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Research paper

An optimization model for the distribution of perishable products with consideration of road roughness conditions

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Abstract

In this article, we discuss a vehicle routing problem with time windows (VRPTW) for the transport of perishable products with considera-tion of road roughness constraints. The proposed model includes simultaneous pickup and delivery operations. Unlike almost all previous studies, which mainly consider travel distance and temperature as factors in product deterioration, we take into account the roughness condi-tions of the roads in order to preserve their quality during transport. The objective is therefore to satisfy a set of customers, while respecting the constraints related to multi-product transport, simultaneous pickup and delivery operations, time windows and roughness conditions of the roads. We express the problem in the form of a mixed linear integer program. The model is solved with CPLEX's tradi-tional Branch & Cut (B&C) and a two-phase decomposition heuristic (TPDH). The test results show that TPDH produces satisfactory solutions in a short time for all instances studied, with an average time of 290,19 seconds compared to 2941,61 seconds for B&C. In addition, TPDH has an average deviation of +18,3 % from the total cost of the objective compared to B&C, making it a relevant option for applications that require fast computation.

Keywords: *Multi-Product VRPTW; Mechanical Damage; Perishable Products; Road Roughness Conditions.*

1. Introduction

According to the FAO (Food and Agriculture Organization), 14% of the world's food production is lost between harvest and retail sale, mainly due to inadequate transport and storage conditions[1]. In addition, in developing countries, where logistics infrastructure is often insufficient, fruit and vegetable losses can be as high as 30 to 40 percent[2].

This study is part of the context of the vehicle routing problem (VRP), which is a category of combinatorial optimization problems aimed at determining the shortest routes for a fleet of vehicles to serve a set of customers with deterministic demands, from a depot. Originally introduced in 1959 by [1] in the context of the distribution of petroleum products, this problem is distinguished by its complexity and belongs to the class of NP-hard problems. It can have various constraints, such as time windows, simultaneous pickup and delivery, or multi-product transport.

In recent years, route optimization within the framework of the VRP has become essential for the distribution of perishable products. These products require efficient transport solutions, due to their sensitivity over time and their fragility. It is therefore crucial to preserve their freshness and integrity during the route in order to minimize losses. This poses a growing challenge for suppliers in the face of high customer expectations for quality, delivery, and the speed of degradation of these products. It is therefore imperative to keep perishable food in optimal conditions during transport to ensure food safety and reduce waste [2].

Many studies have been carried out on this subject, but the main focus has been on temperature and distance of routes. These factors were considered to be essential elements influencing the quality of the products during transport. One aspect that is overlooked is the roughness of the roads. However, the vibrations and jolts caused by the roughness of the roads can seriously compromise the integrity of the products, resulting in additional losses during the route.

Here we propose a VRPTW model applied to perishable products taking into account road roughness conditions. This model incorporates multiple product constraints, simultaneous pickup and delivery, as well as time windows.

[1] https://www.fao.org/cote-divoire/actualites/detail-events/fr/c/1607089/
[2] https://www.fao.org/in-action/seeking-end-to-loss-and-waste-of-food-along-production-chain/fr/

This document is structured as follows. In the second section, we begin by examining the existing work to situate our study in the literature. Then we formulate the problem. After presenting the methods of solving, we analyze the results of the tests performed. The final section is devoted to the conclusion and prospects for future research.

2. Literature review

In a recent study, [3] review a VRP with time windows and heterogeneous fleet applied to perishable products. Their aim is to minimise the total cost of transport, taking into account various factors, such as the loss of value due to the degradation of foodstuffs, which depends in particular on the duration of transport and temperature. To solve this problem, they use three methods, namely, an exact algorithm, a heuristic based on a genetic algorithm, and a hybrid approach combining the first two.
Continuing with a view to improving the quality of the products transported, [2] offer a new variant called Quality-Driven VRP (QDVRP), which analyzes the impact of hop-on hop-off routes on the quality of fresh and frozen produce in a cooperative transportation context. The study focuses on temperature fluctuations caused by frequent opening and closing of doors, affecting food quality. The model is solved with an exact algorithm.
Also [4] present a model to optimize routes in cold chain logistics, minimizing losses during distribution, while taking into account various objectives, including damage to goods based on transport time. Route modeling is done using a heuristic approach to incorporate real-world traffic conditions. The problem is solved by an ant colony algorithm (ACO) combined with a local Pareto search.
For their part, [5] propose an optimization model for the problem of vehicle routing in the delivery of multi-product frozen foodstuffs. The objective of the model is to minimize delivery costs for a fleet of identical vehicles leaving from a depot. Delivery costs include transport, refrigeration, penalty costs, as well as those related to accumulated damage to the cargo due to transit time and depending on the specific characteristics of the different frozen products. A genetic algorithm is used to solve the problem.
However, the majority of the studies reviewed indicate that temperature and travel time or distance are the major factors influencing the quality of perishable products during transport. However, few of them address the roughness of roads, which play a key role in the deterioration of foodstuffs.
This is how [6] stress the importance of road conditions in the distribution of fresh fruit and vegetables. They offer an improved genetic algorithm to optimize delivery routes, reducing logistics costs and ensuring product quality. An evaluation coefficient δ_{ij} is introduced to quantify the impact of road irregularities during distribution, but the article does not show how this coefficient impacts the quality of the products during transport.
Yet, research on mechanical damage caused by rough road conditions examines how pavement imperfections can alter the integrity of goods, especially sensitive ones like perishables. Research in this area takes into account a variety of factors, including the frequency and amplitude of vibrations experienced by food in vehicles. Several studies such as [7] and [8], explored this issue.
In this way, [9] are based on the results of [8] to propose a multi-objective VRPTW model aimed at optimizing the distribution of mandarins taking into account the roughness conditions of the roads. Their study seeks to reduce the percentage of products damaged during transport. The model is solved with two heuristics and a metaheuristic.
The study of [9] however is limited to a single type of product, thus restricting the scope of the results in a more realistic logistical context. The consideration of multiple commodities could indeed require more complex transport conditions due to the respective sensitivity of the products. Also, the authors limit themselves to delivery operations. However, the pickup of packaging during a delivery is a common practice in reality.
The above points to the need to broaden the study of [9] including a variety of products, as well as the operations of collecting packaging during delivery.
In our study, we therefore propose a single-objective VRPTW model applied to the distribution of multiple perishable products by simultaneously integrating product delivery and packaging pickup operations during delivery. Our approach is based on the results of the work of [7], which analysed the correlation between road roughness and damage to different types of products during transport.
Indeed [7] analysed four fresh products, allowing their findings to be applied to more complex logistics contexts. In addition, the authors measured physical damage such as cuts and bruises, to provide a more accurate view of the impact of roads on product quality, which was not done in [8]. The vibrations experienced in vehicles are also compared to international standards (ASTM and ISTA), thus increasing the credibility of the results and clearly showing the link between roughness conditions of the roads and the quality of the products transported.
So, based on the results of [7], we will be able to model each road segment in such a way as to measure the impact of roughness conditions in a context of transport of multiple perishable products with consideration of simultaneous pickup and delivery operations.

