



## Computational Study of CPLEX and Genetic Algorithms for the Vehicle Routing Problem

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### ABSTRACT

The Vehicle Routing Problem (VRP) is a well-known combinatorial optimization problem classified as NP-hard, with significant applications in logistics and transportation systems. This study presents a comparative analysis between an exact method based on CPLEX and a Genetic Algorithm (GA) as a metaheuristic approach for solving VRP instances of increasing sizes. The main objective is to evaluate the trade-off between solution quality and computational efficiency. The exact method using CPLEX provides optimal or near-optimal solutions with lower total costs across all tested instances; however, its performance may vary depending on the complexity of the problem. In contrast, the Genetic Algorithm demonstrates high computational efficiency and stable execution times, although it produces solutions with higher costs compared to the exact method. The results also indicate that the Genetic Algorithm effectively satisfies the imposed constraints while sacrificing optimality due to its stochastic nature. The comparative evaluation highlights that exact methods remain the benchmark for small- and medium-sized instances, whereas metaheuristic approaches such as Genetic Algorithms offer better scalability and greater computational flexibility for larger or more complex cases. The findings are consistent with previous literature on VRP optimization and confirm the well-known trade-off between accuracy and efficiency.

**Keywords:** Vehicle Routing Problem, Genetic Algorithm, CPLEX Optimization, Combinatorial Optimization, Metaheuristic Methods.



## المخلص

تُعدّ مشكلة التوجيه بالمركبات (VRP) إحدى مسائل التحسين التوافقي المعروفة بأنها من نوع-NP-hard، ولها تطبيقات مهمة في مجالات اللوجستك وأنظمة النقل. تقدم هذه الدراسة تحليلاً مقارناً بين طريقة دقيقة تعتمد على CPLEX وخوارزمية جينية (GA) كطريقة ميتاهيوريسية لحل حالات من مشكلة VRP ذات أحجام متزايدة. يتمثل الهدف في تقييم المفاضلة بين جودة الحل والكفاءة الحسابية. توفر الطريقة الدقيقة باستخدام CPLEX حلاً مثلياً أو شبه مثلياً بتكاليف إجمالية أقل عبر جميع الحالات المختبرة، إلا أن أدائها قد يتغير حسب تعقيد المشكلة. في المقابل، تُظهر الخوارزمية الجينية كفاءة حسابية عالية وثباتاً في زمن التنفيذ، لكنها تنتج حلاً ذات تكاليف أعلى مقارنة بالطريقة الدقيقة. كما تُظهر النتائج أن الخوارزمية الجينية تحافظ بشكل فعال على القيود المفروضة، لكنها تتنازل عن المثالية بسبب طبيعتها العشوائية. ويزر التقييم المقارن أن الطرق الدقيقة تظل مرجحاً للحالات الصغيرة والمتوسطة، بينما توفر الطرق الميتاهيوريسية مثل الخوارزميات الجينية قابلية أفضل للتوسع ومرونة حسابية أعلى في الحالات الأكبر أو الأكثر تعقيداً. وتتوافق النتائج مع الأدبيات السابقة حول تحسين VRP، وتؤكد المفاضلة المعروفة بين الدقة والكفاءة.

**الكلمات المفتاحية:** مشكلة التوجيه بالمركبات، الخوارزمية الجينية، تحسين CPLEX، التحسين التوافقي، الطرق الميتاهيوريسية.

## 1. Introduction

Efficient management of transportation and delivery operations has become a major challenge in modern logistics systems, due to its direct impact on operational costs, service times, and customer satisfaction [1]. In a context characterized by globalization, increasing distribution volumes, and the growing complexity of logistics networks, the optimization of routing decisions—known as the Vehicle Routing Problem (VRP)—has become a central issue in operations research and combinatorial optimization [2].

The VRP consists of determining an optimal set of routes for a fleet of vehicles in order to serve a set of customers while satisfying various constraints such as vehicle capacity, customer demand, and routing requirements. This problem belongs to the class of NP-hard combinatorial optimization problems, meaning that obtaining exact optimal



solutions becomes computationally expensive as the size of the instances increases. As a result, a wide range of exact and approximate methods has been developed to efficiently address this problem [3].

Among exact approaches, integer linear programming-based solvers such as CPLEX are able to provide optimal or near-optimal solutions for small- to medium-sized instances by ensuring a rigorous formulation of all problem constraints. However, their applicability is often limited by computational time when dealing with larger or more complex instances.

In contrast, metaheuristic approaches, particularly Genetic Algorithms, have gained significant attention due to their ability to efficiently explore large search spaces and provide high-quality solutions within reasonable computational time. Although they do not guarantee optimality, they represent a flexible and robust alternative for solving large-scale optimization problems.

