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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.

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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,

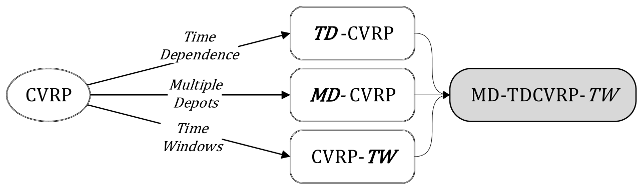


FIGURE 1. **Outline of the problem.**

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 automatized. 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 CO_2 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 contributions in the last decades), and pure heuristics (in the order of 15%), while all other methods are used only in 5% of the contributions.

Exact techniques (in small instances) have been used in [16], [20], [27], [28]. Among the *heuristical methods* used we can find *local search* [39], *two-phase heuristics* [22] and *insertion heuristics* [32], and *combination heuristics* [26].

The *meta-heuristics* that have been applied in the UFT context are *ant colony optimization* [30], *artificial bee colony* [34], *biogeography-based* algorithms [23], the *firefly* algorithm [19], *evolutionary algorithms* [15], [17], [18], [24], [25], [31], [21], *taboo search* [33], [38] and *simulated annealing* [29], [40], among others. From the articles that address multi-objective versions of VRP with more than 20 nodes (clients), in more than 80% of them use, as said, meta-heuristics, and among them, in particular *Evolutionary Multi-Objective Algorithms* (MOEAs) [36]. The successes in the use of MOEAs for the treatment of problems related to ours lead us to adopt this approach for our analysis. A summary of CVRP literature and its variants, relevant for our analysis, is presented in Table XIV (in the Appendix).

III. CHARACTERIZATION OF THE PROBLEM

As indicated previously, we focus on the case faced by the head of logistics of a fresh foods distribution company that works on daily schedules, delivering its merchandise with a fleet of trucks to wholesale sellers in four regional marketplaces, which have contracts with two hundred grocery stores in the Buenos Aires metropolitan area (GBA). Tables 10 and 11 of the Appendix present detailed information about the distribution centers and the clients.

These goods are distributed in urban settings. Several of the delivery *routes* are congested during working hours, and thus the average speed of the vehicles on them are lower than in other routes. We consider then t_{ij}, the time that takes to go from site i site j on a given route, independently of the distance traversed.

The *load unit* consists of a homogeneous cardboard box weighting 20 kg, with a length of 50 cm, width 32 cm and height 30 cm. These boxes can be piled up, ensuring a compact use of space in the truck. The *vehicle fleet* consists of homogeneous trucks with capacity and speed that agree with normative rulings for urban transportation. We assume here that each of them can load 8.000 kg (400 *load units*).

Each *client* prepares a request detailing the number of load units and the time window at which it is able to receive it. This means that no delays can be admitted and, if a truck arrives earlier it has to wait to carry out the deliverance. The *service times* at the facilities of the clients involves the times from arrival to departure, which depend in particular from the intermediate activities of parking, unloading, signing documentation, etc.

With respect to the objectives, we consider the agent in charge of designing the distribution plan seeks to minimize the *distribution times* (a proxy for the costs in urban contexts) 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, $V = V_L \bigcup V_R$, where $V_L = \{1, 2, \ldots, L\}$ 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 $ts_i > 0$ 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 $l \in V_L$ we assume $ts_l = 0$, 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 tr_{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, ts_j.

A. BINARY VARIABLES

We use the following binary variables:

- x_{ij}^{sl}, which equals 1 if vehicle s goes from i to j, departing from storage site l and 0, otherwise.
- z_i^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}^{sl} : indicates the load of truck s when going from i to j having departed from depot l.
- t_i^s : indicates the time at which the vehicle s reaches client i.
- u_i^s : 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:

$$\min_{x_{ij}^{sl}} F\left(x_{ij}^{sl}\right) = (f_1, f_2) \tag{1}$$

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

$$f_1 : \sum_{\substack{l\in V_L \\ s\in S_l}} \sum_{\substack{i,j\in V_R \\ i\neq j}} \left(tr_{ij} \cdot x_{ij}^{sl}\right) + \sum_{i\in V_R} \left[z_i^s \cdot \left(o_i - t_i^s\right)\right] \tag{1.1}$$

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

$$f_2 : \left\{ \frac{1}{\sum_{s\in S_l} \sum_{j\in V_R} x_{lj}^{sl}} \cdot \sum_{l\in V_L} \sum_{s\in S_l} \left(\sum_{\substack{i,j\in V_R \\ i\neq j}} \left(tr_{ij} \cdot x_{ij}^{sl}\right) + \sum_{i\in V_R} \left[z_i^s \cdot \left(o_i - t_i^s\right)\right] - \frac{\sum_{l\in V_L} \sum_{s\in S_l} \left(\sum_{\substack{i,j\in V_R \\ i\neq j}} \left(tr_{ij} \cdot x_{ij}^{sl}\right) + \sum_{i\in V_R} [z_i^s \cdot (o_i - t_i^s)]\right)}{\sum_{s\in S_l} \sum_{j\in V_R} x_{lj}^{sl}} \right)^2 \right\}^{1/2} \tag{1.2}$$

D. CONSTRAINS

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 ($|S_l| = K_l, \forall l \in V_L$).

$$\sum_{s\in S_l} \sum_{j\in V_R} x_{lj}^{sl} \leq K_l \quad \forall l \in V_L \tag{2}$$

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

$$\sum_{r\in V_R} d_r \sum_{j\in V_R} x_{rj}^{sl} \leq Q \quad \forall s \in S, \ \forall l \in V_L \tag{3}$$

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

$$\sum_{j\in V_R} x_{lj}^{sl} = \sum_{j\in V_R} x_{jl}^{sl} \leq 1 \quad \forall s \in S, \ \forall l \in V_L \tag{4}$$

