# 2-phase algorithm using clustering and tabu search for solving the Multi-Trip Vehicle Routing Problem (MTVRP)

Víctor Salazar[1], Daniel Morillo[2] , Rodrigo Linfati[3], and Gustavo Gatica[1]

[1] Universidad Andres Bello, Santiago, Chile
[2] Pontificia Universidad Javeriana, Cali, Colombia
[3] Universidad del Bío-Bío, Concepción, Chile

v.salazarvasquez@uandresbello.edu

**Abstract.** Vehicle routing and its generalizations propose a classic optimization problem. This paper presents a two-phase method to address the complexities of the Multi-Trip Vehicle Routing Problem (MTVRP). Initially, nodes are clustered to streamline routing, followed by tabu search applied to each sub-route to obtain an initial solution. A 2-OPT algorithm further enhances routing efficiency by exploring edge exchanges. Results are rigorously evaluated, comparing them with mathematical modeling using AMPL and Cplex engine for a 6-hour run, The comparison of results demonstrates computational efficiency and practical applicability..

Node clustering organizes routing effectively, with tabu search and the 2-OPT algorithm refining solutions iteratively. The methodology achieves an approach to the solution within a limited time. Results demonstrate the method's effectiveness in addressing MTVRP, surpassing traditional mathematical modeling approaches. This two-phase framework offers a versatile solution for optimizing vehicle routes with multiple trips, contributing to transportation logistics optimization.

Experimentally, results show a percentage gap (GAP) ranging from 2.66% to 19.73%, indicating the difference between the best-known solution and the optimal solution. This gap varies with instances, nodes, and vehicles involved. Additionally, there is a significant reduction in computation time, from no solutions found in 6 hours using AMPL to approximate solutions found within 0.35 to 3.66 seconds, respectively.

**Keywords:** Heuristic, VRP, Optimization.

## 1 Introduction

In 1990, Fleischmann [1] proposed a first approach to address the Multi-Trip Vehicle Routing Problem (MTVRP), a generalization of the classical Vehicle Routing Problem (VRP). Since the VRP is NP-Hard [2] and this problem is a variation of it, the MTVRP is also considered NP-Hard. However, in this first approach, a heterogeneous fleet was included, and time window constraints were imposed on customers. While existing algorithms address this challenge, the computational time required is often prohibitive. Recognizing the need to reduce computational times without compromising the quality of the solution. It is a challenge where we can contribute a new two-phase algorithm. The goal of this algorithm is to significantly reduce the search space, resulting in high quality solutions in a considerably shorter time.

Although there are accurate methods for dealing with this type of problem, it is important to note that computation times tend to be significantly high, especially when dealing with large-scale instances [3].

In response to this challenge, our proposed two-phase algorithm promises a paradigm shift in addressing the Multiple Trips Vehicle Routing Problem (MTVRP). By strategically segmenting the optimization process into three distinctive phases, our algorithm not only mitigates the computational burden but also enhances the overall efficiency of solution derivation.

The fundamental objective of this study is to introduce an innovative algorithmic alternative to address the challenge of the Multi-Trip Vehicle Routing Problem (MTVRP). We aim to strike a balance between computational efficiency and the quality of the generated solutions. Our two-phase algorithm seeks to transform the traditional MTVRP approach by significantly accelerating the routing optimization process. This end-to-end solution aims to provide an efficient and practical response to the complexities of home delivery logistics.

By delving into the specifics of the proposed algorithm and its phased structure, we aim to demonstrate its efficacy in achieving optimal routes for multiple trips, thereby meeting the evolving demands of contemporary logistics and e-commerce [4].The subsequent sections will delve into the details of each phase, highlighting the unique contributions and advantages offered by our novel approach.

### 1.1 Presentation of the problem

The Multi-Trip Vehicle Routing Problem (MTVRP) is the task of visiting multiple customers at designated locations using a fleet of vehicles initially parked at a depot. Each customer requires a specific quantity of a product, and each vehicle has a predetermined capacity [5]. The main objective is to efficiently visit all customers in the shortest possible time, taking into account the maximum allowable working hours for each driver. It is important to note that, in this particular problem, each vehicle has the capacity to perform more than one route, implying a return to the depot and departure for additional trips [6].

In the literature, the Multi-Trip Vehicle Routing Problem (MTVRP) has been defined in various ways. For the present research, we adopt the definition proposed in [5], who state the following.

