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A new metaheuristic approach for the meat routing problem by considering heterogeneous fleet with time windows

Hernando Barreto Riaño[a], John Willmer Escobar[b*] and Nicolas Clavijo-Buritica[c,d]

[a]*School of Industrial Engineering, Universidad del Valle, Cali, Cali 760001, Valle del Cauca, Colombia*
[b]*Department of Accounting and Finance, Universidad del Valle, Cali, Cali 760001, Valle del Cauca, Colombia*
[c]*Department of Industrial Management, University of Porto, Portugal*
[d]*Institute for Systems and Computer Engineering, Technology and Science – INESCTEC University of Porto, Porto 4000-008, Portugal*

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A B S T R A C T

Guided by a real case, this paper efficiently proposes a new metaheuristic algorithm based on Simulated Annealing to solve the Heterogeneous Vehicle Routing Problem with Time Windows to deliver fresh meat in urban environments. Our proposal generates an initial feasible solution using a hybrid heuristic based on the well-known Travelling Salesman Problem (TSP) solution and, subsequently, refining it through a Simulated Annealing (SA). We have tested the efficiency of the proposed approach in a company case study related to the planning of the transportation of a regional distribution center meat company to customers within the urban and rural perimeter of Bogotá, Colombia. The main goal is to reach a service level of 97% while reducing operational costs and several routes (used vehicles). The results show that the proposed approach finds better routes than the current ones regarding costs and service level within short computing times. The proposed scheme promises to solve the refrigerated vehicle routing problem.

1. Introduction

While Food Security is one of the significant issues of the modern world, the Fresh Food Supply Chains (FFSC) represent a crucial role in serving urban and rural consumption centers fairly and under adequate organoleptic conservation criteria. Meat is consumed massively worldwide and is considered one of the primary protein sources. Besides, extensive livestock farming is one of the direct generators of environmental issues, such as deforestation and CO_2 generation, without considering the transportation process. For instance, beef's average footprint is around $104m^2$ per 100 grams of protein (Ritchie & Roser, 2020). The meat distribution to local and regional markets could be performed via road transportation and generate a high fossil fuel consumption (Diesel). Thus, it causes a significant impact on the environment due to CO_2 emissions. For example, according to Schroeder et al. (2012), in Brazil and the UK, the CO_2 emissions factor per liter of diesel consumed in road transport is 2.7425(CO_2e-100/lt). This value could be increased by at least a third if it is a refrigerated vehicle (Aguiar, 2020). Traffic levels could significantly increase GHG emissions in the most congested cities in Latin America, such as Bogota (Bocarejo, 2020).

Consequently, sustainability is the primary motivation for developing our research since efficient route planning for delivering fresh products provides economic benefits and environmental concerns. Our study addressed the vehicle routing problem (VRP) for delivering fresh-meat products in urban environments. Specifically, the actual conditions arising from the case study, such as the vehicles' different capacities and the time constraints to receive the product at the retail points, suggest using a variant of VRP called the VRP with Heterogeneous Fleet and Time Windows (HFVRPTW).

* Corresponding author
E-mail: john.wilmer.escobar@correounivalle.edu.co (J. W. Escobar)

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The challenge of solving (HFVRPTW), given its NP-hard nature, translates into the need to design an efficient algorithm that can find a set of routes contemplating different capacities of vehicles and customers receiving within specific time windows (Bernal et al., 2017). Thus, each vehicle must visit each customer only once on each route to deliver the exact demand without violating its carrying capacity. Since the delivery time is finite, the routes must be performed within the maximum allowed time. Inspired by a real case, this paper presents the development of a new metaheuristic algorithm to solve the Vehicle Routing Problem with Heterogeneous Fleet and Time Windows - HFVRPTW. In addition, this paper contributes to the practitioner community by addressing real-world conditions of fresh-meat delivery in cities and proposing a novel design of a solution algorithm.

The subsequent sections of this paper are organized as follows. Section 2 presents the attributes of the meat delivery problem in urban environments. These characteristics of the problem are reflected in the formulation of the HFVRPTW model. Section 3 proposes the solution approach for the HFVRPTW using an algorithm based on Simulating Annealing by considering probabilistic neighborhood selection. The initial solutions, the neighborhood structures, and the operations are presented in section 3. Then, Section 4 shows the numerical results and motivates the case study discussion and the general instances. Finally, concluding remarks and key findings are presented, stating the benefits and limitations of this study to project future research suggestions.

2. Review of Literature

The well-known Vehicle Routing Problem (VRP) is the name given to the different types of problems arising when determining routes for a fleet of vehicles to deliver or collect goods to specific customers. The customers are geographically dispersed and consider several constraints, such as time windows (Bernal et al., 2018; Barros et al., 2020; Escobar-Falcón et al., 2021; Bolanos et al., 2018). Some of the best-known variants of the VRP are the Heterogeneous Fleet Vehicle Routing Problem (HVRP) (Escobar et al., 2017; Puenayán et al., 2014) and the Vehicle Routing Problem with Time Windows (VRPTW) (Sepúlveda et al., 2014). According to Taillard et al. (1996) and Cordeau et al. (1997), in the HVRP, customers are served by a set of vehicles with different characteristics.

The VRPTW considers time intervals stipulated by customers for the delivery of products. Sometimes, these time windows could be considered soft or hard. Hashimoto et al. (2006) and Taniguchi et al. (2001) describe three penalty functions of the time windows for metaheuristic algorithms. If the penalty is maximum, the consequences could be the product's return, and the customer could be lost or reprocess the product if it can be recovered. The penalty could be intermediate, given the possibility of delivering the product at a time interval. It is possible to reach negotiations and agreements if certain products cannot be carried out daily. If the penalty is low, the customer does not establish a fixed schedule for delivery, probably because it has enough safety inventory. The penalty is low and allows considering high slack for distribution schedule; sometimes, this feature could be a problem. As there is so much flexibility, the customers require them for payments and could be vulnerable to receiving competitive offers.