3. Description of the problem

3.1. Presentation of the problem

Our approach, called multi-product vehicle routing problem with simultaneous pickup and delivery and time windows (MP-VRPSPDTW), is a variant of the VRP. It is illustrated in Fig. 1. The problem is to plan multiple routes for a homogeneous fleet of vehicles, starting from a depot to serve geographically distributed customers, while meeting deterministic demands for packaging pickup and delivery of various perishable products. All this must be done in accordance with the time constraints of the customers and taking into account the roughness conditions of the roads. The objective is to minimize all the routes, by satisfying the following assumptions:

- (1) A homogeneous fleet of vehicles serves all customers.
- (2) Each vehicle starts and ends its route at the depot no more than once.
- (3) Each customer has a request for the pickup of packaging and delivery of various perishable products, which must be fully met.
- (4) The total demand for pickup and delivery on a route must comply with the capacity constraints of the vehicle assigned to that route and the perishability constraints of the products.
- (5) Customers have time windows during which they must be served.
- (6) Each customer is visited exactly once by a single vehicle.
- (7) The total cost of transport and the loss of economic value of products during transport are minimised.

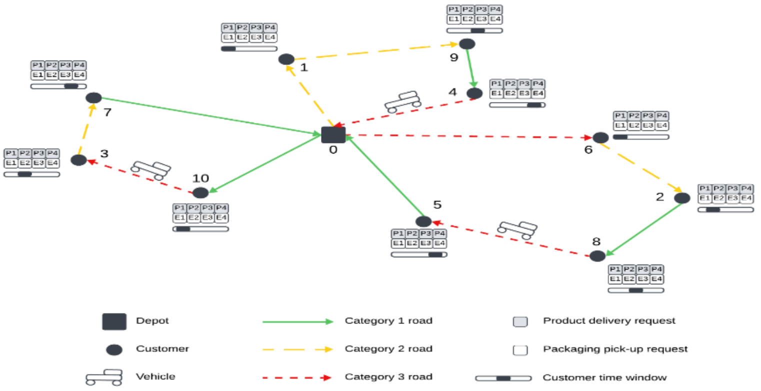

Fig. 1: MP-VRPSPDTW Schematic.

3.2. Mathematical formulation

The MP-VRPSPDTW can be defined as a directed graph $G = (V, A)$, where $V = \{0, \dots, n\}$ is the set of nodes comprising the depot $\{0\}$ and $A = \{(i,j) : i,j \in V, i \neq j\}$, the set of edges. A homogeneous fleet of $K = \{1, \dots, m\}$ vehicles is available at the depot. The problem can be formulated as a mixed linear integer program using the following notation:

The indices	
i, j	represent the indices of the nodes of the set $N = \{0, \dots, n\}$
k	represents the vehicle index in the set $K = \{1, \dots, m\}$
p	represents the index of the products in the set $P = \{1, \dots, l\}$
The Sets	
$N = \{0, \dots, n\}$	is the set of nodes composed by the clients and the depot
$N \backslash \{0\} = \{1, \dots, n\}$	is the set of customers
$K = \{1, \dots, m\}$	is the set of vehicles
$P = \{1, \dots, l\}$	is the set of products
The settings	
d_{ij}	is the distance from the node i to the node j
P_{ijp}	represents the percentage of damage per unit load per unit of time experienced by the product p on the arc (i, j)
dpi_{ip}	is the customer's i product p packaging pickup request
dde_{ip}	is the customer's i product p delivery request
Q_p	is the capacity of the vehicle reserved for the product p
f_i	is the client's i lower time window
g_i	is the client's i upper time window
S_i	represents the service time at the node i
t_{ij}	represents the travel time between the node i and the node j
pu_p	represents the unit price of the product p
α	represents a weighting factor related to the economic value losses of the products
c_1	represents the cost of fuel consumption per unit distance due to rough road conditions
c_2	represents the maintenance/repair cost per unit of distance due to rough road conditions
c_3	is the cost to the tires per unit of distance due to rough road conditions
c_4	represents the depreciation of the vehicle per unit distance due to rough road conditions
Decision variables	
x_{ij}^k	is a binary variable that is equal to 1 if the vehicle k travels directly from the node i to the node j and 0 otherwise
y_{ik}	is a binary variable that is equal to 1 if the vehicle k visits the node i and 0 otherwise
pi_{ijp}	represents the sum of requests collected from customers, routed to the node i (including the node i), and transported over the arc (i, j)
de_{ijp}	represents the sum of the requests to be delivered to customers, routed past the node i, and transported over the arc (i, j)
λ_{ik}	indicates the time it takes for the vehicle k to arrive at the node i
ξ_{jp}	represents the accumulation of the percentage of damage sustained by the product p delivered to the customer j