*"Let G = (N, A) be a directed graph, where N = {0 , 1 , ..., N } is the set of nodes and A = { (i, j) | i, j ∈ N } is the set of arcs. The arcs (i, j) ∈ A are characterized by their travel time Tij . Node 0 represents the depot where a fleet V of identical vehicles with a limited capacity Q is available at time 0 and has to be returned at time TH. Nodes 1 , ... , N represent the customers to be served, each of which requires a certain non-negative quantity Qi of a product".*

The 4-index vehicle flow formulation mathematical model (4VFF-VRP) provides a flexible and adaptable representation for vehicle fleet management problems by incorporating an additional index to represent individual trips and by including trip length constraints. This structure facilitates the understanding and resolution of complex logistics problems by allowing a more detailed representation of transportation and delivery operations.

Taillard et al. [7] present a two-phase algorithm designed to address the Multi-Trip Vehicle Routing Problem (MTVRP). Initially, in the first phase, the algorithm uses tabu search with adaptive memory to generate solutions for the VRP, which are then stored in a list. Subsequently, in the second phase, solutions for the MTVRP are constructed using a heuristic inspired by the Bin Packing Problem (BPP). In this case, trips are treated as objects to be packed into containers, each of which has a capacity equal to the maximum vehicle time (TH). The BPP heuristic employed is a direct greedy algorithm, complemented with trip exchanges, which aims to improve the efficiency of trip-to-container assignments and to optimize the loading capacity of each vehicle in the context of MTVRP.

Figure 1 illustrates an example route for 3 vehicles, 5 routes and 14 customers [6]. In this specific case, it is observed that vehicles 1 and 3 run two routes each, while vehicle 2 runs only one route. Notably, it can be seen that each vehicle starts and ends its route at the depot. This example graphically visualizes the complexity and diversity of routes that can be generated to optimize the delivery service, highlighting the ability of some vehicles to perform multiple routes in a single trip.

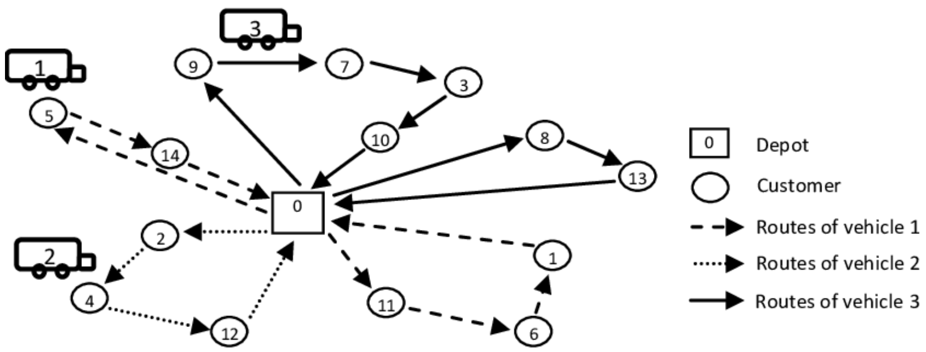


**Fig. 1.** Example route for a MTVRP

### 1.2 Mathematical model

For the present investigation, the 4-index 3VFF-VRP mathematical model developed by [8], [9], [10], [11] was selected as the theoretical framework. However, in order to simplify its implementation in AMPL, it was decided to replace some specific constraints by those proposed by Lei et al. [12]. These constraints play an essential role in guaranteeing compliance with the maximum vehicle capacity requirements, while preventing the generation of subroutes within the problem solution. The resulting version of the mathematical model, with the proposed modifications, is presented below.

$$x_{ij}^{vr} = \begin{cases} 1 \; if \; travel \; r \in R \; of \; the \; vehicle \; v \in V \; travels \; through \; the \; arc \; (i,j) \in A \\ 0 \; otherwise \end{cases}$$

$$y_i^{vr} = \begin{cases} 1 \; if \; trip \; r \in R \; of \; the \; vehicle \; v \in V \; visits \; vertex \; i \in N \\ 0 \; otherwise \end{cases}$$

$Where \; R = \{ 0 , \ldots , N - 1 \}$.

$$min \sum_{(i,j) \in A} T_{ij} \sum_{v \in V} \sum_{r \in R} x_{ij}^{vr} \qquad (1)$$

