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Vehicle routing problem for the minimization of perishable food damage considering road conditions

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ABSTRACT

Transportation is one of the activities in which perishable food products may suffer mechanical damage, which translates into a substantial loss of quality and product value. The main source of this type of damage in transportation is vibration, influenced, among others factors, by road conditions, a factor that can be considered in the vehicle routing problem. To address this issue, we propose a multi-objective model that seeks to minimize the damaged products during transport and the distance traveled by vehicles. To evaluate the model, we examined 10 instances adapted from the literature for the vehicle routing with time windows. Small size instances were solved using an augmented ε-constraint method (AUGMECON) and for large size instances, we applied a non-dominated sorting genetic algorithm (NSGA-II). The results allowed us to observe the relationship between the damaged products and the distance traveled and showed that the proposed solution approaches are capable of providing feasible routes considering trade-offs between these objectives. Hence, our model provides decision makers with a tool for an effective determination of vehicle routes that considers the damage that perishable food products may experience during transport.

KEYWORDS vehicle routing problem · time windows · perishable food products · mechanical damage · road conditions · multi-objective

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1 INTRODUCTION

Vehicle routing is one of the operational decisions in product logistics [20]. This decision is faced each day by thousands of companies and organizations engaged in the delivery and collection of products [12]. Food distribution especially has additional challenges related to transportation, in areas such as quality, safety, and sustainability of products [2]. This first area shows the changes throughout the supply chain until products reach the final consumer, which influences customer satisfaction. Additionally, during distribution the perishable nature of food products plays an important role in the distribution costs because the timely delivery of these type of products affects the delivery operator's co stand the retailer's revenues [23].

Perishable food products, such as fresh fruits and vegetables, are susceptible to mechanical damage (bruises, cuts, punctures, abrasions) at different stages of the distribution network: from collecting centers to packing houses, then to distribution centers, and finally from this centers to retailers [46]. This damage affects the product's appearance and increases their susceptibility to decay and the growth of microorganisms [33], which may also increase their chance of being rejected and ultimately wasted. During transport, this mechanical damage is mainly caused by vehicle vibrations, which are influenced by various factors such as distance, speed, load, truck characteristics, such as the suspension and number of axles, and road roughness [6]. This last factor refers to the superficial characteristics of the roads on which the vehicle travels, which affects the dynamic of the load [4, 25, 27, 57].

The natural and fast decay experienced by perishable food and the increasing customer demands for high-quality products, encourage the inclusion of perishability issues in the vehicle routing problem. In this research, we analyze the impact of perishable products' damage in vehicle routing. For this purpose, we include in the problem the aforementioned damage to which these products are susceptible during transit, which affects the product's quality defined not only by the physical properties of food but also by the way products are perceived by the consumer [21].

In this paper, we present a vehicle routing problem with time windows (VRPTW) under a multi-objective framework where two objectives are proposed: minimize the total damaged products and the distance traveled. To cope with the first objective, the model considers a damage rate assigned according to road conditions. To explore the proposed trade-off and deal with the hard task of providing feasible routes, we solve five 10-customer instances using an improved version of the ε-constraint method. Afterwards, we solve five well-known Solomon [49] instances with 50 customers using a multi-objective evolutionary algorithm, as the exact method fails to generate feasible solutions in reasonable computational time.

The remainder of this paper is organized as follows. In the following section, we provide an overview of the related literature. Section 3 and 4 describe the methodology and the computational experiments, respectively. The results are later analyzed in section 5. Finally, we summarize the main findings and provide some ideas for future research in section 6.

2 LITERATURE REVIEW

The vehicle routing problem (VRP) has been widely studied in the literature. This problem in its traditional version, known as capacitated vehicle routing problem, seeks to determine a set of feasible routes to satisfy a set of transportation requests at the minimum cost given a fleet of vehicles. In its extension that includes time windows (VRPTW) each client service must take place within a known time interval. For a deeper description of the properties, solutions, methods, extensions, and applications of the vehicle routing problem, the reader may refer to Toth and Vigo [54]. The following review will focus on the vehicle routing problem for the distribution of perishable food products, mechanical damage during transport, the modeling of road conditions and multi-objective vehicle routing.

2.1 Vehicle routing problem for perishable food products

In the last several years, the distribution of perishable food products has received special attention, and various authors have addressed it as a vehicle routing problem. As noted by Amorim and Almada-Lobo [3], some of the authors focus on the distribution of perishable food without explicitly taking into account quality loss, degradation (loss of freshness), or decay of products; such is the case of Tarantilis and Kiranoudis [52, 53], who deal with the distribution of milk and meat, and Faulin [18], who applied a procedure in a routing problem to optimize food delivery. On the other hand, perishability is explicitly modeled by authors such as Hsu, Hung, and Li [23], who develop a stochastic VRPTW dealing with the randomness proper to the delivery of this type of product, with the objective of minimizing the inventory, energy costs, and penalties for time window violations. Osvald and Stirn [40] formulate a VRPTW considering perishability as a critical factor, where the travel times depend on distance and time of day; this model considers the negative effect of perishability in the overall distribution cost, estimating the loss of quality on the load as a function of time. Chen, Hsueh, and Chang [10] combine the scheduling problem with the VRPTW; in their paper, the perishable goods have a decay rate, and their initial price is negatively affected by the product decay when finally delivered. Amorim and Almada-Lobo [3] present a multi-objective VRPTW that studies different scenarios and describes the cost-freshness trade-off. To deal with perishability, the shelf life of the most perishable product contained in the customers' requests is known, and this parameter is used to maximize the average freshness of the demanded products. Recently Wang, Wang, Ruan, and Zhan [60] consider a VRPTW model with the same objectives, where the loss of freshness is calculated using a nonlinear freshness factor; as a novelty the authors consider temporal-spatial distance to solve the problem. So far, only Li, He, Zheng, Huang, and Fan [32] have acknowledged road conditions and their influence in the deterioration and bruising in the distribution of fresh fruits and vegetables. In their study, with the aim to minimize the total cost in a VRPTW with soft time windows, they propose a single objective model that includes a coefficient of road surface evenness for four different road types; this coefficient is added in the objective function to calculate the running cost. Finally, they use an improved genetic algorithm to solve a 12-customer instance, and they conclude that considering road irregularities can significantly influence total delivery costs compared with traditional VRP models. In contrast with the work of Li, we propose a multi-objective model with hard time windows, include small and large size instances and use two solution methods to solve each instance size.

2.2 Mechanical damage during transport and road conditions

The effect of vibrations during transport and the mechanical damage that they can cause in perishable food has been widely studied for different products, as shown in Table 1. Several authors consider the relationship among road conditions,vibration, and mechanical damage in perishable food, including Schoorl and Holt [27, 43], who propose a model to predict the damage to horticultural products during transport, taking into account elements such as the road profile, tires, chassis and suspension of the vehicle, packaging, and the cushioning of the load. In this study, a direct relationship was observed between the road profile and damage. Jarimopas, Singh, and Saengnil [25] measure the vibration levels for two different types of trucks in Thailand and their effect on the damage caused to transported tangerines as a function of road condition and vehicle speed. The results show that both factors have a significant influence on product damage. In their experiment greater damage was caused by unpaved roads, followed by concrete highways and then asphalt roads. Zhou, Su, Yan and Li [62] also evaluated the effect of vibration levels on the mechanical damage to pears under using different road conditions such as highways, main, secondary, tertiary, and unpaved roads. As a point to highlight, different acceleration levels for the vibration were obtained for different roads. Pretorius and Steyn [41] experiment with different road conditions in Africa: national, provincial, and gravel roads were used in this study, which concludes that as road roughness increases, more vibrations occur and more energy must be absorbed by the vehicle, which can trigger more damage to the transported products. Steyn et al. [50] evaluate the effect of rural roads conditions on tomato transport in California; in their research, they observe a direct relationship between the percentage of damaged goods, road roughness, and transportation costs. As one of the conclusions, the authors state that damage and failure levels can be related to road conditions for the development of performance indicators and their implementation in freight transport models.