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

$$\sum_{\substack{i\in V_R, s\in S, \\ l\in V_L}} x_{ir}^{sl} = \sum_{\substack{i\in V_R, s\in S, \\ l\in V_L}} x_{ri}^{sl} = 1 \quad \forall r \in V_R \tag{5}$$

A vehicle cannot go from a depot to another:

$$\sum_{j\in V_L} x_{jl}^{sl} = \sum_{j\in V_L} x_{lj}^{sl} = 0 \quad \forall s \in S, \ \forall l \in V_L \tag{6}$$

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

$$0 \leq w_{ij}^{sl} \leq Q \cdot x_{ij}^{sl} \forall i, j \in V, \quad \forall s \in S, \ \forall l \in V_L (7) \tag{7}$$

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

$$\sum_{j\in V_R} \sum_{s\in S} x_{jr}^{sl} \cdot w_{jr}^{sl} - x_{jr}^{sl} \cdot w_{rj}^{sl} = d_r \quad \forall r \epsilon V_R, \ \forall l \in V_L \tag{8}$$

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

$$\sum_{\substack{i,j\in V_R \\ i\neq j}} x_{ij}^{sl} \cdot \left(tr_{ij} + u_i^s\right) \leq r_s \quad \forall s \in S, \ \forall l \in V_L \tag{9}$$

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

$$\sum_{s\epsilon S} t_l^s = \sum_{s\epsilon S} u_l^s = 0 \quad \forall l \in V_L \tag{10}$$

(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:

$$\sum_{\substack{i\in V_R \\ i\neq j}} x_{ij}^{sl} \cdot \left(t_i^s + tr_{ij} + u_i^s\right) \leq t_j^s \quad \forall j \in V_R, \ \forall l \in V_L, \ \forall s \in S \tag{11}$$

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

$$o_i - \sum_{s\in S} t_i^s \leq c_i \cdot \sum_{s\in S} z_i^s \quad \forall i \in V_R \tag{12}$$

$$\sum_{s\in S} t_i^s - o_i \leq c_i \cdot \left(1 - \sum_{s\in S} z_i^s\right) \quad \forall i \in V_R \tag{13}$$

$$\sum_{s\in S} t_i^s - c_i \leq r_s \quad \forall i \in V_R \tag{14}$$

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

$$x_{ij}^{sl} \in \{0, 1\}, \quad z_i^{s1} \in \{0, 1\}, \ t_i^s \in \mathbb{R}, u_i^s \in \mathbb{R}, \ w_{ij}^{sl} \in \mathbb{R} \tag{15}$$

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.

Start
$t = 0$ // *Generation*
$P_0 \leftarrow$ Generate at random the *Initial Population*
Evaluate$_g$ individuals of P_t
$P_t = (FP_1, FP_2, \ldots) \leftarrow$ Apply *Undominated ordering* on P_t
For $\forall FP_i \in P_0$ **do**:
    Compute the Crowding Distance to FP_i
End-For
$t \leftarrow 0$
While the *stopping criterion* is not reached **do**
  Parents $\leftarrow$ Apply *Tournament Selection* to P_t
  $Q_t \leftarrow$ Apply *evolutionary operators* to *Parents* // *Children*
  Evaluate$_g$ *Offspring*, Q_t
  $R_t = P_t \cup Q_t$
  $R_t = (FP_1, FP_2, \ldots) \leftarrow$ Apply *Undominated ordering* on R_t
  $i \leftarrow 1$ // *number of front*
  $P_{t+1} \leftarrow \emptyset$
  While $|P_{t+1}| + |FP_i| < N$ **do:** // *N, number of individuals in P_t*
    Compute the Crowding Distance to FP_i
    $P_{t+1} \leftarrow P_{t+1} \cup FP_i$
    $i \leftarrow i + 1$
  End-While
  $FP_i' \leftarrow$ Apply *Ordering by Crowding Distance* FP_i
  $P_{t+1} \leftarrow P_{t+1} \cup FP_i[N - |P_{t+1}|]$
  $t \leftarrow t + 1$
End-While

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: {[G1] [G2] [G3] [G4]}

Genomes:

- *G1:* Sequence of client nodes to be visited on each route ($Dim = 1 \times R$).
- *G2:* Information about the interpretation of *G1* ($Dim = 1 \times (L \times K)$).
- *G3:* Sequence of number of routes per depot ($Dim = 1 \times L$).
- *G4:* Parameters to evolve at the calibration stage.

In this example *G1* has twenty places, each one corresponding to one of the clients; each permutation of *G1* is a sequence of visits. *G2* has twelve entries, indicating where the routes are to be distinguished in *G1* for each depot (we assume here that each depot has the same amount of potential routes assigned to it, K). So, for instance, in *G2* 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 *G2* represent empty routes (non-contracted services) at each depot. The three places in *G3* indicate the amount of active routes per depot. Finally *G4*, represents the parameters to be calibrated.

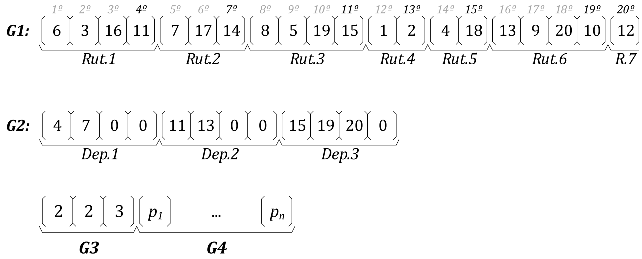


FIGURE 2. Structure of the chromosome.

