A Decision Support Tool for Urban Freight Transport Planning Based on a Multi-Objective Evolutionary Algorithm

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ABSTRACT We present an optimization procedure based on a hybrid version of an evolutionary multi-objective decision-making algorithm for its application in urban freight transportation planning problems. This tool is intended to solve the planning problems of a merchandise distribution firm that dispatches small volume fractional loads of fresh foods on daily schedules. The firm owns a network of distribution centers supplying a large number of small businesses in Buenos Aires and its surroundings. The recombination operator of the evolutionary algorithm used here has been designed specifically for this problem. It is intended to embody a strategy that takes into account constraints like temporary closeness, closeness time window and connectivity in order to improve its performance in the clustering phase. The representation allows incorporating specific information about the actual instances of the problem and uses adaptive control of the parameters in the calibration stage. The performance of the proposed optimizer was tested against the results obtained by two evolutionary algorithms, NSGA II and SPEA 2, widely used in similar problems. We use hypervolume as a measure of convergence and dispersion of Pareto fronts. The statistical analysis of the results obtained with the three algorithms uses the Wilcoxon rank sum test, which yields evidence that our procedure provides good results.

INDEX TERMS Decision making, decision support systems, evolutionary computation, genetic algorithms, logistics, Pareto optimization, road transportation, urban areas.

I. INTRODUCTION

Decision-making tools based on bio-inspired algorithms have been successfully used in logistics during the last decades. They have been continuously improved in the context of urban freight transport (UFT). The goal has always been increasing the efficiency and competitiveness of the firms, an objective usually hampered by the atomization of the sector and the complexity of logistic management at this stage of supply chains. A frequent issue involves taking into account in the decision-making process the needs of third parties since externalities over the relations with other agents may lead to quality and competitiveness losses in merchandise deliverance.

We seek here to overcome those limitations by changing to a multi-objective cooperative objective approach, taking into account the interests of all the parties involved in the process, ranging from managers of distribution centers to the final customers. We proceed by developing a hybrid version of an evolutionary multi-objective algorithm addressing the problem of a firm delivering perishable fresh goods from several distribution centers, carrying relatively small fractional volumes to a large number of grocery stores in Buenos Aires and its satellite counties.

II. LITERATURE REVIEW

Herbert A. Simon pioneered the view of decision-making as an iterative process in which rationality is bounded by the inherent features of the decision-maker and the context in which the decision has to be made [1]. Simon insisted that this process can be enhanced with the help of computational tools,
providing rational information to human decision-makers, that will be able to interpret it in the light of their knowledge and beliefs [2]. This does not mean that the entire process should become automated. On the contrary, the computational contribution consists in providing data and computer processing to help in the decision process [3], being human judgement the source of the final decision.

The study of decision-making in UFT indicates that agents make decisions evaluating simultaneously different objectives, usually conflicting ones [4]. Salazar, Carrasquero and Galván [5], took Simon’s insight, developing a decision-aid tool for this framework. The ensuing process proceeds by stages.

The first stage involves the construction of the decision-making model. That is, to state analytically a multi-objective optimization model and to choose a solution technique. A second stage involves the actual process of searching solutions. The human decision maker intervenes here by expressing her preferences with respect to the alternative solutions (see [6]–[12] and [13]). Finally, in the last stage, the decision-maker chooses the final solution from among several alternatives.

The initial characterization of the decision problem requires revising the different approaches to the UFT vehicle routing and truck loading problems. These approaches can be classified according to the characteristics of the distribution network. Miguel, Frutos and Tohmé [14] present such taxonomy. Considering that classification, we find that our problem of interest has features proper of certain variants of the Vehicle Routing Problem (VRP), namely the Capacitated Vehicle Routing Problem with Time Windows (CVRP-TW), the Multi Depot Vehicle Routing Problem (MD-CVRP) and the Time Dependent Vehicle Routing Problem (TD-CVRP). Figure 1 highlights the main components of our own problem (in the gray box).

The Capacitated Vehicle Routing Problem (CVRP) starts by considering the existence of a certain number of clients to be supplied with a given volume of merchandise from a single depot. To carry out the distribution there are a certain number of vehicles with given capacities. Each vehicle visits exactly once each of its assigned clients and each client is visited by a single vehicle. The sum of the demands of the clients assigned to each vehicle should not exceed its capacity. The objective is to determine the sequence of deliveries minimizing the total cost of distribution, which is assumed to be proportional to the distances traveled [15]–[22]. The Multi Depot Vehicle Routing Problem (MD-CVRP), is a variant of the CVRP which assumes multiple depots or storage sites with different locations [23]–[25]. The Vehicle Routing Problem with Time Windows (CVRP-TW), is the variant that assumes the existence of allowable time intervals for the deliverance to each client. The CVRP-TW, in turn, can adopt different variants, since time windows may exit for different elements of the service, be it the time of arrival at the clients’ stores, the working time of drivers, the hours of activity of depots, etc. [26]–[33]. Finally, the Time Dependent Vehicle Routing Problem (TD-CVRP), takes into account the variations of traffic density in different areas, causing fluctuations in the speed of the vehicles, independently of the distances traveled. Because of this, we focus on the minimization of traveling times and not the distance traveled by the vehicles [34].