The Heterogeneous Vehicle Routing Problem with Time Windows (HVRPTW) is studied by Nagle & Panneerselvam (2018). A genetic algorithm is proposed to solve the HVRPTW. The genetic operators, such as selection, crossover, and mutations, determine its usefulness. Susilawati et al. (2018) consider a version of the VRPTW in which the vehicle fleet is heterogeneous due to different customer demand sizes. The authors use an integer programming model and a feasible neighborhood approach to solve the problem. Yu et al. (2019) suggest an improved branch-and-price (B&P) algorithm to solve the Heterogeneous Fleet Green Vehicle Routing Problem with Time Windows (HFGVRPTW). The authors create a multi-vehicle approximate dynamic programming (MVADP) approach based on the labeling algorithm.

Molina et al. (2020a) present a strategy for solving the HVRPTW based on an Ant Colony System (ACS). A hybridized ACS combined with a local search algorithm is proposed to increase the efficiency of the HVRPTW. A Variable Neighborhood Tabu Search algorithm generates the performed local search. Molina et al. (2020b) present the HVRPTW and a small number of resources (HVRPTW-LR), which describes a functional evolution of the HVRPTW for which the routes must share similar resources. The HVRPTW-LR considers a small number of services, such as trucks, drivers, and instruments, to be available but inadequate to satisfy all the customers on route planning. A statistical linear programming model is implemented to explicitly define and explain all the constraints. A semi-parallel injection heuristic is used to obtain an initial solution. A hybrid vector neighborhood descent metaheuristic built on a Tabu Search (Chávez et al., 2018) algorithm for neighborhood discovery and a holding list improves the initial solutions.

Ghannadpour & Zarrabi (2019) propose a new model and approach for the Multi-Objective Heterogeneous Vehicle Routing and Scheduling Problem by considering energy minimization as an objective. A new mathematical formulation for the Vehicle Routing Problem with Time Windows (VRPTW) is also introduced. An evolutionary algorithm-based is compared with a Non-Dominated Sorting Genetic Algorithm II (NSGA II) on the entirely random instances. Multiple Vehicle Routing Problems with a Soft Time Window and Heterogeneous Vehicles (HMVRPTW) are investigated by Kang and Lee (2018). The problem is solved using mixed-integer programming (MIP) and a genetic algorithm (GA). The MIP model seeks to minimize the total transportation cost, including the assignment cost, the traveling cost, and the tardiness cost, for the manufacturer. The GA solves the problem of finding a near-optimal solution when the problem is too complex to solve using the MIP. A food manufacturing company is used to examine the proposed MIP model's practicality and the GA approach. Chowmali & Sukto (2020) study the Multi-Compartment Vehicle Routing Problem (MCVRP) with a heterogeneous fleet of vehicles. The authors propose the fuel delivery problem where the main objective is to minimize the total driving distance by using a minimum number of vehicles. A novel two-phase heuristic based on the Fisher and Jaikumar Algorithm (FJA) is proposed to solve a case study of twenty petrol stations in Northeastern Thailand. The study first formulates an MCVRP model, and then a mixed-integer linear programming (MILP) model is introduced for selecting the numbers and types of the vehicles.

A systematic analysis of the Vehicle Routing Problems for Perishable Goods (VRPPG) is presented by Utama et al. (2020). The results show that the proposed metaheuristic algorithm for the VRPPG is a standard optimization tool for solving single and multi-objective problems. Tirkolaee et al. (2020) propose a novel robust mixed-integer linear programming model for a green vehicle routing problem with intermediate depots considering various urban traffic conditions, fuel usage, service time windows, and perishable product demand uncertainty. A case study tests the proposed model's applicability and assesses the optimal managerial insights and the policies on real-world conditions using sensitivity tests.

Rezaei et al. (2019) consider the Green Vehicle Routing Problem (GVRP) with a heterogeneous fleet of vehicles and filling stations with time window constraints. The study's essential contribution is to consider these aspects, making the problem more realistic. A genetic algorithm and population-based simulated annealing are created to find high-quality solutions for large-scale instances. Liu et al. (2020) introduce the Joint Distribution-Green Vehicle Routing Problem (JD-GVRP), for which cold chain logistics companies cooperate to supply goods while considering a carbon tax policy. A simulated annealing (SA) algorithm is used to solve the considered problem. The results show that joint distribution efficiently minimizes the overall costs and the carbon emissions instead of a single distribution. The overall cost is positively associated with the carbon price, while the carbon emissions differ depending on the carbon price.

Flamini et al. (2011) address quantitative methods for estimating the value of information from ITS on urban freight distribution. A real-life application to the retail distribution of perishable goods is considered. The problem is formulated as a vehicle routing problem with soft time windows and time-dependent travel times. The problem is solved using information affected by different degrees of detail. Osvald & Stirn (2008) devised a delivery algorithm for fresh vegetables in which perishability is a crucial element. The problem has been described as a vehicle routing problem with time windows and time-dependent travel times (VRPTWTD). In the VRPTWTD, distance and time of day affect the travel times between two places. The model considers perishability as part of the total delivery costs, and the problem is solved using a heuristic approach based on tabu search.

Ma et al. (2017) address a real-world distribution for deliveries of perishable products. Failure to deliver results in losses for suppliers, such as product degradation or failure to meet customers' deadlines, particularly when delivery orders exceed the suppliers' delivery ability. The authors propose a model combining order selection and time-dependent vehicle routing problems with time windows to evaluate the delivery order, the service level, and the timing to begin a delivery task with benefit maximization. Amorim et al. (2014) consider a complex vehicle routing problem regularly encountered by a Portuguese food delivery firm. This problem could be defined as a Multi-Time Window Heterogeneous Fleet site-based vehicle routing problem. The authors use an adaptative broad neighborhood search system to solve several vehicle routing problems. Finally, Wu et al. (2020) propose a new routing scheme to solve the HFVRPTW rapidly to mitigate distribution disruptions. A disruption recovery model for inter-path redress is built based on an initial time-dependent vehicle routing model with time windows, synthesizing the perishable existence of the delivered goods and the complex travel route choices on urban road networks.