The first component of the objective function (1) aims to minimise transport costs, while the second component minimises losses in the economic value of all products during transport.

$$\min Z = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} (c_1 + c_2 + c_3 + c_4) d_{ij} x_{ij}^k + \alpha \sum_{j=0}^{n} \sum_{p=1}^{l} dde_{jp} pu_p \xi_{jp} \quad (1)$$

Under constraints:

Constraints (2) require that each vehicle can leave and return to the depot only once.

$$\sum_{j=1}^{n} x_{0j}^k \leq 1 \qquad \forall\, k = 1, \dots, m \quad (2)$$

Constraints (3) to (5) ensure that a customer is visited exactly once by a single vehicle.

$$\sum_{j=0}^{n} \sum_{k=1}^{m} x_{ij}^k = 1 \qquad \forall\, i = 1, \dots, n, i \neq j \quad (3)$$

$$\sum_{j=0}^{n} x_{ij}^k = y_i^k \qquad \forall\, i = 0, \dots, n, k = 1, \dots, m, i \neq j \quad (4)$$

$$\sum_{k=1}^{m} y_i^k = 1 \qquad \forall\, i = 1,\dots,n \qquad (5)$$

The constraints (6) limit the number of vehicles leaving the depot to the size of the available fleet.

$$\sum_{k=1}^{m} y_0^k \le m \qquad (6)$$

The constraints (7) ensure the conservation of flows, i.e. a vehicle must leave a node after serving it.

$$\sum_{i=0}^{n} x_{ij}^k = \sum_{i=0}^{n} x_{ji}^k \qquad \forall\, j = 1,\dots,n, k = 1,\dots,m, i \ne j \qquad (7)$$

Constraints (8) and (9) define the pickup and delivery flows, respectively.

$$\sum_{i=0}^{n} pi_{jip} - \sum_{i=0}^{n} pi_{ijp} = dpi_{jp} \qquad \forall\, j = 1,\dots,n, p = 1,\dots,l, i \ne j \qquad (8)$$

$$\sum_{i=0}^{n} de_{ijp} - \sum_{i=0}^{n} de_{jip} = dde_{jp} \qquad \forall\, j = 1,\dots,n, p = 1,\dots,l, i \ne j \qquad (9)$$

Constraints (10) to (12) ensure that the capacity of the vehicle assigned to a route is not exceeded.

$$pi_{ijp} + de_{ijp} \le Q_p \sum_{k=1}^{m} x_{ij}^k \qquad \forall\, i,j = 0,\dots,n, p = 1,\dots,l, i \ne j \qquad (10)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} dpi_{ip} x_{ij}^k \le Q_p \qquad \forall\, k = 1,\dots,m, p = 1,\dots,l, i \ne j \qquad (11)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} dde_{ip} x_{ij}^k \le Q_p \qquad \forall\, k = 1,\dots,m, p = 1,\dots,l, i \ne j \qquad (12)$$

Constraints (13) and (14) ensure that all customer pickup and delivery requests are met.

$$\sum_{i=1}^{n} pi_{i0p} = \sum_{i=1}^{n} dpi_{ip} \qquad \forall\, p = 1,\dots,l \qquad (13)$$

$$\sum_{i=1}^{n} de_{0ip} = \sum_{i=1}^{n} dde_{ip} \qquad \forall\, p = 1,\dots,l \qquad (14)$$

Constraints (15) and (16) apply time windows. Constraints (16) also help eliminate sub-towers.

$$f_i \le \lambda_{ik} \le g_i \qquad \forall\, i = 0,\dots,n, k = 1,\dots,m \qquad (15)$$

$$\lambda_{ik} + S_i + t_{ij} - \lambda_{jk} \le \left(1 - x_{ij}^k\right)M \qquad \forall\, i,j = 0,\dots,n, k = 1,\dots,m, i \ne j, j \ne 0 \qquad (16)$$

Constraints (17) accumulate the percentage of damage per unit load per unit of time inflicted on products delivered to customers.

$$\xi_{jp} \ge \xi_{ip} + P_{ijp} t_{ij} + \left(x_{ij}^k - 1\right)M \qquad \forall\, i,j = 0,\dots,n, k = 1,\dots,m, p = 1,\dots,l, i \ne j, j \ne 0 \qquad (17)$$

Constraints (18) and (19) ensure that the cumulative percentage of damaged products varies between 0 and 1.

$$\xi_{jp} \ge 0 \qquad \forall\, j = 0,\dots,n, p = 1,\dots,l \qquad (18)$$

$$\xi_{jp} \le 1 \qquad \forall\, j = 0,\dots,n, p = 1,\dots,l \qquad (19)$$

Finally, constraints (20) and (21) specify the domains of the decision variables.

$$x_{ij}^k, y_i^k \in \{0,1\} \qquad \forall\, i,j = 0,\dots,n, k = 1,\dots,m, i \ne j \qquad (20)$$

$$\lambda_{ik}, pi_{ijp}, de_{ijp} \ge 0 \qquad \forall\, i,j = 0,\dots,n, k = 1,\dots,m, p = 1,\dots,l, i \ne j \qquad (21)$$

