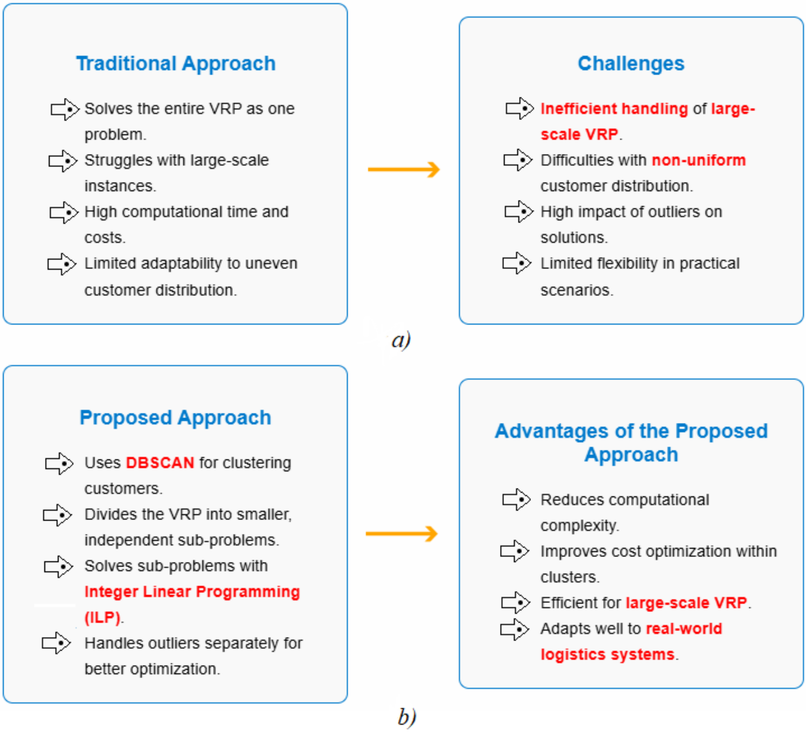


Fig. 1. Cluster-Based Optimization for Large-Scale Vehicle Routing Problems

2. Related work. The Vehicle Routing Problem (VRP) has been extensively studied due to its critical role in logistics, supply chain management, and transportation. Over the years, various approaches have been developed to address its complexity, especially for large-scale and real-world scenarios. This section reviews recent works (from 2022 onward) that focus on clustering techniques, optimization models, and hybrid methodologies to solve VRP and its variations.

One of the popular directions in VRP research involves the application of clustering techniques to divide large-scale problems into smaller, more manageable sub-problems. For instance, an enhanced DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm for VRP with heterogeneous fleets has been proposed, clustering customers based on geographic proximity and handling outliers separately, which significantly improves the efficiency of the optimization process [21–24]. Similarly, hybrid clustering algorithms have been demonstrated to solve VRP with time windows, showing that clustering reduces computational complexity by breaking the problem into smaller sub-problems, which can then be solved independently [9, 25, 26].

DBSCAN has gained attention for its ability to automatically determine the number of clusters based on data density, unlike traditional methods like K-Means which require predefined parameters. This feature makes DBSCAN particularly suitable for real-world logistics systems where customer distributions are often non-uniform. Research highlights the effectiveness of clustering techniques, including DBSCAN, in addressing Green VRP, where the goal is to minimize both transportation costs and environmental impact [7, 21, 27]. These studies underscore the potential of clustering to optimize routes while considering sustainability metrics. Another key aspect of VRP research is the integration of clustering with optimization models. Hybrid approaches that combine clustering with genetic algorithms have been explored to solve multi-depot VRP with time windows. These methods improve routing efficiency by leveraging the strengths of both clustering and metaheuristic optimization [26]. Similarly, the combination of clustering with reinforcement learning has been used to tackle large-scale VRPs. This method involves clustering customers first and then using reinforcement learning to optimize routes within each cluster, achieving significant reductions in computational time and costs [28].

Integer Linear Programming (ILP) models have also been widely employed to solve VRP sub-problems after clustering. An ILP-based framework has been presented that incorporates constraints like vehicle capacity, customer service requirements, and depot return conditions. It has been emphasized that clustering before applying ILP not only reduces problem size but also enhances the overall solution quality [29]. This aligns with findings from reviews of various clustering and optimization techniques, concluding that combining DBSCAN with ILP provides a robust framework for solving VRPs in large-scale logistics systems [5, 30].

Recent studies have also focused on handling VRP variations, such as VRP with Time Windows (VRPTW) and Multi-Depot VRP. A hybrid approach integrating Ant Colony Optimization (ACO) with clustering techniques has been proposed to solve capacitated VRPs. It has been shown that clustering customers before applying ACO significantly improves its performance, especially in problems with capacity and time constraints [31]. Similarly, research addressing VRP with multiple depots partitions customers into clusters based on depot proximity, followed by route optimization using genetic algorithms, indicating substantial improvements in both computational efficiency and route quality [26].

The ability to handle outliers effectively is another important consideration in VRP research. Outliers, or customers located far from densely populated areas, can significantly impact routing efficiency. Research emphasizes the need to treat outliers separately to minimize their negative effects on overall routing and transportation costs [6]. By isolating and optimizing routes for outliers independently, these approaches ensure that the main clusters remain unaffected, leading to better overall solutions.