Table 1: Papers by product dealing with vibrations during transport and their effect on mechanical damage

Product	Author
Peaches	Vergano, Testin and Newall [58]
Tangerines	Jarimopas et al. [25]
Tomatoes	Hinsch, Slaughter, Craig and Thompson [22], Olorunda and Tung [38], Singh and Singh [45], Steyn et al. [50], Van Zeebroeck [56]
Strawberries	Chaiwong [8]
Apples	Acican, Alibaş, and Özelkök [1], Eissa and Azam [4], Chonhenchob et al. [11], Schoorl and Holt [43], Soleimani and Ahmadi [48], Van Zeebroeck et al. [57], Vursavus and Ozguven [59].
Pears	Berardinelli et al. [7], Zhou et al. [62]
Watermelons	Shahbazi, Rajabipour, Mohtasebi and Rae [44]
Kiwis	Tabatabaekoloor, Hashemi and Taghizade [51]
Eggs	Berardinelli et al.[6]

2.3 Modeling road conditions

In this article, when referring to road conditions or roughness, we refer to the unevenness of the road. The road roughness indices are single values to evaluate and manage road systems. These are calculated using mathematical equations and measured road profiles. Two very widespread internationally recognized indices are the International Roughness Index (IRI) and the ISO 8606:1995 specification index. The IRI is the most commonly used standardized roughness measurement and its use is more appropriate when road roughness is looked at in relation to vehicle operating costs, riding quality, dynamic wheel loads and overall surface conditions [24]. The mathematical model to obtain this index is a system of differential equations derived from a dynamic system of masses, spring, and dampers [31]. The ISO specification index is obtained using the fit of a parametric function to a measured profile's Power Spectral Density (PSD) (a set of distribution frequencies with accompanied amplitudes) [31]. To a better understanding of models for road roughness, the reader may refer to Lemken [31], Klas and Krzysztof [29]. When examining the influence of road conditions on cargo damage, the IRI is used by only a few papers. Pretorius and Steyn [41] experiment with the average IRI values of national, provincial and gravel roads to study the damage during transportation and Steyn et. al [50] use the IRI as a riding quality indicator to analyze the effect of road conditions on the potential damage to tomatoes. To do so, once the dominant frequencies for each road types were obtained, a laboratory simulation was executed to show the relationship of damage percentage to road roughness. In general, when addressing road conditions, most of the authors obtain representative frequencies for each road and then simulate these frequencies in a laboratory setting [1, 22, 50].

2.4 Multi-objective vehicle routing

Because in real-life cases, most of the problems in logistics have a multi-objective nature, the inclusion of more than one objective in the VRP has gained more attention in the last years. Jozefowiez, Semet and Talbi [28] elaborated a classification of objectives according to the components of the problem i.e. the tour, the node/arc activity and the resources. In their review, the most common objective related to the tour is to minimize the cost of the solutions in terms of distance traveled or time; other approaches include the minimization of the makespan, tour balance and so on. Node-related objectives include the maximization of customer satisfaction or customer waiting times. The most frequent resource-related objective is the minimization of the number of vehicles as addressed by Sivaram et al. [47].

In the last decade growing environmental concerns regarding the economic activity has been transferred to the field of transport and logistics. Thus, environmental targets have been added to the economic targets in the vehicle routing problem. Some common objectives include minimizing the CO_2 emissions [19, 55], minimizing the emission of air pollutants such as NOx [36], and minimizing fuel consumption [17, 37, 42]. Regarding multi-objective vehicle routing problems with perishable issues, only a few papers were found. Two of them consider the cost-freshness trade-off [3, 60]; Wang et al. [61] propose to maximize customer satisfaction and minimize cost, and Kuo [30] addresses a bi-objective model with the purpose of minimizing total cost and balancing the load in each vehicle.

Most of the reviewed works consider time as the main factor in perishable food quality loss. In this paper, we consider road conditions as a factor affecting product quality. Thus, this study will extend the scope into a multi-objective problem by considering another objective corresponding to the minimization of the damaged product. Then, the model will seek to obtain a trade-off between the damaged products, by minimizing the time spent in bad conditions roads, and the distance traveled. For this purpose, unlike the only related work including road conditions, we rely on data found in the transportation literature on the damaged products under three different road conditions. Then we analyze the inclusion of this factor on the solution structure, and, finally provide some managerial insights.

3 METHODOLOGY

In the following section, we explain the notation and model formulation for the multi-objective vehicle routing problem considering road conditions and later describe in detail the ε-constraint method and NSGA-II used to respectively solve the small and large size instances.

3.1 Notation and model formulation

This section describes a vehicle routing problem with time windows for the distribution of a perishable product. Road conditions and their effect on the load are considered in the model with the inclusion of a parameter later explained based on the results of Jarimopas et al. [25].

The problem can be defined on a directed graph $G = (V, A)$ where $V = \{0, \dots, N + 1\}$ denotes the set of vertices, N the set of customers, and $A = \{(i, j) | i, j \in V, i \neq j\}$ represents the arc set. The vertices 0 and $N + 1$ correspond to the depot where a homogeneous fleet of vehicles of size K with capacity C is assumed to be stationed. To each vertex $i \in V$, there is an associated nonnegative demand $q_i (q_0 = q_{N+1} = 0)$, a hard time window $[e_i, l_i]$ that represents the earliest and latest times for service to customer i to start (the depot also has a time window corresponding to the scheduling horizon of the problem), and non-negative service times $S_{ik}(S_0 = S_{N+1k} = 0)$. Associated with each arc there is a distance d_{ij} and a travel time t_{ijk} that represents the time it takes the vehicle k to travel from i to j. A damage rate P_{ij} that indicates the ratio of damage produced per load unit per unit of time is associated to each arc. The binary decision variable x_{ijk} equals 1 if vertex j is traversed after i by the vehicle k and 0 otherwise. Variable τ_{ik} indicates the start of service of vehicle k at vertex i. Finally, an auxiliary variable H_j is added to accumulate the percentage of damaged products delivered at the vertex j , the initial damage is considered to be zero ($H_0 = 0$).

According to the given notation, the mathematical formulation can be stated as follows:

$$\text{Minimize} \quad F_1 = \sum_{j \in N} H_j \, q_j \tag{1}$$

$$\text{Minimize} \quad F_2 = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} d_{ij} \, x_{ijk} \tag{2}$$

Subject to:

$$\sum_{k \in K} \sum_{\substack{j \in V \setminus \{0\} \\ i \neq j}} x_{ijk} = 1 \qquad \forall i \in V \tag{3}$$

$$\sum_{j \in V \setminus \{0\}} x_{0jk} \leq 1 \qquad \forall k \in K \tag{4}$$

$$\sum_{\substack{i \in N \\ i \neq j}} x_{ijk} - \sum_{\substack{i \in V \setminus \{0\} \\ i \neq j}} x_{jik} = 1 \qquad \forall j \in V, \forall k \in K \tag{5}$$

$$\tau_{ik} + S_{ik} + t_{ijk} - \tau_{jk} \leq (1 - x_{ijk})M \qquad \forall (i, j) \in A, \forall k \in K \tag{6}$$

$$e_i \leq \tau_{ik} \leq l_i \qquad \forall i \in V, \forall k \in K \tag{7}$$

$$\sum_{i \in V} \sum_{\substack{j \in V \\ i \neq j}} q_i \, x_{ijk} \leq C \qquad \forall k \in K \tag{8}$$

$$H_j \geq H_i + P_{ij} t_{ijk} + (x_{ijk} - 1)M \qquad \forall (i,j) \in A, \forall k \in K \tag{9}$$

$$H_j \geq 0 \qquad \forall j \in N \tag{10}$$

$$H_j \leq 1 \qquad \forall j \in N \tag{11}$$

$$x_{ijk}\{0,1\} \qquad \forall (i,j) \in A, \forall k \in K \tag{12}$$

$$\tau_{ik} \geq 0 \qquad \forall i \in V, \forall k \in K \tag{13}$$

The objective function (1) minimizes the accumulated damaged products along the routes. The objective function (2) minimizes the distance covered by the vehicle. Constraints (3) state that each customer is visited by exactly one vehicle. Constraints in (4) indicate that the vehicles must start from the depot. The flow conservation in each vertex is ensured by constraints (5), while time windows are enforced through constraints (6) and (7). Regarding the vehicle capacity, constraints in (8) force it to be respected by not allowing the sum of the demands on a given route to exceed it. The set of constraints in (9) accumulates the damage of the products for each client based on the previously traveled arcs. The constraints in (10) and (11) avoid all the accumulated damaged percentage of products per client to exceed the demand of each client. Finally, constraints from (11) to (13) define the domains of the remaining decision variables. Figure 1 illustrates the parameters of the problem. In the Figure, road conditions are assigned to each arc. In this particular solution, formed by the routes D-5-3-1-D and D-2-4-D, the dashed lines show the parts of the route in which the damage to products takes place.

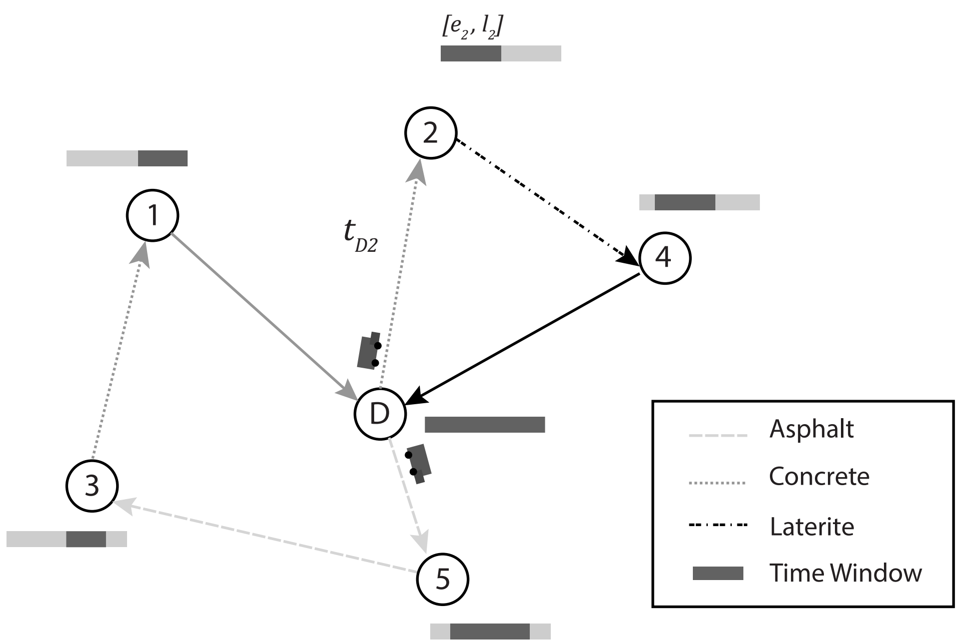

Figure 1: A solution for a 5-customer instance showing different road conditions.