3.3. Calculation of the percentage of damage per unit load per unit of time inflicted on products delivered to customers (P_{ijp})

[7] are examining the impact of truck vibration on mechanical damage to fresh fruits and vegetables during transport in Thailand. The study measured vibration levels (vertical, lateral and longitudinal) over a number of routes, focusing on the main distribution routes from producers to packing houses, then to distribution centers and finally to retailers.
The objective of this work is to measure the percentages of damage suffered by products according to the type of road taken by the vehicle. Four products were tested: head lettuce, cabbage, Chinese pear and Chinese plum.
Vehicle speeds are between 30 and 90 km/h, with an average speed of 80 to 90 km/h on roads in good condition, and 30 to 40 km/h on roads in poor condition.
The vibration measurements presented by the authors were carried out on the following specific paths:

- From the pickup centers located in Chiang Mai to the Chiang Mai Packing House.
- From Chiang Mai Packing House to Bangkok Distribution Center.
- From the distribution center in Bangkok to retailers located in Bangkok.

The test results showed that the roads between the pickup centers (Chiang Mai) and the packing house (Chiang Mai) had GRMS (G Root Mean Square) levels of 0.238 vertical, 0.106 lateral, and 0.061 longitudinal. The road between the packing house (Chiang Mai) and the distribution center (Bangkok) had GRMS levels of 0.224 (vertical), 0.079 (lateral), and 0.050 (longitudinal). Finally, the roads between the distribution center (Bangkok) and retailers (Bangkok) had GRMS of 0.191 (vertical), 0.072 (lateral), and 0.054 (longitudinal).
GRMS, which measures the intensity of vibrations, is used to assess their impact on goods during transport.
The authors concluded that roads with the highest vibration levels increase the damage to products during the route.
Based on the results of [7], we determine the percentage of damage suffered per product per unit load per unit of time (P_{ijp}) which will allow us to quantify the accumulation of mechanical damage suffered by the products as a function of the roughness conditions of the roads used.
The expression for this percentage is given by equation (23). It is obtained from the average travel time, given by equation (22), and the percentage of loss per unit load measured over the total length of the path.

$$\text{Average travel time (mn)} = \frac{\text{Travel distance (km)}}{\text{Average speed (km/h)}} \times 60 \tag{22}$$

$$P_{ijp}\ (\%) = \frac{\text{Percentage of loss per unit load (\%)}}{\text{Average travel time (mn)}} \tag{23}$$

Table 1 shows the value of P_{ijp} for each type of product on the different road categories. The calculation is made from the data provided by [7].

Table 1: Rate of Damage Inflicted on Products Per Unit Load Per Unit of Time (P_{ijp})

Road Origin	Destination	Average travel time (min)	P_{ijp}(%) Head lettuce	Cabbage	Chinese pear	Chinese Plum
Pickup centres (Chiang Mai)	Packing House (Chiang Mai)	96	0,469	0,521	0,406	0,156
Packing House (Chiang Mai)	Distribution Center (Bangkok)	600	0,05	0,067	0,048	0,017
Distribution Center (Bangkok)	Retailers (Bangkok)	15	0,667	1	1,4	0,333

3.4. Classification of roads

Based on data from Table 1 and the map of Thailand showing transport routes, provided by [7], we propose a classification of the different roads studied in three categories:

- Rural roads: Average vibration levels are similar to the route between the pickup centers (Chiang Mai) and the packing house (Chiang Mai).
- Intercity roads: Average vibration levels are similar to the route from the packing house (Chiang Mai) to the distribution center (Bangkok).
- Urban roads: Average vibration levels are similar to the route between the distribution center (Bangkok) and retailers (Bangkok).

It can be seen in Table 1 that all products show a higher percentage of deterioration per unit load per unit of time when travelling between the distribution center (Bangkok) and retailers (Bangkok). This could be due to frequent vibrations in urban areas and the speeds practiced that could further affect the quality of the products despite the short travel time.

4. Resolution methods

We propose two resolution methods for the MP-VRPSPDTW: an exact resolution method and a two-phase decomposition heuristic (TPDH).

4.1. Exact resolution method

As the exact method, we use the traditional Branch & Cut (B&C) algorithm of CPLEX.

4.2. Two-phase decomposition heuristic (TPDH)

Here we present a two-phase decomposition algorithm that combines a clustering phase based on customer aggregation and a local optimization phase.

4.2.1. Phase 1: customer aggregation

The objective of this phase is to assign customers to available vehicles taking into account the following constraints:

- Vehicle capacity: Each vehicle has a maximum capacity that cannot be exceeded.
- Time windows: Each customer must be served within a predefined time window.
- Product degradation: the cumulative percentage of degradation of products transported on a road must not exceed 100%.

Phase 1 methodology

a) Initialization

Each vehicle is initialized with an empty road.

b) Aggregation

The first customer of the vehicle is randomly selected from all the customers not yet visited. The other customers are assigned to the vehicle, in the vicinity of the customer in front of them, according to:

- The remaining capacity of the vehicle.
- Compatibility with the time windows of customers already assigned to this vehicle.

- The contribution to the percentage of degradation of products transported on the road.

Outcome of Phase 1
An initial solution where each vehicle has an assigned route that respects the defined constraints.

4.2.2. Phase 2: local search (crossroad optimization)

This phase aims to improve the initial solution by optimizing vehicle routes.
Phase 2 methodology

a) Initialization

- The solution obtained in Phase 1 is used as a starting point.
- An evaluation criterion is defined, combining the minimization of the cost of transportation and the cost of losses in the economic value of products due to roughness conditions of the roads, and compliance with time window constraints.

b) Local search operations

Two clients belonging to two different routes are randomly selected. The positions of the two clients are swapped if and only if:

- The new roads respect vehicle capacity constraints.
- New roads respect customers' time windows.
- The cumulative percentage of product degradation remains less than or equal to 100%.