*Subject to*

$$\sum_{v \in V} \sum_{r \in R} y_i^{vr} = 1 \quad \forall \; i \in N \setminus \{0\} \qquad (2)$$

$$\sum_{j \in N} x_{ij}^{vr} = \sum_{j \in N} x_{ji}^{vr} = y_i^{vr} \quad \forall \; i \in N, v \in V, r \in R \qquad (3)$$

$$\sum_{j \in N} q_{ji}^{vr} - \sum_{j \in N} q_{ij}^{vr} = Q_i \quad \forall \; \mathrm{i} \in N \setminus \{0\}, \mathrm{v} \in \mathrm{V}, \mathrm{r} \in R \qquad (4)$$

$$q_{ij}^{vr} \leq Q x_{ij}^{vr} \qquad \forall \; (\mathrm{i},\mathrm{j}) \in \mathrm{A}, \; v \in \mathrm{V}, \mathrm{r} \in \mathrm{R} \qquad (5)$$

$$\sum_{r \in R} \sum_{(i,j) \in A} T_{ij} x_{ij}^{vr} \leq T_H \quad \forall \; v \in V \qquad (6)$$

$$q_{ij}^{vr} \geq 0 \qquad \forall \; (\mathrm{i},\mathrm{j}) \in \mathrm{A}, \; v \in \mathrm{V}, \mathrm{r} \in \mathrm{R} \qquad (7)$$

$$x_{ij}^{rv} \in \{0,1\} \; \forall \; v \in V, r \in R, (i,j) \in A \qquad (8)$$

$$y_i^{rv} \in \{0,1\} \; \forall v \in V, r \in R, i \in N \qquad (9)$$

It is relevant to note that clustering has proven to be effective in other routing problems. For example, it was successfully applied in a specific case of the Vehicle Routing Problem (VRP) in the city of Turin [13]. Moreover, it was incorporated together with a genetic algorithm in the context of the Vehicle Routing Problem with Time Windows, demonstrating its versatility and applicability in different logistic contexts [14].

In some studies, the success of tabu search in solving specific challenges in vehicle routing problems has been demonstrated. For example, Bernal et al. [15] employed tabu search at the granular level in the Distance Constrained Capacitated Vehicle Routing Problem (DCVRP), managing to obtain high quality solutions in reduced computation times. Furthermore, Ahmed et al. [16], the effectiveness of an improved tabu search in a routing problem involving a heterogeneous fleet and time windows is highlighted, while in [17], an adaptive tabu search was used to address the Two-Dimensional Vehicle Routing Problem with Stochastic Customer and Load Constraints. In both cases, the results support the ability of tabu search to optimize solutions in complex and dynamic logistics scenarios. Finally, the 2-OPT algorithm is implemented to make specific adjustments to the routes and obtain additional improvements [18], [19]. This algorithm focuses on local optimization, exploring arc swaps to refine the configuration of existing routes.

# 2 Proposed method

The proposed methodology for addressing the Multi-Trip Vehicle Routing Problem (MTVRP) is structured in two strategic phases, each meticulously designed with the purpose of optimizing and improving the quality of the solutions obtained. A detailed description of each phase is provided below:

In the first phase, a node grouping process is implemented through the application of clustering techniques. This approach seeks to efficiently organize the service points, thus reducing the search space and facilitating an initial segmentation of the routes.

The second phase incorporates the application of tabu search to the subroutes derived in the previous phase. By using the initial solution obtained by the nearest neighbor method in each cluster, we seek to refine the routes and improve the quality of the overall solution.

The sequential approach of these phases seeks to leverage synergies between different optimization techniques, thus providing a comprehensive and effective strategy to address MTVRP challenges and obtain high quality solutions in a computationally efficient time.

## 2.1 Clustering

In the initial phase of the methodology, the clustering method is implemented with the objective of fragmenting the Multi-Trip Vehicle Routing Problem (MTVRP) into more manageable subproblems. This strategy involves grouping customers into clusters or groups in order to mitigate the complexity inherent in the overall problem. In this case, the k-means algorithm was used to perform the clustering. The main purpose is to identify patterns of proximity between customers, thus facilitating more efficient routing. The clustering technique plays a crucial role in segmenting customers into groups that can be served more effectively by vehicles, contributing to the overall optimization of the routing process.

At this stage, it is crucial to ensure the feasibility of the solution, ensuring that the sum of customer requirements within each cluster does not exceed the maximum capacity of the vehicles. To achieve this, we start with an initial capacity allocation for the clusters (e.g. 3), perform the clustering of the problem and verify the feasibility of each cluster. In case any cluster exceeds the maximum capacity of the vehicles, a new clustering is performed to dynamically adjust the allocation of customers to clusters and maintain the feasibility of the solution. This iterative and adaptive approach ensures the consistency of the solution in terms of vehicle capacity.