Within this context, this study presents a comparative analysis between an exact method based on CPLEX and a metaheuristic approach based on a Genetic Algorithm for solving the VRP. The main objective is to evaluate the trade-off between solution quality and computational time across a set of instances with increasing size. The study is based on a mathematical formulation of the problem, followed by the implementation of both approaches and an experimental analysis of the obtained results.

This comparison highlights the strengths and limitations of each method and provides insights into the selection of appropriate optimization techniques for real-world logistics problems.

## 2. Problem

The problem under study consists of organizing and optimizing transportation and delivery operations within a complex logistics network. More specifically, it involves determining optimal routing plans as well as efficient allocation of resources (vehicles, capacities, and time) in order to satisfy customer demand while minimizing operational costs and respecting a set of practical constraints. This problem is generally modeled as



a combinatorial optimization problem belonging to the class of NP-hard problems, which implies that finding exact optimal solutions becomes computationally expensive as the size of the network increases.

In this context, several conflicting objectives must be considered simultaneously. On the one hand, minimizing transportation costs represents a fundamental objective, including expenses related to fuel consumption, vehicle maintenance, labor, and infrastructure usage. On the other hand, meeting delivery deadlines constitutes a critical constraint, particularly in last-mile delivery systems where customers often impose strict time windows. Consequently, any feasible solution must ensure that goods are delivered within the required time limits in order to maintain a high level of customer satisfaction.

Another important aspect of the problem lies in demand satisfaction. Each customer has a specific demand in terms of product quantity, and the logistics system must be able to fulfill this demand without service disruption. This requires rigorous planning of transportation flows and appropriate allocation of available resources. Furthermore, the vehicles used in the logistics network are subject to capacity constraints, meaning that they can only carry a limited volume or weight of goods. This constraint imposes an optimal structuring of routes in order to avoid overloads and ensure efficient resource utilization.

Moreover, the problem becomes even more complex in the presence of temporal dynamics and uncertainty. Indeed, real-world transportation conditions may vary due to several factors such as traffic congestion, unexpected incidents, delivery delays, or demand fluctuations. These elements introduce a stochastic and dynamic dimension to the problem, requiring methods capable of adapting decisions in real time or near real time. Traditional static approaches therefore show their limitations in such evolving environments.

From a theoretical perspective, this problem is closely related to concepts from graph theory and routing problems. The logistics network can be modeled as a directed graph where nodes represent distribution points (warehouses, logistics centers, and customers)



and edges represent possible connections between these points, associated with costs (distance, time, or financial cost). In this framework, part of the problem reduces to solving variants of the shortest path problem, which consists of determining the optimal path between two nodes by minimizing a given cost function.

The shortest path problem thus constitutes a fundamental building block in the modeling of transportation and delivery problems, although it is often integrated into more complex problems such as the Vehicle Routing Problem (VRP), where multiple vehicles must serve a set of customers while satisfying various operational constraints. The combination of these aspects makes the problem both theoretically rich and computationally challenging, justifying the use of advanced approaches such as mathematical optimization and artificial intelligence.

### 3. Mathematical Modeling

We consider a logistics network represented by a complete directed graph:  $G = (V, E)$

where:

- $V = \{0, 1, 2, \dots, n\}$  is the set of nodes, with 0 representing the depot (logistics center) and  $\{1, \dots, n\}$  representing the customers,
- $E = \{(i,j) \mid i,j \in V, i \neq j\}$  is the set of arcs.

Each customer  $i \in V \setminus \{0\}$  has a demand ( $d_i > 0$ ).

A fleet of  $K$  homogeneous vehicles is available, each with a maximum capacity  $Q$ .

Each arc  $(i,j) \in E$  is associated with a cost  $c_{ij}$ , representing typically a distance, a travel time, or a monetary cost.

#### ❖ Decision Variables

We introduce the following decision variables:

$$x_{ij}^k = \begin{cases} 1 & \text{si le vehicule } k \text{ se déplace directement de } i \text{ à } j \\ 0 & \text{sinon} \end{cases} \quad \forall i, j \in V, \forall k \in \{1, \dots, K\}$$



$u_i^k \in R^+$  : the cumulative load transported by vehicle k after serving customer i.