In addition to these methodological advancements, Green VRP (G-VRP) has emerged as a critical area of research in recent years [32–35]. Studies have explored the integration of clustering and optimization techniques to minimize fuel consumption and greenhouse gas emissions in logistics systems. The findings demonstrate that clustering techniques like DBSCAN can significantly contribute to reducing environmental impact while maintaining high efficiency in route planning [36].

In summary, recent studies highlight the growing importance of combining clustering and optimization techniques to solve VRP and its variations. Clustering algorithms, particularly DBSCAN, have proven effective in handling non-uniform customer distributions and reducing computational complexity. Prior studies have demonstrated that, as long as clusters are balanced and geographically coherent, clustering-based routing strategies, especially those that use DBSCAN or other density-based techniques, remain computationally efficient for problem sizes up to several hundred customers [37, 38]. When integrated with optimization models like ILP or metaheuristic algorithms, these methods offer robust solutions for large-scale and real-world VRP instances. The ability to handle VRP variations, such as VRPTW, Multi-Depot VRP, and Green VRP, further underscores the versatility of these approaches. These findings lay the foundation for the proposed method, which leverages DBSCAN and ILP to address the challenges of large-scale VRPs more efficiently.

Although digital twin-based solutions offer full-scale simulations of logistics operations, their adaptability for real-time decision-making is limited by their frequent need for substantial system modeling and high processing power. The approach proposed in this paper, on the other hand, emphasizes computational efficiency by utilizing independent route optimization and clustering without recreating the dynamics of the entire system. Due to this distinction, which allows for faster response to dynamic logistical environments, the method is especially well-suited for large-scale real-world applications where quick re-optimization is required.

3. Proposed Model. The proposed model is designed to address the challenges associated with optimizing transportation costs in large-scale logistics systems, particularly those involving uneven customer distributions and significant computational complexity. By leveraging a two-step framework, the model integrates Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for customer clustering and Integer Linear Programming (ILP) for route optimization within each cluster. This approach effectively divides the Vehicle Routing Problem (VRP) into manageable sub-problems, significantly reducing computational demands while maintaining the accuracy and cost-efficiency of the solution.

The novelty of the proposed model lies in its ability to flexibly adapt to real-world scenarios. DBSCAN not only identifies clusters of customers based on geographic proximity and density but also detects outliers – customers located far from densely populated regions. These outliers, if untreated, can disrupt overall optimization and inflate costs. The model addresses this by allowing for the integration of additional strategies, such as heuristic or metaheuristic methods, to manage outliers effectively.

Once customers are grouped into clusters by DBSCAN, the ILP model is applied to each cluster to determine the optimal routes while respecting vehicle capacity constraints and minimizing travel costs. This modular approach ensures that the scalability of the solution is enhanced, making it well-suited for large-scale and dynamic logistics environments. Furthermore, the framework provides a strong foundation for extending the methodology to handle variations of VRP, such as Multi-Depot VRP, VRP with Time Windows (VRPTW), and Green VRP, thereby addressing both operational and environmental considerations.

In the following sections, we delve into the detailed components of the proposed model, including the problem description, mathematical formulation, and algorithmic implementation. These sections outline the technical underpinnings and demonstrate how the model achieves an efficient balance between computational feasibility and solution quality.

3.1. Problem Description. The Vehicle Routing Problem (VRP) is a classic optimization problem in logistics and transportation. It involves designing optimal routes for a fleet of vehicles to deliver goods to a set of customers. Each customer has a specific demand, and each vehicle has a limited capacity. The goal is to minimize the total travel cost while ensuring that all operational constraints are satisfied.

In this problem, the depot serves as the starting and ending point for all vehicle routes. It is represented as node 0 in the network. Each route begins at the depot, serves a subset of customers, and then returns to the depot. The customers are represented as nodes in the network, and there are n customers in total. Each customer is associated with a specific demand q[i] that must be met. Importantly, each customer must be visited exactly once by one vehicle, and no customer can be skipped.

The vehicles used in this problem have a maximum capacity of Q, which limits the total demand that can be served on a single route. This capacity constraint ensures that the total demand of the customers served on a single route does not exceed the vehicle's capacity. All vehicles are assumed to be homogeneous, meaning they have the same capacity and operational characteristics.

The objective of the VRP is to minimize the total travel cost, which is calculated as the sum of the distances traveled by all vehicles. This travel cost is influenced by the sequence in which customers are visited, as well as the assignment of customers to specific vehicles.