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:
A node j becomes a child of i if it yields the lowest of the costs ϑ obtained by weighing these three measures:

- $\boldsymbol{tr_{ij}}$: *Temporary Closeness*: it is obtained as the average speed of traveling the edge between nodes i and j.
- $\boldsymbol{\delta_j}$: *Connectivity*: computes the number of forward nodes from j.
- $\boldsymbol{\varphi_j}$: *Closeness Time Window*: gives priority to a node j with the closest time window, i.e. the urgency to insert it in a route.

The *next* node is obtained by comparing the values $\vartheta_{ij} = \alpha_1 \cdot tr_{ij} + \alpha_2 \cdot \delta_j + \alpha_3 \cdot \varphi_j$, of the candidate j nodes connected to i.

Figure 3 presents the schematics of this procedure.

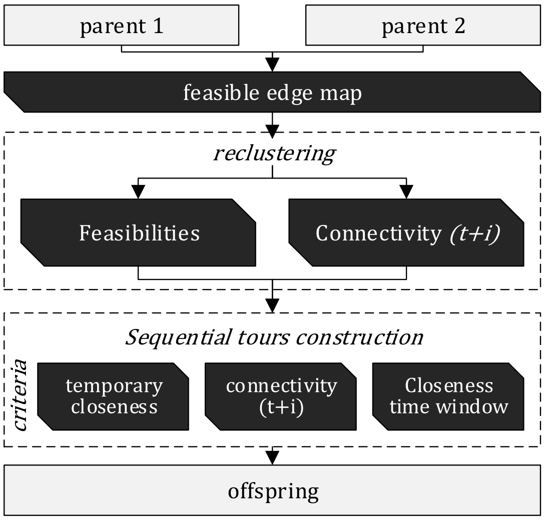
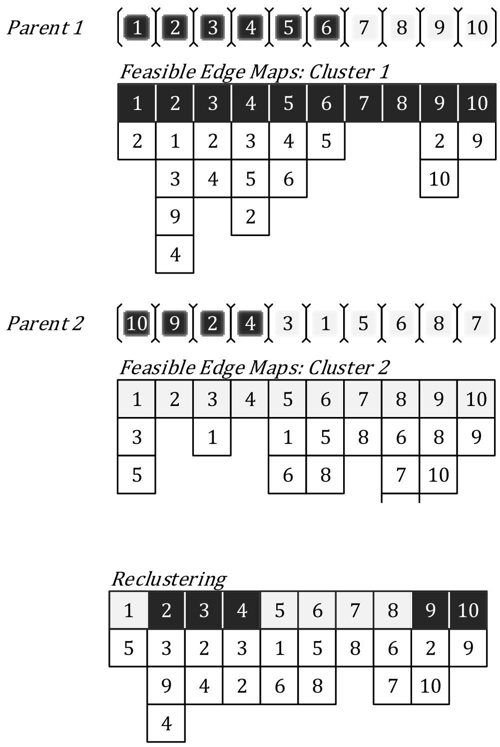


FIGURE 3. Schematics of ERX-MD.



Reclustering

FIGURE 4. Reclustering.

Figure 4 show a reclustering of two parent 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).

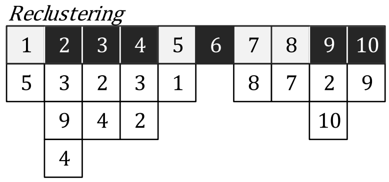


FIGURE 5. First step of reclustering.

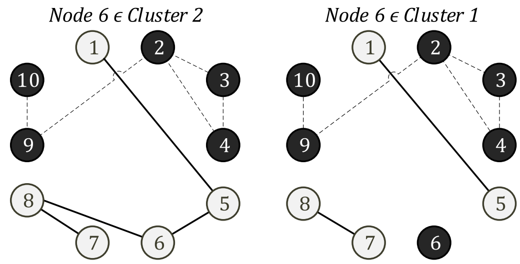


FIGURE 6. Sub-graphs of clusters 1 and 2 according to how node 6 is assigned.

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. That is, it 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[1] 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].

[1] The person in charge of scheduling the daily distribution of merchandise.

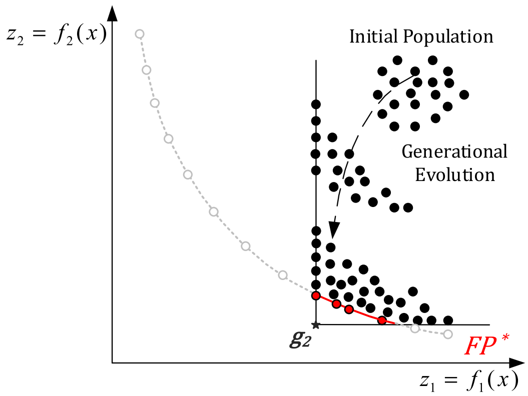


FIGURE 7. Evolution with g-dominance.

TABLE 2. Pseudocode of g-dominance.

$Evaluate_g\ F(x)$
Start
Evaluate $f_i(x)$, $i=1, \ldots, p$
Compute $flag_g(F(x))$
If $flag_g(F(x)) = 0$ **Then**
$f_i(x) = f_i(x) + M$, $i=1, \ldots, p$
End-If
End

Figure 7 represents how this method impacts on the evolution of the population, starting from a point in which the decision maker gives priority to *objective 2* over *objective 1*. We show an initial population that evolves towards the region of interest of the decision maker, denoted FP^*. So, instead of constructing the entire Pareto front, this method quickly leads to the region of interest.

To implement *g-dominance* penalties are applied on solutions outside the preferred regions. The corresponding pseudo-code is as follows:

Therefore, *g-dominance* penalizes the solutions that are dominated by the given reference point g. In other words, if $f_1(x) \geq g_1 \bigwedge f_2(x) \geq g_2 \Rightarrow flag_g(F(x)) = 1$ or if $f_1(x) \leq g_1 \bigwedge f_2(x) \leq g_2 \Rightarrow flag_g(F(x)) = 1$; on the contrary, if $f_1(x) \geq g_1 \bigwedge f_2(x) \leq g_2 \Rightarrow flag_g(F(x)) = 0$ or if $f_1(x) \leq g_1 \bigwedge f_2(x) \geq g_2 \Rightarrow flag_g(F(x)) = 0$.