Figure 2 shows an example of initial clusters as part of a possible solution. In this visual representation, the initial grouping of customers into specific clusters is illustrated.

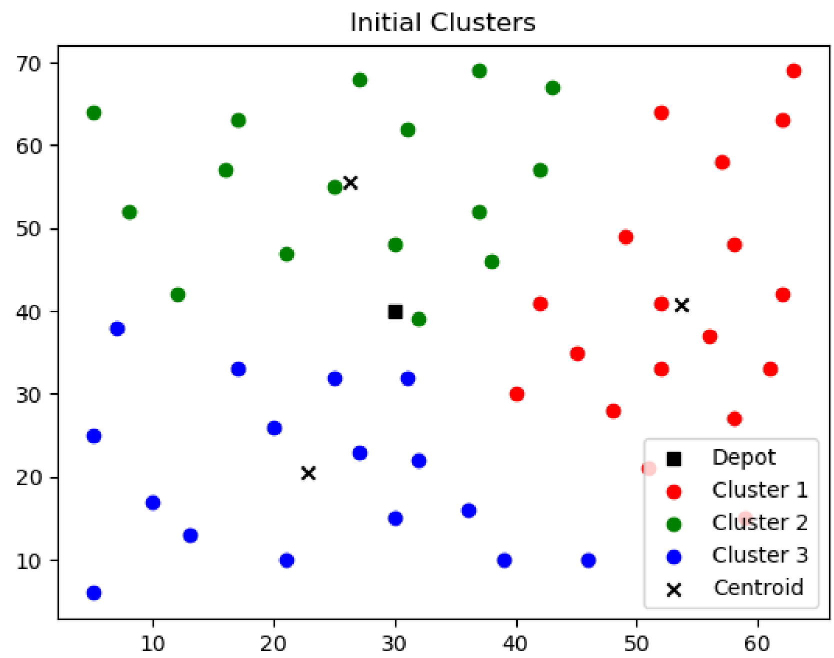


**Fig. 2.** Example of clusters

## 2.2 Tabu search

In the second stage, a tabu search algorithm is applied to each group or subproblem. This choice is based on the proven effectiveness of these methods in previous cases, where they have demonstrated their ability to generate solutions that are remarkably close to optimality. In fact, in many cases, they are considered one of the most effective approaches to address today's logistic challenges [20]. It starts from an initial solution in each cluster obtained using a nearest neighbor algorithm, a common heuristic for generating initial solutions in routing problems. Tabu search progressively improves these solutions iteratively, employing strategies that overcome local optima and bring the solutions closer to the global optimum. This refined approach contributes significantly to obtaining more robust and efficient solutions in the context of the multipath vehicle routing problem (MTVRP).

In this specific implementation, the search neighborhood of the tabu search was restricted to arcs whose length is less than the average of the total length of the arcs. This restriction aims to avoid the inclusion of very distant arcs in possible solutions, thus contributing to the efficiency of the tabu search. In addition, two key parameters were defined for the tabu search: The number of iterations was set to 1000, and the size of the tabu list was set to 5. This list keeps track of recently made moves to avoid repeating them for several iterations, thus expanding the search space. following the recommendation of Toth and Vigo [21]. These parameters play a crucial role in the performance and efficiency of the algorithm, allowing adequate control over the process of searching and optimizing solutions in the framework of the Multi-Trip Vehicle Routing Problem (MTVRP).

Figure 3 illustrates an example of the initial solution constructed using the K-nearest neighbor (KNN) algorithm [22], while Figure 4 presents the solution obtained by applying the tabu search. These visual representations highlight the difference between the initial solution generated by KNN and the improvement achieved after the application of tabu search. This visual contrast provides a clear understanding of how tabu search contributes to route optimization in the context of the Multi-Trip Vehicle Routing Problem (MTVRP).