Qin et al. (2019) implemented a trading scheme to measure carbon emissions costs. Real-world data is combined with a cycle evolutionary genetic algorithm to carry out the computational experiments in the proposed model. A numerical comparison experiment was used to validate the algorithm and model's effectiveness. The model's optimization results show that a modest increase in the overall cost can dramatically boost the average customer satisfaction, resulting in a highly cost-effective solution. Second, the effect of the carbon pricing on overall costs, the carbon emissions, and the average consumer satisfaction have been quantified. Wang & Wen (2020) investigate a low-carbon vehicle routing problem (LC-VRP) derived from an entire cold chain logistics network with various realistic constraints, including customer satisfaction. This paper considers a low-carbon two-echelon heterogeneous-fleet vehicle routing problem (LC-2EHVRP). In the LC-2EHVRP, third-party logistics servers (3PL) with mixed time windows and a carbon trading policy to reduce prices, carbon emissions, and overall customer satisfaction is considered. A numerical benchmark test has validated the use of an adaptive genetic algorithm (AGA).

Amorim & Almada-Lobo (2014) propose a novel multi-objective model that minimizes the delivery costs and maximizes the product's freshness. The main goal of the work is to investigate the connection between the distribution scenarios and the trade-off of cost-freshness. An epsilon-constraint approach is used to solve small-size instances. A multi-objective evolutionary algorithm is used to solve large-size instances. Ganji et al. (2020) consider the interconnected supply chain scheduling challenge, including the due date assignment, the batch distribution, the vehicle assignment based on availability, and the customer order delivery within the time windows. The aim is to reduce the distribution prices, the fixed and the variable fuel costs, the vehicle carbon emissions, the delivery lateness, and the customer dissatisfaction. A mixed-integer non-linear programming model is implemented for this problem. Three multi-objective metaheuristic algorithms are used to solve it: Multi-Objective Particle Swarm Optimization, Non-dominated Sorting Genetic Algorithm II, and Multi-Objective Ant Colony Optimization. Song et al. (2020) studied a canonical vehicle routing problem (VRP) in a cold chain logistic structure with three constraints: dispatching time windows for each customer, different vehicle types, and different energy consumption capacities. The aim is to reduce the network costs as much as possible, including the fixed costs and the electricity usage. An enhanced artificial fish swarm (IAFS) algorithm is suggested, with a particular encoding method that considers various vehicle problem functions.

Hsu et al. (2007) generalized the vehicle routing with time windows (VRPTW) by taking into account the randomness of the perishable food delivery process and designing an SVRPTW model to find the best delivery routes, loads, fleet dispatching, and the departure times for transporting perishable food from a depot. The authors explored how to adjust the objective functions and models' constraints to account for time-dependent travel and temperature variations during the day. Chen et al. (2009) propose a nonlinear mathematical model considering perishable food commodity production scheduling and vehicle routing with time windows in the same context. Demands at retailers are stochastic, and the perishable products degrade after output. As a result, the supplier's revenue is unpredictable and is dependent on the value and transaction volume of perishable goods brought to retailers. The goal of this model is to optimize the supplier's estimated total profit.

Belo-Filho et al. (2015) propose an Adaptive Large Neighborhood Search (ALNS) framework to tackle the perishable products' integrated production and distribution problem. The proposed approach relies on mixed-integer linear programming models and tools. The ALNS outperforms traditional literature procedures, namely, exact methods and fix-and-optimize, regarding the quality of the algorithms' solution and computing time. Song & Ko (2016) explore a vehicle routing problem for multi-commodity perishable food product distribution involving a fleet of refrigerated and general-purpose vehicles. Furthermore, the power, the overall delivery time, and the number of refrigerated and non-refrigerated vehicles are predetermined. The authors propose a nonlinear mathematical model and a heuristic algorithm to produce effective vehicle routes to increase the overall consumer satisfaction based on the freshness of the distributed goods. Nosrati & Khamseh (2020) consider a bi-objective hybrid vehicle routing problem with alternative paths, various lengths, and reliability. The first objective function minimizes the overall system costs, fuel consumption, and greenhouse gas emissions. In contrast, the second objective function maximizes the entire system's reliability with alternative paths and several reliabilities. The proposed model is formulated as mixed-integer nonlinear programming, and the bi-objective simulated annealing (MOSA) algorithm and the e-constraint method are used as a solution strategy.

Esmaili & Sahraeian (2017) consider a Two-Echelon Capacitated Vehicle Routing Problem (2-ECVRP), for which the customer satisfaction and the environmental problems are taken into account for perishable goods distribution. The paper introduces a novel bi-objective model that decreases the total customer waiting time and the travel cost. An environmental issue is limiting the maximum permissible carbon dioxide (CO2) emissions from transportation. The proposed model is solved using the SAW method (Simple Additive Weighting). Sahraeian & Esmaeili (2018) solve a general tri-objective Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) for transporting perishable goods, reducing travel expenses, consumer waiting times, and carbon dioxide emissions. A mixed-integer non-linear programming model (MINLP) is proposed. The mathematical model is solved using a non-dominated sorting genetic (NSGA-II) algorithm. The obtained performance shows the NSGA-II algorithm's efficiency.

Hanum et al. (2019) study the vehicle routing problem by considering the rice-for-the-poor distribution and present a generic mathematical formulation to solve the considered problem. The proposed generic model is formulated to encompass three distinct features, namely multiple depots (MD) establishment, multiple trips (MT) transportation, and split delivery (SD) mechanisms. This model is implemented for a real-world problem of rice-for-the-poor distribution in the Ponorogo district of Indonesia. It is involved in deliveries among three depots—8, 17, and 23 villages depending on the distribution period—using a fleet of 5 vehicles of homogeneous capacity.

Finally, for the vehicle routing and scheduling problem with cross-docking for perishable goods, Rahbari et al. (2019) present a bi-objective MILP model. Two robust models are developed when the outbound vehicles' travel time and the freshness-life of the goods are unknown. Due to their short shelf lives, certain perishable goods, such as snacks and medications, need careful handling during shipping. All perishable products must be shipped as soon as practicable before spoiling (Zulvia et al., 2020). Zulvia et al. (2020) introduce a green vehicle routing problem (VRP) for perishable goods minimizing the operational costs, the degradation costs, the carbon emissions, and the customer satisfaction. A many-objective gradient evolution (MOGE) algorithm is used to solve the problem. The gradient evolution (GE) algorithm is a metaheuristic developed to solve continuous problems with a single objective. This analysis strengthens the original GE algorithm with discretization, non-dominated sorting, and crowding distance approaches. Jafari & Behnamian (2020) consider the integration of scheduling and vehicle routing problems for perishable products. This study tries to minimize the costs and maximize the customers' purchase probability. A flexible flow shop scheduling problem considering production quality is studied for the scheduling stage. After completing the last job, the distribution stage begins, and each product must be delivered in its time window.