Gayialis, Konstantakopoulos and Tatsiopoulos in a review of the literature on the Vehicle Routing Problem (VRP) [35], found that 92% of the contributions take into account capacity constraints (C-VRP); 39% of the works analyzed consider the time windows for delivery (VRP-TW); 12% minimizes the travel distance (TD-VRP) while 18% analyzes deliveries up from different centers (MD-VRP). According to [36] and [37], from all the studies of UFT problems with multiple storage sites, only 10% consider multiple objectives, and from these only a few assume simultaneously time windows and capacity constraints (MD-VRP-TW), but without considering temporal dependencies [38] and [39]. On the other hand, few articles consider simultaneously time dependences, time windows and capacity constraints (TD-CVRP-TW) [40] but without assuming multiple storage constraints. We compose these different formulations in a single framework. We call the resulting overall problem to be addressed in this paper the Multi-depot Time Dependent Capacitated Vehicle Routing Problem with Time Windows (MD-TDCVRP-TW).

With respect to the optimization criteria, according again Vega-Mejía et al. [37], among the multi-objective approaches, 52% minimize the total distance traveled, while the minimization of travelling time is an objective only in 13% of those contributions. Other objectives, as pointed out by those and other reviewers, are the minimization of the number of vehicles, as a way of reducing the sub-use of the vehicles [32] and [39]; the load balance in the vehicles, be it respect to the total time on each route, the amount of merchandise on each route, or the number of clients served by route [39]. This goal is particularly interesting from the point of view of the use of human resources [41]. Other objectives in the literature are the minimization of risks, present in the delivery of hazardous materials [23]; the minimization of CO₂ emissions [40] or the maximization of client satisfaction, derived from the satisfaction of the time constraints posed by them to minimize tardiness or earliness.

With respect to the selection of the solution method, since the problem is NP-hard ([42]–[44]), exact methods can only solve relatively small instances of the aforementioned types. It is natural then, that most of the methods applied in the literature are based on the use of meta-heuristics (80% of the
complying with the requirements of the clients; another goal is to balance the workload among the different vehicles.

In summary, the Multi-objective Multi-Depot Time Dependent Capacitated Vehicle Routing Problem with Time Windows (MO-MDTDCVRP-TW), can be defined as follows: Find the Pareto-optimal solutions (i.e. the Pareto front) obtained by simultaneously minimizing the total time of distribution and balancing the workload of the different vehicles, while satisfying the requests of many clients at the committed delivery times, departing from several distribution centers, using a fleet of vehicles with homogeneous load capacities and restricted working hours, taking into account the traffic flow density on the respective routes.

Upon the determination of the Pareto front, the decision-maker picks one solution on it.

IV. THE MODEL

The MO-MDTDCVRP-TW can be represented as a graph $G = (V, E)$, where $V$ is the set of nodes and $E$ the set of edges. $V$ can be partitioned in two subsets, that of storing sites and that of retailers, $V = V_S \cup V_R$, where $V_S = \{1, 2, \ldots, L\}$ is the set of $L = 4$ depots while $V_R = \{L+1, L+2, \ldots, L+R\}$ is the set of $R = 200$ grocery stores.

Each client $i \in V_R$ has a demand $d_i$, a service time $s_i > 0$ and time window $[o_i, c_i]$. These windows are of the “hard” type, meaning that if the vehicle reaches $i$ before $o_i$, it will not be received and will have to wait until $o_i$. In turn, if it reaches node $i$ after time $c_i$, it will be unable to deliver the request, making the program unfeasible. Besides, to ensure feasibility, vehicle $s$ cannot exceed $r_s$, defined as the maximal time of operation allowed in a day for that truck.

For each deposit $l \in V_S$ we assume $s_l = 0$, implying that the vehicle is already loaded at the start of the program. The fleet is $S_l = \{1, 2, \ldots, K_l\}$ consisting of $K_l$ vehicles. Each $s \in S_l$ has a load capacity of $Q = 400$ load units.

Each edge $(i, j) \in E$, has assigned a time $t_{ij}$, including $t_{ij}$, the time required to go from node $i$ to node $j$ on a given route, plus the service time at the destination node, $s_j$.

A. BINARY VARIABLES

We use the following binary variables:

- $x_{ij}^s$: which equals 1 if vehicle $s$ goes from $i$ to $j$, departing from storage site $l$ and 0, otherwise.
- $z_{ij}^s$: that equals 1 if vehicle $s$ reaches client $i$ before $e_i$ (in its time window), and 0 otherwise.