D. THE DECISION PROCESS

Figure 8 describes the process of decision making followed daily. It starts by the consolidation of the data compiled from different sources, first with respect to origins or destinations, as well those generated in the process of *Enterprise Resource Planning*(ERP) as for instance the *inventory available in the depots*, the *amounts of merchandise to deliver to each client*, the *average stop delivering time* or the *time windows delivery constraints, etc.* Secondly, data provided by the *Geographic Information System* (GIS) on the *road network*, or *traffic-times* is also consolidated. On the basis of this information,

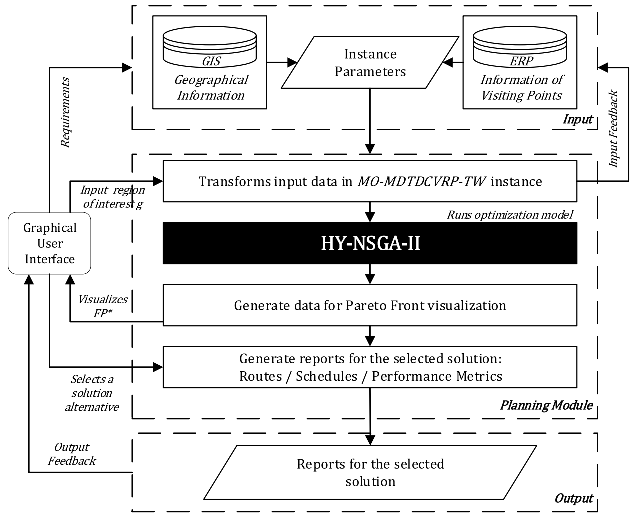


FIGURE 8. Logical design of the decision-aid tool.

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].

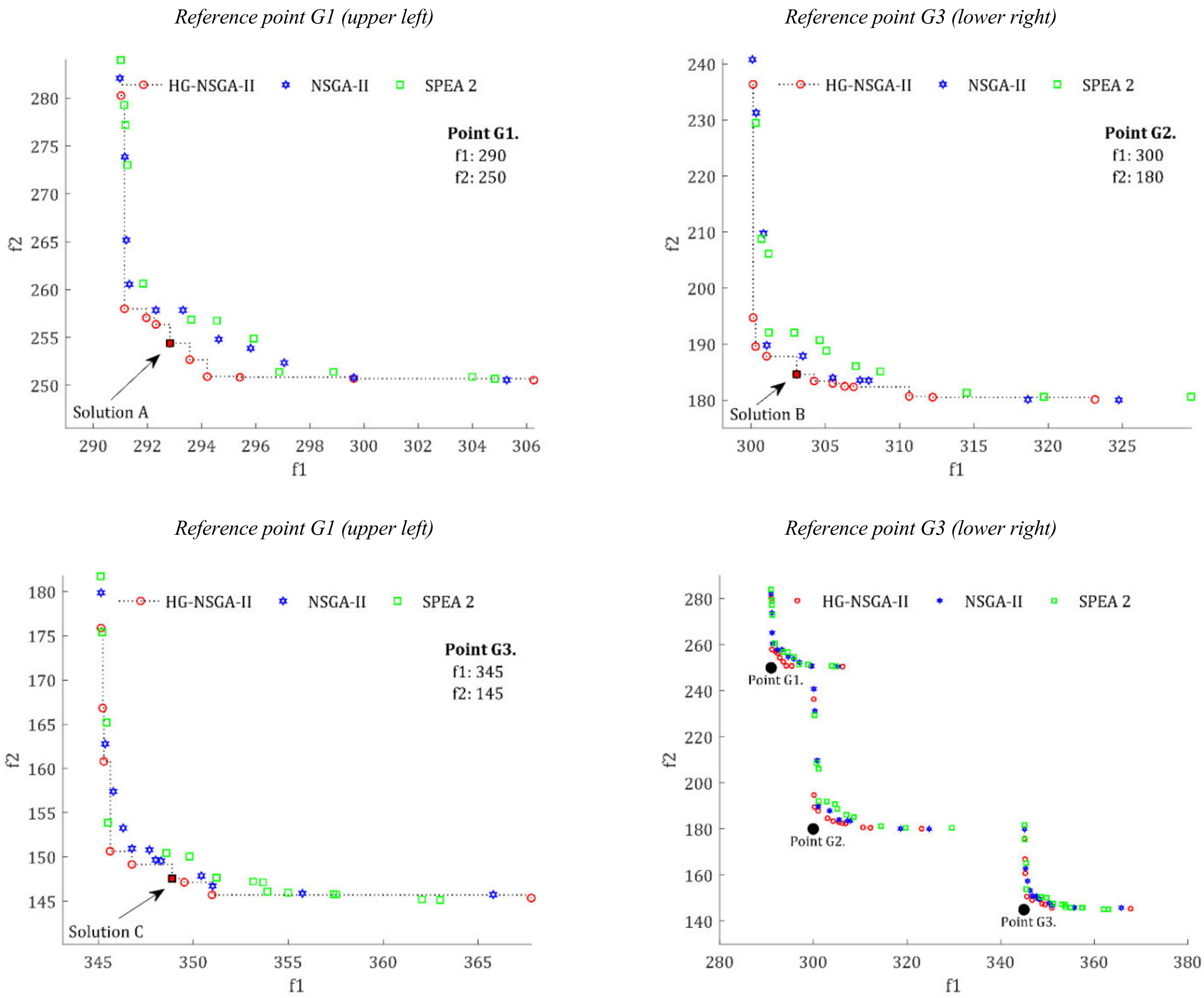


FIGURE 9. Simulation results.