2.1. Problem description

The HFVRPTW for the meat delivery could be modeled by a weighted graph $G = (V, E, T)$. Set V represents the nodes (customers and depot) and set E contains the arcs connecting nodes. Node 0 denotes the depot, and nodes $1, \dots, n$ the customers. The arc $(i, j) \in E$ denotes the best arc to travel from node i to j, with an associated cost d_{ij} and travel time t_{ij}. The set T corresponds to the available vehicles that supply customers, where C_k is the capacity of each vehicle k. Each customer must be visited only once, and each of them could have time windows.

Each customer $i = 1, .., n$, has a positive specific demand q_i, a service time s_i, and a time window $[e_i, l_i]$. The variable s_i corresponds to the loading and the unloading times, e_i shows the moment when the products can be delivered, and l_i when the customer's time window ends. Note that the vehicle must wait until e_i if it reaches the customer before the time window. Also, the proposed problem could be detailed by using a mathematical formulation as follows:

2.1.1. Parameters

q_i = Demand of the customer $i \epsilon V$.
s_i = Service time for the customer $i \epsilon V$, within a range $[e_i , l_i]$
d_{ijk} = Distance from the customer $i \epsilon V$ to $j \epsilon V$ by using the vehicle $k \epsilon T$
t_{ijk} = Travel time from the customer $i \epsilon V$ to $j \epsilon V$ by using the vehicle $k \epsilon T$
c_{ijk} = Associated costs from $i \epsilon V$ to $j \epsilon V$ by using the vehicle $k \epsilon T$
f_k = Fixed cost of the vehicle $k \epsilon T$
C_k = Capacity of the vehicle $k \epsilon T$
e_i = Starting time of the time window of the customer $i \epsilon V$
l_i = Ending time of the time window of the customer $i \epsilon V$
K = Number of vehicles
N = Number of customers

2.1.2. Decision Variables

$$x_{ij}^k = \begin{cases} 1 & \text{If the vehicle } k \epsilon T \text{ travels from the customer } i \epsilon V \text{ to the customer } j \epsilon V \\ 0 & \text{Otherwise} \end{cases}$$

$$Z_k = \begin{cases} 1 & \text{If the vehicle } k \epsilon T \text{ is used} \\ 0 & \text{Otherwise} \end{cases}$$

a_i = Arrival time of the customer $i \epsilon V$, where $a_1 = 0$ (Depot).
p_i = Departure time of the customer $i \epsilon V$
Q_k = Load of the vehicle $k \epsilon T$

2.1.3. Objective function

The objective function minimizes the total costs, including the variable and the fixed costs associated with the performed routes.

$$\sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ijk} x_{ij}^k + \sum_{k=1}^{K} f_k Z_k \tag{1}$$

2.1.4. Constraints

Constraints (2) and (3) ensure the continuity of the flow for each route. In other words, they guarantee that a vehicle type k must visit a customer, delivers the order, and then continues serving other customers.

$$\sum_{i=1}^{n} \sum_{k=1}^{K} x_{ij}^k = 1. \qquad \forall\, j = 2.3. \dots . n \tag{2}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{K} x_{ij}^{k} = 1. \qquad \forall\, i = 2.3. \dots . n \tag{3}$$

Constraints (4) ensure that the vehicle type k serves all customers for the scheduled route.

$$x_{ij}^{k} \leq Z_{k}. \qquad \forall\, i = 2.3. \dots . n\,;\; j = 2.3. \dots . n;\; k = 1.2. \dots . K \tag{4}$$

Constraints (5) and (6) indicate that vehicle type k must visit a customer, delivering the corresponding order, and then travels to another customer or returns to the depot.

$$\sum_{j=2}^{n} x_{1j}^{k} \leq 1. \qquad \forall\, k = 1.2. \dots . K \tag{5}$$

$$\sum_{i=2}^{n} x_{i1}^{k} \leq 1. \qquad \forall\, k = 1.2. \dots . K \tag{6}$$

Constraints (7) ensure that each node has an entry and an exit arc.

$$\sum_{i=1}^{n} x_{iu}^{k} - \sum_{j=1}^{n} x_{uj}^{k} = 0. \qquad \forall\, k = 1.2. \dots . K;\; u = 1.2.3. \dots . n \tag{7}$$

Eq. (8) and Eq. (9) guarantee that for each pair of adjacent nodes i and j on a route assigned to vehicle k, the arrival time at customer j must be equal to the departure time of customer i plus the time to travel from i to j. M is a large number to determine the total number of routes.

$$a_{j} \geq \left(p_{i} + t_{ijk}\right) - \left(1 - x_{iu}^{k}\right)M. \qquad \forall\, i = 2.3. \dots . n\,;\; j = 2.3. \dots . n;\; k = 1.2. \dots . K \tag{8}$$

$$a_{j} \leq \left(p_{i} + t_{ijk}\right) - \left(1 - x_{iu}^{k}\right)M. \qquad \forall\, i = 2.3. \dots . n\,;\; j = 2.3. \dots . n;\; k = 1.2. \dots . K \tag{9}$$

The relationship between arrival time, departure time, and service time between customers i and j are described by Eq. (10) and Eq. (11).

$$a_{i} \leq (p_{i} - s_{i}). \qquad \forall\, i = 2.3. \dots . n \tag{10}$$

$$e_{i} \leq (p_{i} - s_{i}) \leq l_{i}. \qquad \forall\, i = 2.3. \dots . n \tag{11}$$

Constraints (12) express the calculation of the total load of a vehicle k, Q_{k}. This value must be less than the capacity of the assigned vehicle.

$$\sum_{i=1}^{n} q_{i}\left(\sum_{j=1}^{n} x_{ij}^{k}\right) \leq C_{k}. \qquad \forall\, k = 1.2. \dots . K \tag{12}$$

Constraints (13) and (14) determine the nature and integrity of the variables

$$x_{ij}^{k} \in \{0.1\}. \qquad \forall\, i = 2.3. \dots . n\,;\; j = 2.3. \dots . n;\; k = 1.2. \dots . K \tag{13}$$

$$Z_{k} \in \{0.1\}. \qquad \forall\, k = 1.2. \dots . K \tag{14}$$

The proposed model can find the optimal solution for small instances (less than 20 customers). Therefore, the proposed approach can solve large instances as the case of the real routing problem.

