A PARALLEL PROGRAMMING APPROACH TO THE SOLUTION OF THE LOCATION-INVENTORY AND MULTI-ECHELON ROUTING PROBLEM IN THE HUMANITARIAN SUPPLY CHAIN

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ABSTRACT

Disasters around the world are becoming more frequent, diverse, complex and extremely challenging, causing millions of casualties and affecting both human development and available resources. Consequently, the present study addresses a multi-objective location, inventory and multi-scale routing (2E-LIRP) problem, which supports comprehensive decision making, so that the logistics network designer and manager can obtain adequate strategic planning in the face of uncertainty and the negative impact that an adverse event can generate.

Moreover, the problem is formulated as an integer linear programming model, having as main objectives to minimize private logistics costs and maximize the welfare of the affected areas, considering dynamic demand, multiple products and heterogeneous fleet.

Due to the computational complexity associated with the model, a new solution approach is proposed, based on the design of evolutionary metaheuristic algorithms; the first one, known as Non-dominated Sorting Genetic Algorithm version II (NSGA-II), the second one, Strength Pareto Evolutionary Algorithm version II (SPEA-II) and the third one, called Genetic Algorithm (GA), programmed in parallel and executed individually under a cooperative environment. Finally, the experimentation carried out on a test set, composed of twenty instances of varying complexity, allows inferring that the parallel-cooperative and purely parallel approach applied to NSGA-II, substantially improves the processing times and the number of non-dominated solutions, if compared to the results obtained by SPEA-II, designed under identical conditions. Moreover, by building a GA with these same characteristics, it improves up to 50% of the solutions, in terms of social costs (logistic and humanitarian costs), with computation times similar to its sequential counterpart.

1. INTRODUCTION

The occurrence of natural disasters and their devastating consequences are a reality experienced year after year around the world. Approximately 75% of the world's population lives in regions affected at least once between 1980 and 2017 by an earthquake, tropical cyclone, flood or drought. As a consequence of these phenomena, more than 184 people die every day in different parts of the world and they result in a toll that includes the destruction of fixed assets, physical capital, the interruption of production, trade and the decrease in public and private savings and investments, which wipe out progress in economic development (Nagurney et al., 2019). This problematic has generated a deep interest in seeking and establishing the most efficient mechanisms, which allow improving the response to emergency situations, thus giving rise to the emergence of humanitarian logistics as a means to cope with the negative effects of adverse events that put at risk the integrity or the very life of the human being.

Despite research and technological progress, it is still not possible to predict when and where a natural disaster will occur in advance; therefore, activities or actions before, during and after its occurrence are important to reduce the associated losses. Moreover, when a disaster occurs in a certain part of the world, many organizations come forward to provide the required relief items, e.g., food, water, medicine, among others, to the affected people. In these situations, coordination between the different members is crucial and it becomes difficult for a single organization to carry out all the necessary activities, such as repairing damaged infrastructure and delivering relief items.

Moreover, humanitarian logistics becomes a complex network with different actors, including, non-governmental organizations (NGOs) of local or international origin, donors, armed forces, corporations and private companies; each of them with different and sometimes, conflicting interests, obligations, capabilities, budget allocation structure and logistical skills (Nikkhoo et al., 2018).

For this reason, the design and management necessary in the logistics network during the pre- and post-disaster phases cannot be improvised; they must be the result of a correct and rigorous planning, in which very important aspects can be identified and established in advance, such as, the location of facilities, the availability and quality of resources through proper inventory management, flexibility in route plans according to the established budget, among others, which ultimately allow guaranteeing an optimal response when the deployment of humanitarian operations is carried out.

1.1 Justification

Currently, disasters, regardless of their origin (whether natural or human), are considered social phenomena whose damages could be prevented and mitigated to reduce or at least control their effects (Cecchini et al., 2017).