One of the main challenges of solving the VRP is its computational complexity. As the number of customers increases, the number of possible routes grows exponentially, making the problem increasingly difficult to solve. To address this challenge, the problem is simplified using DBSCAN clustering, a density-based clustering algorithm. DBSCAN groups customers into clusters based on their geographic proximity. Each cluster is then treated as a smaller, independent VRP instance. This approach significantly reduces the computational complexity while ensuring that the overall solution remains feasible and cost-effective. In addition to the issues discussed, another significant challenge in optimizing logistics systems is the efficient management of outliers – customers located far from densely populated clusters. While the DBSCAN algorithm effectively identifies such outliers during the clustering process, the manner in which they are handled greatly influences the overall solution quality and cost. Outliers can result in inefficient routes, as they may require vehicles to travel long distances for a single delivery. To address this challenge, future enhancements could incorporate specialized heuristic or metaheuristic methods, such as Ant Colony Optimization (ACO) or Genetic Algorithms (GA), to design dedicated routes for outliers. Furthermore, integrating outlier-handling strategies into the main optimization framework – such as assigning outliers to neighboring clusters based on cost-impact analysis or serving them with dedicated vehicles – can help reduce their negative impact on total travel costs and computational efficiency. By explicitly addressing the issue of outliers, the proposed method can further improve its scalability and robustness, ensuring its effectiveness even in scenarios with uneven customer distributions.

By using clustering, the problem is broken down into manageable subproblems, making it possible to solve larger instances of the VRP more efficiently while still minimizing the total travel cost.

On the other hand, Figure 2 illustrates the architecture of a generalized flowchart designed to optimize the fleet planning system, which consists of three core components. First, the Customer Data Collection component gathers essential input data, including customer addresses and demand requirements. This data is then processed by the Fleet Planning System, which optimizes vehicle allocation and route planning to efficiently meet customer demands while minimizing operational costs. Finally, the system generates a Report that provides detailed information, including the total number of vehicles required, optimized routes for each vehicle, a breakdown of customers assigned to each route, and route-specific details such as total distance traveled. This architecture streamlines operations, enhances decision-making processes, and ensures the effective allocation of resources to meet customer needs.

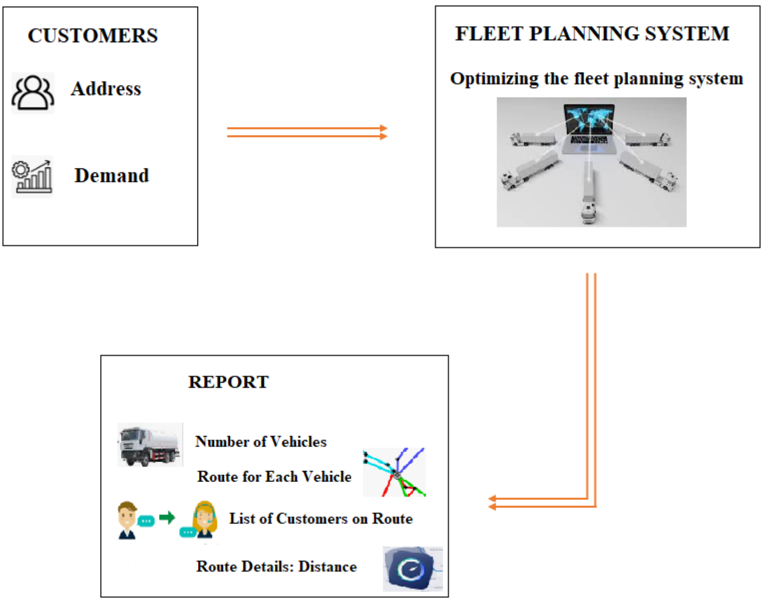


Fig. 2. Framework for the Proposed System Architecture

The **Compute Distance Matrix** is designed to calculate the distance matrix C for a given set of coordinates, which include the depot and customer locations. The input is a list of coordinates, represented as pairs (x, y), denoted as

$$\text{coords} = \{(x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)\}. \tag{1}$$

The output is a matrix $C = [c_{ij}]$, where each element c_{ij} represents the Euclidean distance between two points i and j. The algorithm iterates over all points i and, for each point i, iterates overall points j to compute the Euclidean distance using the formula:

$$c_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{2}$$

The calculated distances are stored in the matrix C, which is then returned as the result. This algorithm is commonly applied in optimization problems, such as the Traveling Salesman Problem (TSP) or Vehicle Routing Problem (VRP), where distance calculations between locations are essential.

The algorithm 1 **Cluster Customers Using DBSCAN** is used to group customer locations into clusters based on their spatial proximity, using the DBSCAN clustering method. The input consists of a set of customer coordinates coords = $\{(x_1, y_1), \ldots, (x_n, y_n)\}$ (excluding the depot), along with two key parameters: ϵ, which defines the radius for neighborhood calculation, and min_samples, which specifies the minimum number of points required to form a cluster. The algorithm applies the DBSCAN method to the input coordinates, assigning each customer a cluster ID c_i. If a customer does not belong to any cluster, it is marked as noise with a cluster ID of -1. Customers with valid cluster IDs (i.e., $c_i \neq -1$) are added to their respective clusters.

Algorithm 1. Cluster Customers Using DBSCAN

– $\mathbf{coords} = [(x_1, y_1), \ldots, (x_n, y_n)]$: Customer coordinates (excluding the depot).
– ϵ: Radius parameter for DBSCAN.
– $min\_samples$: Minimum number of points for a cluster.
Cluster assignments $\mathbf{clusters}$ for each customer.
Apply DBSCAN to the customer coordinates.
customer $i \in \{1, 2, \ldots, n\}$ Assign a cluster ID c_i to customer i (or -1 if it is noise).
Add customer i to the corresponding cluster if $c_i \neq -1$.
return $\mathbf{clusters}$.