3.2 Solution approach

To explore the proposed trade-off, first, an exact method is used to solve the 10 customer instances. Afterwards, the model is tested in large size instances by employing an approximate method. This will allow us to obtain the set of equally important solutions for each problem.

3.2.1 Small-size instances

To solve the 10-customer instances, we employ an improved version of the ε-constraint method, which is one of the best-known methods to solve multi-objective problems [13]. It basically consists of creating a single-objective model where only one of the objective functions will be optimized, and the remaining functions become constraints in the model [16]. The AUGMECON method is an improved version of the ε-constraint method that avoids the production of weakly Pareto optimal solutions and also redundant iterations [34]. This method is applied for 10-customer instances as follows:

> *Step 1.* Create a payoff table to obtain the range of each one of the $p-1$ objectives. This is done by optimizing each objective individually and finding the values of the other objective functions at this optimal point. Then, the range corresponds to the interval between the ideal and the worst value. To overcome the ambiguity of obtaining non-Pareto optimal solutions under the presence of alternative optima the use of lexicographic optimization for every objective function is used.
>
> *Step 2.* Choose one objective function $(f_j(x))$ as the main objective and transform the others into constraints.
>
> *Step 3.* Divide the range of each i th objective function into y_i equal intervals using $y_i - 1$ equidistant step points.
>
> *Step 4.* Solve the AUGMECON mathematical model in equation (13) separately for each combination of step points in the objective function. In the model eps is a small number usually between 10^{-6} and 10^{-3} , where X is the feasiblearea of the original problem, s_i is a slack variable for the objective function i , and r_i is the length of the objective function's range.

$$Minimize \quad f_j(x) - eps\left(\sum_{i \neq i} \frac{s_i}{r_i}\right) \tag{14}$$

$$Subject\ to:$$
$$f_i(x) + s_i = \varepsilon_i, \forall i \neq j$$
$$x \in X, s_i \in R^+$$

To solve the 10 customer instances, we decided to optimize (2) and transform (1) into a constraint. Then, according to (13), our problem becomes:

$$Minimize \quad \sum_{i \in V} \sum_{i \in V} \sum_{k \in K} d_{ij}\, x_{ijk} - eps\left(\frac{s_1}{r_1}\right) \tag{15}$$

$$Subject\ to:$$
$$Set\ of\ constraints\ from\ (3)\ to\ (12)$$
$$\sum_{j \in N} H_j\, q_j + s_1 \leq \varepsilon_1$$

To perform step 3, the range of F_1 was divided into a 100 equal intervals. Algorithm 1 shows the pseudo-code to find the Pareto front with the AUGMECON method. In it the values z_u^1 and z_l^1 represent the theoretical worst and best values for the first objective, respectively. These values are shown in Table 2 per instance for all the objectives.

Algorithm 1 Pseudo-code to find the Pareto front with the AUGMECON method.

```
for all instances do
    ε1 = z_u^1
    step = r1/100
    while ε1 ≥ z_l^1 do
        Solve (14) with exact solver
        F ← Solution(14)
        ε1 = ε1 − step
    end while
end for
return  Pareto solutions for all instances
```

Table 2: Payoff table

Instance	z_l		z_u	
	F_1	F_2	F_1	F_2
1	16.83	286	24.84	485
2	13.83	159	49.27	311
3	8.62	306	19.48	462
4	6.95	145	25.13	260
5	6.99	144	32.04	321

3.2.2. Large-size instances

To test the model in larger size instances we employ a non-dominated sorting genetic algorithm (NSGA-II). This algorithm has been used in several multi-objective VRP variants [3, 9, 26, 35] and widely applied in different problems, showing competitive results when compared to other multi-objective evolutionary algorithms [15]. The readers are refereed to Deb, Agrawal, Pratap, and Meyarivan [14] for more details on the NSGA-II. The NSGA-II structure is presented in Figure 2.

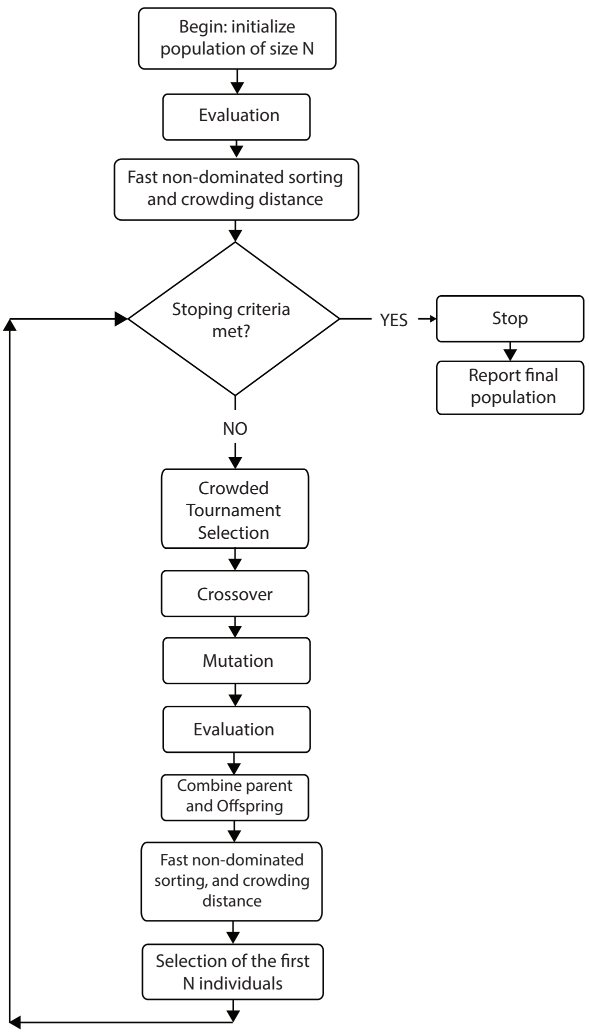

Figure 2: Flowchart of NSGA-II

3.2.2.1 Encoding and initial population.

To represent a solution, we use a permutation encoding where every chromosome is a string of numbers from 1 to the number of customers representing the sequence in which they are assigned to the routes. Figure 3 shows the solution representation. The initial population of size N is randomly generated.

3.2.2.2 Evaluation and decoding.

Because the order of serving customers in a chromosome may lead to infeasible routes, the evaluation was designed to not let solutions violate any constraint. The evaluation starts assigning customers to routes in the permutation order. When a customer cannot be served in the route, because of capacity or time windows violations, a new route is created. In Figure 3 customers 1 and 2 can be sequentially served and form a route leaving customers 5, 4 and 3, which can be sequentially served, into the next route.

Figure 3: Solution representation and decoding.

3.2.2.3 Selection and elitism.

To rank the population in the algorithm, we implement two operators called fast non-dominated sorting and crowding distance [14]. After the population is ranked, according to a fitness equal to its non-domination level, a binary tournament selection takes place. In this tournament, two individuals are randomly selected and their ranks compared. Then the individual with lower rank is selected. In case the solutions belong to the same front, the solution with the greater crowded distance is chosen.

3.2.2.4 Crossover.

After two chromosomes are randomly selected as parents, they are crossed by employing an specialized operator known as "Best Route Cost Route Crossover"(BCRC), which looks forward simultaneously tominimize the number of vehicles and distance while checking feasibility constraints [39, 47].To execute this operator, first one random route is selected from each parent, and then the customers in each chosen route are removed from the opposite parent to create the offspring, as shown in Figure 4, (part a). Next, each removed customer in the route is reinserted in the best feasible position (the one resulting in total minimum cost routes) to create the offspring. If no feasible insertion is found for a given customer, a new route is created.