The difficulty in predicting the place where it will occur, the time and magnitude with which it will occur, in addition to the uncertainty associated with the characteristics of the population, the existing infrastructure conditions and the demand required to meet the emergency situation, give rise to one of the greatest challenges in humanitarian logistics, such as unpredictability, defined as the occurrence of unexpected events (Balcik et al., 2010). L'Hermitte et al. (2016) state that unpredictability creates barriers and affects efficiency in the supply chain.

Thus, the proper management of the logistics supply chain for disaster relief and humanitarian support becomes a very important challenge worldwide, since it is responsible for estimating, providing, storing, storing, transporting and distributing personnel, resources and services required to the affected areas (Talebian Sharif & Salari, 2015), through a set of activities carried out in different instances of time, which are intended to assist the survivors after a disaster, reduce its impact and maintain social stability (Aghajani et al., 2020; Vahdani et al., 2018).

For this reason, the need arises to develop a model capable of providing sufficient information to the logistics network manager to make the best decisions related to the location, distribution and inventory management, which ultimately guarantee a timely delivery of goods (products or services) to the stakeholders (affected areas), thus minimizing the negative economic and social impacts caused by the occurrence of adverse events. This model is associated with the 2E-LIRP, which integrates three types of very important decisions within the comprehensive planning of humanitarian logistics, as stated by Rafie-Majd et al. (2018), i.e., strategic decisions: with long-term effects (location and allocation of facilities); tactical decisions: medium-term (inventory control and transportation) and operational decisions: daily or weekly (scheduling and routing), which ultimately determine the responsiveness, flexibility, efficiency and effectiveness of the supply chain.

2. LITERATURE REVIEW

By way of summary, the most common solution techniques used to solve multi-echelon location, inventory and routing problems are presented below; in parallel, some characteristics (see Table 1-2) considered to be of great relevance in the different studies found to date are described.

Convention	Interpretation
1	Mathematical formulation
2a	Mono-objective
2b	Multi-objective
3a	Multi-period
3b	Multi-product
4a	Deterministic parameters
4b	Stochastic parameters
4c	Fuzzy parameters
5	Method / Solution algorithm
6a	Parallel programming techniques
6b	Paradigm of cooperation between metaheuristics
7	Deprivation costs in the model

Table 1 - Characteristics associated with multi-echelon LIRP

Author (year)	**1***	**2**		**3**		**4**			**5***	**6**		**7**
		a	**b**	**a**	**b**	**a**	**b**	**c**		**a**	**b**	
(Tavakkoli-Moghaddam et al., 2013)	MINLP		**X**				**X**		LINGO			
(Bozorgi-Amiri & Khorsi, 2016)	MILP		**X**	**X**	**X**		**X**		ε-CM			
(Ghorbani & Akbari Jokar, 2016)	MILP	**X**		**X**	**X**	**X**			HIC-SA			
(R. Tavakkoli-Moghaddam & Raziei, 2016)	MILP		**X**	**X**	**X**			X	GAMS CPLEX			
(Zhalechian et al., 2016)	MINLP		**X**	**X**	**X**		**X**	X	SGA/VNS			
(Nakhjirkan & Mokhatab Rafiei, 2017)	MINLP	**X**			**X**		**X**		GA			
(Rayat et al., 2017)	MINLP		**X**	**X**	**X**		**X**		AMOSA			