B. CONTINUOUS VARIABLES

The model includes the following continuous variables:

- $w_{ij}^l$: indicates the load of truck $s$ when going from $i$ to $j$ having departed from depot $l$.
- $t_{ij}^l$: indicates the time at which the vehicle $s$ reaches client $i$.
- $u_{ij}^l$: is the delay on the route due to arriving earlier at $i$.
C. OBJECTIVE FUNCTIONS

As discussed before, the problem consists of the simultaneous minimization of two functions:

\[
\min_{x_{ij}^l} F \left( x_{ij}^l \right) = (f_1, f_2)
\]  

(1)

Function \( f_1 \) represents the total time spent on all routes as well as the costs induced by early arrivals (i.e. waiting times):

\[
f_1 : \sum_{i \in V_L} \sum_{j \in V_R} \left( t_{ij} \cdot x_{ij}^l \right) + \sum_{i \in V_R} \left[ z_i^l \cdot (o_i - t_i) \right]
\]  

(1.1)

Function \( f_2 \), represents the standard deviation of work times between vehicles. Its minimization generates balanced workloads on all routes:

\[
f_2 := \sum_{s \in S} \sum_{i \in V_R} \sum_{j \in V_L} \sum_{i \in V_R} \left( \frac{1}{\sum_{s \in S} \sum_{i \in V_R} x_{ij}^l} \sum_{i \in V_R} \left( t_{ij} \cdot x_{ij}^l \right) + \sum_{i \in V_R} \left[ z_i^l \cdot (o_i - t_i) \right] \right) \]

\[ + \sum_{i \in V_R} \left[ z_i^l \cdot (o_i - t_i) \right] \]

\[ - \sum_{i \in V_R} \sum_{i \in V_R} \sum_{i \in V_R} \left( \frac{1}{\sum_{s \in S} \sum_{i \in V_R} x_{ij}^l} \sum_{i \in V_R} \left( t_{ij} \cdot x_{ij}^l \right) + \sum_{i \in V_R} \left[ z_i^l \cdot (o_i - t_i) \right] \right)^{1/2} \]

(1.2)

D. CONSTRAINTS

These constraints indicate that the number of vehicles used on a route cannot exceed the size of the fleet at the depot at its origin (|Sl| = Kl, ∀l ∈ VL).

\[
\sum_{s \in S} \sum_{i \in V_R} x_{ij}^l \leq K_l \quad \forall l \in V_L
\]  

(2)

The following constraints indicate that the total load cannot exceed the capacity of each vehicle:

\[
\sum_{r \in V_R} d_r \sum_{j \in V_R} x_{ij}^l \leq Q \quad \forall s \in S, \forall l \in V_L
\]  

(3)

The following ensure that each vehicle starts and ends at the same depot:

\[
\sum_{j \in V_R} x_{ij}^l = \sum_{j \in V_R} x_{ij}^l = 1 \quad \forall s \in S, \forall l \in V_L
\]  

(4)

These constraints preserve the flow. That is, if a vehicle \( s \) reaches client \( i \), it has to depart next from there:

\[
\sum_{i \in V_R, s \in S, j \in V_L} x_{ij}^l = \sum_{i \in V_R, s \in S, j \in V_L} x_{ij}^l = 1 \quad \forall r \in V_R
\]  

(5)

A vehicle cannot go from a depot to another:

\[
\sum_{j \in V_R} x_{ij}^l = \sum_{j \in V_R} x_{ij}^l = 0 \quad \forall s \in S, \forall l \in V_L
\]  

(6)

(7) indicates that the load on a truck traversing edge \((i, j)\) should not exceed the capacity of the vehicle:

\[
0 \leq x_{ij}^l \leq Q \cdot x_{ij}^l \forall i, j \in V, \forall s \in S, \forall l \in V_L
\]  

(7)

In turn (8) indicates that the merchandise unloaded at \( r \) must be equal to the demand of that client:

\[
\sum_{j \in V_R} \sum_{i \in V_R} x_{ij}^l \cdot (t_{ij} + u_r) \leq r \quad \forall s \in S, \forall l \in V_L
\]  

(8)

These constraints establish that the total time spent by a vehicle on a route cannot exceed the total time allowed for the route:

\[
\sum_{i \in V_R} t_{ij}^s \cdot (t_{ij} + u_r) \leq t_j^s \quad \forall j \in V_R, \forall l \in V_L, \forall s \in S
\]  

(9)

The following constraints that delays at the depots cannot be allowed:

\[
\sum_{s \in S} \sum_{i \in V_R} t_{ij}^s = \sum_{s \in S} u_r = 0 \quad \forall l \in V_L
\]  

(10)

(11) indicates that if a client \( j \) is served by \( s \) starting of a depot \( l \), after serving client \( i \), then the arrival time at \( j \) must be later than the departure time from \( i \):

\[
\sum_{i \in V_R} t_{ij}^s \cdot (t_{ij} + u_r) \leq t_j^s \quad \forall j \in V_R, \forall l \in V_L, \forall s \in S
\]  

(11)

The following constraints ensure that the deliveries verify the time windows:

\[
o_i - \sum_{s \in S} t_{ij}^s \leq c_i \cdot \sum_{s \in S} z_j^s \quad \forall i \in V_R
\]  

(12)

\[
\sum_{s \in S} t_{ij}^s - o_i \leq c_i \cdot \left( 1 - \sum_{s \in S} z_j^s \right) \quad \forall i \in V_R
\]  