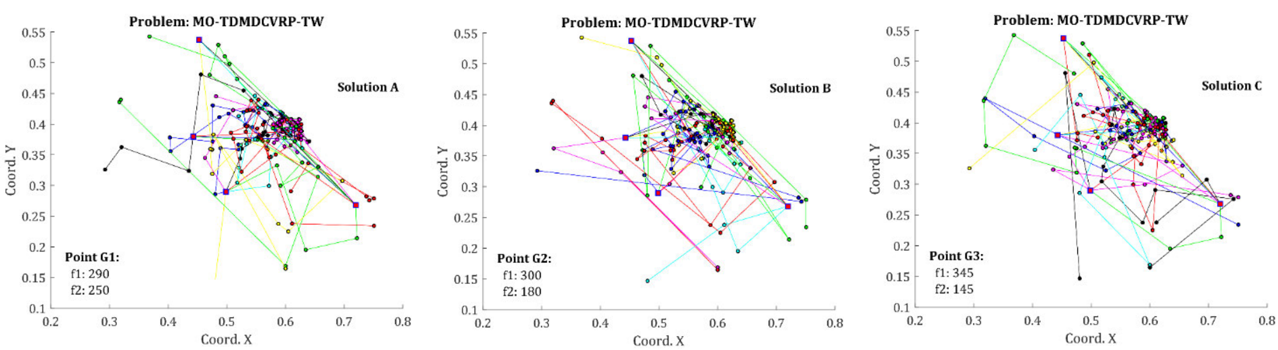


FIGURE 10. Solutions in the decision space.

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|
	r2	*12:00*	*19:42*	297	|175| |051| |161| |067| |174| |176| |054| |121| |092| |089| |085| |127|
	r3	*8:00*	*19:38*	388	|007| |094| |143| |076| |101| |034| |139| |184| |009| |163| |070| |162| |043| |117| |012| |084|
	r4	*8:00*	*18:45*	196	|065| |168| |192| |167| |021| |002| |015| |169|
d2	*r1*	*16:00*	*19:27*	175	|004| |027| |071| |010| |105| |106| |148|
	r2	*12:00*	*19:40*	327	|020| |032| |165| |081| |035| |154| |151| |109| |129| |170| |079| |155|
	r3	*8:00*	*19:49*	360	|030| |104| |111| |095| |113| |038| |132| |190| |078| |062| |064| |056| |178| |180| |198|
	r4	*8:00*	*19:44*	257	|041| |140| |160| |058| |055| |066| |080| |177| |128| |200|
	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|
	r2	*12:00*	*19:56*	367	|013| |114| |145| |118| |120| |130| |036| |146| |090| |098| |033| |039| |017| |135| |037|
	r3	*8:00*	*18:49*	357	|018| |122| |137| |023| |138| |126| |159| |147| |082| |040| |029| |074| |179| |156|
	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|
	r2	*8:00*	*18:41*	398	|008| |072| |087| |052| |131| |048| |099| |158| |073| |068| |077| |050| |049| |044| |042| |026|
	r3	*16:00*	*19:26*	151	|022| |125| |100| |150| |124| |152|
	r4	*8:00*	*19:37*	241	|025| |093| |103| |112| |171| |186| |188| |197| |196| |195|
	r5	*8:00*	*16:49*	133	|141| |164| |187| |183| |189|

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*: $G1 = (290, 250)$, $G2 = (300, 180)$ and $G3 = (345, 145)$.

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. We transformed the geographical coordinates of the nodes representing the clients into Cartesian ones, as $x \in [0, 1]$ and $y \in [0, 1]$ while the edges (of a corresponding color) indicate the prescription of the chosen solution.

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_σ; and the maximum value attained, H_{best}. We obtained the following results:

TABLE 4. Reference point G1: ($f_1 = 290, f_2 = 250$).

MOEA	$\bar{H}$	H_σ	H_{best}
HY-NSGA-II	2,91962	0,05926	3,01882
NSGA-II	2,85121	0,06322	2,93778
SPEA2	2,81307	0,07359	2,91731

TABLE 5. Reference point G2: ($f_1 = 300, f_2 = 180$).

MOEA	$\bar{H}$	H_σ	H_{best}
HY-NSGA-II	2,91056	0,06570	3,02609
NSGA-II	2,89708	0,06144	2,98495
SPEA2	2,86198	0,06955	2,92922

TABLE 6. Reference point G3: ($f_1 = 345, f_2 = 145$).

MOEA	$\bar{H}$	H_σ	H_{best}
HY-NSGA-II	3,01506	0,07105	3,06521
NSGA-II	2,90283	0,06745	2,97089
SPEA2	2,88483	0,07624	2,96358

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.

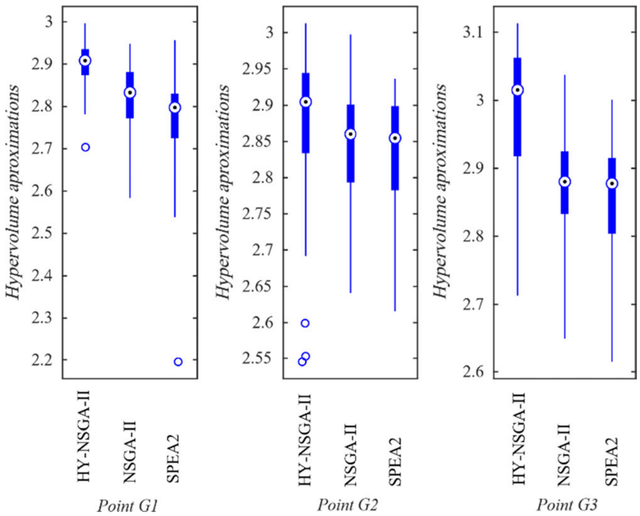


FIGURE 11. Boxplots based on data of the Hypervolume Indicator.