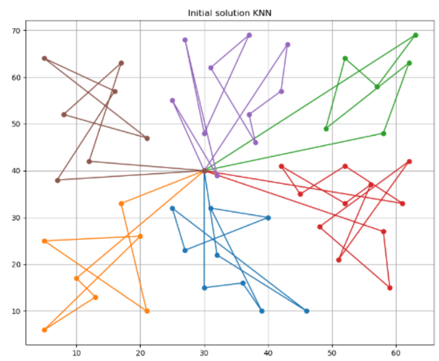


**Fig. 3.** KNN Initial solution

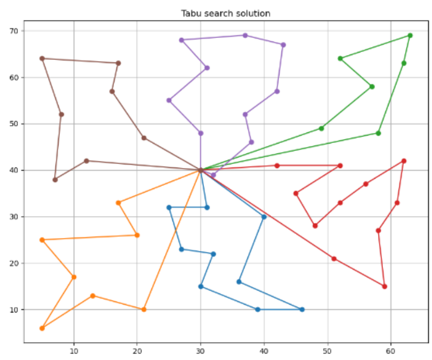


**Fig. 4.** Tabu search solution

To conclude the second phase, an improvement will be applied to the solutions obtained by applying the 2OPT improvement method, as previously used in multi-depot vehicle routing problems [23] and has also shown promising results in the Split Delivery Vehicle Routing Problem (SDVRP) [25]. This method is used to reorganize existing routes by modifying the order in which customers are visited, with the clear purpose of decreasing the total length of the routes and, therefore, minimizing the associated travel time. The 2OPT technique proves to be very effective in optimizing already established routes, playing a significant role in increasing the overall quality of previously achieved solutions. Its ability to make precise and strategic adjustments to the sequence of customer visits provides a further improvement in routing efficiency, thus contributing to more optimal solutions in the context of the multi-trip vehicle routing problem (MTVRP).

Figure 5 presents the result after applying the 2OPT improvement method, thus representing the final solution obtained by the algorithm. All that remains is to assign each route to a vehicle that has the necessary time to complete it efficiently. This final stage of vehicle assignment completes the optimization process, consolidating the final solution of the algorithm.

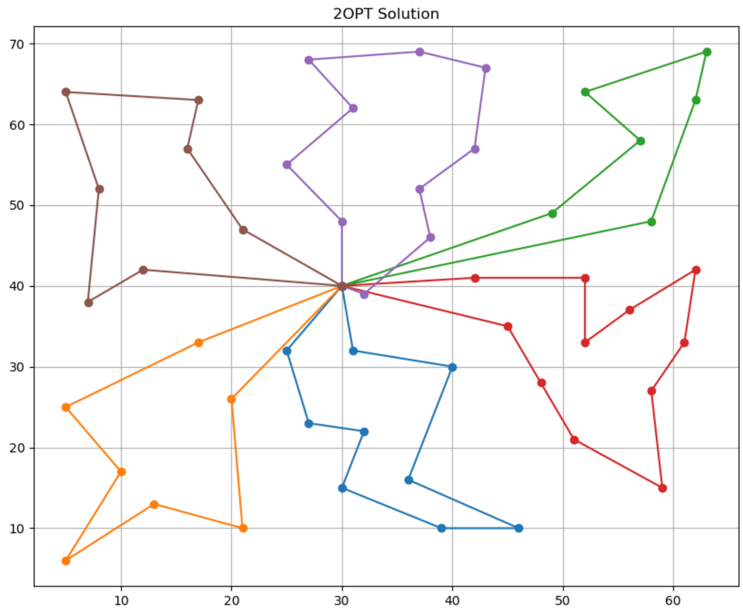


**Fig. 5.** 2-OPT and final solution

## 3 Preliminary Results

To evaluate the performance of the proposed algorithm, the instances presented by [7]) were used as a starting point. However, it is crucial to note that these instances are defined in spatial coordinates, whereas the MTVRP addresses the problem in terms of time between points. To fit the description of the problem, a conversion of the distances between points to time units was made, considering a speed of 50 km/h, because this is the maximum speed in Chilean legislation. It is essential to note that the reference values were also transformed using the same conversion formula. This approach ensures a fair and consistent comparison in the temporal context of the problem.

These instances were also adapted for implementation in AMPL using the Cplex engine [26], which provides a second additional benchmark for comparison by evaluating both the quality of the solution and the time required to obtain it. The integration of these instances into the AMPL environment not only broadens the evaluation perspective, but also provides a solid basis for analyzing the performance of the proposed algorithm compared to another benchmark framework. This approach not only enriches the evaluation of the solution but also contributes to the comprehensive understanding of its effectiveness in different computational contexts.