(13)

\[
\sum_{s \in S} t_{ij}^s - c_i \leq r_s \quad \forall i \in V_R
\]  

(14)

Finally, the following define the range of values of the variables:

\[
x_{ij}^l \in [0, 1], \quad z_j^s \in [0, 1], \quad t_{ij}^s \in \mathbb{R}, \quad u_r \in \mathbb{R}, \quad w_{ij}^l \in \mathbb{R}
\]  

(15)

V. SOLUTION METHOD

The algorithm we use to run the optimization process is a hybrid variant of the elitist non-dominated sorting genetic algorithm (NSGA-II), developed by Deb, Agrawal, Pratap and Meyarivan [45]. NSGA-II is flexible enough to admit a representation and a crossover operation specifically defined for our problem. The knowledge of the decision maker contributes to guide the algorithm towards the best solutions. Here, in particular, we replace the Pareto dominance originally assumed in NSGA-II by the criterion of g-dominance [6].

We call our variant, HY-NSGA-II. Table 1 presents its pseudocode.
TABLE 1. Pseudocode HY-NSGA-II.

A. REPRESENTATION
We apply a path representation, based on the permutation of integers with a single chromosome consisting of four genomes for the calibration stage and three for the optimization stage. The first genome contains the sequence of clients; genomes 2 and 3 contain information about genome 1. In turn, genome 4 contains information about the parameters to be evolved in the calibration stage.

We present, as an example, the case of an individual representing the potential solution of an instance with 20 clients, 3 depots and at most four trucks per depot:

Chromosome: \{G_1\} \{G_2\} \{G_3\} \{G_4\}

Genomes:
- G_1: Sequence of client nodes to be visited on each route (Dim = 1 × R).
- G_2: Information about the interpretation of G_1 (Dim = 1 × (L × K)).
- G_3: Sequence of number of routes per depot (Dim = 1 × L).
- G_4: Parameters to evolve at the calibration stage.

In this example G_1 has twenty places, each one corresponding to one of the clients; each permutation of G_1 is a sequence of visits. G_2 has twelve entries, indicating where the routes are to be distinguished in G_1 for each depot (we assume here that each depot has the same amount of potential routes assigned to it, K). So, for instance, in G_2 the first route of depot 3 ends at 15 while the second one ends at 19, meaning that the second route from depot 3 covers the clients at positions 16 to 19 of genome 1, i.e. (13, 9, 20, 10).

Figure 2 shows the scheme of the chromosome.

The zeros of G_2 represent empty routes (non-contracted services) at each depot. The three places in G_3 indicate the amount of active routes per depot. Finally G_4, represents the parameters to be calibrated.

B. RECOMBINATION OPERATOR
We use an operator which we call ERX-MD, inspired in the edge recombination operator of Whitley, Starkweather and Fuquay [46]. The offspring is obtained by combining edges present in the chromosomes of the parents. This method has the better performances on representations based on integer permutations [47].

The improvements introduced in the progeny stems from the feasible edges of the parents, obtained according to the following steps:

1st. Feasible edge map: a list of feasible edges for each cluster corresponding to each depot is obtained.
2nd. Reclustering: the nodes in different clusters are regrouped, seeking to maximize the forward connections in each new cluster.
3rd tour construction: the progeny is obtained from feasible edge map and the forward connections, using a variant of the insertion heuristic of [48] as follows:

\begin{itemize}
  \item A node \( j \) becomes a child of \( i \) if it yields the lowest of the costs \( \vartheta \) obtained by weighing these three measures:
    \begin{align*}
      \vartheta_{ij} &= \alpha_1 \cdot tr_{ij} + \alpha_2 \cdot \delta_j + \alpha_3 \cdot \phi_j,
    \end{align*}
    \end{itemize}

The next node is obtained by comparing the values \( \vartheta_{ij} \) of the candidate \( j \) nodes connected to \( i \).

Figure 3 presents the schematics of this procedure.
Figure 3 shows a reclustering of two parents with ten nodes each and two clusters (depot 1 in dark gray and depot 2 in light gray), assuming a single route per cluster.

In the feasible edge map of each cluster, we can see that node 6 belongs to both clusters. In the reclustering, node 6 has to be assigned to cluster 2, given that it has a higher degree of connectivity than in cluster 1. If, instead, node 6 were assigned to cluster 1, it would become isolated after node 5 is assigned to cluster 2 (see Figure 5).

Figure 6 illustrates the graphs of the maps of the feasible edges, assigning node 6 to clusters 1 or 2. In this figure, we can see that by assigning node 6 to cluster 1, it reduces the feasible edges in cluster 2, leaving it only with two feasible edges.

In summary, ERX-MD assigns first clients to depots and then it determines the routes, defining how the clients of each depot have to be visited. This takes the information of the parents and regroups the over-assigned nodes to improve the connectivity in the subgraph of each cluster. Afterwards, the routes are determined without any further corrections.

This strategy solves, in a relatively cheap way, the problem of determining an offspring satisfying the constraints of this kind of problems. This is particularly relevant, considering the usual costs of eliminating unfeasible individuals.