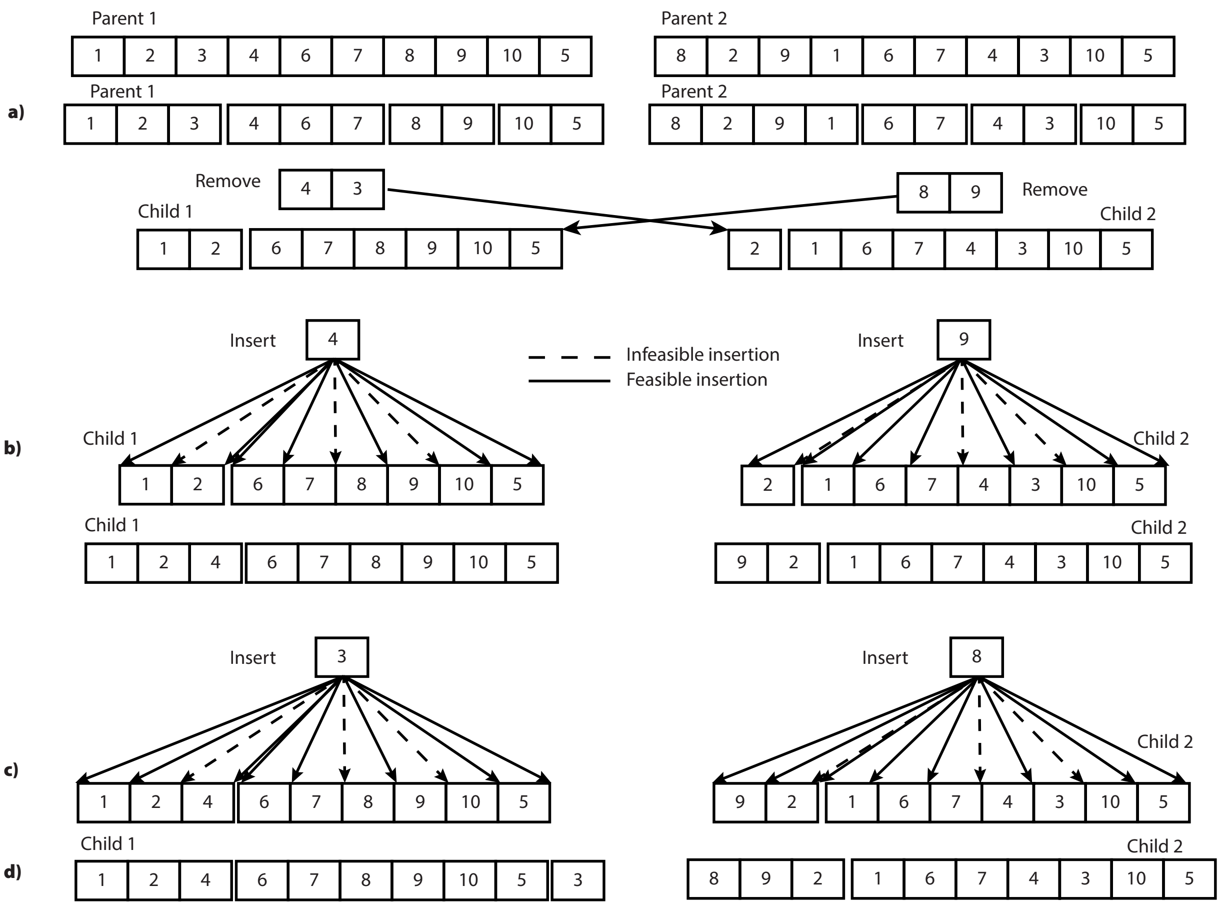

Figure 4. BCRC crossover.

3.2.2.5. Mutation.

If the mutation rate is met, a swap mutation is applied. In this mutation technique, two positions on the chromosome are randomly selected, and their values are interchanged, as in Figure 5.

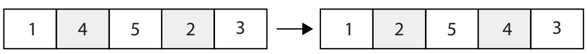

Figure 5: Mutation operator.

3.2.2.6 Offspring evaluation, sort, and selection of the first N individuals.

After cross-over and mutation, the offspring population is evaluated. Then, at iteration t , parent P_t and offspring populations Q_t are combined to form a larger population R_t. In this step, fast non-dominated sorting is applied to create the next iteration population P_{t+1} with the same size as P_t. To do so, fronts are added to the population in increasing rank order. A crowding sort procedure is performed in case a front can not be fully inserted in the new population P_{t+1}. This procedure is illustrated in Figure 6 [14].

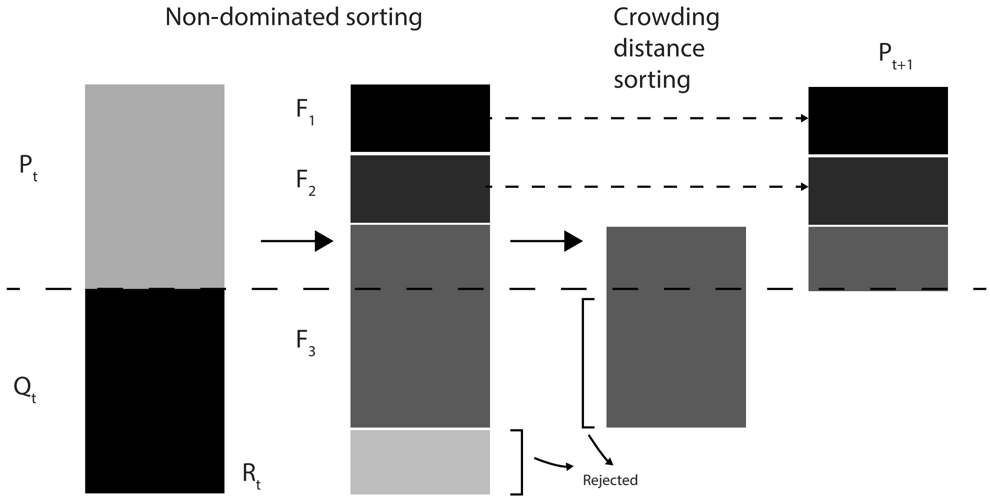

Figure 6: Schematic procedure of NSGA-II.

4 COMPUTATIONAL EXPERIMENTS

In order to perform the computational experiments, as previously mentioned, we will use small and large size instances. The first group of small instances will allow us to observe the existence of the trade-off and easily analyze the impact on the solution structure. On the other hand, we test five large Solomon [49] instances under four different scenarios (road combinations) to further analyze the impact of road conditions in the VRPTW.

For all instances, to relate the damage in the load with the road conditions, we used the results by Jarimopas et al. [25], who obtained the average damage percentage per load unit for two vehicle types in three road conditions corresponding to laterite, asphalt, and concrete roads. From these results we selected the average damage percentage in the two-ton truck at a speed of $40km/h$ for the three different road conditions. Then, the average damage was divided by 30 minutes, corresponding to the time at which the author conducted his experiment for each combination of speed and road condition, to obtain a rate in terms of time that we denominated P_{ij}. Table 3 shows the average damage per load unit percentages [25] and the P_{ij} for each road type. Finally, in every instance according to the road types present and considering that finding a specific road is equally probable, a damage rate was associated to each arc.

Table 3: Average damage and damage rate

Road type	Average damage (%/load unit) [25]	P_{ij} $(\%/min * load\ unit)$
Laterite	8.67	0.289
Asphalt	2	0.067
Concrete	4.67	0.156

In the following, we report on results for the small, and large size instances, respectively.

4.1 Small-size instances

Due to the absence of instances from the literature for this problem (with the inclusion of road types), and with the aim to validate the model, we proceeded to create new small size instances based on the ones proposed by Solomon for the VRPTW. Because the minimum number of customers in Solomon's instances is 25, to create each 10-customer instance, the number of needed customers was randomly selected from the 25 customer instances following a uniform distribution. Table 4 shows the selected 25-customer instances and the customers per instance.

Table 4: Instances and selected clients

Instance	Customers
RC201	{10; 19; 5; 7; 6; 3; 16; 22; 2; 25}
RC205	{16; 21; 17; 11; 2; 8; 13; 22; 7; 3}
RC105	{9; 25; 21; 13; 3; 11; 2; 15; 16; 4}
C105	{3; 23; 22; 8; 12; 5; 15; 25; 9; 7}
C207	{1; 5; 16; 17; 25; 2; 18; 7; 9; 23}

The small instances were solved using the AUGMECON method. For each 10-customer instances, 100 runs were performed by changing the ε_1 values according to the different ranges. The MIP model for all the instances was coded in GAMS 23.6 and optimally solved (0% GAP) with the solver CBC on a notebook with an Intel Dual I3 4005U processor at 1.7 GHz and 4 GB RAM running Windows 10 Home. Figure 7 shows the results for all 10-customer instances. The obtained graphs allow us to observe a conflict between the objectives and show the trade-off between delivering fewer damaged products and traveling shorter distances, under different road conditions.