Finally, the algorithm returns the list of clusters, where each cluster groups customers that are spatially close to each other. This approach is particularly useful in applications like logistics and delivery optimization, as it can identify clusters with arbitrary shapes and detect outliers effectively.

In addition, the algorithm 2 solves this optimization problem. If a feasible solution is found, the optimal objective value C_k is computed and returned as the result. Otherwise, the algorithm outputs "No solution found for Cluster k" and returns ∞. This approach is commonly used in Vehicle Routing Problems (VRP) to minimize travel costs while satisfying delivery constraints for a specific cluster of customers.

Algorithm 2. Solve VRP for a Single Cluster

– Cluster k: Set of customer nodes cluster$_k$.
– Q: Maximum vehicle capacity.
– $\mathbf{q} = [q_0, q_1, \ldots, q_n]$: Customer demands.
– Distance matrix $\mathbf{C} = [c_{ij}]$.
Cost C_k of the optimal route for cluster k.
Define the set of nodes for the cluster:

$$\text{nodes}_k \leftarrow \{0\} \cup \text{cluster}_k \cup \{n+1\},$$

where 0 is the depot and $n+1$ is the virtual depot.
Decision Variables:
– x_{ij}: Binary variable indicating travel from i to j.
– u_i: Load at node i.
Objective Function: Minimize total travel cost:

$$\min \sum_{i \in \text{nodes}_k} \sum_{j \in \text{nodes}_k,\, i \neq j} c_{ij} \cdot x_{ij}.$$

Constraints:
– Each customer is visited and departed exactly once.
– Ensure load balancing and respect vehicle capacity limits.
– Start at the depot and end at the virtual depot.
Solve the optimization problem using a solver (e.g., Gurobi).

if a feasible solution is found **then** Compute $C_k \leftarrow$ Optimal objective value.
return C_k.

else Print: "No solution found for Cluster k."
return ∞.

On the other hand, the algorithm 3 **Clustering and Solving VRP** is designed to solve the Vehicle Routing Problem (VRP) by combining clustering and route optimization. The input includes the number of customers n, the vehicle's maximum capacity Q, customer demands $q = [q_0, q_1, \ldots, q_n]$, and the coordinates of the depot and customers coords $= \{(x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)\}$. Additionally, the parameters ϵ (the radius for DBSCAN) and min_samples (the minimum number of points required for clustering) are provided.

Algorithm 3. Clustering and Solving VRP

– n: Number of customers.
– Q: Maximum vehicle capacity.
– $\mathbf{q} = [q_0, q_1, \ldots, q_n]$: Customer demands.
– $\mathbf{coords} = [(x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)]$: Coordinates of depot and customers.
– ϵ: Radius parameter for DBSCAN.
– $min\_samples$: Minimum number of points for DBSCAN.
Total cost C_{total} and optimal routes.
Step 1: Compute Distance Matrix.
Call **Formula 2** to compute $\mathbf{C}$.
Step 2: Cluster Customers Using DBSCAN.
Call **Algorithm 1** to compute $\mathbf{clusters}$.
Step 3: Solve VRP for Each Cluster.
Initialize total cost: $C_{\text{total}} \leftarrow 0$.
cluster k in $\mathbf{clusters}$ Call **Algorithm 2** for cluster k.

if a feasible solution is found **then** Update total cost: $C_{\text{total}} \leftarrow C_{\text{total}} + C_k$.
return C_{total}.

The algorithm computes the total cost C_{total} and the optimal routes using the following steps:

Step 1: Compute Distance Matrix. Call Algorithm 1 to calculate the distance matrix C, which represents pairwise distances between customers and the depot.

Step 2: Cluster Customers Using DBSCAN. Call Algorithm 2 to group customers into clusters based on their spatial proximity.

Step 3: Solve VRP for Each Cluster. For each cluster k, call Algorithm 3 to determine the optimal route and cost C_k. Initialize the total cost as $C_{\text{total}} = 0$. For every cluster, if a feasible solution is found, update the total cost as $C_{\text{total}} \leftarrow C_{\text{total}} + C_k$.. If no feasible solution is found for a cluster, the algorithm terminates for that cluster.

Finally, the algorithm 3 returns the total cost C_{total}, which represents the minimum travel cost for all clusters. This approach effectively combines clustering (using DBSCAN) and routing (using VRP optimization) to solve complex logistics problems efficiently.

3.2. Mathematical Formulation. The Vehicle Routing Problem (VRP) is mathematically formulated as a **Mixed Integer Linear Programming (MILP)** problem, which involves defining sets, parameters, decision variables, an objective function, and constraints. The following provides a detailed explanation of the mathematical model.

Sets. The problem involves the following sets:

– N – the set of customer nodes, indexed as $1, 2, \ldots, n$.

– V – the set of all nodes, including the depot (0) and the artificial end node $(n + 1)$, i.e., $V = \{0, 1, 2, \ldots, n, n + 1\}$.

– C – the set of clusters identified by the DBSCAN clustering algorithm, where each cluster contains a subset of customers.