With respect to the mutation operator, the relevant question is to introduce diversity by adapting a standard insertion operator. A gene from G1 is inserted in a feasible position of the same genome of a single individual, chosen at random. The change can have either inter-route, intra-route or inter-depot effects.

C. INTRODUCING PARTIAL PREFERENCES (G-DOMINANCE)

In the context of our problem, the decision-maker knows approximately well the zone of the objective space that is desirable according to the goals of all the parties. This information is used to guide the search towards feasible and efficient solutions. We use the concept of g-dominance to incorporate preferences up from a reference point g that determines the alternatives that are more or less preferred than g[6].

1The person in charge of scheduling the daily distribution of merchandise.
The g-dominance procedure is applied once a reference point is defined. This instance of a decision process is then solved by the application of our proposed HY-NSGA-II, yielding the portion of interest in the Pareto front \((FP^*)\). By visualizing the resulting solutions the decision maker will select an alternative, upon which she will generate departures, route assignments, time tables, metrics of performance, amount of vehicles used, average speed on the road, etc. If this resulting information is not satisfactory, the decision maker can select another solution from the portion of interest or even introduce a new reference point to start from scratch the search. This can be repeated until a solution acceptable for the decision maker is found.

The reports generated by the chosen solution are translated into the documents necessary for the execution of the distribution schedule (e.g. the roadmap for the drivers) and for the accounting and traceability activities associated to the delivery of goods.

VI. COMPUTER EXPERIMENTS

Given the features of the problem analyzed here, we lack of published benchmarks to which to compare the pros and cons of our algorithm. Therefore, we proceed to validate and test its performance on a real world instance, comparing the results to those obtained from the application of Deb, Agrawal, Pratap and Meyarivan’s [45] version of NSGAII without our variations and Zitzler, Laumanns and Thiele’s SPEA2 [49].

In order to generate significant comparisons we incorporate in the benchmarks the g-dominance strategy as well as the same mutation operator. We use a quantitative measure of both the convergence to the Pareto front and the distribution of solutions on that front, namely the Hypervolume Indicator (or S metric) [50]. This choice facilitates the evaluation of the relative performance of multi-objective optimizers, in particular when the actual Pareto front of the problem is unknown [50].
At the calibration stage we used a self-adapting strategy of parameter control, according to which the parameters evolve with the individuals, being codified as part of the chromosomes (see the Representation subsection) and subject to the same rules of variation and selection. The strategy of selecting successful parameters takes simultaneously into account the results from the three optimizers, as to avoid biases in favor of any of them. We obtained thus optimal parameters to run the experiments, with a crossing probability of 0.8, a probability of mutation of 0.01, a maximum of 1000 generations and a population of 500 individuals.
TABLE 3. Routes in solution B for G2.

| Dep. | Route | Start | End   | Load  |
|------|-------|-------|-------|-------|
| d1   | r1    | 8:00  | 19:51 | 389   | 185 | 166 | 086 | 088 | 046 | 031 | 144 | 011 | 006 | 134 | 157 | 053 | 060 | 063 | 001 |
| d1   | r2    | 12:00 | 19:42 | 297   | 175 | 051 | 161 | 067 | 174 | 176 | 054 | 121 | 092 | 089 | 085 | 127 |
| d1   | r3    | 8:00  | 19:38 | 388   | 007 | 094 | 143 | 076 | 101 | 034 | 139 | 184 | 009 | 163 | 070 | 162 | 043 | 117 | 012 | 084 |
| d1   | r4    | 8:00  | 18:45 | 196   | 065 | 168 | 192 | 167 | 021 | 002 | 015 | 169 |
| d2   | r1    | 16:00 | 19:27 | 175   | 064 | 027 | 071 | 010 | 015 | 015 | 016 | 091 | 102 | 096 | 142 |
| d2   | r2    | 12:00 | 19:40 | 327   | 020 | 032 | 165 | 081 | 035 | 154 | 151 | 109 | 129 | 170 | 079 | 155 |
| d2   | r3    | 8:00  | 19:49 | 360   | 030 | 104 | 111 | 095 | 113 | 038 | 132 | 190 | 078 | 062 | 064 | 056 | 178 | 180 | 198 |
| d2   | r4    | 8:00  | 19:44 | 257   | 041 | 140 | 160 | 058 | 055 | 066 | 080 | 177 | 128 | 200 |
| d2   | r5    | 8:00  | 16:00 | 98    | 110 | 172 | 194 | 193 |
| d3   | r1    | 8:00  | 16:36 | 391   | 005 | 119 | 057 | 069 | 083 | 173 | 133 | 047 | 045 | 075 | 016 | 091 | 102 | 096 | 142 |
| d3   | r2    | 12:00 | 19:56 | 367   | 013 | 114 | 145 | 118 | 120 | 130 | 036 | 146 | 090 | 098 | 033 | 039 | 017 | 135 | 037 |
| d3   | r3    | 8:00  | 18:49 | 357   | 018 | 122 | 137 | 023 | 138 | 126 | 159 | 147 | 082 | 040 | 029 | 074 | 179 | 156 |
| d3   | r4    | 8:00  | 17:38 | 122   | 149 | 191 | 181 | 182 | 199 |
| d4   | r1    | 8:00  | 15:38 | 384   | 003 | 123 | 116 | 107 | 019 | 097 | 028 | 024 | 014 | 136 | 108 | 115 | 153 | 059 | 061 |
| d4   | r2    | 8:00  | 18:41 | 398   | 008 | 072 | 087 | 052 | 131 | 048 | 099 | 158 | 073 | 068 | 077 | 050 | 049 | 044 | 042 | 026 |
| d4   | r3    | 16:00 | 19:26 | 151   | 022 | 125 | 100 | 150 | 124 | 152 |
| d4   | r4    | 8:00  | 19:37 | 241   | 025 | 095 | 103 | 112 | 171 | 186 | 188 | 197 | 196 | 195 |