❖ **Fonction objectif**

The objective is to minimize the total transportation cost:

$$\min Z = \sum_{k=1}^K \sum_{i \in V} \sum_{j \in V, j \neq i} c_{ij} x_{ij}^k \quad (1)$$

❖ **Constraints**

(1) Unique visit of customers

Each customer must be visited exactly once:

$$\sum_{k=1}^K \sum_{i \in V} x_{ij}^k = 1 \quad \forall j \in V \setminus \{0\} \quad (2)$$

(2) Flow conservation

For each vehicle, the number of incoming arcs to a node is equal to the number of outgoing arcs:

$$\sum_{i \in V} x_{ij}^k = \sum_{i \in V} x_{ji}^k \quad \forall j \in V, \forall k \quad (3)$$

(3) Depot departure and return constraints

Each vehicle departs from the depot and returns to it:

$$\sum_{j \in V \setminus \{0\}} x_{0j}^k = 1 \quad \forall k \quad (4)$$

$$\sum_{i \in V \setminus \{0\}} x_{i0}^k = 1 \quad \forall k \quad (5)$$

(4) Capacity constraints

The load carried by each vehicle must not exceed its capacity:

$$d_i \leq u_i^k \leq Q \quad \forall i \in V \setminus \{0\}, \forall k \quad (6)$$

And to ensure load consistency:

$$u_j^k \geq u_i^k + d_j - Q(1 - x_{ij}^k) \quad \forall i, j \in V, i \neq j, \forall k \quad (7)$$

(5) Subtour elimination constraints (MTZ – Miller-Tucker-Zemlin formulation)

To prevent cycles that do not include the depot:

$$u_i^k - u_j^k + Qx_{ij}^k \leq Q - d_j \quad \forall i \neq j, \forall k \quad (8)$$

(6) Domain constraints

$$x_{ij}^k \in \{0,1\} \quad \forall i, j \in V, \forall k \quad (9)$$

$$u_i^k \geq 0 \quad \forall i \in V, \forall k \quad (10)$$

The objective function (1) aims to minimize the total transportation cost by summing, over all vehicles k, the costs associated with the used arcs, weighted by binary variables



indicating whether a vehicle traverses a given arc. Constraint (2) ensures that each customer is visited exactly once by a single vehicle, thereby guaranteeing the completeness and uniqueness of deliveries. The flow conservation constraint (3) maintains route consistency by enforcing, for each vehicle and each node, that the number of incoming arcs equals the number of outgoing arcs, which allows the formation of continuous and uninterrupted routes.

Constraints (4) and (5) specify that each vehicle must depart from the depot and return to it exactly once, ensuring the closed-route structure characteristic of routing problems. Capacity constraints (6) impose that the cumulative load carried after visiting each customer remains within the range defined by the customer's demand and the vehicle's maximum capacity, thereby ensuring compliance with physical vehicle limitations. The load consistency constraint (7) updates the carried load correctly when moving from one customer to another, linking successive load variables and activating or deactivating the constraint depending on whether the arc is used.

The subtour elimination constraint (8), based on the Miller–Tucker–Zemlin (MTZ) formulation, prevents the formation of isolated cycles that do not include the depot by enforcing an ordering relation among customer visits. Finally, domain constraints (9) and (10) define the binary nature of the decision variables and the non-negativity of load variables, respectively, ensuring the mathematical and physical consistency of the model.

#### 4. Methodology

This study adopts an experimental approach aimed at solving the Vehicle Routing Problem (VRP) by comparing an exact method and a metaheuristic approach. The methodological objective is to evaluate the relative performance of CPLEX, based on integer linear programming, and a Genetic Algorithm, in terms of solution quality and computational time.

First, the problem instances are defined using a dataset characterized by the number of customers, vehicle capacity, and the maximum number of available vehicles. Each instance represents a distinct optimization problem on which both approaches are applied.



For the exact method, the CPLEX solver is used to generate optimal or near-optimal solutions by minimizing the total traveled distance while respecting capacity constraints.

Second, a Genetic Algorithm-based approach is developed. This metaheuristic relies on a permutation-based representation of customers, excluding the depot, and uses a split procedure to generate routes. The algorithm incorporates classical operators such as tournament selection, Order Crossover (OX), and swap mutation. The fitness function combines total route cost with a penalty for constraint violations in order to guide the search toward feasible solutions.

Experiments are conducted on several instances of increasing size in order to observe the performance evolution of both methods. For each instance, the following metrics are measured: total routing cost, number of vehicles used, computational time (CPU), and constraint satisfaction. A direct comparison is then performed between the results obtained by CPLEX and those obtained by the Genetic Algorithm.

Finally, the methodological analysis is based on a comparative evaluation highlighting the trade-off between optimality and computational efficiency. This approach is consistent with classical VRP literature, where exact methods are used as a benchmark for solution quality, while metaheuristics are assessed for their ability to handle large-scale problems within reasonable computational times.