If an improvement is achieved, the local best solution is updated, otherwise, the client exchange is canceled.
Phase 2 discontinuation Criteria
Phase 2 stops after a maximum number of iterations without improving the local best solution.

4.2.3. Criterion for stopping the main program (global research)

An evaluation criterion is defined in the main program. This criterion combines the minimization of the cost of transportation with the cost of losses in the economic value of products due to rough road conditions.
If an improvement is obtained after the local search, then the overall best solution is updated, otherwise, it is retained.
Phases 1 and 2 are repeated over a number of iterations and the algorithm must stop after a maximum number of iterations without improving the overall best solution.

4.2.4. General TPDH process

The general TPDH process is illustrated in Fig. 2.

5. Experiments

5.1. Hardware and software

The implementation of the two resolution methods, B&C and TPDH, was carried out in C++. CPLEX version 12.6 was used for the B&C method. The experiments were conducted on a 64-bit personal computer, with an 8th Gen Intel Core i7 processor at 2.3 GHz and 8 GB of RAM.

5.2. Tested instances

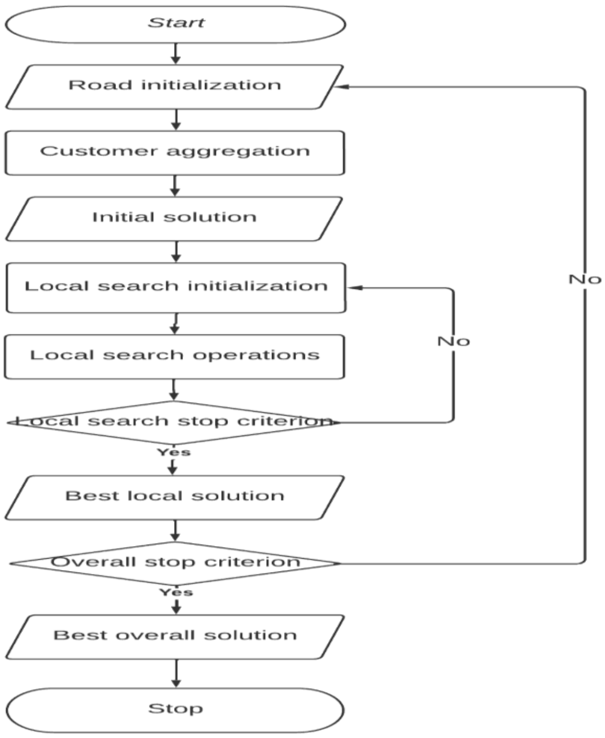

Fig. 2: General TPDH Process.

For our experiments, we use three instances of VRPTW from [10][3]: C101, R104 and RC107.
Instances C101, R104 and RC107 of [10] are distinguished from each other by the geographical distribution of customers and the constraints of time windows. The C101 (Clustered) instance presents clients that are geographically clustered with very strict time windows. In the R104 (Random) instance, clients are randomly distributed across the service area, with equally strict time windows. The Mixed Clustered and Random (RC107) instance combines clustered clients with randomly distributed clients, with moderately strict time windows.
In these three instances, the maximum number of customers is 100, and a maximum of 25 homogeneous vehicles is allocated, each with a capacity of 200.

5.3. Scenarios

The different instances are tested according to four defined scenarios in order to examine in more detail the influence of road roughness conditions and the impact of the diversity of product sensitivity on the quality of the solutions obtained.
Scenario 1 includes all three categories of roads: interurban, rural and urban, each representing a third of all arcs. Scenario 2 is limited to interurban and rural roads, divided equally (50% each). Scenario 3 covers interurban and urban roads, which are equally distributed at 50%. Finally, Scenario 4 includes roads in both rural and urban categories, with an equal distribution of 50% for each category.

5.4. Economic value of products

To accurately assess the impact of roughness conditions on product economic value losses, we offer prices based on real data[4]. These prices are shown in Table 2.

Table 2: Product Price in Dollars ($) Per Kg

Product	Range of Change in Unit Price per kg	Average unit price per kg
Head lettuce	1,57 - 2,20	1,90
Cabbage	0,60 - 1,20	0,90
Chinese pear	2,50 - 3,00	2,75
Chinese Plum	2,50 - 3,50	3,00

5.5. Types of vehicles

The study of [7] does not mention the impact of vehicle types on mechanical damage to products, but focuses on analyzing vehicle vibration and quantifying damage to products during transport. We therefore consider in our study a homogeneous fleet of vehicles.

5.6. Vehicle capacity

The capacity of each vehicle is subdivided into four separate compartments, each dedicated to a specific product. The capacity allocated to each compartment thus makes it possible to manage the pickup and delivery operations for the corresponding product.

5.7. Vehicle operating costs

To represent the operating costs of vehicles, we use the results of [11] which show that rough road conditions impact vehicle operating costs, particularly in terms of repair/maintenance, fuel consumption, depreciation and tyres. Table 3 shows the operating costs of vehicles per km.

Table 3: Vehicle Operating Costs in Dollars ($) Per Km

Parameter	Value
c_1	0,214
c_2	0,131
c_3	0,044
c_4	0,10

6. Results and discussions

Table 4 compares the performance of B&C and TPDH for the different instances and scenarios of the MP-VRPSPDTW. The simulation is limited to a maximum duration of 7200 seconds. For TPDH, the number of iterations is limited to 10 for local search and 15 for the main program. We vary the number of clients from 10 and gradually adjust this value to analyze its impact on algorithm performance, taking into account the specifics of each instance and scenario.