2.2. Proposed approach

The former algorithm consists of two stages. An initial solution is created using a heuristic algorithm in the first stage. The initial solution is improved using a Simulated Annealing (SA) algorithm in the second stage. The proposed approach considers (I) the penalization of infeasible solutions, (II) the diversification scheme during the local search using the concept of granularity proposed by Toth & Vigo (2003) and Linfati et al. (2014b), (III) the intensification based on the criteria used to choose and accept a move, and (IV) a perturbation procedure to avoid getting a local minimum given several iterations. The proposed algorithm contemplates different vehicle capacities, a single depot, and a constant vehicle speed.

2.2.1. Stage I – Initial Solution

The initial solution is generated by using an extension of the method proposed in Helsgaun (2000) for the TSP. First, considering all customers, a giant TSP (Traveling Salesman Problem) is formulated. Indeed, the distance between consecutive nodes has been minimized. Second, customers are sorted based on the length of the time window. Therefore, a priority is proposed since customers with a shorter time window (hard time window) are more restrictive than those with a longer interval (soft time window). Finally, an iterative step is carried out until all customers have been considered: (I) the first available customer in the priority list is removed and added to a new route containing the depot twice (indicating exit and arrival); (II) following the recently inserted customer through the giant TSP, nodes are inserted when and where is possible considering the total demand, the route duration, and the time window constraints (for example, if the route is 0-1-2-3-0, and customer one has been added, the next to check is two then three and so on); (III) Once all the customers have been checked, the process returns from (I). If the heuristic requires building more routes than vehicles, a dummy vehicle with a capacity equal to zero is assigned to the additional route.

2.2.2. Stage II – Improvement Algorithm

The proposed algorithm penalizes infeasible solutions concerning the vehicle's capacity or the time windows. The penalty scheme has been adapted from published works on location routing problems (Escobar & Linfati, 2012; Escobar et al., 2013; Linfati et al., 2014a; Bernal et al., 2017, Escobar et al., 2015b). Given a solution, the value of the objective function within the SA procedure is the following:

$$F(S) = \sum_{k \in T} \sum_{i \in V} \sum_{j \in V} c_{ijk} \cdot x_{ij}^{k} + \rho_q \cdot F(S_0) \cdot \sum_{k \in K} \max(Q_k - C_k . 0) + \rho_{tw} \cdot F(S_0) \cdot \sum_{i \in V} \max(a_i - l_i . 0) \tag{15}$$

Note that terms two and three of the objective function are proportional to solution S of the total vehicle overload and the arrival delay. In this particular case, ρ_q and ρ_{tw} are parameters that are updated during the search. If S is a feasible solution, these two penalty terms are zero. Depending on the type of solutions explored during the last N_{fact} iterations, the values of ρ_q and ρ_{tw} are increased or decreased. If a feasible solution has been found given N_{fact} iterations, both factors are decreased. Both values are increased if no feasible solution has been found during N_{fact} iterations. Similar strategies have proven to be useful experimentally in solving some location routing and multi-depot vehicle routing problems (Escobar et al., 2013; Escobar et al., 2014a; Escobar et al., 2014b; Escobar et al., 2015a). This strategy restricts the search space dynamically, allowing the algorithm to explore feasible regions easily. These parameters have upper and lower limits (ρ_{min} and ρ_{max}). These parameters N_{fact}, ρ_{min} , ρ_{max}, ρ_q and ρ_{tw} are adjusted during the parameterization phase.

2.2.2.1. Selection of the neighborhoods

The proposed approach contemplates a local search procedure using inter-route and inter-route operators. Five traditional operators adapted from the well-known vehicle routing literature have been considered: Insertion, Swap, Double Insertion, Double Swap, and 2-opt. The proposed algorithm probabilistically selects the neighborhoods using a procedure based on a granular tabu search introduced by Bernal et al. (2018) for the DCVRP. Initially, all operators have the same probability of being selected. The algorithm starts by selecting one randomly. If the operator improves, the algorithm increases its probability of selection. On the other hand, if no improvements are found, the probability of being selected as a penalty is reduced. It is blocked until a different solution than the current one is found (incorporated into a $blacklist$).

The neighborhood selection algorithm is described as follows. First, $S^* = \bar{S} = \hat{S} = S_0$, where $\bar{S}$ is the current best solution (feasible or not feasible) and $\hat{S}$ is the current solution, S_0 is the initial solution, and S^* is the best solution found so far. The SA is executed until a local minimum S' is reached by using a single neighborhood structure N_k. Each neighborhood N_k has a dynamically updated probability $f(N_k)$ to be selected at a given time (Initially, all the neighborhoods have the same probability $f(N_k) = \frac{1}{|N_k|}$). Depending on the viability of S', the solution is considered or discarded: (I) if the found solution S is better than the current best solution $\bar{S}$ in terms of the objective function, update $\bar{S}$ to the found solution S'; (II) if S' is feasible and also improves the best feasible solution found so far $\hat{S}$, update $\hat{S}$, to S'; and (III) the probability of selecting the neighborhood $f(N_k)$ leading to such a solution is decreased by a factor of f_{down}. If the opposite occurs, the probability of selecting the neighborhood $f(N_k)$ is increased by a factor f_{up}. Finally, the best feasible solution found so far, S^* is kept. The pseudo-code of the operator selection is shown below.

```
Procedure pN (S_0, IT_max)
  Ŝ ← S_0
  'S ← Ŝ
  ops ← {2 − opt, insertion, swap, double − insertion, double − swap}
  props ← {0.2, 0.2, 0.2, 0.2, 0.2}
  blacklist ← { }
  op ← choose(props, ops)
  iterate ← true
  While iterate do
    S' ← SA('S, op, IT_max)
    increase? ← false
    If not feasible(S') and F_2(S') < F_2('S) then
      'S ← S'
    If feasible(S') then
      If F_1(S') < F_1(Ŝ) then
        'S ← S'
        Ŝ ←' S
        increase? ← true
      If F_1(S') < F_1('S) then
        'S ← S'
        increase? ← true
    If increase? then
      increase(props[op], f_up)
      adjust(props)
      blacklist ← { }
    Else
      decrease(props[op], f_down)
      adjust(props)
      blacklist ← blacklist ∪ {op}
      op ← choose(props, ops)
    While op ∈ blacklist do
      op ← choose(props, ops)
      If size(blacklist) == size(ops) then
        iterate ← false
  Return Ŝ
```