TABLE 7. Reference point G1: ($f_1 = 290, f_2 = 250$).

	z	$p-value$	$\alpha = 0.05$
HY-NSGA-II vs NSGA-II	4.98749	3.0585e-07	YES
HY-NSGA-II vs SPEA2	6.31257	1.3722e-10	YES

TABLE 8. Reference point G2: ($f_1 = 300, f_2 = 180$).

	z	$p-value$	$\alpha = 0.05$
HY-NSGA-II vs NSGA-II	2.33731	0.0097116	YES
HY-NSGA-II vs SPEA2	2.79373	0.0026052	YES

TABLE 9. Reference point G3: ($f_1 = 345, f_2 = 145$).

	z	$p-value$	$\alpha = 0.05$
HY-NSGA-II vs NSGA-II	5.00957	2.7276e-07	YES
HY-NSGA-II vs SPEA2	5.70892	5.6847e-09	YES

TABLE 10. Coordinates of the distribution centers.

l	V_l	x_i	y_i
1	Mercado Central de Buenos Aires	0,4987	0,2897
2	Mercado de Abasto 1	0,4431	0,3798
3	Mercado de Abasto 2	0,4528	0,5376
4	Mercado de Abasto 3	0,7200	0,2679

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. Summary information about the clients.

i	x	y	d_i	TW		s_i
				a_i	b_i	
1	0,55	0,42	24	16:00	20:00	15
2	0,63	0,37	21	16:00	20:00	15
3	0,6	0,41	22	8:00	12:00	15
4	0,57	0,42	20	16:00	20:00	15
5	0,56	0,38	23	8:00	12:00	15
6	0,61	0,39	22	12:00	16:00	15
7	0,6	0,38	25	8:00	12:00	15
8	0,53	0,45	26	8:00	12:00	15
9	0,48	0,37	25	12:00	16:00	15
10	0,61	0,4	28	16:00	20:00	15
11	0,6	0,39	27	12:00	16:00	15
12	0,62	0,4	21	16:00	20:00	15
13	0,61	0,4	23	12:00	16:00	15
14	0,63	0,39	27	12:00	16:00	15
15	0,62	0,41	23	16:00	20:00	15
16	0,6	0,4	25	12:00	16:00	15
17	0,61	0,41	22	16:00	20:00	15
18	0,62	0,38	25	8:00	12:00	15
19	0,6	0,39	21	8:00	12:00	15
20	0,62	0,38	23	12:00	16:00	15
21	0,6	0,39	25	16:00	20:00	15
22	0,49	0,41	23	16:00	20:00	15
23	0,6	0,41	29	8:00	12:00	15
24	0,62	0,38	30	8:00	12:00	15
25	0,63	0,37	25	8:00	12:00	15
26	0,59	0,39	27	16:00	20:00	15
27	0,6	0,41	25	16:00	20:00	15
28	0,62	0,37	23	8:00	12:00	15
29	0,54	0,4	29	16:00	20:00	15
30	0,59	0,4	29	8:00	12:00	15
31	0,58	0,4	30	8:00	12:00	15
32	0,64	0,37	26	12:00	16:00	15
33	0,58	0,4	24	16:00	20:00	15
34	0,61	0,37	23	8:00	12:00	15
35	0,58	0,4	28	12:00	16:00	15
36	0,63	0,36	21	12:00	16:00	15
37	0,6	0,36	22	16:00	20:00	15
38	0,63	0,36	24	8:00	12:00	15
39	0,58	0,41	27	16:00	20:00	15
40	0,58	0,37	26	12:00	16:00	15
41	0,57	0,43	28	8:00	12:00	15
42	0,57	0,38	20	16:00	20:00	15
43	0,56	0,38	28	16:00	20:00	15
44	0,57	0,39	22	16:00	20:00	15
45	0,56	0,4	27	12:00	16:00	15
46	0,57	0,37	20	8:00	12:00	15
47	0,56	0,4	27	12:00	16:00	15
48	0,56	0,39	21	12:00	16:00	15
49	0,56	0,38	21	16:00	20:00	15
50	0,56	0,37	23	16:00	20:00	15
51	0,57	0,36	20	12:00	16:00	15
52	0,58	0,35	29	8:00	12:00	15
53	0,55	0,38	27	12:00	16:00	15
54	0,57	0,43	24	16:00	20:00	15
55	0,55	0,37	24	8:00	12:00	15
56	0,55	0,43	20	16:00	20:00	15
57	0,54	0,37	23	8:00	12:00	15
58	0,54	0,4	21	8:00	12:00	15
59	0,55	0,44	20	12:00	16:00	15
60	0,53	0,4	29	12:00	16:00	15
61	0,54	0,42	30	12:00	16:00	15
62	0,53	0,4	21	12:00	16:00	15
63	0,53	0,4	30	16:00	20:00	15
64	0,53	0,37	30	16:00	20:00	15
65	0,55	0,45	21	8:00	12:00	15
66	0,52	0,37	23	8:00	12:00	15

TABLE 11. ***(Continued.)*** **Summary information about the clients.**

67	0,52	0,41	30	12:00	16:00	15
68	0,52	0,37	25	12:00	16:00	15
69	0,52	0,36	26	8:00	12:00	15
70	0,53	0,36	22	16:00	20:00	15
71	0,6	0,41	24	16:00	20:00	15
72	0,51	0,42	23	8:00	12:00	15
73	0,51	0,39	29	12:00	16:00	15
74	0,5	0,42	25	16:00	20:00	15
75	0,59	0,41	24	12:00	16:00	15
76	0,63	0,39	21	8:00	12:00	15

information in Tables 4 to 6. The median of the H indicator for HY-NSGA-II is above that of the two other algorithms in all the reference points, but the improvement shows more clearly in regions requiring better balances of the loads, as in point G3.