A. GRAPHICAL REPRESENTATION OF THE SIMULATIONS

We start by running a simulation of the three algorithms, assuming that the regions of interest are at the extremes and the middle of the objectives space. We took the following as the reference points for g-dominance: \( G_1 = (290, 250) \), \( G_2 = (300, 180) \) and \( G_3 = (345, 145) \).

Figure 9 presents the results for HY-NSGA-II, NSGA-II and SPEA2.

Not knowing the actual Pareto front makes it impossible to compare the simulations with the actual front. But it is still possible to compare them with those obtained with the benchmark algorithms. In this sense, HY-NSGA-II seems to perform acceptably well.

We distinguished in the graphs the alternatives chosen by the decision maker. In Figure 10 we highlight those solutions (A, B and C, respectively) in the space of decisions.

The next table specifies solution B, chosen for reference point G2:

In this solution, between 48 and 58 clients are served per distribution center, using 4 or 5 vehicles in each route. Around a 70% of the capacity of the vehicle is used to transport the merchandise.

B. ANALYSIS OF THE RESULTS OF THE COMPUTER EXPERIMENTS

We evaluate the Hypervolume Indicator (H) for the solutions chosen by the decision maker, assuming a given reference point. We consider a point \( Q \) with \( f_1 = 1.000, f_2 = 2.000 \), dominated by all the solutions generated by the three algorithms. We consider three measures based on H, namely its average in 30 runs, for each algorithm, denoted \( \bar{H} \); the standard deviations, \( H_{\sigma} \); and the maximum value attained, \( H_{best} \). We obtained the following results:

These results show that our algorithm yields a higher average hypervolume, achieving a better degree of convergence than the benchmarks. This means that HY-NSGA-II ensures, according to this measure, better approximations to the relevant region of the (unknown) Pareto front.

On the other hand, the variability, measured by the standard deviation is similar and sometimes worse than that of the other two algorithms.
Another relevant consequence is that our algorithm performs better for reference points that demand more equilibrium between the tasks. Tables 4, 5 and 6 indicate that the average hypervolume obtained with HY-NSGA-II is higher than that of NSGA-II and SPEA2, for reference points leaning towards the right, as G3.

Figure 11 present the Boxplots capturing graphically the localization, variability and degree of asymmetry of the Hypervolume Indicator on the three reference points analyzed in Tables 4, 5 and 6.

This provides a graphical confirmation of the assessment already made on the basis of the statistical
TABLE 11. (Continued.) Summary information about the clients.

| Client | 67  | 68  | 69  | 70  | 71  | 72  | 73  | 74  | 75  | 76  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| H      | 0.52| 0.52| 0.52| 0.53| 0.6  | 0.53| 0.51| 0.5  | 0.59| 0.63|
| L      | 0.41| 0.37| 0.36| 0.36| 0.41| 0.42| 0.39| 0.42| 0.41| 0.39|
| Time   | 30  | 25  | 26  | 22  | 24  | 23  | 29  | 25  | 24  | 21  |
| 12:00  | 12:00| 8:00| 16:00| 12:00| 8:00| 16:00| 12:00| 8:00| 16:00| 8:00|
| 15     | 15  | 15  | 15  | 15  | 15  | 15  | 15  | 15  | 15  | 15  |

We provide a further assessment of the algorithm, using the Wilcoxon Rank Sum Test [51]. This is a non-parametric test based on pairwise comparisons between the hypervolumes generated by the algorithms. Tables 7, 8, and 9 presents the results for the three reference points, at a significance level of 5%, with the null hypothesis: the algorithms yield the same median.

The results allow us to reject the null hypothesis and conclude that the median value of the hypervolume under HY-NSGA-II is higher than with the other algorithms.