(Zhao & Ke, 2017)	MILP		**X**			**X**	TOPSIS			
(Guo et al., 2018)	MINLP	**X**				**X**	GA/SA			
(Tavana et al., 2018)	MILP		**X**	**X**	**X**	**X**	ε-CM NSGA-II RPBNSGA-II			
(Vahdani et al., 2018)	MILP		**X**	**X**	**X**	**X**	NSGA-II MOPSO			
(Yuchi et al., 2018)	MINLP		**X**			**X**	TS/ SA			
(Fatemi Ghomi & Asgarian, 2019)	MINLP		**X**	**X**		**X**	PSO BBO HBBO			
(Ghorashi et al., 2019)	CMIP		**X**	**X**	**X**	**X**	MOGWO MOPSO NSGA-II			
(Nakhjirkan et al., 2019)	MINLP	**X**			**X**	**X**	GA/NDEA			
(Saragih et al., 2019)	MINLP	**X**				**X**	SA			
(Biuki et al., 2020)	MILP		**X**	**X**	**X**	**X**	GA/PSO		**X**	
Current study	MILP		**X**		**X**	**X**	NSGA-II SPEA-II GA	**X**	**X**	**X**

Table 2 - Classification of studies related to multi-echelon LIRP

*Note.**MILP= Mixed Integer Linear Programming; MINLP = Mixed Integer Non-Linear Programming; CMIP=Constrained Mixed Integer Programming; ε-CM= Epsilon Constraint Method ε; HIC-SA= Hybrid Imperialist Competitive-Simulated Annealing; SGA = Self-adaptive Genetic Algorithm; VNS= Variable Neighborhood Search; GA= Genetic Algorithm; AMOSA= Archived Multi-Objective Simulated Annealing; TOPSIS= Technique for Order of Preference by Similarity to Ideal Solution; SA= Simulated Annealing; NSGA-II= Non-dominated Sorting Genetic Algorithm II; RPBNSGA-II= Reference Point Based Non-dominated Sorting Genetic Algorithm II; MOPSO= Multi-objective Particle Swarm Optimization; TS= Tabu Search; PSO= Particle Swarm Optimization; BBO= Biogeography-Based Optimization; HBBO= Habitat Biogeography-Based Optimization; MOGWO= Multi-Objective Gray Wolf Optimizer; NDEA= Network Data Envelopment Analysis.

3. PROBLEM DESCRIPTION AND MATHEMATICAL FORMULATION

The following is a schematic representation, with the purpose of facilitating the interpretation and understanding of the problem addressed (see Figure 1).