### 5. Implementation Details and Experimental Setup

The Vehicle Routing Problem (VRP) was solved using both an exact method based on IBM ILOG CPLEX and a metaheuristic approach based on a Genetic Algorithm (GA). To ensure reproducibility and a fair comparison, all implementation parameters and experimental conditions are explicitly defined. For the exact approach, IBM ILOG CPLEX was used to solve the Mixed-Integer Linear Programming formulation of the problem. The solver was configured with a time limit of 300 seconds per instance, a relative optimality gap of 1%, and 4 processing threads. Default settings for presolve and cut generation were maintained. The Genetic Algorithm was implemented in Python using a permutation-based representation of customers. Each chromosome represents an



ordered sequence of customers, which is decoded into feasible routes using a split procedure that respects vehicle capacity constraints. The fitness function minimizes the total routing cost while incorporating a penalty term to handle constraint violations. The main GA parameters were set as follows: population size of 100 individuals, 200 generations, tournament selection with size 3, Order Crossover (OX) with a probability of 0.8, and swap mutation with a probability of 0.1. Elitism was applied by preserving the best individual in each generation. The stopping criteria for the Genetic Algorithm were defined as reaching the maximum number of generations (200) or no improvement in the best solution for 50 consecutive generations. To account for the stochastic nature of the Genetic Algorithm, each instance was executed 10 independent times. The reported results include average, best, and standard deviation values of the solution cost. All experiments were conducted on a computer equipped with an Intel Core i5 processor and 8 GB of RAM, using Python 3.10.0 and IBM ILOG CPLEX.

## 6. Results and Discussion

The results obtained using CPLEX (Table 1), considered as an exact method for solving the Vehicle Routing Problem (VRP), provide an optimal benchmark for evaluating the performance of the developed Genetic Algorithm. Overall, CPLEX produces higher-quality solutions in terms of total cost across all tested instances. For example, for VRP\_1, CPLEX achieves a cost of 224.44 compared to 345.10 for the Genetic Algorithm, representing a significant deviation. This trend is consistent across all instances, with notable gaps such as VRP\_3 (197.99 vs. 405.90) and VRP\_5 (226.14 vs. 385.53). These differences indicate that the Genetic Algorithm converges toward feasible but suboptimal solutions compared to the optimal or near-optimal solutions obtained by CPLEX (Table 2).

Table 1 : CPLEX Results

Instance	Clients	Véhicules	Coût total	CPU (s)	Véhicules utilisés	Coût min / max véhicule	Violations
VRP_1	5	2	224.44	0.86	2	84.85 / 139.59	0
VRP_2	6	2	231.51	0.04	2	28.28 / 203.22	0
VRP_3	7	2	197.99	0.06	2	84.85 / 113.14	0
VRP_4	8	2	235.12	0.07	2	81.02 / 154.10	0
VRP_5	9	2	226.14	0.18	2	87.67 / 138.47	0
VRP_6	10	2	127.28	0.39	2	0.00 / 127.28	0
VRP_7	10	3	291.75	0.36	3	0.00 / 263.47	0



**Table 2 : Genetic Algorithm Results**

Instance	Clients	Véhicules	Coût total	CPU (s)	Véhicules utilisés	Coût min / max véhicule	Violations
VRP_1	5	2	345.10	0.17	1	345.1 / 345.1	0
VRP_2	6	2	316.70	0.17	1	316.7 / 316.7	0
VRP_3	7	2	405.90	0.18	2	92.09 / 313.82	0
VRP_4	8	2	328.68	0.18	1	328.68 / 328.68	0
VRP_5	9	2	385.53	0.20	2	84.55 / 300.97	0
VRP_6	10	2	307.43	0.23	1	307.43 / 307.43	0
VRP_7	10	3	432.68	0.23	2	78.41 / 354.27	0
VRP_20	20	3	828.06	0.47	3	0.42	0
VRP_50	50	5	2178.14	1.02	4	1.14	0
VRP_100	100	8	4453.12	2.58	5	2.38	0

In contrast, an analysis of computational time highlights a fundamental difference between the two approaches. CPLEX exhibits variable execution times ranging from 0.04 to 0.86 seconds, which remains competitive but may increase significantly for more complex instances in real-world settings. The Genetic Algorithm, on the other hand, shows remarkable stability with execution times between 0.17 and 0.23 seconds, regardless of problem structure. This confirms that metaheuristics offer advantages in terms of computational efficiency and stability, at the expense of solution quality.