Table 4: Comparison of B&C and TPDH Test Results

Instance name	Sce-nario	n	Total cost of the objective (B&C)	Total cost of the objective (TPDH)	Total cost of the objective difference between TPDH and B&C (%)	CPU time (B&C)	CPU time (TPDH)	CPU time difference between TPDH and B&C (%)
	1	10	81,6437	87,2798	6,90%	3,272	32,231	885,06%
		15	188,429	193,16	2,51%	2,796	57,673	1962,70%
		20	268,004	307,069	14,58%	3,337	172,69	5075,01%
		25	308,275	362,652	17,64%	196,859	608,097	208,90%
		30	398,894	455,051	14,08%	767,04	695,663	-9,31%
		35	409,019	450,39	10,11%	4352,14	895,098	-79,43%
C101	2	10	67,904	70,7354	4,17%	1,303	157,559	11992,02%

[3] http://vrp.galgos.inf.puc-rio.br/index.php/en/
[4] https://rnm.franceagrimer.fr/

		15	138,392	171,19	23,70%	14,701	279,232	1799,41%
		20	245,64	264,998	7,88%	18,615	442,668	2278,02%
		25	272,986	294,071	7,72%	382,009	749,493	96,20%
		30	307,752	364,473	18,43%	7216,54	458,669	-93,64%
	3	10	70,6117	77,8952	10,31%	2,676	105,789	3853,25%
		15	148,084	185,209	25,07%	7,955	135,885	1608,17%
		20	229,486	283,157	23,39%	9,6	668,704	6865,67%
		25	320,796	306,625	-4,42%	85,198	518,472	508,55%
		30	347,782	408,156	17,36%	3707,3	774,258	-79,12%
		35	1183,62	1093,42	-7,62%	7215,76	1208,15	-83,26%
	4	10	129,224	129,637	0,32%	4,416	75,066	1599,86%
		15	252,478	255,38	1,15%	299,96	142,372	-52,54%
		20	443,204	466,672	5,30%	7207,52	584,579	-91,89%
Average for C101			290,61122	311,36102	7,14%	1574,94985	438,1174	-72,18%
R104	1	10	131,852	168,134	27,52%	54,808	105,564	92,61%
		15	178,327	257,548	44,42%	7200,81	152,206	-97,89%
	2	10	144,227	197,162	36,70%	68,288	20,835	-69,49%
		15	193,054	276,972	43,47%	7207,96	119,374	-98,34%
	3	10	180,514	190,733	5,66%	73,996	60,115	-18,76%
		15	204,922	285,413	39,28%	7201,19	105,924	-98,53%
	4	10	257,508	293,312	13,90%	2113,47	62,962	-97,02%
		15	229,319	279,076	21,70%	7208,31	119,505	-98,34%
Average for R104			189,965375	243,54375	28,20%	3891,104	93,310625	-97,60%
RC107	1	10	110,125	179,894	63,35%	17,453	43,496	149,22%
		15	133,758	239,863	79,33%	7200,47	146,964	-97,96%
	2	10	98,2648	132,686	35,03%	7213,73	45,692	-99,37%
		15	176,377	329,094	86,59%	7213,73	94,125	-98,70%
	3	10	107,681	144,698	34,38%	7,201	102,048	1317,14%
		15	167,789	358,349	113,57%	7210,05	157,934	-97,81%
	4	10	315,436	350,14	11,00%	7200,76	70,405	-99,02%
		15	534,108	707,912	32,54%	7206,6	123,162	-98,29%
Average for RC107			205,44235	305,3295	48,62%	5408,74925	97,97825	-98,19%

In Table 4 the instance name identifies the specific test cases (C101, R104, or RC107). The scenario (1, 2, 3, or 4) corresponds to the particular configurations of an instance. n is the number of customers to be served in a given scenario. The total cost of the objective is the optimized cost obtained using the B&C or TPDH methods for each scenario. This cost includes the total cost of transportation and the economic value losses of products weighted by the α factor. The difference in total objective cost between TPDH and B&C measures the relative difference between the costs obtained by these two methods. A positive value indicates that the cost of TPDH is higher than that of B&C, which means that TPDH is less optimal. A negative value, on the other hand, indicates a better performance of the TPDH. CPU time, expressed in seconds, represents the amount of time it takes for each method to solve a given scenario. The CPU time gap between TPDH and B&C reflects the relative difference between the CPU times of the two approaches. A negative value indicates that TPDH is faster than B&C.

The results in Table 4 highlight the performance of the two methods for different instances and scenarios. For C101, the average total cost of the objective is 290.61 for B&C, compared to 311.36 for TPDH, an average deviation of 7.14%. Regarding CPU time, the B&C requires an average of 1574.95 s, compared to 438.12 s for TPDH. As a result, TPDH is approximately 72% faster than B&C across all scenarios tested for this instance.

For the R104 instance, the average total cost of the objective is 189.97 for B&C and 243.54 for TPDH, a significant average deviation of 29.08%. However, TPDH stands out for its noticeable speed, with a reduction in CPU time of almost 98% (with an average CPU time of 3891.10 s for B&C and 93.31 s for TPDH).

For RC107, the total objective cost gap between B&C and TPDH is particularly large, reaching 56.97% (with average costs of 205.44 for B&C and 305.33 for TPDH). For CPU time, TPDH is about 98% faster, with average times of 5408.75 s for B&C and 97.98 s for TPDH.