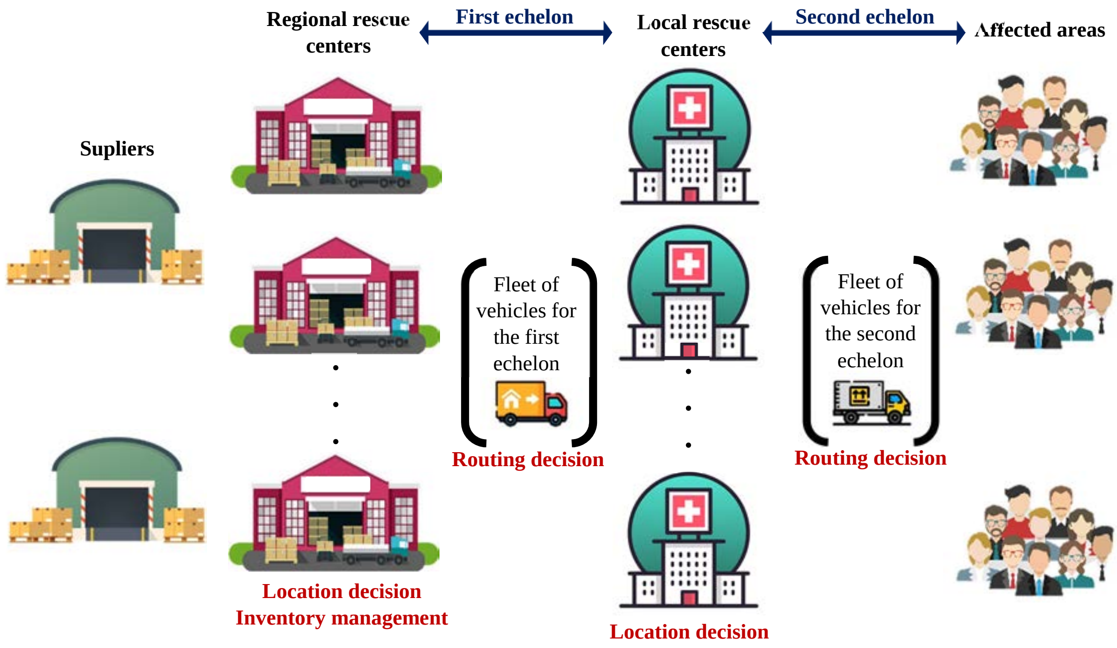

Fig 1 - Graphical illustration of 2E-LIRP

Taking as a reference the research developed by Pérez-Rodríguez & Holguín-Veras (2016), Tavana et al. (2018), Cotes & Cantillo (2019) and Dai et al. (2019), in addition to taking into account the considerations established by the researcher, the mathematical model is formulated as presented below.

3.1 Sets

R = Set of possible regional rescue centers
L = Set of possible local rescue centers
C = Set of areas affected (AA) by a disaster
V = Set of vehicles for first level routes
W = Set of vehicles for second level routes
P = Set of products required in the AA
T = Humanitarian deployment time periods

3.2 Indexes

r = Index for possible regional rescue centers
l = Index for possible local rescue centers
c = Index for areas affected (AA) by a disaster
v = Index for first level vehicles

w = Index for second level vehicles
p = Index for products required in the AA
t = Index for time periods

3.3 Parameters

K_{ip} = Facility capacity $i \in R \cup L$, for product $p \in P$
H_{ip} = Vehicle capacity $i \in W \cup V$, for product $p \in P$
F_i = Cost of opening the facility $i \in R \cup L$
G_i = Cost of using the vehicle $i \in W \cup V$
D_{cp}^t = Customer demand $c \in C$, for product $p \in P$, in period $t \in T$
S_{ij} = Cost of traveling between node i and node j for the first echelon
E_{ij} = Cost of traveling between node i and node j for the second echelon
CS_p^t = Cost of buying the product $p \in P$ in period $t \in T$
CT_{pr}^t = Unit cost of transporting the product $p \in P$ from the supplier to the regional rescue center $r \in R$ during the period $t \in T$
CMI_{pr} = Unit cost of keeping the product $p \in P$, in inventory at the regional rescue center $r \in R$
I_{pr}^0 = Initial inventory of product $p \in P$, at the regional rescue center $r \in R$
F_{jt} = Deprivation time presented by the affected area $j \in C$ in the period $t \in T$
TV_{ij} = Travel time between node i and node j, for $i \wedge j \in L \cup C$
P_j = Number of individuals at the point of demand (affected area) $j \in C$
VP_j^t = Average economic value of well-being perceived by an individual in the affected region $j \in C$ (it is possible to take as a base value, the GDP per capita of the last year) for the period $t \in T$
$(VP_j^t * F_{jt}^{-1} * P_j)$ = Deprivation function (DF)
$\left(VP_j^t * TV_{ij}^{-1} * P_j\right)$ = Impact function on distribution (IFD)

3.4 Decision variables

$$y_i = \begin{Bmatrix} 1 & \text{If the facility } i \in R \cup L \text{ is open} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

$$m_{ijt}^v = \begin{Bmatrix} 1 & \begin{matrix} \text{If the vehicle } v \in V, \text{travels from node } i \in R \cup L, \text{to node} \\ j \in R \cup L, \text{on the first level route, during the period } t \in T \end{matrix} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

$$n_{ijt}^w = \begin{Bmatrix} 1 & \begin{matrix} \text{If the vehicle } w \in W, \text{travels from node } i \in L \cup C, \text{to node} \\ j \in L \cup C, \text{on the second level route, during the period } t \in T \end{matrix} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

$$L_{rl}^t = \begin{Bmatrix} 1 & \begin{matrix} \text{If the local rescue center } l \in L, \text{is assigned to the regional} \\ \text{rescue center } r \in R, \text{in the period } t \in T \end{matrix} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

$$P_{rc}^{t}=\begin{cases}1 & \text{If the affected area } c\in C\text{, is assigned to the local rescue center } l\in L\text{, in the period } t\in T\\ 0 & \text{Otherwise}\end{cases}$$

$$q_{i}^{t}=\begin{cases}1 & \text{If the vehicle } i\in W\cup V\text{, is used on a route, in the period } t\in T\\ 0 & \text{Otherwise}\end{cases}$$