Each instance of the problem was subjected to 10 runs of the algorithm, due to a stochastic parameter present in k-means, which varies the centroids, therefore, in each run it finds a different solution. After completing the 10 runs of each instance, the solutions obtained were evaluated and the smallest, the largest and the average were obtained. This process was repeated for each instance of the problem, resulting in the identification of the best solution after multiple iterations. This approach of running the algorithm multiple times and selecting the best solution obtained helps mitigate the impact of the inherent randomness of the algorithm and ensures a thorough evaluation of the possible solutions to the problem, these results are presented in table 1.

Table 1. Algorithm results

| Instance | Min | Max | Ave |
|---|---|---|---|
| CMT-1 | 670 | 879 | 815,7 |
| CMT-2 | 1181 | 1652 | 1457 |
| CMT-3 | 1193 | 1538 | 1391 |
| CMT-11 | 1326 | 1343 | 1334 |

Of the values presented, the lowest was used for comparison with the results presented in [26], this comparison is presented in Table 2.

It is important to note that the values presented in the study were adjusted to a constant speed of 50 km/h to facilitate the comparison and that only cases and data with a known optimum were compared, we should also point out that the time presented corresponds to the average of the times obtained in the 10 iterations.

Table 2. comparison of results

| Instance | v | TH | Clustering – Tabu search Algorithm Solution (m) | Computing Time (s) | AMPL (6 hours) | Optimum (m) | GAP |
|---|---|---|---|---|---|---|---|
| CMT-1 | 1 | 692,4 | 670 | 0,48 | Not Found Solution | 629,53 | 6,43% |
| | 2 | 346,8 | 670 | | Not Found Solution | 634,80 | 5,55% |
| | 4 | 172,8 | 670 | | Not Found Solution | 655,20 | 2,26% |
| CMT-2 | 1 | 1102,8 | 1156 | 0,62 | Out of memory | 1002,31 | 15,33% |
| | 2 | 550,8 | 1156 | | Out of memory | 1002,31 | 15,33% |
| | 3 | 367,2 | 1156 | | Out of memory | 1002,31 | 15,33% |
| | 4 | 276 | 1156 | | Out of memory | 1002,31 | 15,33% |
| | 5 | 220,8 | 1156 | | Out of memory | 1002,31 | 15,33% |
| | 6 | 183,6 | 1156 | | Out of memory | 1007,06 | 14,79% |
| CMT-3 | 1 | 1090,8 | 1193 | 0,72 | Out of memory | 991,37 | 20,34% |
| | 2 | 544,8 | 1193 | | Out of memory | 991,37 | 20,34% |
| | 3 | 363,6 | 1193 | | Out of memory | 991,37 | 20,34% |
| | 4 | 272,4 | 1193 | | Out of memory | 991,37 | 20,34% |
| CMT-11 | 1 | 1312,8 | 1326 | 2,7 | Out of memory | 1250,40 | 6,05% |
| | 2 | 656,4 | 1326 | | Out of memory | 1250,40 | 6,05% |
| | 3 | 438 | 1326 | | Out of memory | 1250,40 | 6,05% |
| | 4 | 328,8 | 1326 | | Out of memory | 1250,40 | 6,05% |
| | 5 | 262,8 | 1326 | | Out of memory | 1250,40 | 6,05% |

The difference between the results obtained by our algorithm and the optimal solution presented in [26] was calculated, delivering a percentage difference between these solutions (GAP).

When analyzing the results, it is observed that in CMT-1 and CMT-11 instances, the algorithm shows a favorable performance. However, being limited to a TH (Horizon Time) relatively close to the optimal value, the generated solutions are not feasible for the problem. This is due to the fact that the routes obtained do not manage to be assigned to the vehicles within the maximum time established.

Despite this limitation, the ability of the algorithm to approach feasible solutions faster than in the case of AMPL and with fewer resources stands out. As evidenced in the table, it was only possible to run the CMT-1 instance, while the other instances could not be processed due to the restrictions of the computer used. It is important to mention that the tests were carried out on an HP laptop with Intel(R) Core(TM) i3-6100U CPU @ 2.30GHz and 8GB of RAM.

## 4 Conclusions

In conclusion, the results obtained so far suggest that the two-phase approach based on clustering and tabu has the potential to produce promising results. Although the solutions found so far have not been completely feasible, the proximity to the optimal solution indicates that the method has the capability to effectively address the problem. Furthermore, the fact that significant results have been achieved in a relatively low computational time is encouraging. This suggests that there is scope to further improve the efficiency of the algorithm by implementing new techniques or optimizing existing processes. Given this scenario, it opens the possibility to explore and develop additional strategies to further reduce computational times and improve the quality of the solutions obtained.

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