In addition, for small instances (n = 10), B&C offers optimal costs in a reasonable amount of time for most instances and scenarios. When the number of customers increases (n≥25), TPDH prevails thanks to a significantly reduced computation time, despite an increase in the average cost gap. For example, for instance C101 (scenario 1, n = 35), the B&C requires 4352 s, compared to only 895 s for TPDH, a reduction of 79.43%, for a total cost gap of the objective of only 10.11%.

Table 5 shows the experiments for MP-VRPSPDTW solved with B&C.

In Table 5, α represents the weighting of the economic value losses of products in the objective function. It allows the relative importance of this component to be adjusted according to the complexity of the instance and the scenario studied. The total distance travelled is the sum of the distances travelled by all the vehicles. The total cost of transportation represents the costs associated with the total distance travelled. The total cost of economic value losses quantifies the financial losses due to product spoilage during transportation. The GAP (%) represents the relative deviation between the solution found and the optimal lower bound. Finally, the number of vehicles used indicates how many vehicles were mobilized to solve the problem.

Analyzing the results in Table 5, it can be seen that the B&C produces high-quality solutions, with very low (%) GAP in many cases, or even non-existent. For example, for instance C101 (scenario 1, n = 10), the total cost of the objective is 81.64, with a 0% gap.

However, for more complex instances, the GAP increases. For example, for instance R104 (scenario 4, n = 15), the GAP reaches 44.64%, revealing the limits of the method to achieve an optimal solution in complex scenarios.

When it comes to CPU time, B&C becomes especially expensive for instances with a large number of clients or complex scenarios. As an example, for instance C101 (scenario 1, n = 35), the CPU time is 4352.14 seconds, an exponential increase compared to the same instance with n = 30 (CPU time of 767.04 seconds). This trend is confirmed for R104 and RC107 instances, where computer time frequently exceeds 7200 seconds (or more than 2 hours), even for scenarios with a relatively small number of customers.

On the other hand, when it comes to vehicle allocation, the B&C is very efficient, minimising the number of vehicles while respecting the constraints imposed. For example, for instance C101 (scenario 1, n = 10), only 3 vehicles are used. Even for n = 35, the model allocates only 6 vehicles, demonstrating an effective adaptation to the growth in demand.

These results lead to the conclusion that B&C is particularly effective for small and low-complexity instances such as C101, where it provides optimal or near-optimal solutions with near-zero GAPs. In addition, the algorithm accurately handles complex constraints, such as optimal vehicle allocation. However, its main disadvantage is its limited scalability: for large instances, CPU time explodes.
Table 6 presents the results of the experiments for the MP-VRPSPDTW resolved with TPDH.

Table 5: Results of Experiments for MP-VRPSPDTW Solved with B&C

Instance Name	Scenario	n	α	Total distance traveled	Total cost of transportation	Total Cost of Economic Value Losses	Total cost of the objective	GAP (%)	CPU (s)	Number of vehicles used
C101	1	10	0,5	122	59,658	43,9714	81,6437	0	3,272	3
		15	0,5	250	122,25	132,358	188,429	0	2,796	3
		20	0,5	365	178,485	179,038	268,004	0	3,337	3
		25	0,5	409	200,001	216,548	308,275	4,15929E-005	196,859	5
		30	0,5	469	229,341	339,106	398,894	0	767,04	5
		35	0,4	580	283,62	313,4975	409,019	0	4352,14	6
	2	10	0,5	97	47,433	40,942	67,904	0	1,303	2
		15	0,5	210	102,69	71,404	138,392	0	14,701	3
		20	0,5	324	158,436	174,408	245,64	0	18,615	3
		25	0,5	369	180,441	185,09	272,986	8,67533E-005	382,009	4
		30	0,4	437	213,693	235,1475	307,752	30,92	7216,54	5
	3	10	0,5	118	57,702	25,8194	70,6117	0	2,676	3
		15	0,5	242	118,338	59,492	148,084	0	7,955	4
		20	0,5	394	192,666	73,64	229,486	0	9,6	4
		25	0,4	396	193,644	317,88	320,796	7,29642E-005	85,198	5
		30	0,4	528	258,192	223,975	347,782	9,80799E-005	3707,3	6
		35	4	601	293,889	222,43275	1183,62	6,67	7215,76	6
	4	10	0,5	192	93,888	70,672	129,224	0	4,416	5
		15	0,4	406	198,534	134,86	252,478	9,92197E-005	299,96	8
		20	0,7	600	293,4	214,006	443,204	20,81	7207,52	10
R104	1	10	0,5	214	104,646	54,412	131,852	8,70616E-005	54,808	2
		15	0,7	299	146,211	45,88	178,327	10,70	7200,81	3
	2	10	1,5	220	107,58	24,43	144,227	5,34897E-005	68,288	2
		15	2	326	159,414	16,82	193,054	25,59	7207,96	4
	3	10	2	266	130,074	25,22	180,514	3,23846E-005	73,996	2
		15	1,5	358	175,062	19,91	204,922	17,09	7201,19	3
	4	10	2,5	242	118,338	55,668	257,508	7,612E-005	2113,47	3
		15	0,7	360	176,04	76,11	229,319	44,64	7208,31	6
RC107	1	10	0,5	177	86,553	47,144	110,125	7,29338E-005	17,453	2
		15	0,5	229	111,981	43,554	133,758	16,77	7200,47	2
	2	10	0,5	176	86,064	24,4016	98,2648	40,28	7213,73	2
		15	3	217	106,113	23,42	176,377	40,28	7213,73	2
	3	10	0,5	176	86,064	43,234	107,681	7,74685E-005	7,201	2
		15	2	227	111,003	28,393	167,789	39,56	7210,05	2
	4	10	2	248	121,272	97,082	315,436	36,33	7200,76	3
		15	3	340	166,26	122,616	534,108	74,57	7206,6	4
Average				310,67	151,92	111,74	249,32	11,23	2941,61	3,81