$FN_{prlv}^{t}=$ Product flow $p\in P$ to be transported, from the regional rescue center $r\in R$ to the local rescue center $l\in L$ in vehicle $v\in V$, for period $t\in T$

$Q_{pr}^{t}=$ Quantity of product $p\in P$ to be purchased at regional rescue center $r\in R$, in period $t\in T$

$I_{pr}^{t}=$ Units of product $p\in P$ in inventory, for regional rescue center $r\in R$, during period $t\in T$

$Z_1=$ Total logistics cost (Private Costs)

$Z_2=$ Total wellness of the areas ($-Z_2=$ External Costs/ Human suffering)

3.5 Objective function

$$Minimize\{Z_1\}=Minimize\left\{\sum_{r\in R}F_r*y_r+\sum_{l\in L}F_l*y_l+\sum_{t\in T}\sum_{v\in V}G_v*q_v^t+\sum_{t\in T}\sum_{v\in V}G_w*q_w^t+\right.$$
$$\sum_{t\in T}\sum_{(i,j)\in R\cup L}\sum_{v\in V}S_{ij}*m_{i\ jt}^{v}+\sum_{t\in T}\sum_{(i,j)\in L\cup C}\sum_{w\in W}E_{ij}*n_{i\ jt}^{w}+\sum_{p\in P}\sum_{r\in R}\sum_{t\in T}CS_p^t*Q_{pr}^t+$$
$$\left.\sum_{p\in P}\sum_{r\in R}\sum_{t\in T}CT_{pr}^t*Q_{pr}^t+\sum_{p\in P}\sum_{r\in R}\sum_{t\in T}CMI_{pr}*I_{pr}^t\right\} \quad (1)$$

$$Maximize\{Z_2\}=Maximize\left\{\sum_{w\in W}\sum_{t\in T}\sum_{(i,j)\in L\cup C}\left[VP_j^t*p_j*\left(F_{jt}^{-1}+TV_{ij}^{-1}\right)\right]*n_{ijt}^{w}\right\} \quad (2)$$

3.6 Constraints

3.6.1 Second echelon constraints

$$\sum_{l\in L}P_{lc}^t=1;\quad \forall c\in C\wedge\forall t\in T \quad (3)$$

$$\sum_{c\in C}D_{cp}^t*P_{lc}^t\le k_{lp}*y_l;\quad \forall l\in L,\forall p\in P\wedge\forall t\in T \quad (4)$$

$$\sum_{w\in W}\sum_{j\in L\cup C}n_{jct}^{w}=1;\quad \forall c\in C,\forall t\in T\wedge j\ne c \quad (5)$$

$$\sum_{h\in L\cup C}n_{hjt}^{w}-\sum_{h\in L\cup C}n_{jht}^{w}=0;\quad \forall j\in L\cup C,\forall w\in W,\forall t\in T\wedge h\ne j \quad (6)$$

$$\sum_{i\in A'}\sum_{j\in A'}n_{ijt}^{w}\le|A'|-1;\quad \forall w\in W,\forall t\in T,A'\subseteq A,|A'|\ge 2\wedge i\ne j \quad (7)$$

$$\sum_{i\in L}\sum_{j\in C}n_{ijt}^{w}\le 1;\quad \forall w\in W\wedge\forall t\in T \quad (8)$$

$$\sum_{b\in L\cup C}n_{cbt}^{w}+\sum_{b\in L\cup C}n_{lbt}^{w}-P_{lc}^t\le 1;\quad \forall l\in L,\forall c\in C,\forall w\in W,\forall t\in T,c\ne b\wedge l\ne b \quad (9)$$

$$\sum_{c\in C}\sum_{j\in L\cup C} D_{cp}^{t} * n_{cjt}^{w} \le H_{wp} * q_{w}^{t}; \quad \forall w\in W, \forall t\in T, \forall p\in P \wedge c\neq j \tag{10}$$