2.2.2.2. Simulated Annealing Scheme

After constructing the initial solution S_0, an algorithm based on Simulated Annealing is applied to improve that solution. The strategy is to explore different neighborhoods $N_k(\cdot)$ during a certain number of iterations to find a better solution S^* in the process. A neighborhood solution of the current best solution is generated for each iteration. Whether it improves or not, the current solution is accepted or discarded. The probability of selecting a neighborhood depends on the temperature T at the time of evaluation. This parameter has its maximum value (T_0) in the first iterations, and many solutions tend to be accepted. As the number of iterations increases, the process's temperature decreases, and, therefore, the search space is reduced to promising neighborhoods that improve the objective function. The temperature is updated at the end of each iteration by multiplying it by a cooling factor α. The pseudocode of the proposed algorithm is:

```
Input: Initial solution S_0, initial temperature T_0, and max number of  iterations Iter_max
Output: Final solution S*
 S ← S* ← S_0
  T ← T_0
 iter ← 0
   While iter < Iter_max do
           S' ← N_k // Generate random solution from the neighborhood
       If F_2(S') < F_2(S) Then
           S ← S'
           If F_2(S') < F_2(S*) Then S* ← S'
           Else
               r ← random (0,1) // Generate a random number
                     If r < e^( −(F_2(S') − F_2(S))/T) Then S ← S'
                     T ← α*T // decrease the current temperature T.
                     iter ← iter + 1
    Return S*
```

3. Computational results

3.1. Case of study

Carnes Los Sauces S.A. is dedicated to producing and distributing raw and processed meat products. The main products are beef, chicken, pork, roasts, veal, sausages, hamburgers, turkeys, and legs. The person responsible for scheduling and dispatching the vehicles does not have computer tools or clear procedures to carry out their company's function. The route schedule is performed by a simple heuristic procedure, which increases the transportation cost and affects the level of service. Therefore, we seek to minimize the transportation costs, ensuring deliveries according to customers' time windows. The company has 131 customers located in the city of Bogotá. The available fleet is made up of 11 heterogeneous vehicles. The characteristics of the fleet are shown in Table 1:

Table 1
Characteristics of the vehicles

Vehicle	Maximum Capacity of Load (kg)	Volume (m^3)
SLJ–984	3.600	12
CPR–878	5.400	16
UFR–463	7.200	20
UPS–489	9.000	24
VED–379	5.000	17
UPR–424	3.600	12
WXN–711	740	8
WXN–712	740	8
SWL–776	575	5
SQB–577	1.200	10
SKI–843	4.835	20

Source: Owner

The customers have been grouped into 15 categories according to the available days and hours of attention (see Table 2). Currently, the company dispatches the first vehicles at 6:00. In the afternoon, the deliveries are performed from 2:00 p.m. until the end of the routes.

Table 2
Customers with corresponding time windows

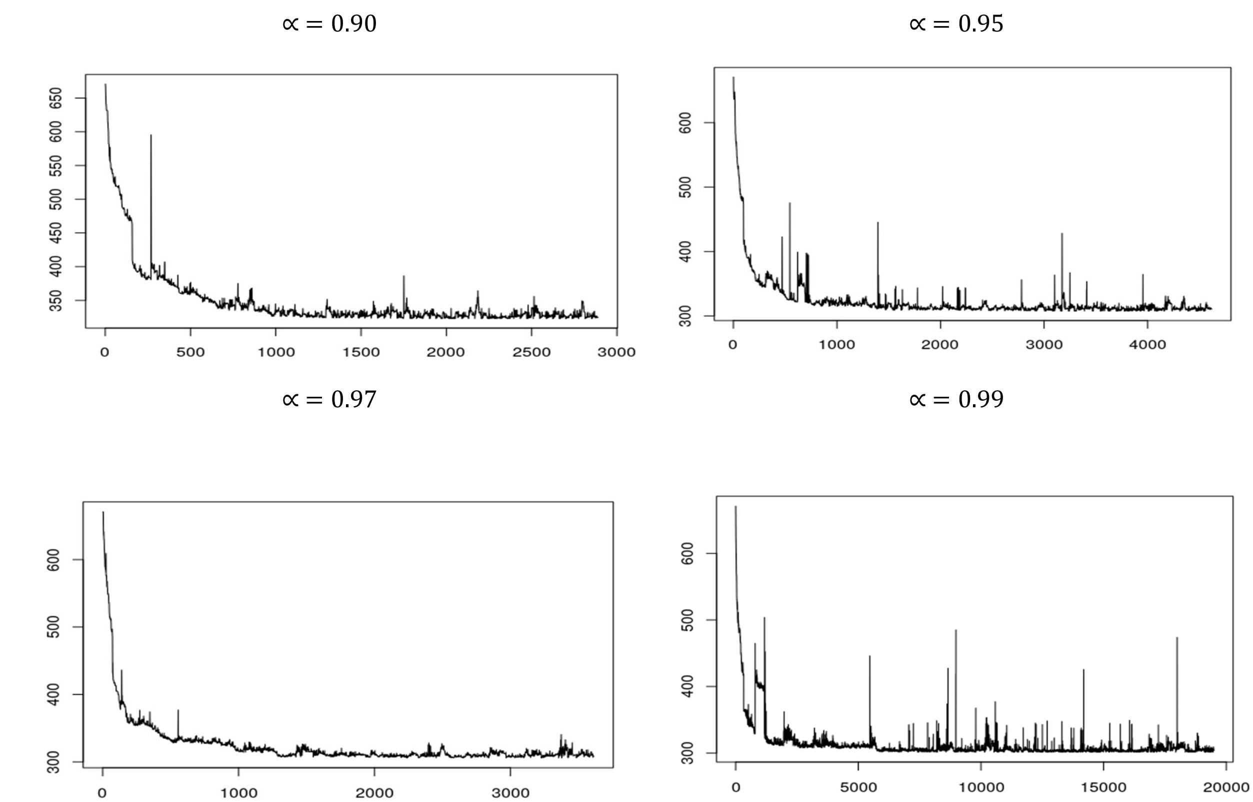
Type Customer	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Chain Restaurants	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	
Compensation Fund		7:00 – 8:00					
Owner Restaurant	14:00 – 17:00		14:00 – 17:00		14:00 – 17:00		
Catering				7:00 – 12:00			
Club	7:00 – 9:00						
Fast Food	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00
Education	8:00 – 12:00 13:00 – 22:00	8:00 – 12:00 13:00 – 22:00	8:00 – 12:00 13:00 – 22:00	8:00 – 12:00 13:00 – 22:00	8:00 – 12:00 13:00 – 22:00		
Food Companies			8:00 – 12:00				
Events						8:00 – 11:00	
Fama Supermarket	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00	7:00 – 12:00 14:00 – 19:00
Groceries	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00
ONG					8:00 – 11:00		
Hotels	7:00 – 9:00	7:00 – 9:00	7:00 – 9:00	7:00 – 9:00	7:00 – 9:00		
Restaurants	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00
Supermarkets	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00	7:00 – 10:00 15:00 – 17:00