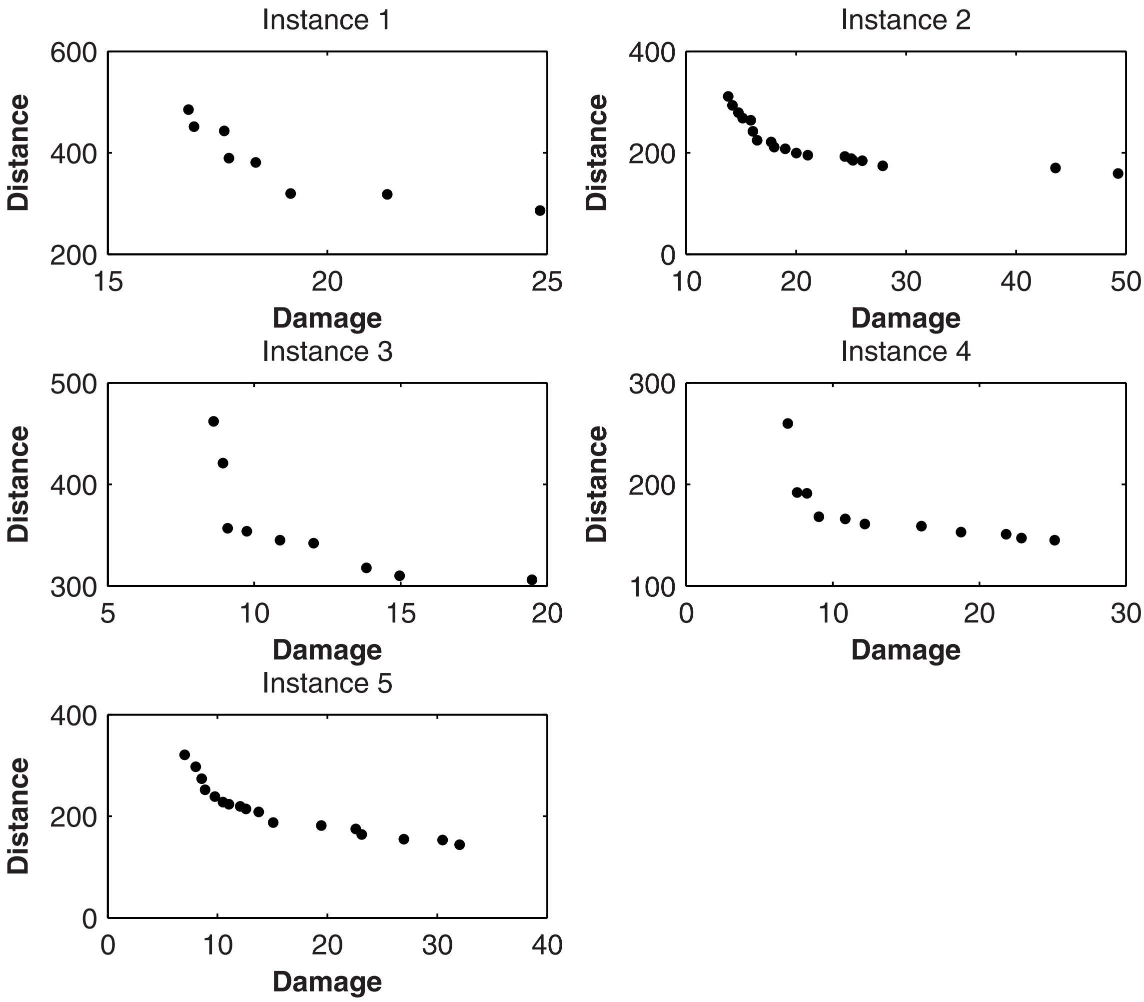

Figure 7: Pareto fronts for 10-customer instances.

To exemplify the change in the solution structure Figure 8 shows solutions for instance 1 in three cases: a) when the distance is minimized , b) when there is a trade-off between the objectives and c) when damage is minimized. It can be noted that, unlike a), solutions b) and c) select alternate arcs in order to avoid long bad conditions roads. As a result both solutions yield an increase in distance. Additionally, more routes are observed in c) than in cases a) or b).

4.2 Large-size instances

Instances C101, C202, R204, RC206, and C206 were randomly selected for evaluation. After, the NSGA-II was coded in MATLAB 2014a, and each instance was executed according to the parameters in Table 5. To select the crossover and mutation rates, we rely on the literature where this problem has been tested, showing good results with high crossover rates and low mutation rates [39, 47]. To choose the population size, tests were executed changing the population from 100 to 350 using a 50 individuals step.

Table 5: Parameters of the NSGA-II.

Parameter	Value
Crossover rate	0.95
Mutation rate	0.05
Running time	30 min
Population size	100

Each instance was executed for four different scenarios characterized by different road combinations as shown in Table 6. That is, the quantity of damaged products in every scenario is expected to be different. In scenario 1, each road type has a participation of one third of all arcs. Scenarios 2, 3, and 4 are formed by combinations of two road types, each of which has 50% of the arcs. As shown in our experiment, no scenario including only one type of road was considered.This is because when the roads are homogeneous (one type), the problem becomes a classical VRPTW. In that case, time could be considered the main factor influencing perishability. Each scenario was executed three times, after which the obtained fronts were combined and

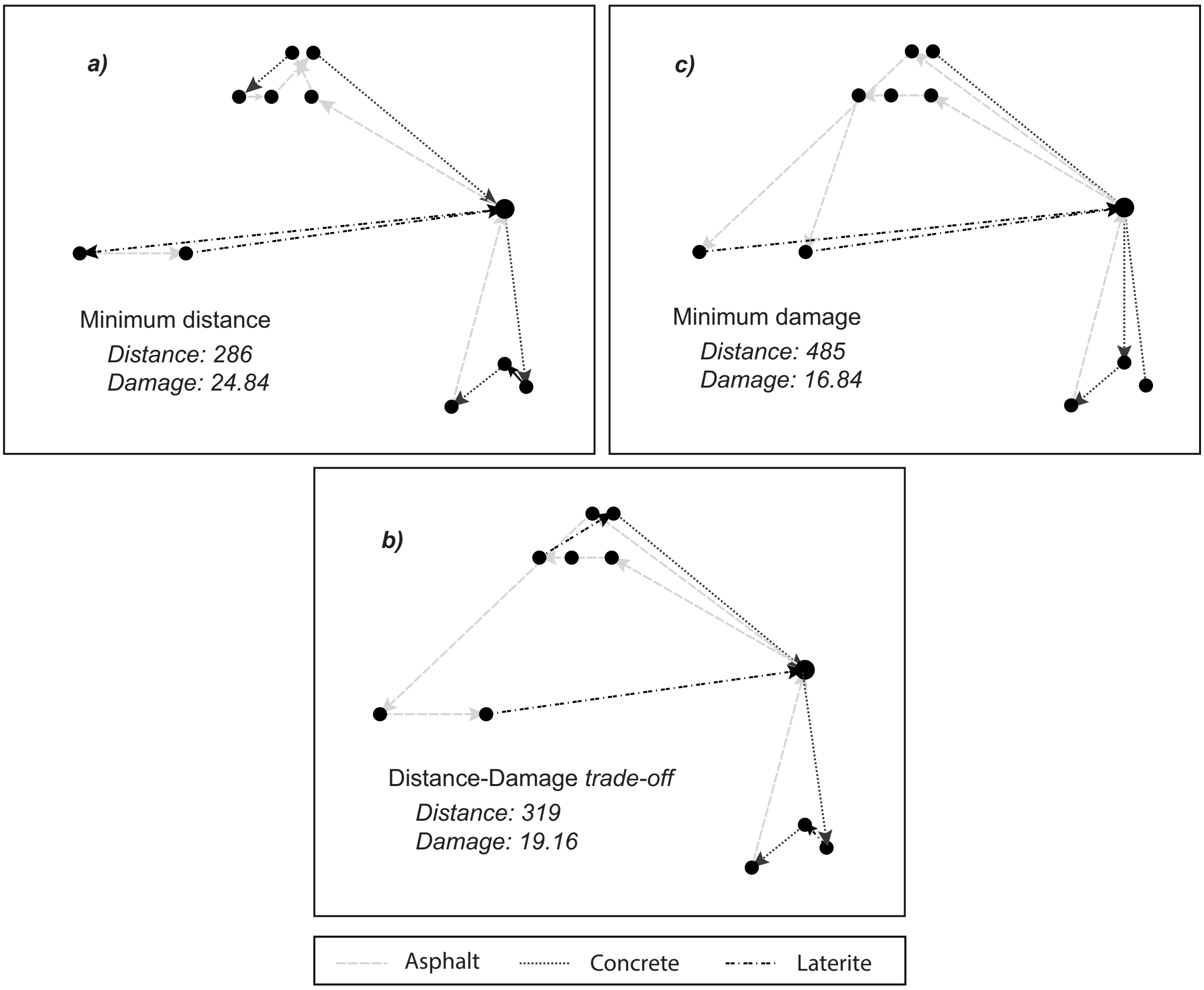

Figure 8: Change in solution structure under cases a, b and c.

sorted to form a final approximation to the Pareto front. Figure 9 shows the results for all 50-customer instances in all the scenarios.

Table 6: Road types combinations for each scenario

Scenario	Laterite	Concrete	Asphalt
1	✓	✓	✓
2		✓	✓
3	✓		✓
4	✓	✓	

Table 7 shows the average values for both objectives in each scenario for all 50-customer instances. It is possible to observe that, for every instance, less damage takes place in scenario 2, where roads are formed by a combination of asphalt and concrete roads. In contrast, scenario 4 showed the highest average damage corresponding to the combination of laterite and concrete roads. On average, the damaged products increased 111% when changing from scenario 2 to scenario 4 for all instances. Thus, we can say that the road conditions play an important role in the final number of damaged products. Regarding scenarios 1 and 3, in four of five instances scenario 3 showed less damaged products, only in instance C202 was the average damage greater in scenario 1 than scenario 3. Finally, it can be noted that distances values between the best an worst scenario (from left to right) are similar in each instance, but the number of damaged products increases according to the road combination of each scenario.