3.6.2 First echelon constraints

$$\sum_{r\in R} L_{rl}^{t} = y_{l}; \quad \forall l\in L \wedge \forall t\in T \tag{11}$$

$$\sum_{l\in L} K_{lp} * L_{rl}^{t} \le K_{rp} * y_{r}; \quad \forall r\in R, \forall p\in P \wedge \forall t\in T \tag{12}$$

$$\sum_{h\in R\cup L} m_{hjt}^{v} - \sum_{h\in R\cup L} m_{jht}^{v} = 0; \quad \forall j\in R\cup L, \forall v\in V, \forall t\in T \wedge h\neq j \tag{13}$$

$$\sum_{i\in Q'}\sum_{j\in Q'} m_{ijt}^{v} \le \left|Q'\right| - 1; \quad \forall v\in V, \forall t\in T, Q'\subseteq Q, \left|Q'\right| \ge 2 \wedge i\neq j \tag{14}$$

$$\sum_{i\in R}\sum_{j\in L} m_{ijt}^{v} \le 1; \quad \forall v\in V \wedge \forall t\in T \tag{15}$$

$$\sum_{s\in R\cup L} m_{lst}^{v} + \sum_{s\in R\cup L} m_{rst}^{v} - L_{rl}^{t} \le 1; \quad \forall r\in R, \forall l\in L, \forall v\in V, \forall t\in T, l\neq s \wedge r\neq s \tag{16}$$

$$\sum_{r\in R}\sum_{v\in V} FN_{prlv}^{t} - \sum_{c\in C} D_{cp}^{t} * P_{lc}^{t} = 0; \quad \forall l\in L, \forall t\in T \wedge \forall p\in P \tag{17}$$

$$H_{vp} \sum_{h\in R\cup L} m_{lht}^{v} - FN_{prlv}^{t} \ge 0; \quad \forall v\in V, \forall d\in D, \forall l\in L, \forall p\in P, \forall t\in T \wedge l\neq h \tag{18}$$

$$H_{vp} \sum_{h\in R\cup L} m_{rht}^{v} - FN_{prlv}^{t} \ge 0; \quad \forall v\in V, \forall r\in R, \forall l\in L, \forall p\in P, \forall t\in T \wedge r\neq h \tag{19}$$

$$\sum_{r\in R}\sum_{l\in L} FN_{prlv}^{t} \le H_{vp} * q_{v}^{t}; \quad \forall v\in V, \forall p\in P \wedge \forall t\in T \tag{20}$$

$$I_{pr}^{t} = I_{pr}^{0}; \quad \forall p\in P, \forall r\in R \wedge t=0 \tag{21}$$

$$I_{pr}^{t} = I_{pr}^{t-1} + Q_{pr}^{t} - \sum_{v\in V}\sum_{l\in L} FN_{prlv}^{t}; \quad \forall p\in P, \forall r\in R \wedge \forall t\in T \tag{22}$$

$$I_{pr}^{t} \le k_{rp} * y_{r}; \quad \forall p\in P,\ \forall t\in T \wedge \forall r\in R \tag{23}$$