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.**

<table>
<tr><th>Rout</th><th>Dep.</th><th>Start</th><th>End</th><th>Load</th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th></tr>
<tr><td>d1</td><td>r1</td><td>8:25</td><td>18:57</td><td>389</td><td>|185|</td><td>|164|</td><td>|080|</td><td>|069|</td><td>|066|</td><td>|119|</td><td>|062|</td><td>|161|</td><td>|174|</td><td>|009|</td><td>|188|</td><td>|193|</td><td>|022|</td><td>|074|</td><td>|029|</td><td>|049|</td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>17:04</td><td>380</td><td>|173|</td><td>|072|</td><td>|041|</td><td>|031|</td><td>|104|</td><td>|143|</td><td>|144|</td><td>|082|</td><td>|151|</td><td>|040|</td><td>|102|</td><td>|020|</td><td>|130|</td><td>|106|</td><td>|012|</td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>18:41</td><td>371</td><td>|052|</td><td>|034|</td><td>|024|</td><td>|018|</td><td>|101|</td><td>|093|</td><td>|113|</td><td>|118|</td><td>|036|</td><td>|177|</td><td>|128|</td><td>|183|</td><td>|129|</td><td>|170|</td><td></td><td></td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>19:26</td><td>288</td><td>|131|</td><td>|191|</td><td>|192|</td><td>|181|</td><td>|167|</td><td>|187|</td><td>|179|</td><td>|156|</td><td>|004|</td><td>|125|</td><td>|089|</td><td>|015|</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r5</td><td>16:00</td><td>19:47</td><td>177</td><td>|162|</td><td>|070|</td><td>|043|</td><td>|042|</td><td>|026|</td><td>|027|</td><td>|148|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r6</td><td>16:00</td><td>17:42</td><td>79</td><td>|169|</td><td>|079|</td><td>|084|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r7</td><td>16:00</td><td>16:00</td><td>27</td><td>|199|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d2</td><td>r1</td><td>16:00</td><td>19:48</td><td>193</td><td>|002|</td><td>|096|</td><td>|100|</td><td>|021|</td><td>|098|</td><td>|033|</td><td>|090|</td><td>|155|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>12:00</td><td>19:38</td><td>328</td><td>|006|</td><td>|136|</td><td>|013|</td><td>|016|</td><td>|075|</td><td>|035|</td><td>|011|</td><td>|081|</td><td>|037|</td><td>|152|</td><td>|010|</td><td>|017|</td><td>|176|</td><td></td><td></td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>19:14</td><td>384</td><td>|019|</td><td>|097|</td><td>|094|</td><td>|122|</td><td>|023|</td><td>|107|</td><td>|025|</td><td>|134|</td><td>|147|</td><td>|047|</td><td>|099|</td><td>|051|</td><td>|190|</td><td>|050|</td><td>|182|</td><td>|189|</td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>16:26</td><td>136</td><td>|046|</td><td>|055|</td><td>|168|</td><td>|194|</td><td>|197|</td><td>|196|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d3</td><td>r1</td><td>12:00</td><td>19:25</td><td>361</td><td>|032|</td><td>|145|</td><td>|146|</td><td>|153|</td><td>|045|</td><td>|048|</td><td>|053|</td><td>|044|</td><td>|121|</td><td>|039|</td><td>|085|</td><td>|117|</td><td>|105|</td><td>|150|</td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>17:42</td><td>376</td><td>|038|</td><td>|076|</td><td>|112|</td><td>|116|</td><td>|138|</td><td>|140|</td><td>|065|</td><td>|158|</td><td>|067|</td><td>|157|</td><td>|068|</td><td>|077|</td><td>|175|</td><td>|064|</td><td>|056|</td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>17:57</td><td>222</td><td>|083|</td><td>|086|</td><td>|166|</td><td>|087|</td><td>|171|</td><td>|186|</td><td>|184|</td><td>|163|</td><td>|195|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d4</td><td>r1</td><td>16:00</td><td>19:29</td><td>166</td><td>|001|</td><td>|063|</td><td>|054|</td><td>|092|</td><td>|127|</td><td>|135|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>16:00</td><td>396</td><td>|003|</td><td>|123|</td><td>|030|</td><td>|137|</td><td>|111|</td><td>|095|</td><td>|103|</td><td>|115|</td><td>|114|</td><td>|108|</td><td>|132|</td><td>|091|</td><td>|014|</td><td>|120|</td><td>|124|</td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>17:38</td><td>385</td><td>|005|</td><td>|058|</td><td>|088|</td><td>|057|</td><td>|126|</td><td>|160|</td><td>|159|</td><td>|061|</td><td>|059|</td><td>|060|</td><td>|073|</td><td>|133|</td><td>|078|</td><td>|071|</td><td>|142|</td><td></td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>19:34</td><td>242</td><td>|007|</td><td>|028|</td><td>|139|</td><td>|149|</td><td>|165|</td><td>|154|</td><td>|109|</td><td>|180|</td><td>|178|</td><td>|198|</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r5</td><td>8:00</td><td>16:00</td><td>131</td><td>|008|</td><td>|141|</td><td>|172|</td><td>|110|</td><td>|200|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