Regarding solution structure, CPLEX consistently ensures optimal vehicle utilization and a well-balanced distribution of routes, with more homogeneous minimum and maximum route costs. In contrast, the Genetic Algorithm exhibits greater variability in route cost distribution and sometimes suboptimal use of available vehicles (e.g., VRP\_1 and VRP\_4 using only one vehicle). This reflects a less precise exploration of the solution space, which is typical of stochastic approaches.

The results obtained on larger instances (20, 50, and 100 nodes) provide additional evidence regarding the scalability behavior of the Genetic Algorithm. It can be observed that as the problem size increases, both the average solution cost and computational time increase gradually and consistently. Despite this growth in complexity, the algorithm maintains feasibility across all instances, with no constraint violations observed. However, the standard deviation also increases with instance size, indicating higher variability in solution quality when exploring larger search spaces. This behavior is



expected for stochastic metaheuristics and reflects the increasing difficulty of maintaining solution consistency as the problem dimension grows. Overall, these results suggest that the Genetic Algorithm remains computationally efficient for larger instances, while highlighting a trade-off between performance and solution quality.

From an academic perspective, these results are consistent with the literature. Exact methods such as CPLEX (based on integer linear programming) are known to provide optimal solutions for small- and medium-sized instances, as discussed by [4]. In contrast, Genetic Algorithms, while powerful for exploring complex search spaces, generally produce approximate solutions, as demonstrated by [5], [6] and [7], reflecting a trade-off between solution quality and computational time [8].

In conclusion, the comparison highlights a classical trade-off in VRP problems: CPLEX provides optimal solutions but with limited scalability for large instances, whereas the Genetic Algorithm offers a fast and flexible approach but with lower solution accuracy. Thus, in real-world contexts, metaheuristics are suitable for larger instances where exact methods become computationally expensive, while exact solvers remain the reference for solution evaluation and validation [9] [10].

**Table 3: Relative Optimality Gap**

Instance	CPLEX Cost	GA Cost	Gap (%)
VRP_1	224.44	345.10	53.78%
VRP_2	231.51	316.70	36.78%
VRP_3	197.99	405.90	105.05%
VRP_4	235.12	328.68	39.80%
VRP_5	226.14	385.53	70.50%
VRP_6	127.28	307.43	141.60%
VRP_7	291.75	432.68	48.30%

#### Relative Optimality Gap Analysis

The relative optimality gap between the Genetic Algorithm and CPLEX solutions is presented in Table 3. The results indicate that the Genetic Algorithm exhibits significant deviations from the optimal solutions, with gap values ranging from 36.78% to 141.60%. In particular, larger gaps are observed for instances such as VRP\_3 and VRP\_6, where the GA solution cost exceeds twice the optimal value. This behavior reflects the difficulty of the Genetic Algorithm in effectively exploring the solution space for certain problem structures.



However, for some instances (e.g., VRP\_2 and VRP\_4), the gap remains relatively moderate, suggesting that the GA is capable of producing acceptable solutions within a significantly lower computational time. Overall, these results confirm the classical trade-off between solution quality and computational efficiency: while CPLEX guarantees optimal solutions, the Genetic Algorithm provides faster but less accurate results.

## 7. Conclusions

This study focused on solving the Vehicle Routing Problem (VRP) using two different approaches: an exact method based on CPLEX and a metaheuristic based on a Genetic Algorithm. The main objective was to evaluate the trade-off between solution quality and computational time, which are two fundamental criteria in combinatorial optimization problems.

The experimental results show that CPLEX consistently provides higher-quality solutions in terms of total cost, confirming its ability to achieve optimal or near-optimal solutions for the small-scale instances considered. In contrast, the Genetic Algorithm produces feasible solutions with significantly lower computational time, but with a noticeable performance gap compared to the exact method. This gap is mainly attributed to the stochastic nature of the metaheuristic and the absence of advanced local search enhancement mechanisms.

However, the experimental evaluation remains limited to small and medium-scale instances. Therefore, the obtained results do not allow for strong generalizations regarding large-scale industrial performance or full scalability behavior.

Despite this limitation, the Genetic Algorithm demonstrates computational efficiency and robustness in generating feasible solutions within acceptable time limits, making it a relevant approach when exact methods become computationally expensive.

Overall, the results confirm the classical trade-off between optimality and computational efficiency in VRP problems. Exact methods such as CPLEX remain reliable benchmarks for solution quality assessment, while Genetic Algorithms represent flexible heuristic approaches suitable for larger and more complex instances.

Future research may focus on hybrid optimization strategies combining metaheuristics with local search or exact methods in order to improve solution quality and reduce the performance gap.



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