$$I_{pr}^{t} = 0; \quad \forall p\in P,\ \forall r\in R \wedge t=T \tag{24}$$

3.6.3 Variable decision constraints

$$y_{l} \in \{0,1\}; \quad \forall l\in L \tag{25}$$

$$n_{ijt}^{w} \in \{0,1\}; \quad \forall i\in L\cup C, \forall j\in L\cup C, \forall w\in W \wedge \forall t\in T \tag{26}$$

$$P_{lc}^{t} \in \{0,1\}; \quad \forall l\in L, \forall c\in C \wedge \forall t\in T \tag{27}$$

$$q_{w}^{t} \in \{0,1\}; \quad \forall w\in W, \wedge \forall t\in T \tag{28}$$

$$y_{r} \in \{0,1\}; \quad \forall r\in R \tag{29}$$

$$m_{ijt}^{v} \in \{0,1\}; \quad \forall i\in R\cup L, \forall j\in R\cup L, \forall v\in V \wedge \forall t\in T \tag{30}$$

$$L_{rl}^{t} \in \{0,1\}; \quad \forall r\in R, \forall l\in L \wedge \forall t\in T \tag{31}$$

$$q_{v}^{t} \in \{0,1\}; \quad \forall v\in V \wedge \forall t\in T \tag{32}$$

$$FN_{prlv}^{t} \in \mathbf{Z}^{+} \cup \{0\}; \quad \forall v\in V, \forall l\in L, \forall r\in R, \forall p\in P \wedge \forall t\in T \tag{33}$$

$$I_{pr}^{t} \in \mathbf{Z}^{+} \cup \{0\}; \quad \forall p \in P, \forall r \in R, \wedge \forall t \in T \tag{34}$$

$$Q_{pr}^{t} \in \mathbf{Z}^{+} \cup \{0\}; \quad \forall p \in P, \forall r \in R, \wedge \forall t \in T \tag{24}$$

3.7 Optimization model interpretation

Equation (1) minimizes the private costs, related to the opening of regional rescue centers (first term) and local rescue centers (second term), the use of vehicles at the first and second level (third and fourth terms), the routing at each echelon (fifth and sixth terms) and, in addition, the costs caused by managing the inventory at the first level facilities (regional centers), composed of the quantity purchased (seventh term), transported (eighth term) and in inventory (ninth term).

Moreover, equation (2) maximizes the total welfare of the demand points, which for convenience, is translated into a deprivation cost function (DCF), understood as the welfare that can be foregone by an affected area, given a deprivation time (F_{jt}) and a time required to supply humanitarian goods (TV_{ij}) to that area; thus obtaining two very important components: the deprivation function (first sub-terms, $VP_j^t * P_j * F_{jt}^{-1}$) and the distribution impact function (second sub-terms, $VP_j^t * P_j * TV_{ij}^{-1}$), which together represent the DCF, when the route plan is defined at the second echelon (third sub-terms, n_{ijt}^{w}).

On the other hand, equation (3) guarantees the assignment of each affected area to a single local rescue center; equation (4) ensures that the demand of the regions assigned to the same local rescue center does not exceed the capacity of that facility; equation (5) imposes that each affected area must be visited by exactly one second echelon vehicle; equation (6) allows each vehicle in use to return to the same local center from which it departed.

Furthermore, equation (7) prevents the formation of sub-tours or illegal routes in the second echelon; equation (8) ensures the unique assignment of a vehicle to a specific local rescue center, if it is enabled; equation (9) ensures that the local rescue center r serves the affected region c, if and only if there is a vehicle w leaving r and arriving at c and equation (10) allows that the demand satisfied by a vehicle in the second echelon does not exceed its capacity, if it is used in a facility during period t.

Continuing with the interpretation of the model, equation (11) allows the assignment of each enabled local rescue center to a single regional rescue center; equation (12) refers to the capacity restriction in the regional centers, since, as can be seen, the capacity of an enabled regional center must be greater or equal to the capacity of the local centers assigned to it; equation (13) guarantees the return to the same regional rescue center, the vehicle v assigned. Equation (14) avoids the formation of sub-tours or illegal routes in the first echelon; equation (15) allows a vehicle to be assigned to at most one regional rescue center, if it is used; equation (16) ensures that regional center r serves local center l, if there is a vehicle v leaving r and arriving at l; equation (17) is associated with the conservation of the flow in the local rescue center l, taking into account that the amount of product p entering it must be equal to the total demand of the assigned areas/regions.