Parameters. The parameters used in the model are:

– $c[i][j]$ – the distance or cost of traveling from node i to node j.

– $q[i]$ – the demand of customer i. For the depot, $q[0] = 0$.

– Q – the maximum capacity of each vehicle. This parameter ensures the vehicle cannot exceed its load limit.

Decision Variables. Two decision variables are defined in this model:

– $x[i][j]$ – a binary variable that indicates whether a vehicle travels directly from node i to node j. It is defined as:

$$x[i][j] = \begin{cases} 1 & \text{if a vehicle travels from node } i \text{ to node } j, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

– $u[i]$ – a continuous variable representing the load of a vehicle after visiting node i. This variable ensures that the vehicle's capacity is respected throughout the route.

Objective Function. The objective of the VRP is to minimize the total travel cost. This cost is calculated as the sum of the distances between all pairs of nodes i and j, weighted by the decision variable $x[i][j]$. The objective function is expressed as:

$$\text{Minimize} \quad Z = \sum_{i \in V} \sum_{\substack{j \in V \\ i \neq j}} c[i][j] \cdot x[i][j]. \tag{4}$$

Constraints. The model includes several constraints to ensure the feasibility of the solution.

Customer Visit Constraints. Each customer must be visited exactly once by one vehicle. This is enforced using the following constraints:

$$\sum_{\substack{i \in V \\ i \neq j}} x[i][j] = 1, \quad \forall i \in N. \tag{5}$$

$$\sum_{\substack{j \in V \\ i \neq j}} x[i][j] = 1, \quad \forall j \in N. \tag{6}$$

The first constraint ensures that exactly one vehicle arrives at each customer, while the second ensures that exactly one vehicle leaves each customer.

Depot Flow Constraints. Vehicles must start and end their routes at the depot. These constraints are given by:

$$\sum_{j \in N} x[0][j] = 1. \tag{7}$$

$$\sum_{i \in N} x[i][n+1] = 1. \tag{8}$$

The first constraint ensures that exactly one vehicle departs from the depot, while the second ensures that exactly one vehicle returns to the depot.

Subtour Elimination Constraints. To prevent invalid routes (subtours that do not include the depot), the following constraints are introduced:

$$u[j] \geqslant u[i] + q[j] - Q \cdot (1 - x[i][j]), \quad \forall i, j \in N, i \neq j. \tag{9}$$

If $x[i][j] = 1$, meaning a vehicle travels from node i to node j, the load at node j must be at least the load at i plus the demand at j. Otherwise, if $x[i][j] = 0$, the constraint is relaxed.

Vehicle Capacity Constraints. The load at each node must respect the vehicle's capacity. The following constraints ensure that the load at any node does not exceed the vehicle's capacity:

$$q[i] \leqslant u[i] \leqslant Q, \quad \forall i \in N. \tag{10}$$

Binary Decision Constraints. The decision variables $x[i][j]$ are binary, meaning they can only take values of 0 or 1:

$$x[i][j] \in \{0,1\}, \quad \forall i,j \in V. \tag{11}$$

Explanation of the Model. This model captures the essential components of the VRP and ensures that all operational constraints are satisfied. The **objective function** minimizes the total cost, while the **constraints** ensure that vehicles respect their capacity, visit all customers exactly once, and prevent the creation of invalid routes. The **subtour elimination constraints** are particularly important to ensure that all routes are connected and include the depot.

By solving this mathematical model for a given cluster of customers, an optimal or near-optimal route can be obtained for that cluster. The total solution is then constructed by solving the VRP for all clusters and combining their results. This approach balances computational efficiency and solution quality.

4. Performance Evaluation

4.1. Experimental Settings. The approach in this study involves a fleet of vehicles starting and ending at a single depot while serving a set of customers with specific demands. Each customer is associated with a demand value (q), and the vehicles have a maximum load capacity (Q). The distances between customers were calculated as a cost matrix (c) using the Euclidean distance derived from their coordinates. This setup ensures that all necessary data for modeling the VRP is precomputed and ready for optimization.

To improve computational efficiency, customers were grouped into clusters using the DBSCAN algorithm from the sklearn library. DBSCAN was applied to the coordinates of the customers, excluding the depot, with a radius (epsilon) of 5 and a minimum sample size ($min\_samples$) of 2, and customers change, Figure 3 is an illustration of 20 customers. This clustering approach organizes customers into manageable groups based on their spatial proximity, reducing the complexity of solving the VRP for large datasets. Outliers identified by DBSCAN were excluded from further optimization. For each identified cluster, a separate VRP was formulated and solved using the Gurobi optimization solver. Binary decision variables $(x[i,j])$ were used to represent whether a vehicle travels directly between two nodes, while continuous variables $(u[i])$tracked the load at each node. Constraints ensured that each customer was served exactly once, vehicle load limits were respected, and all routes started and ended at the depot. This modular approach allows solving smaller subproblems, which are computationally more efficient.