These results can also be observed in Figure 9 where equally efficient solutions per instance and scenario are shown, providing diverse useful alternatives to the decision maker. The difference in damage among the given scenarios can be easily observed because the Pareto fronts from lesser to greater damage go from left to right.

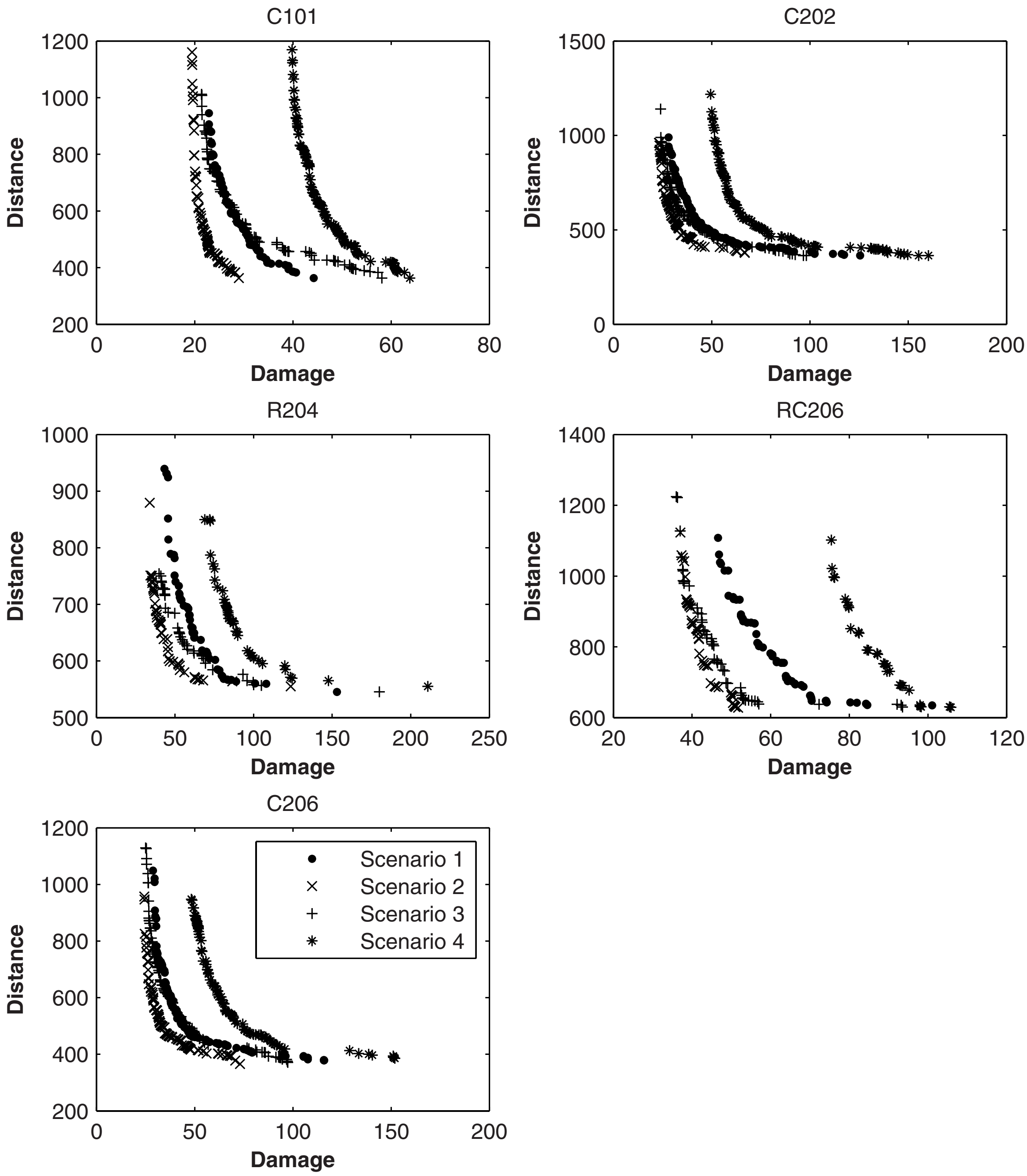

Figure 9: Pareto fronts of all scenarios for 50-customer instances.

Table 7: Average damage and distance by scenario.

Instance	Scenario	Damage (Average)	Damage increase	Distance (Average)	Distance variation
C101	1	28.68	25.4%	614.59	9.8%
	2	22.87	-	559.98	-
	3	33.62	47.0%	590.62	5.5%
	4	47.83	109.1%	644	15.0%
C202	1	51.32	56.4%	582.82	-3.8%
	2	32.81	-	606.07	-
	3	44.12	34.5%	601.19	-0.8%
	4	81.53	148.5%	607.93	0.3%
R204	1	65.75	39.4%	674.82	3.0%
	2	47.18	-	654.99	-
	3	62.51	32.5%	649.75	-0.8%
	4	93.84	98.9%	674.1	2.9%
RC206	1	61.41	43.2%	797.77	-2.6%
	2	42.89	-	818.79	-
	3	49.52	15.5%	808.7	-1.2%
	4	87.9	104.9%	791.32	-3.4%
C206	1	52.35	37.4%	552.16	3.1%
	2	38.11	-	535.35	-
	3	44.59	17.0%	619.31	15.7%
	4	73.49	92.8%	613.7	14.6%

5 MANAGERIAL IMPLICATIONS

It is possible to analyze the results from two perspectives: an economic perspective, where a penalty on the price for the damaged products can take place to quantify the effect in the total cost, and another where the damage could be seen as an intangible measure of customer satisfaction. In the first case, we could assign a coefficient to the first objective to quantify the cost of delivering damaged products. In the second case, because we want to maximize customer satisfaction, it would be equivalent to minimizing damaged products, which the first objective naturally does.

The first case might depend on parameters like the penalty percentage (dp) on the product's price for the incurred damage and the product's price (p). It is also possible to calculate the cost for the traveled distance by including a constant c_1 representing the transportation cost per kilometer, which will allow us to obtain the participation of the damage in the total cost. As an example, let's consider the parameters in Table 8 and the solutions for all instances under three different cases like the ones in Figure 8 (minimum distance, minimum damage, and a trade-off). Given those parameters, the economic loss due to damaged products can be calculated according to (15). Table 9 shows the related costs under cases a, b, and c for all instances. For the following analysis, we used scenario 1 (with the participation of the three road types) for 50-customer instances.

Table 8: Parameters to calculate costs.

Parameter	Value
c_1*(USD / km)* [5]	*0.78*
dp (%)	*30*
p (USD / load unit)	*5*

Table 9: Related costs under cases a, b and c for all instances.

Instance	Case	Damaged products	Distance	Damage Loss (USD)	Distance Cost (USD)
1	a	24.84	286	37.26	223.08
	b	19.16	319	28.74	248.82
	c	16.82	485	25.24	378.3
2	a	49.27	159	73.90	124.02
	b	18	211	27	164.58
	c	13.83	311	20.74	242.58
3	a	19.82	306	29.74	238.68
	b	10.89	345	16.32	269.1
	c	8.61	462	12.91	360.36
4	a	25.13	145	37.69	113.1
	b	10.85	166	16.27	129.48
	c	6.94	260	10.41	202.8
5	a	32.03	144	48.04	112.32
	b	12.06	219	18.09	170.82
	c	6.99	321	10.48	250.38
C101	a	44.22	363.24	66.34	283.33
	b	27.44	591.28	41.16	461.2
	c	22.88	945.63	34.32	737.59
C202	a	125.59	363.42	188.385	283.46
	b	34.82	707.31	52.23	551.70
	c	28.05	988.87	42.075	771.31
R204	a	153.19	545.4	229.785	425.41
	b	71.88	604.05	107.82	471.15
	c	43.16	939.22	64.74	732.59
RC206	a	101.06	635.02	151.59	495.31
	b	62.68	754.88	94.02	588.80
	c	46.64	1108.34	69.96	864.50
C206	a	115.89	378.27	173.835	295.05
	b	69.16	735	103.73	573.71
	c	28.79	1048.63	43.185	817.93

$$Damage\ loss(USD) = p * (damaged\ quantity) * dp \tag{16}$$

As seen in Table 9 the damaged products are greater in the 50-customer instances than 10-customer instances. Nevertheless, the average participation in the total transportation cost (damage loss and distance cost) is similar, being 13% and 17% for 10-and 50-customer instances, respectively. When addressed from an economic perspective, because both objectives are in cost terms, the problem reduces to finding the minimum cost, which can be done by calculating the costs in all the solutions on the Pareto front set using the adequate parameters.

Table 10: Damage reduction and distance increase when changing from case a to b in scenario 1.