Source: Owner

The customers' geographical coordinates have been calculated using the Google Maps tool to identify X (latitude) and Y (longitude), finding the depot's position and customers. Google Maps found the distances between origin and destination. The availability of Carnes Los Sauces S.A.'s offer is from Sunday to Sunday, between 6:00 - 22:00 from Monday to Saturday, and on Sundays from 6:00 - 17:00. All customers must be visited once a week.

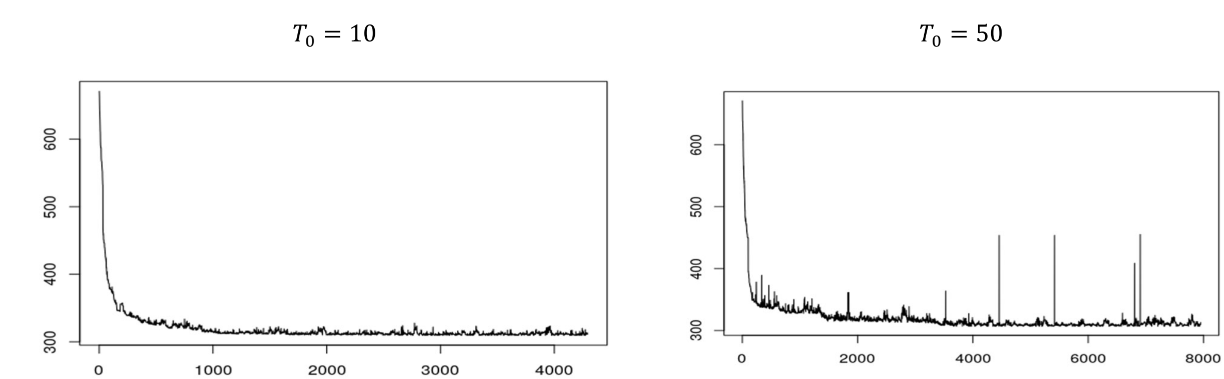
3.2. Algorithm parameterization

Since the performance of the proposed approach depends on the value of the above-described parameters, a calibration process has been carefully performed. The initial values of these inputs were established, taking into account the methodologies proposed by Escobar et al. (2014a), Bernal et al. (2018), and Linfati et al. (2014a). The values of the obtained parameters are the following: $IT_{max} = 100\,n$ (where n is the total number of customers), $T_0 = 100$, $\propto = 0.97$, $f_{up} = 0.1$, $f_{down} = 0.1$, average vehicle speed 60km / h, $\rho_{min} = 1$, $\rho_{max} = 100$, $N_{fact} = 0.1\,n$. Likewise, seven instances each by a day of a week have been considered. We have defined independent parameters whose values must be determined by extensive computational experiments for the proposed approach. For each instance, five runs were carried out, considering the experiences of Escobar & Linfati (2012). These parameters are considered candidate settings for any given factor. This procedure is iteratively performed by considering every single factor (variable) and finding its "best value," giving the lower objective function.



Source: Owner

Fig. 1. Variation of the objective function of the complete algorithm with respect to the geometric cooling factor $\propto$ with $T_0 = 100$



$T_0 = 100$ $T_0 = 1000$

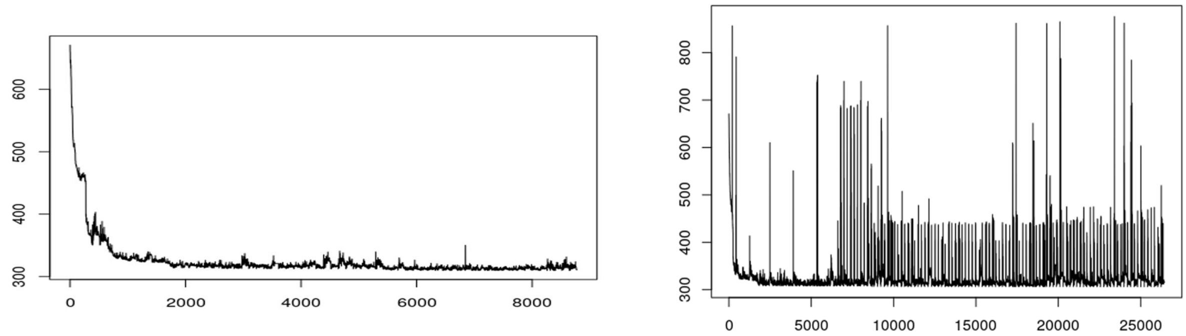


Fig. 2. Variation of the objective function of the complete algorithm with respect to the temperature with $\propto\propto = 0.97$

Fig. 1 and Fig. 2 show that all the tests arrive at approximately the same endpoint. There is no significant deviation in the value of the parameters for the entire set of instances. The algorithm restricts the search to neighborhoods with a shallow temperature ($T_0 = 10$). In contrast, a very high temperature ($T_0 = 1000$) generates the acceptance of many neighborhoods during the search, which does not necessarily improve the objective function. Likewise, when the initial temperature increases, the number of iterations increases. Therefore, an initial temperature $T_0 = 100$ has been set, allowing a balance between neighborhood exploration and time to reach a good quality solution. A very high value of $\propto = 0.99$ indicates a high number of iterations. At the same time, there is a greater probability that solutions are accepted, which do not necessarily improve the initial solution but allow exploring the search space. On the other hand, a very low $\propto = 0.90$ indicates that there are few iterations and, at the same time, there is a lower probability of exploring the search space.