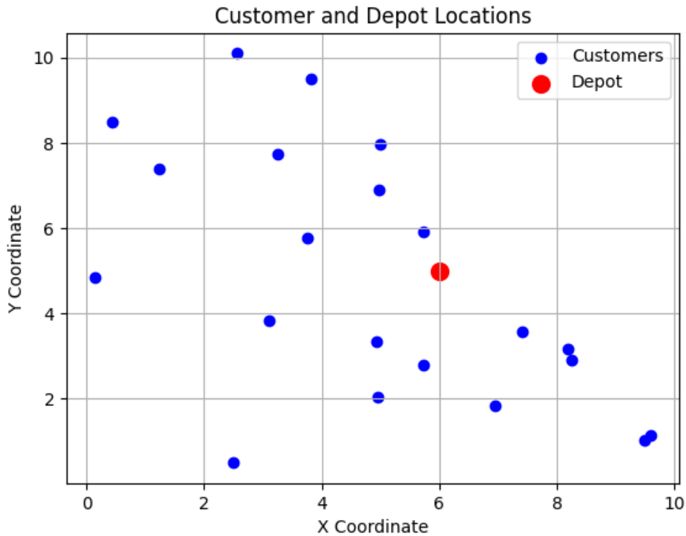


Fig. 3. An example of customer data (20 customers)

The objective function aimed to minimize the total travel cost across all routes within each cluster, defined as the sum of distances between n odes. The optimization results for all clusters were combined to calculate the overall cost. If no feasible solution was found for a particular cluster, this was reported. This clustering-based solution strategy provides an effective way to address large-scale VRP instances by dividing the problem into smaller, more tractable subproblems.

The testing process was conducted using the Python programming language. The program was executed on Gurobi Optimizer version 12.0.0 (build v12.0.0rc1) running on a Windows 10 operating system (version 19045.2). The hardware environment consisted of an Intel® Core™ i7-6500U CPU operating at 2.50 GHz, equipped with instruction sets [SSE2, AVX, AVX2]. The system featured 2 physical cores and 4 logical processors, with a maximum utilization of 4 threads. For further details on the Gurobi software, refer to Gurobi Optimization[1].

4.2. Experimental Results. In this section, we present a detailed analysis and comparison of the empirical results obtained from our approach against those achieved by other established methods. To ensure a comprehensive evaluation, we consider multiple performance metrics, including solution

[1] https://www.gurobi.com/

quality, computational efficiency, and scalability. Our approach is benchmarked against three well-known approaches commonly used in the field:

– Integer Linear Programming (ILP), outlined in [39], which targets freight issues faced by Vietnamese logistics companies. By modeling the Vehicle Routing Problem (VRP) for small-scale logistics companies, this approach accounts for challenges such as traffic congestion, poor infrastructure, and limited technology use. The ILP model produced optimal solutions with small additional costs, highlighting its practicality and effectiveness for addressing real-world problems in the Vietnamese logistics sector.

– Genetic Algorithms (GAs), as described in [1], which solve the Vehicle Routing Problem (VRP) by encoding the problem into chromosomes, applying crossover and mutation operators to generate new solutions, and using fitness functions to select the best candidates. This method iteratively evolves solutions to achieve optimal or near-optimal routes, reducing costs and optimizing resources, with proven applicability in real-world transportation and logistics.

– Hybrid Genetic Algorithm-Solomon Insertion Heuristic (HGA-SIH), introduced in [40], which addresses the Vehicle Routing Problem with Time Windows (VRPTW). This approach combines a Hybrid Genetic Algorithm (HGA) with the effective Solomon Insertion Heuristic (SIH) to optimize vehicle routes. Tested on Solomon's benchmark instances, HGA-SIH delivered Best-Known Solutions (BKS) for 11 cases and improved one BKS, consistently achieving results comparable to or better than state-of-the-art algorithms. It effectively minimizes travel distance and manages vehicle usage, demonstrating adaptability and efficiency for diverse VRPTW scenarios.

By analyzing these results, we aim to highlight the strengths and potential limitations of our approach. This comparison not only demonstrates the effectiveness of the approach in solving the problem but also provides insights into how it performs relative to existing methods in terms of achieving optimal or near-optimal solutions within acceptable computational times. The evaluation emphasizes the practical applicability of our approach in addressing complex real-world scenarios, particularly in transportation and logistics optimization.

In Figure 4(a), where the vehicle load capacity is set to $Q = 5$, our approach demonstrates a clear advantage over the other methods (VRPA, VRPTW, and GA) in minimizing costs across all customer scenarios (10, 15, and 20). As the number of customers increases, the cost difference between our approach and the others becomes more significant. This highlights the robustness of our approach to handling larger customer demands, even with limited vehicle capacity.