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

<table>
<tr><th>Route</th><th>Dep.</th><th>Start</th><th>End</th><th>Load</th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th></tr>
<tr><td>d1</td><td>r1</td><td>8:58</td><td>16:34</td><td>384</td><td>|066|</td><td>|087|</td><td>|088|</td><td>|119|</td><td>|046|</td><td>|007|</td><td>|019|</td><td>|102|</td><td>|014|</td><td>|130|</td><td>|036|</td><td>|165|</td><td>|118|</td><td>|132|</td><td>|012|</td><td>|096|</td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>18:19</td><td>390</td><td>|173|</td><td>|080|</td><td>|159|</td><td>|008|</td><td>|123|</td><td>|153|</td><td>|016|</td><td>|091|</td><td>|134|</td><td>|174|</td><td>|001|</td><td>|039|</td><td>|089|</td><td>|092|</td><td>|098|</td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>19:52</td><td>378</td><td>|024|</td><td>|101|</td><td>|103|</td><td>|003|</td><td>|094|</td><td>|030|</td><td>|112|</td><td>|186|</td><td>|169|</td><td>|079|</td><td>|037|</td><td>|100|</td><td>|021|</td><td>|002|</td><td>|152|</td><td></td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>18:15</td><td>195</td><td>|191|</td><td>|192|</td><td>|181|</td><td>|187|</td><td>|054|</td><td>|026|</td><td>|050|</td><td>|064|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r5</td><td>8:00</td><td>16:00</td><td>57</td><td>|141|</td><td>|199|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d2</td><td>r1</td><td>12:00</td><td>19:47</td><td>333</td><td>|006|</td><td>|011|</td><td>|151|</td><td>|154|</td><td>|045|</td><td>|059|</td><td>|167|</td><td>|056|</td><td>|090|</td><td>|085|</td><td>|010|</td><td>|127|</td><td>|148|</td><td></td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>17:40</td><td>395</td><td>|023|</td><td>|143|</td><td>|097|</td><td>|034|</td><td>|025|</td><td>|093|</td><td>|038|</td><td>|032|</td><td>|040|</td><td>|053|</td><td>|099|</td><td>|068|</td><td>|073|</td><td>|155|</td><td>|129|</td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>19:47</td><td>235</td><td>|031|</td><td>|122|</td><td>|041|</td><td>|072|</td><td>|052|</td><td>|078|</td><td>|188|</td><td>|196|</td><td>|189|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>16:00</td><td>155</td><td>|139|</td><td>|149|</td><td>|185|</td><td>|172|</td><td>|177|</td><td>|183|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d3</td><td>r1</td><td>12:00</td><td>19:27</td><td>356</td><td>|009|</td><td>|163|</td><td>|133|</td><td>|060|</td><td>|062|</td><td>|161|</td><td>|158|</td><td>|121|</td><td>|125|</td><td>|027|</td><td>|071|</td><td>|117|</td><td>|109|</td><td>|105|</td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>12:00</td><td>19:38</td><td>358</td><td>|013|</td><td>|115|</td><td>|114|</td><td>|146|</td><td>|082|</td><td>|047|</td><td>|048|</td><td>|043|</td><td>|033|</td><td>|015|</td><td>|106|</td><td>|142|</td><td>|150|</td><td>|124|</td><td></td><td></td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>19:53</td><td>371</td><td>|028|</td><td>|104|</td><td>|137|</td><td>|113|</td><td>|055|</td><td>|058|</td><td>|061|</td><td>|157|</td><td>|077|</td><td>|175|</td><td>|184|</td><td>|170|</td><td>|128|</td><td>|195|</td><td></td><td></td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>18:49</td><td>193</td><td>|065|</td><td>|160|</td><td>|164|</td><td>|194|</td><td>|162|</td><td>|070|</td><td>|176|</td><td>|193|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r5</td><td>8:00</td><td>18:27</td><td>68</td><td>|168|</td><td>|178|</td><td>|200|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>d4</td><td>r1</td><td>16:00</td><td>19:55</td><td>163</td><td>|004|</td><td>|156|</td><td>|029|</td><td>|049|</td><td>|044|</td><td>|042|</td><td>|135|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r2</td><td>8:00</td><td>16:52</td><td>396</td><td>|005|</td><td>|069|</td><td>|057|</td><td>|126|</td><td>|140|</td><td>|138|</td><td>|111|</td><td>|144|</td><td>|108|</td><td>|136|</td><td>|020|</td><td>|120|</td><td>|145|</td><td>|081|</td><td>|017|</td><td>|084|</td></tr>
<tr><td></td><td>r3</td><td>8:00</td><td>18:45</td><td>394</td><td>|018|</td><td>|076|</td><td>|107|</td><td>|095|</td><td>|116|</td><td>|131|</td><td>|190|</td><td>|051|</td><td>|075|</td><td>|035|</td><td>|147|</td><td>|067|</td><td>|074|</td><td>|022|</td><td>|063|</td><td>|180|</td></tr>
<tr><td></td><td>r4</td><td>8:00</td><td>18:32</td><td>170</td><td>|083|</td><td>|086|</td><td>|166|</td><td>|110|</td><td>|197|</td><td>|198|</td><td>|179|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>r5</td><td>8:00</td><td>16:00</td><td>40</td><td>|171|</td><td>|182|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

TABLE 14. CVRP and its variants: literature overview.

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.	--
Gayialis et al. [35]	2019	Survey			
Montoya-Torres et al. [36]	2015	Survey			
Vega-Mejía et al. [37]	2019	Survey			
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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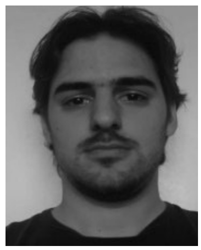

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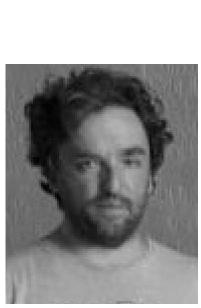

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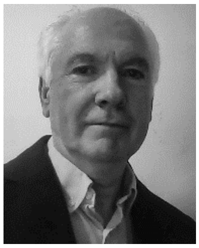

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