Instance	Damage reduction (%)	Distance increase (%)
1	2.2%	11.5%
2	14.2%	32.7%
3	4.0%	12.7%
4	7.1%	14.4%
5	9.5%	52.0%
C101	2.0%	62.8%
C202	10.6%	94.7%
R204	11.3%	10.8%
RC206	3.9%	18.9%
C206	3.4%	57.7%

It is more suitable to analyze the proposed trade-off from a customer satisfaction perspective. In this case, it is useful to take into account the percentage of damaged-product reduction when the trade-off is considered, in order to compare it with the increase in traveled distance. For example, Table 10 shows the percentage of damage reduction and increase of distance when changing from scenario a to b. Then, as an example, it is up to the decision maker in instance 3 whether to sacrifice a 12.7% increase over the minimum distance to gain a 4% reduction in damage. The trade-off is likely to be accepted when greater damage reduction is achieved rather than a case, such in instance 5 where a large increase in distance resulted in little change to damage. To ease the decision, a manager could consider to accepting the trade-off under certain situations, like when the reduction and increase are greater or less than a percentage.

Regarding the average damage for 10-and 50-customer instances the percentage of damaged products in relation to the total demand is shown in Table 11. There we can observe that there is not a wide difference in the average percentage of damaged load for the different instance sizes. However, the 10-customer instances showed a slightly greater (1.4%) average percentage of damaged load than 50-customer instances.

Solomon's instances are clustered in six classes [39] C1, C2, R1, R2, RC1, and RC2. C-categorized problems are clustered geographically or according to time windows. Problems in category R have customer locations uniformly distributed, and RC instances have a hybrid nature. In addition problems C1, R1 and RC1 have narrow time windows. Considering this classification, clustered instances (C and RC-type) showed less average damage percentage than the R204 instance. Similarly, the evaluated instance with narrow time windows (C101) showed less average damage than instances of type C2, R2 and RC2, which have wider time windows.

Table 11: Average damage per instance and participation in total demand.

Instance	Average Damage	Demand	Percentage of total demand
1	19.1	250	8%
2	22.3	220	11%
3	12.0	220	6%
4	14.5	200	8%
5	16.0	210	8%
C101	28.7	860	4%
C202	51.3	860	6%
R204	65.8	721	10%
RC206	61.4	970	7%
C206	52.4	860	7%

6 CONCLUSIONS

In this paper, the authors proposed a model for a vehicle routing problem that deals with the distribution of a perishable product. The model addressed two distinct objectives: the minimization of damaged products and the minimization of the distance traveled. To achieve the first objective, the damage caused during transit under different road conditions was considered based on data found in the literature. The inclusion of this factor is relevant due to the products' perishability and the effects thatmechanical damage may have on the consumer-perceived quality.

To cope with the stated multi-objective problem, first five 10-customer instances from the literature were adapted and then solved using the AUGMECON method. Because the employed exact solution method presented limitations by not being able to find efficient solutions for large-size instances in reasonable time, five large Solomon instances were solved using an evolutionary algorithm. The results allowed us to observe trade-offs between the objectives and show that the proposed solutions methods are capable of finding sets of equally efficient solutions for the problem. For large instances, four different scenarios were explored. As a result, scenario 2 where only asphalt and concrete roads are present, showed the least damaged products. The results were analyzed from two perspectives: the economic, where the damage was quantified in terms of costs and expressed in relation with the transportation cost, and a perspective when the proposed trade-off is more suitable, where the perishable nature of the product is highly important to the planner in order to improve customer satisfaction.

In general, the proposed model could be used on a small scale when products are transported to wholesale distributors, factories, distribution centers, or on a greater scale when products are transported to retail distributors (supermarkets) and particular customers. The decision to consider a solution with the mentioned trade-off will depend on the extend to which the decision-maker is willing to improve customer satisfaction.

The application of the model in real life is limited by the available information on the road conditions and the associated mechanical damage to the products, as well as by the study of the effects of different factors on damage during transport. Future work shall be devoted to ascertaining the damage to different kinds of perishable food products under different road conditions and to better understand damage-causing factors such as vehicle speed, vehicle characteristics, and packaging, to ease their consideration on the vehicle routing problem. Finally, further research could focus on the resolution of larger instances of the problem and the development of variants to the proposed model, such as the use of a heterogeneous fleet of vehicles or multiproduct delivery.

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REFERENCES

1. Acican T, Alibaş K, Özelkök IS (2007) Mechanical Damage to Apples during Transport in Wooden Crates. Biosystems Engineering 96(2):239–248, doi:10.1016/j.biosystemseng.2006.11.002
2. Akkerman R, Farahani P, Grunow M (2010) Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. OR Spectrum 32(4):863–904, doi:10.1007/s00291-010-0223-2, URL https://doi.org/10.1007/s00291-010-0223-2
3. Amorim P, Almada-Lobo B (2014) The impact of food perishability issues in the vehicle routing problem. Computers and Industrial Engineering 67(1):223–233, doi:10.1016/j.cie.2013.11.006
4. Ayman H Amer Eissa NSA, Azam MM (2013) Vibration analysis influence during crisis transport of the quality of fresh fruit on food security. Cigr 15(3):181–190, URL http://www.cigrjournal.org/index.php/Ejounral/article/view File/2393/1780
5. Barnes G, Langworthy P (2004) Per mile costs of operating automobiles and trucks 1864:71–77
6. Berardinelli A, Donati V, Giunchi A, Guarnieri A, Ragni L (2003) Effects of Transport Vibrations on Quality Indices of Shell Eggs. Biosystems Engineering 86(4):495–502, doi:10.1016/j.biosystemseng.2003.08.017
7. Berardinelli A, Donati V, Giunchi A, Guarnieri A, Ragni L (2005) Damage to pears caused by simulated transport. Journal of Food Engineering 66(2):219–226, doi:10.1016/j.jfoodeng.2004.03.009
8. Chaiwong S (2016) Effect of impact and vibration on quality and damage in the british strawberries (March)
9. Chand P, Mohanty JR (2013) Solving Vehicle Routing Problem with Proposed Non-Dominated Sorting Genetic Algorithm and Comparison with Classical Evolutionary Algorithms. International Journal of Computer Applications 69(26):975–8887, doi:10.5120/12137-8421
10. Chen HK, Hsueh CF, Chang MS (2009) Production scheduling and vehicle routing with time windows for perishable food products. Computers and Operations Research 36(7):2311–2319, doi:10.1016/j.cor.2008.09.010
11. Chonhenchob V, Singh SP, Singh JJ, Sittipod S, Swasdee D, Pratheepthinthong S (2010) Measurement and analysis of truck and rail vibration levels in Thailand. Packaging Technology and Science 23(2):91–100, doi:10.1002/pts.881
12. Cordeau JF, Laporte G, Savelsbergh MW, Vigo D (2007) Chapter 6 vehicle routing. In: Barnhart C, Laporte G (eds) Transportation, Handbooks in Operations Research and Management Science, vol 14, Elsevier, pp 367–428, doi:https://doi.org/10.1016/S0927-0507(06)14006-2, URL http://www.sciencedirect.com/science/article/pii/S0927050706140062
13. Dabiri N, J Tarokh M, Alinaghian M (2017) New mathematical model for the bi-objective inventory routing problem with a step cost function: A multi-objective particle swarm optimization solution approach. Applied Mathematical Modelling 49:302–318, doi:10.1016/j.apm.2017.03.022
14. Deb K (2001) Multi-Objective Optimization Using Evolutionary Algorithms. doi:10.1109/TEVC.2002.804322
15. Deb K, Member A, Pratap A, Agarwal S, Meyarivan T (2002) A Fast and Elitist Multiobjective Genetic Algorithm : 6(2):182–197
16. Donoso, Yezid; Fabregat R (2007) Multi-Objective Optimitation in computer Network Using Metaheuristics
17. Ehmke J, Campbell A, Thomas B (2016) Optimizing for Costs and Emissions in Vehicle Routing in Urban Areas
18. Faulin J (2003) Applying MIXALG procedure in a routing problem to optimize food product delivery. Omega 31(5):387–395, doi:10.1016/S0305-0483(03)00079-3, URL http://www.sciencedirect.com/science/article/pii/S0305048303000793
19. Figliozzi M (2010) Vehicle Routing Problem for Emissions Minimization. Transportation Research Record: Journal of the Transportation Research Board 2197(2197):1–7, doi:10.3141/2197-