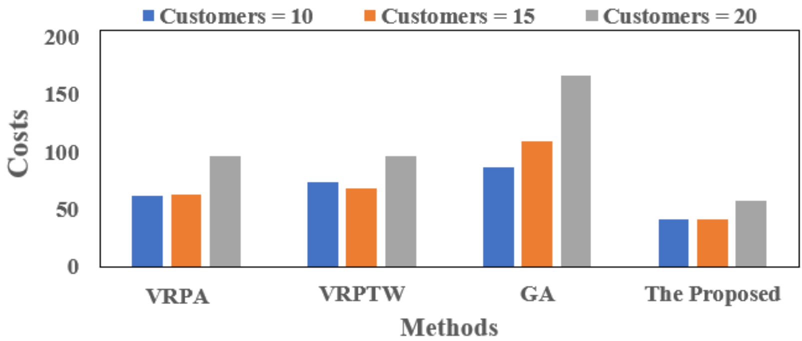
For Figure 4(b), with a vehicle load capacity of Q = 10, a similar trend is observed. Our approach consistently achieves the lowest costs, maintaining its efficiency regardless of the number of customers. In contrast, the GA (Genetic Algorithm) method produces the highest costs, particularly when the customer count reaches 20, indicating its limitations in managing larger and more complex routing problems. The VRPA and VRPTW methods perform moderately but remain less effective compared to our approach.

a) Cost Comparison of Methods for Vehicle Routing Problem with Q = 5

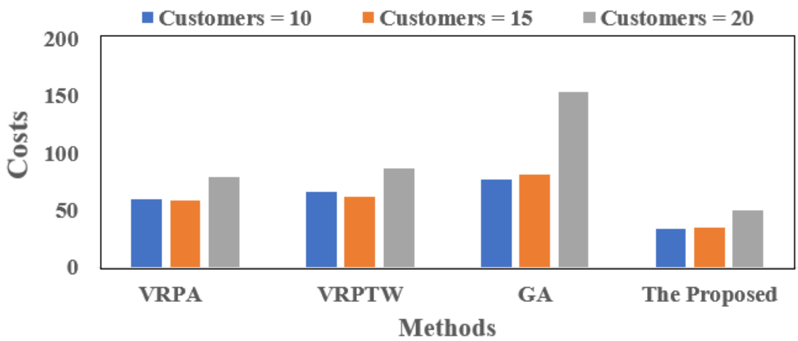
b) Cost Comparison of Methods for Vehicle Routing Problem with Q = 10

Fig. 4. Cost Comparison of Methods for Vehicle Routing Problem Under Different Vehicle Load Capacities (with Q = 5 and Q = 10)

In Figure 5, the results depicted in both charts indicate that our approach consistently outperforms the other methods (VRPA, VRPTW, and GA) in terms of cost minimization across different scenarios of customer numbers (10, 15, and 20) and vehicle load capacities (Q = 15 and Q = 20). Specifically, our approach achieves significantly lower costs compared to the other approaches, particularly as the number of customers increases, demonstrating its scalability and efficiency.



a) Cost Comparison of Methods for Vehicle Routing Problem with Q = 15



b) Cost Comparison of Methods for Vehicle Routing Problem with Q = 20

Fig. 5. Cost Comparison of Methods for Vehicle Routing Problem Under Different Vehicle Load Capacities (with Q = 15 and Q = 20)

The GA (Genetic Algorithm) method, on the other hand, incurs the highest costs among the compared methods, especially when dealing with a larger number of customers. This trend is evident in both cases where Q = 15 and Q = 20, suggesting that GA may not be as effective in handling complex and large-scale vehicle routing problems. The VRPA and VRPTW methods show relatively stable performance, with costs increasing moderately as the number of customers grows. However, their costs are consistently higher than our approach, indicating a less optimized solution.

Overall, the analysis of both figures highlights that our approach, with its ability to significantly reduce costs, stands out as the most efficient solution. Its adaptability to varying vehicle load capacities and customer demands further emphasizes its robustness.

Although Genetic Algorithms (GAs) can produce high-quality solutions, they are fundamentally heuristic and depend on stochastic processes, for example, selection, crossover, and mutation. Computational time and hyperparameter adjustment frequently influence on their performance. In order to replicate real-world circumstances in logistics planning, when quick decisions are essential, GA was implemented in our studies with the same time constraints as other methods. In these circumstances, GA was found to converge more frequently to poor solutions, particularly when outliers are present or the datasets have uneven spatial distributions.

In contrast, our approach decomposes the VRP into more manageable and homogeneous subproblems using clustering techniques to reduce computational complexity. This structure guarantees that outliers do not disproportionately impact on the global solution and enables the ILP solver to function more efficiently inside each cluster. Consequently, given practical time and data constraints, our approach performs better in terms of cost reduction and computing efficiency.

We admit that GA may be able to match or surpass the quality of our approach with much more runtime and appropriate tuning. However, our hybrid clustering-optimization approach is more dependable in practice due to the requirement for consistent, scalable, and explicable performance in actual logistical scenarios. By excelling under strict vehicle load constraints (Q = 5 and Q = 10), our approach demonstrates superior performance compared to other approaches. Its remarkable ability to handle complex scenarios while maintaining low costs solidifies its suitability for practical applications that demand both optimization and flexibility.

Our approach was tested using synthetic datasets of up to 20 customers. This choice indicates computational constraints at this stage of development, however, it allows us to compare the relative performance of ILP, GA, and our proposed DBSCAN-ILP framework. We acknowledge that further testing on greater, more complex routing situations is necessary to adequately assess scalability, even if findings consistently demonstrate cost and time improvements in smaller datasets.