VII. CONCLUSION

We presented a multi-objective optimization procedure for Urban Freight Transport planning. Starting from an actual problem of scheduling the delivery of merchandise to a network of clients, aligned on different routes departing from

### TABLE 12. Routes corresponding to solution A with reference point G1.

| Route | Dep. | Start | End | Load |
|-------|------|-------|-----|------|
| d1    | 1    | 8:25  | 18:57| 389  |
| r1    | 2    | 8:00  | 17:04| 380  |
| r3    | 3    | 8:00  | 18:41| 371  |
| r4    | 4    | 8:00  | 19:26| 288  |
| r5    | 5    | 16:00| 19:47| 177  |
| r7    | 7    | 16:00| 16:00| 27   |
| d2    | 1    | 16:00| 19:48| 193  |
| r1    | 2    | 12:00| 19:38| 328  |
| r3    | 3    | 8:00  | 19:14| 384  |
| r4    | 4    | 8:00  | 16:26| 136  |
| d3    | 1    | 12:00| 19:25| 361  |
| r1    | 2    | 8:00  | 17:42| 376  |
| r3    | 3    | 8:00  | 17:57| 222  |
| d4    | 1    | 16:00| 19:29| 166  |
| r1    | 2    | 8:00  | 16:00| 396  |
| r3    | 3    | 8:00  | 17:38| 385  |
| r4    | 4    | 8:00  | 19:34| 242  |
| d5    | 1    | 12:00| 19:27| 356  |
| r1    | 2    | 8:00  | 18:15| 195  |
| r5    | 5    | 8:00  | 16:00| 57   |
| d2    | 1    | 12:00| 19:47| 333  |
| r1    | 2    | 8:00  | 17:40| 395  |
| r3    | 3    | 8:00  | 19:47| 235  |
| r4    | 4    | 8:00  | 19:00| 155  |
| d3    | 1    | 12:00| 19:27| 356  |
| r1    | 2    | 12:00| 19:38| 358  |
| r3    | 3    | 8:00  | 19:53| 371  |
| r4    | 4    | 8:00  | 18:49| 193  |
| r5    | 5    | 8:00  | 18:27| 68   |
| d4    | 1    | 16:00| 19:53| 163  |
| r1    | 2    | 8:00  | 16:52| 396  |
| r3    | 3    | 8:00  | 18:45| 394  |
| r4    | 4    | 8:00  | 18:52| 170  |
| r5    | 5    | 8:00  | 16:00| 40   |

### TABLE 13. Routes corresponding to solution C with reference point G3.

| Route | Dep. | Start | End | Load |
|-------|------|-------|-----|------|
| d1    | 1    | 8:58  | 16:34| 384  |
| r1    | 2    | 8:00  | 18:19| 390  |
| r3    | 3    | 8:00  | 19:52| 378  |
| r4    | 4    | 8:00  | 18:15| 195  |
| r5    | 5    | 8:00  | 16:00| 57   |
| d2    | 1    | 12:00| 19:47| 333  |
| r1    | 2    | 8:00  | 17:40| 395  |
| r3    | 3    | 8:00  | 19:47| 235  |
| r4    | 4    | 8:00  | 19:00| 155  |
| d3    | 1    | 12:00| 19:27| 356  |
| r1    | 2    | 12:00| 19:38| 358  |
| r3    | 3    | 8:00  | 19:53| 371  |
| r4    | 4    | 8:00  | 18:49| 193  |
| r5    | 5    | 8:00  | 18:27| 68   |
| d4    | 1    | 16:00| 19:53| 163  |
| r1    | 2    | 8:00  | 16:52| 396  |
| r3    | 3    | 8:00  | 18:45| 394  |
| r4    | 4    | 8:00  | 18:52| 170  |
| r5    | 5    | 8:00  | 16:00| 40   |
| Reference           | Year | Model type | Method                          | Objective                                                                 | Preferences |
|---------------------|------|------------|--------------------------------|---------------------------------------------------------------------------|-------------|
| Frutos et al. [15]  | 2016 | CVRP       | Genetic Algorithm              | Minimization of the total distance traversed by all vehicles              | --          |
| Letchford et al. [16]| 2019 | CVRP       | Primal and dual simplex        | Minimize the cost of the routes.                                          | --          |
| Lin et al. [17]     | 2019 | CVRP       | Hybrid Genetic Algorithm       | Minimize the total cost of the distribution.                              | --          |
| Sooktip et al. [18] | 2015 | CVRP       | NSGA-II                        | Minimize transportation distance. Minimize transportation time.           | R-NSGA-II [13] |
| Altabeeb et al. [19]| 2019 | CVRP       | Firefly algorithm (FA)         | Minimize the total routing cost.                                          | --          |
| Pecin et al. [20]   | 2017 | CVRP       | Exact branch-cut-and-price algorithm (BCP) | Minimize the total routing cost.                                          | --          |
| Frutos et al. [21]  | 2012 | CVRP       | Genetic Algorithm              | Minimize the total distance traversed by all vehicles.                    | --          |
| Roch et al. [22]    | 2019 | CVRP       | Hybrid method based on the 2-phase-heuristic | Optimal routes from one depot to a number of geographically scattered customers. | --          |
| Jiaoman et al. [23] | 2017 | MD-CVRP    | Improved biogeography based algorithms (BBO) | Minimize the total risk of accident. Minimize time for non-fixed destination. | --          |
| Filipec et al. [24] | 2000 | MD-CVRP    | Genetic Algorithm              | Minimize cost set of routes between depots.                               | --          |
| Skok et al. [25]    | 2000 | MD-CVRP    | Genetic Algorithm              | Minimize a combination of distance and vehicle acquisition costs.          | --          |
| Miguel et al. [26]  | 2016 | CVRP-TW    | Mathematical programming + genetic algorithm | Minimize the total routing cost.                                          | --          |
| Khachay et al. [27] | 2018 | CVRP-TW    | Improved Polynomial Time Approximation Scheme (EPTAS) | Minimize the total transportation costs.                                   | --          |
| Bujel et al. [28]   | 2019 | CVRP-TW    | Recursive-DBSCAN clustering algorithm | Determine a route schedule which minimizes the travelled distance.         | --          |
| González et al. [29] | 2017 | CVRP-TW    | Memetic algorithm with simulated annealing | Minimize the cost of the routes.                                          | --          |
| Soenandi et al. [30] | 2019 | CVRP-TW    | Ant colony optimization (ACO) algorithm | Minimize total transportation costs.                                       | --          |
| Rochman et al. [31] | 2017 | CVRP-TW    | Biased Random Key Genetic Algorithm | Minimize the total distribution costs.                                     | --          |
| Cardoso et al. [32] | 2015 | CVRP-TW    | Push Forward Insertion Heuristic (PFIH) | Minimize the total number of vehicles required. Minimize the total traveled distances. | --          |
| Kirci et al. [33]   | 2016 | CVRP-TW    | Tabu search                     | Minimize total distance travelled by vehicles.                             | --          |
| Ng et al. [34]      | 2017 | TD-CVRP    | Artificial Bee Colony (ABC) algorithm | Minimize the total travelling time.                                        | --          |
| Gayallis et al. [35] | 2019 | Survey     |                                 | Minimize the delivery cost with respect to travel distance. Minimize the travel time. | --          |
| Montoya-Torres et al. [36] | 2015 | Survey     |                                 | Minimize the delivery cost with respect to travel distance. Minimize the travel time. | --          |
| Vega-Mejía et al. [37] | 2019 | Survey     |                                 | Minimize the delivery cost with respect to travel distance. Minimize the travel time. | --          |
| Shankar et al. [38] | 2014 | MD-CVRP-TW | Tabu search algorithm           | Minimize the delivery cost with respect to travel distance. Minimize the travel time. | --          |
| Novoa-Flores et al. [39] | 2018 | MD-CVRP-TW | Adaptive Large Neighborhood Search | Minimize the total distance traveled by trucks. Minimize the number of trucks used. Maximize the number of collected requests. | --          |
| Kazemian et al. [40] | 2017 | TD-CVRP-TW | Simulated annealing algorithm   | Minimize the fuel consumption and GHG emission.                           | --          |
| Present study       |      | MD-TD-CVRP-TW | Hybrid NSGA-II                | Minimize the total time spent on all routes. Minimize the standard deviation of work times between vehicles. g-dominance [6] | --          |
several distribution centers, we modeled this situation as an optimization problem in which different objectives can be satisfied.