01, URL http:// trrjournalonline.trb.org/doi/10.3141/2197-01
20. Govindan K, Jafarian A, Khodaverdi R, Devika K (2014) Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. International Journal of Production Economics 152:9–28, doi:10.1016/j.ijpe.2013.12.028, URL http://dx.doi.org/10.1016/j.ijpe.2013.12.028
21. Grunert KG (2005) Food quality and safety: Consumer perception and demand. European Review of Agricultural Economics 32(3):369–391, doi:10.1093/eurrag/jbi011, arXiv:1011.1669v3
22. Hinsch RT, Slaughter DC, Craig WL, Thompson JF (1993) Vibration of fresh fruits and vegetables during refrigerated truck transport. Transactions of the ASAE 36(4):1039–1042
23. Hsu CI, Hung SF, Li HC (2007) Vehicle routing problem with time-windows for perishable food delivery. Journal of Food Engineering 80(2):465–475, doi:10.1016/j.jfoodeng.2006.05.029
24. Ittmann H, Schoeman C, King D, Bean W, Viljoen N (2010) 6th Annual state of logistics survey for South Africa 2009
25. Jarimopas B, Singh SP, Saengnil W (2005) Measurement and analysis of truck transport vibration levels and damage to packaged tangerines during transit. Packaging Technology and Science 18(4):179–188, doi:10.1002/pts.687
26. Jemai J, Zekri M, Mellouli K (2012) An NSGA-II Algorithm for the Green Vehicle Routing Problem. Springer, Berlin, Heidelberg, pp 37–48, doi:10.1007/978-3-642-29124-1 4, URL http://link.springer.com/10.1007/978-3-642-29124-1{_}4
27. Jones CS, Holt JE, Schoorl D (1991) A model to predict damage to horticultural produce duringtransport. Journal of Agricultural Engineering Research 50(C):259–272, doi:10.1016/S0021-8634(05)80019-8
28. Jozefowiez N, Semet F, Talbi EG (2008) Multi-objective vehicle routing problems.European Journal of Operational Research 189(2):293–309, doi:10.1016/j.ejor.2007.05.055, URL http://linkinghub.elsevier.com/retrieve/pii/S0377221707005498
29. Klas B, Krzysztof P (2012) Models for road surface roughness. Vehicle System Dynamics URL http://lup.lub.lu.se/record/2906395
30. Kuo RJ (2017) A Fuzzy Multi-Objective Vehicle Routing Problem for Perishable Products Using Gradient Evolution Algorithm
31. Lemken A (2015) Modeling road roughness with conditional random fields
32. Li P, He J, Zheng D, Huang Y, Fan C (2015) Vehicle Routing Problem with Soft Time Windows Based on Improved Genetic Algorithm for Fruits and Vegetables Distribution. Discrete Dynamics in Nature and Society 2015, doi:10.1155/2015/483830
33. Li Z, Thomas C (2014) Quantitative evaluation of mechanical damage to fresh fruits. Trends in Food Science & Technology 35(2):138–150, doi:10.1016/j.tifs.2013.12.001
34. Mavrotas G (2009) Effective implementation of the E-constraint method in Multi-Objective Mathematical Programming problems. Applied Mathematics and Computation 213(2):455–465, doi:10.1016/j.amc.2009.03.037, URL http://dx.doi.org/10.1016/j.amc.2009.03.037
35. Mendes RS, Wanner EF, Sarubbi JFM, Martins FVC (2016) Optimization of the vehicle routing problem with demand responsive transport using the NSGA-II algorithm. In: 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), IEEE, pp 2657–2662, doi:10.1109/ITSC.2016.7795983, URL http://ieeexplore.ieee.org/document/7795983/
36. Molina JC, Eguia I, Racero J, Guerrero F (2014) Multi-objective Vehicle Routing Problem with Cost and Emission Functions. Procedia - Social and Behavioral Sciences 160(Cit):254–263, doi:10.1016/j.sbspro.2014.12.137, URL http://linkinghub.elsevier.com/retrieve/pii/S1877042814062387
37. Norouzi N, Sadegh-Amalnick M, Tavakkoli-Moghaddam R (2017) Modified particle swarm optimization in a time-dependent vehicle routing problem: minimizing fuel consumption. Optimization Letters 11(1):121–134, doi:10.1007/s11590-015-0996-y, URL http://link.springer.com/10.1007/s11590-015-0996-y
38. Olorunda AO, Tung MA (2007) Simulated transit studies on tomatoes; effects of compressive load, container, vibration and maturity on mechanical damage. International Journal of Food Science & Technology 20(6):669–678, doi:10.1111/j.1365-2621.1985.tb01964.x, URL http://doi.wiley.com/10.1111/j.1365-2621.1985.tb01964.x
39. Ombuki B, Ross BJ, Hanshar F (????) Multi-objective genetic algorithms for vehicle routing problem with time windows. Applied Intelligence (1):17–30, doi:10.1007/s10489-006-6926-z
40. Osvald A, Stirn LZ (2008) A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. Journal of Food Engineering 85(2):285–295, doi:10.1016/j.jfoodeng.2007.07.008
41. Pretorius CJ (2012) Influence of Road Roughness on the Transportation of Fresh Produce (July):142–153
42. Rao W, Liu F, Wang S (2016) An Efficient Two-Objective Hybrid Local Search Algorithm for Solving the Fuel Consumption Vehicle Routing Problem. Applied Computational Intelligence and Soft Computing 2016:1–16, doi:10.1155/2016/3713918, URL http://www.hindawi.com/journals/acisc/2016/3713918/

43. Schoorl D, Holt JE (1985) Verification and application of a model for predicting damage to horticultural produce during transport. Agricultural Systems 16(2):67–83, doi:10.1016/0308-521X(85)90001-0
44. Shahbazi F, Rajabipour A, Mohtasebi S, Rafie S (2010) Simulated intransit vibration damage to watermelons. Journal of Agricultural Science and Technology 12:23–34
45. Singh A, Singh Y (1992) Effect of vibrations during transportation on the quality of tomatoes. Agricultural Mechanization in Asia, Africa and Latin America 23(2):70–72
46. Sittipod S, Swasdee D, Singh SP, Singh J (2009) Effect of Truck Vibration during Shipments in Thailand. Journal of Applied Packaging Research 3(1):27 – 38
47. Sivaram Kumar V, Thansekhar MR, Saravanan R, Miruna Joe Amali S (2014) Solving multi-objective vehicle routing problem with time windows by FAGA. Procedia Engineering 97:2176–2185, doi:10.1016/j.proeng.2014.12.461
48. Soleimani B, Ahmadi E (2014) Measurement and analysis of truck vibration levels as a function of packages locations in truck bed and suspension. Computers and Electronics in Agriculture 109:141–147, doi:10.1016/j.compag. 2014.09.009, URL http://dx.doi.org/10. 1016/j.compag.2014.09.009
49. Solomon MM (1987) Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints. Operations Research 35(2):254–265, doi:10.1287/opre.35.2.254, arXiv: 1405.7020v1
50. vdM Steyn WJ, Nokes B, du Plessis L, Agacer R, Burmas N, Popescu L (2015) Evaluation of the Effect of Rural Road Condition on Agricultural Produce Transportation. Transportation Research Record: Journal of the Transportation Research Board 2473(2473):33–41, doi:10.3141/2473-04
51. Tabatabaekoloor R, Hashemi SJ, Taghizade G (2013) Vibration Damage to Kiwifruits during. International Journal of Agriculture and Food Science Technology 4(5):467–474
52. Tarantilis CD, Kiranoudis CT (2001) A meta-heuristic algorithm for the efficient distribution of perishable foods. Journal of Food Engineering 50(1):1–9, doi:10.1016/S0260-8774(00)00187-4
53. Tarantilis CD, Kiranoudis CT (2002) Distribution of fresh meat. Journal of Food Engineering 51(1):85–91, doi:10.1016/S0260-8774(01)00040-1
54. Toth P, Vigo D (2014) Vehicle Routing: Problems, Methods, and Applications, second edi edn. MOS/SIAM
55. Urquhart N, Hart E, Scott C (2010) Building low CO2 solutions to the vehicle routing problem with Time Windows using an evolutionary algorithm. In: IEEE Congress on Evolutionary Computation, IEEE, pp 1–6, doi:10.1109/CEC.2010.5586088, URL http://ieeexplore.ieee.org/document/5586088/
56. Van Zeebroeck M (2005) The Discrete Element Method (DEM) to Simulate Fruit Impact Damage during Transport and Handling The Discrete Element Method (DEM) to Simulate Fruit Impact Damage during Transport and Handling. Phd thesis (643)
57. Van Zeebroeck M, Van linden V, Ramon H, De Baerdemaeker J, Nicola BM, Tijskens E (2007) Impact damage of apples during transport and handling. Postharvest Biology and Technology 45(2):157–167, doi:10.1016/j.postharvbio.2007.01.015
58. Vergano PJ, Testin RF, Newall WC, Jr (1991) Peach bruising: susceptibility to impact, vibration, and compression abuse. doi:10.13031/2013.31846
59. Vursavus K, Ozguven F (2004) Determining the effects of vibration and packaging method on mechanical damage in golden delicious apples. Turkish Journal of Agriculture and Forestry 28(311-320):311–320
60. Wang X, Wang M, Ruan J, Zhan H (2016) The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporalspatial Distance. Procedia Computer Science 96(September):1211–1220, doi:10.1016/j.procs.2016.08.165, URL http://dx.doi.org/10.1016/j. procs.2016.08.165
61. Wang X, Sun X, Dong J, Wang M, Ruan J (2017) Optimizing Terminal Delivery of Perishable Products considering Customer Satisfaction. Mathematical Problems in Engineering 2017:1–12, doi:10.1155/2017/8696910, URL https://www.hindawi.com/journals/mpe/2017/8696910/
62. Zhou R, Su S, Yan L, Li Y (2007) Effect of transport vibration levels on mechanical damage and physiological responses of Huanghua pears (Pyrus pyrifolia Nakai, cv. Huanghua). Postharvest Biology and Technology 46(1):20–28, doi:10.1016/j.postharvbio.2007.04.006