4. Obtained Results

The proposed approach has been implemented in C ++, with the Sublime Text platform code editor and the yEd graphics editor. The computational tests were performed on an Intel (R) Core (TM) i3-2350M CPU @ 2.30 GHz - 4GB of RAM with a Linux Ubuntu 64-bit operating system. The initial heuristic procedure could find acceptable solutions. However, the initial solution is less compliant with the constraints, particularly with the number of vehicles. Besides, the simulated annealing stage finds better solutions concerning the number of routes and the objective function's value, although the execution time is longer. The penalty for refined solutions is zero, independent of the initial routes. Indeed, time window constraints are fulfilled. Customer satisfaction is the main objective of the case study. Note that the proposed approach reduces the used vehicles during the initial solution stage. Table 3 compares the results of the initial and the refined solution.

Table 3
Results of Initial and Refined Solution per each day

	Initial Solution (S_0)			Refined Solution (S^*)		
Day	$F(S)$	Penalty	Time (s)	$F(S)$	Penalty	Time (s)
Monday	670.90	0.00	0.0260	301.48	0	17.6547
Tuesday	778.70	1219.95	0.0254	423.18	0	4.4599
Wednesday	770.90	0	0.0225	312.23	0	2.9026
Thursday	636.99	0	0.0363	304.99	0	3.0055
Friday	677.60	0	0.0224	302.74	0	6.1503
Saturday	510.37	0	0.0134	269.66	0	4.1107
Sunday	543.57	0	0.0310	276.24	0	1.0486

The proposed approach obtains good solutions within short computing times, with a maximum of 18 seconds for Monday. The average speed was 60 km / h, and the service time was 5 seconds per demand unit. Significant improvements are obtained for each route per day, comparing the initial and refined solutions (Table 4).

Table 4
Final Results

	Demand (kg)	Distance (S_0)	Distance (S^*)	Savings (km)	K (S_0)	K (S^*)	Saving (Routes)
Monday	3190	670.90	301.48	369.42	9	4	5
Tuesday	3072	778.70	423.18	355.52	8	6	2
Wednesday	2952	770.90	312.23	458.67	8	5	3
Thursday	3309	636.99	304.99	332.00	8	5	3
Friday	2669	677.60	302.74	374.86	9	4	5
Saturday	2528	510.37	269.66	240.71	5	3	2
Sunday	3040	543.57	276.24	267.33	5	3	2

Table 4 shows that the daily savings costs are considerable. Indeed, the daily cost of the entire fleet is worth 835.025 COP. The daily savings for Monday are an average of 379.557 COP, 151.822 COP on Tuesday, of 227.734 COP on Wednesday, 227.734 COP on Thursday, 379.557 COP on Friday, 151.822 COP on Saturday, and 151.822 COP on Sunday. We have compared the proposed approach with the current solution obtained by the company (see Table 5). The column "Best Known Solution" indicates the best value obtained between the current solution and our final proposed solution. The "Current Real Solution" column shows the obtained values by a simple heuristic approach. The columns "Gap (%)" are the deviation of the algorithm's value concerning the "Best Known Solution." Note that our proposed approach outperforms all the results proposed by the current algorithm. The "Current Real Solution" is obtained by a heuristic approach based on the well-known saving method. The following pseudocode shows the description of this algorithm.

Input: Distance Matrix, Speed, Time Windows, Demand
Output: Final Routes
Calculate the angle of the customers and sort them by decreasing the angle and time windows
Sort the vehicles decreasing according to their capacity
Select the first vehicle
While demand is not fulfilled
If $Current\ Cap + Demand\ Cust < Vehicle\ Cap$ and the $Time\ Window$ is not violated **Then**
Assign customer to the vehicle
$Current\ Cap \leftarrow Current\ Cap + Demand\ Cust$
Update $Current\ Cap$ and $Time\ Window$
Else
Select the next vehicle
Return Final Routes

Route sequencing has been performed using the nearest neighbor algorithm. The current algorithm considers each customer as "initial" to perform the sweep method. In other words, n configurations are evaluated, where n is the number of customers. The algorithm finds the best solution, considering that the number of routes cannot exceed the number of the available vehicles.

Table 5
Comparison of the proposed approach with the current solution

Day	Best Known Solution	Current Real Solution	Time (s)	Gap (%)	Final Solution	Time (s)	Gap (%)
Monday	301.48	342.13	9.40	13.48	301.48	17.65	**0.00**
Tuesday	423.18	484.18	3.20	14.41	423.18	4.46	**0.00**
Wednesday	312.23	358.4	2.70	14.79	312.23	2.90	**0.00**
Thursday	304.99	400.20	2.80	31.22	304.99	3.01	**0.00**
Friday	302.74	360.10	6.02	18.95	302.74	6.15	**0.00**
Saturday	269.66	310.10	4.18	15.00	269.66	4.11	**0.00**
Sunday	276.24	334.44	2.03	21.07	276.24	1.05	**0.00**

5. Concluding Remarks and Future Work

This paper proposes a Simulated Annealing-based metaheuristic algorithm to solve a real-world vehicle routing problem with a heterogeneous fleet and time windows. The case study business's challenge is to deliver meat from a distribution center to customers—the algorithm generates an initial solution based on a heuristic procedure. The initial solution is refined using a Simulated Annealing approach with a probabilistic set of exchange operators. If the operator has proved better solutions, its likelihood of selection increases; otherwise, it reduces.

Several examples demonstrated that the proposed approach could discover feasible, less expensive alternatives regarding the company's existing routing and satisfy the time window constraints. The latter benefit could lead to higher customer satisfaction. The company could benefit from the best routes.

The future analysis must include stochastic variables to model the complexity of the problem (Escobar et al., 2012; Paz et al., 2015; Rodado et al., 2017; Vélez et al., 2021). Our representation of the problem and the contrast become more rational than the current solution. Different vehicle speed (which varies due to potential traffic on the streets), arrival operation, and departure times are critical variables to incorporate into the proposed approach. Finally, a public dataset for the HFVRPTW should be available to compare some published algorithms under the same conditions.

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