Analyzing the results in Table 6, it appears that TPDH generates longer routes on average than B&C, with a notable increase of +25% for all scenarios (the average total distance travelled is 389.36 for TPDH compared to 310.67 for B&C).
Regarding the total cost of transport, the average difference is also +25%, with an average of 190.40 for TPDH against 151.92 for B&C.
For the total cost of economic value losses, the difference is much smaller, with an average difference of +7% (with 119.57 for TPDH versus 111.74 for B&C).
In terms of total cost of the lens, TPDH has an average relative deviation of +18.3% from B&C (with 294.95 for TPDH versus 249.32 for B&C). This gap remains acceptable in several scenarios, confirming that TPDH is a competitive alternative, especially for applications where reducing computation time is a priority.
CPU time shows a crucial difference between the two methods. TPDH takes an average of 290.19 seconds, compared to 2941.61 seconds for B&C, a significant reduction of 90% in favor of TPDH.
As for the number of vehicles used, the B&C is more efficient, mobilizing an average of 3.81 vehicles, compared to 5.75 vehicles for the TPDH.
These results confirm that TPDH is a credible alternative to B&C. TPDH offers a balanced compromise between speed and quality of solutions, making it particularly suitable for large instances or contexts that require rapid resolution.

Table 6: Results of Experiments for MP-VRPSPDTW Solved with TPDH

Instance	Scenario	n	α	Total distance traveled	Total cost of transportation	Total Cost of Economic Value Losses	Total cost of the objective	CPU (s)	Number of vehicles used
C101	1	10	0.5	131	64,059	46,44155	87,2798	32,231	3
		15	0.5	277	135,453	115,41438	193,16	57,673	5
		20	0.5	378	184,842	244,45484	307,069	172,69	6
		25	0.5	493	241,077	243,14905	362,652	608,097	9
		30	0.5	616	301,224	307,65394	455,051	695,663	10
		35	0.4	642	313,938	341,12905	450,39	895,098	9
	2	10	0.5	95	46,455	48,5607	70,7354	157,559	2
		15	0.5	291	142,299	57,62944	171,19	279,232	5
		20	0.5	396	193,644	142,70845	264,998	442,668	5
		25	0.5	392	191,688	204,765885	294,071	749,493	8
		30	0.4	500	244,5	299,9325	364,473	458,669	8
	3	10	0.5	123	60,147	35,49638	77,8952	105,789	3
		15	0.5	293	143,277	83,8638	185,209	135; 885	4
		20	0.5	475	232,275	101,763655	283,157	668,704	7
		25	0.4	450	220,05	216,43651	306,625	518,472	7
		30	0.4	590	288,51	247,76892	408,156	774,258	9
		35	4	765	374,085	179,834032	1093,42	1208,15	12
	4	10	0.5	188	91,932	75,41061	129,637	75,066	5
		15	0.4	399	195,111	150,67227	255,38	142,372	8
		20	0.7	640	312,96	219,588365	466,672	584,579	12
R104	1	10	0.5	301	147,189	41,889773	168,134	105,564	4
		15	0.7	423	206,847	72,4294	257,548	152,206	4
	2	10	1.5	298	145,722	19,949194	197,162	20,835	3
		15	2	455	222,495	27,238615	276,972	119,374	7
	3	10	2	363	177,507	6,612923	190,733	60,115	4
		15	1.5	517	252,813	21,73362	285,413	105,924	6
	4	10	2.5	317	155,013	55,3195	293,312	62,962	4
		15	0.7	424	207,336	102,4853	279,076	119,505	6
RC107	1	10	0.5	311	152,079	55,63057	179,894	43,496	4
		15	0.5	408	199,512	80,7028	239,863	146,964	4
	2	10	0.5	245	119,805	25,76237	132,686	45,692	3
		15	3	398	194,622	44,82397	329,094	94,125	5
	3	10	0.5	245	119,805	49,78608	144,698	102,048	3
		15	2	425	207,825	75,26183	358,349	157,934	4
	4	10	2	320	156,48	96,8298	350,14	70,405	4
		15	3	433	211,737	165,3916	707,912	123,162	5
Average				389,36	190,4	119,57	294,95	290,19	5,75

7. Conclusion

This paper introduces the single-objective MP-VRPSPDTW, for which we have developed a mathematical model solved using the traditional B&C algorithm of CPLEX and a two-phase decomposition heuristic (TPDH). Our study is distinguished by the integration of road roughness conditions in the context of a multi-product VRPTW, by analyzing their impact on the mechanical damage suffered by perishable products during their transport.

Contrary to previous work, we propose a model integrating simultaneous pickup and delivery operations, as well as the management of various products with specific sensitivities. Our experiments are based on an analysis of the vibrations generated by road conditions, using experimental data from [7].

Although the B&C algorithm generates high-quality solutions (with a 0% GAP for the majority of instances and scenarios), its efficiency decreases for large instances, where the GAP can be as high as 74.57%. The two-phase decomposition heuristic (TPDH), although less stable, offers acceptable solutions in a short time (average of 290.19 seconds vs. 2941.61 seconds for B&C), making it particularly suitable for applications requiring fast computations. By optimizing the local and global search parameters, its potential for improvement can be considerable in terms of reducing the total cost of the objective function, although this can increase CPU times.

Finally, a combination of a metaheuristic approach and multi-objective optimization could offer a better compromise between transport costs, loss of economic value of products and vehicle management, especially for large instances, while ensuring low CPU times.

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