Among those objectives we considered the timing of the deliveries and the balance of loads on the vehicles. In both cases the idea is to reduce the costs involved in the distribution of goods. To solve the problem we took into consideration different constraints, ranging from the layout of the network of clients to the driving and parking regulations near the delivery points.

We called this problem MO-TDMDCVRPTW (Multi-objective Time Dependent Multi-Depot Capacitated Vehicle Routing Problem with Time Windows). Given its intractability, we chose to search for solutions applying a Multi-objective Evolutionary Algorithm (MOEA), a hybrid of the Non-dominated Sorting Genetic Algorithm (NSGA-II). We added two improvements, the first consisting in the incorporation of specific knowledge of the problem in the chromosomes of the four genomes on which run the evolutionary process. The second improvement is the use of the recombination procedure ERX-MD, which we specifically designed for this problem. It ensures that solutions satisfy the constraints without requiring costly repairs.

We also use the g-dominance strategy, which allows the introduction of the preferences of the decision maker, in order to lead the search towards regions of interest for her. The experience of the decision maker becomes then an integral part of the whole procedure.

Since the literature does not present previous results on this issue, the only way to assess the quality of our proposal is by comparison with other, more established, procedures. Using data from a real world case, we addressed it using our algorithm, HY-NSGA-II, as well as NSGA-II (in its original form, without our improvements) and SPEA2.

Our computer experiments allow us to conclude that our algorithm HY-NSGA-II is more efficient both in the convergence towards the actual Pareto front and in the distribution of solutions over the front for each of the three reference points. With respect to the variability, represented by the standard deviation of the hypervolume indicators, the results are similar to those obtained with the other two algorithms. We can see that the improvements obtained by HY-NSGA-II are larger for the reference points that correspond to more balanced schedules.

This means that HY-NSGA-II is significantly better than NSGA-II and SPEA2, which constitute, in turn, the best known algorithms for this kind of combinatorial optimization problems.

Future results involve the incorporation of further details of the real world instances of the problem. In particular, we intend to increase the number of objectives, capturing relevant aspects of decision making in logistics. Another extension involves applying other tools of computational intelligence, as fuzzy logic or neural networks, which may contribute to find even better solutions.

APPENDIX

See Tables 10–14.

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