5. Conclusions. In the context of the increasing demand for goods transportation, both in terms of scale and complexity, optimizing transportation costs plays a crucial role in enhancing the efficiency of logistics operations and better meeting customer requirements. In this paper, we have proposed a solution aimed at improving transportation costs by focusing on optimizing the flow of goods and enhancing resource utilization. The initial results demonstrate that applying this solution not only reduces operational costs but also improves the ability to respond quickly and effectively to the diverse needs of customers.

However, with the continuous growth of the market and the increasing volume of goods transactions, customer requirements are expected to become more demanding. This necessitates that the current solutions be further refined and expanded to better address future challenges and also highlights the necessity of incorporating metaheuristic methods and adaptive clustering strategies to preserve computational efficiency at larger scales. The proposed DBSCAN-ILP framework remains most effective when cluster sizes are relatively balanced and the number of outliers is low, making it well-suited for moderately sized logistics problems. Even though the suggested clustering-optimization approach performs well in small-scale synthetic experiments, more testing on bigger datasets is necessary. As problem size increases, cluster imbalance and growing ILP subproblem sizes may reduce the computational efficiency of the solution. We predict that adaptive cluster scaling and integration with metaheuristic algorithms may become crucial for computing efficiency when the number of customers exceeds several hundred. Future study should focus on these improvements as well as the anticipated validation using real-world benchmarks such as Solomon VRP datasets.

Future studies will concentrate on a number of aspects. Firstly, in order to evaluate performance in real-world scenarios, benchmark datasets such as Solomon Benchmark problems will be implemented for real-world validation. Secondly, in order to handle outliers better and enhance scalability, integration with sophisticated metaheuristic techniques like Ant Colony Optimization (ACO) and Genetic Algorithms (GA) will be investigated. Lastly, more research will look into real-time re-optimization and dynamic clustering to adjust to constantly shifting customer needs in extremely dynamic logistical settings. To further validate the scalability of our method, future work will also include comparative runtime evaluations with hybrid and metaheuristic frameworks using larger, more varied datasets.

In general, the solution proposed in this paper represents an important step toward optimizing transportation costs in the context of a rapidly evolving market. We believe that with further enhancements and expansions in the future, this solution has the potential to become a valuable tool for businesses to tackle the challenges of modern logistics.

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ОПТИМИЗАЦИЯ ТРАНСПОРТНЫХ РАСХОДОВ: ПОВЫШЕНИЕ ЭФФЕКТИВНОСТИ ЛОГИСТИКИ И ИСПОЛЬЗОВАНИЯ РЕСУРСОВ В ДИНАМИЧЕСКОЙ СРЕДЕ

Нгок Ань К., Бич Тао Т., Ба Хунг Т., Ту Хуонг Т., Хунг Н.В. **Оптимизация транспортных расходов: повышение эффективности логистики и использования ресурсов в динамической среде.**

Аннотация. Растущий спрос на транспортировку товаров, обусловленный расширением глобальных цепочек поставок и растущими ожиданиями клиентов, подчеркивает острую необходимость оптимизации транспортных расходов для повышения эффективности логистики. В условиях быстро развивающегося и конкурентного рынка предприятия сталкиваются с растущими проблемами в управлении сложными транспортными сетями, минимизации эксплуатационных расходов и удовлетворении разнообразных требований клиентов. Для решения этих проблем в данной статье представлено решение, разработанное для снижения транспортных расходов за счет оптимизации потока товаров и повышения эффективности использования ресурсов. Используя передовые методы оптимизации и стратегии на основе данных, предлагаемое решение позволяет выявить неэффективности, упростить процесс принятия решений и улучшить распределение ресурсов. Первые результаты показывают, что этот подход не только значительно снижает эксплуатационные расходы, но и повышает способность предприятий быстро и эффективно реагировать на меняющиеся требования клиентов, обеспечивая как экономическую эффективность, так и удовлетворенность клиентов. Однако по мере дальнейшего развития логистической отрасли и увеличения объемов транзакций ожидается, что сценарии транспортировки станут более сложными, а требования клиентов – более разнообразными. Эти изменения требуют дальнейшего совершенствования и масштабируемости предложенного решения для работы с расширенными сетями, более сложными логистическими задачами и широким спектром потребительских требований. В будущих исследованиях приоритетное внимание будет уделено разработке крупномасштабных моделей, способных включать больше переменных, повышать вычислительную эффективность и обеспечивать более быстрое и точное принятие решений в условиях растущей сложности логистического сектора. Таким образом, предлагаемое решение представляет собой значительный шаг вперед в оптимизации транспортных расходов и повышении эффективности логистики. Первые результаты показывают, что данное решение позволяет сократить транспортные расходы на 19,02–29,65% и повысить вычислительную эффективность в задачах маршрутизации малого и среднего масштаба (10-20 клиентов). Несмотря на его потенциал, необходимы дополнительные исследования для обоснования масштабируемости для более крупных наборов данных. Таким образом, наш подход обеспечивает прочную основу для оптимизации логистики с четкими перспективами расширения и адаптации в реальных условиях.

Ключевые слова: задача маршрутизации транспортных средств (VRP), линейное программирование (LP), оптимизация методом муравьиных колоний (ACO), целочисленное линейное программирование (ILP), DBSCAN, генетические алгоритмы (GA).

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