Equations (18) and (19) guarantee that the amount of flow in a vehicle v from a regional rescue center r to a local rescue center l is positive if and only if both the regional center and the local rescue center are visited by the same vehicle v; equation (20) is related to the capacity limitation for a vehicle v (the flow or amount of product p transported in a vehicle v from a regional center r to a local center l must be less than or equal to the capacity of that vehicle). Equation (21) allows to include an initial inventory level for each of the products, in the regional centers r enabled; equation (22) represents the inventory balance, which in other words, means that the amount of inventory for a period t, is equal to the units stored in the previous period, plus the purchases made in t, minus the amount transported to each point of demand; Equation (23) prevents the units in inventory for each of the humanitarian products from exceeding the capacity tied to the first level facilities, and equation (24) imposes a zero inventory level for the last period of humanitarian aid in the different facilities (regional rescue centers).

Finally, equations (25)-(35) establish the nature of the decision variables considered in the mathematical model, which as can be seen are mostly binary (25-32) and a small portion take values in the set of positive integers (32-35), thus allowing to address an Integer Linear Programming (ILP) problem.

4. CONSTRUCTION OF EVOLUTIONARY ALGORITHMS

Taking as a reference the logical procedure of each of the chosen algorithms, in addition to the proposed scheme to generate and represent an individual or solution k, it is possible to build a parallel and cooperative version of each technique, using the paradigm of *“distributed systems or islands”* (see Figure 2), which basically consists of the use of a coordinator or collector C (*multi-processing variable*), which fulfills a mediating function in the exchange of information generated by each of the islands. In order to understand its role in the algorithmic process, a summary of its structure is presented below, taking into account the applied technique.

4.1 Parallel-cooperative algorithms

1. **Coordinator *p*-GA_V1**

1.1. Module for the reception and transfer of information generated in island 1

1.2. Module for the reception and transfer of information generated in island 2

1.3. Storage module (starts operation once the stop criterion is met)

1.3.1. Sub-module that stores the set of best individuals obtained in island 1 during each generation $[S^1(T)]$

1.3.2. Sub-module containing the set of best individuals obtained in island 2 during each generation $[S^2(T)]$

2. Coordinator *p*-NSGA-II_V1

2.1. Module for the reception and transfer of information generated on island 1

2.2. Module for the reception and transfer of information generated on island 2

2.3. Storage module (It is activated once the iterative process is finished)

2.3.1. Sub-module that stores the final population $[P_T^1(N/2)]$ of island 1

2.3.2. Sub-module containing the final population $[P_T^2(N/2)]$ of island 2

3. Coordinator *p*-SPEA-II_V1

3.1. Module for reception and transfer of information generated in island 1

3.2. Module for the reception and transfer of information generated in island 2

3.3. Storage module (Executed once the iterative process is finished)

3.3.1. Sub-module storing the final external population $\left[P_{E_1}^T\right]$ of island 1

3.3.2. Sub-module containing the final external population $\left[P_{E_2}^T\right]$ of island 2

4.2 Pure parallel algorithms

4. *p*-NSGA-II _V2

4.1. Module in charge of storing the final population $[P_T^1(N/2)]$ obtained in island 1

4.2. Module in charge of storing the final population $[P_T^2(N/2)]$ obtained in island 2

5. *p*-GA_V2

5.1. Module that stores the set of best individuals obtained in island 1 during each generation $[S^1(T)]$

5.2. Module that stores the set of best individuals obtained in island 2 during each generation $[S^2(T)]$

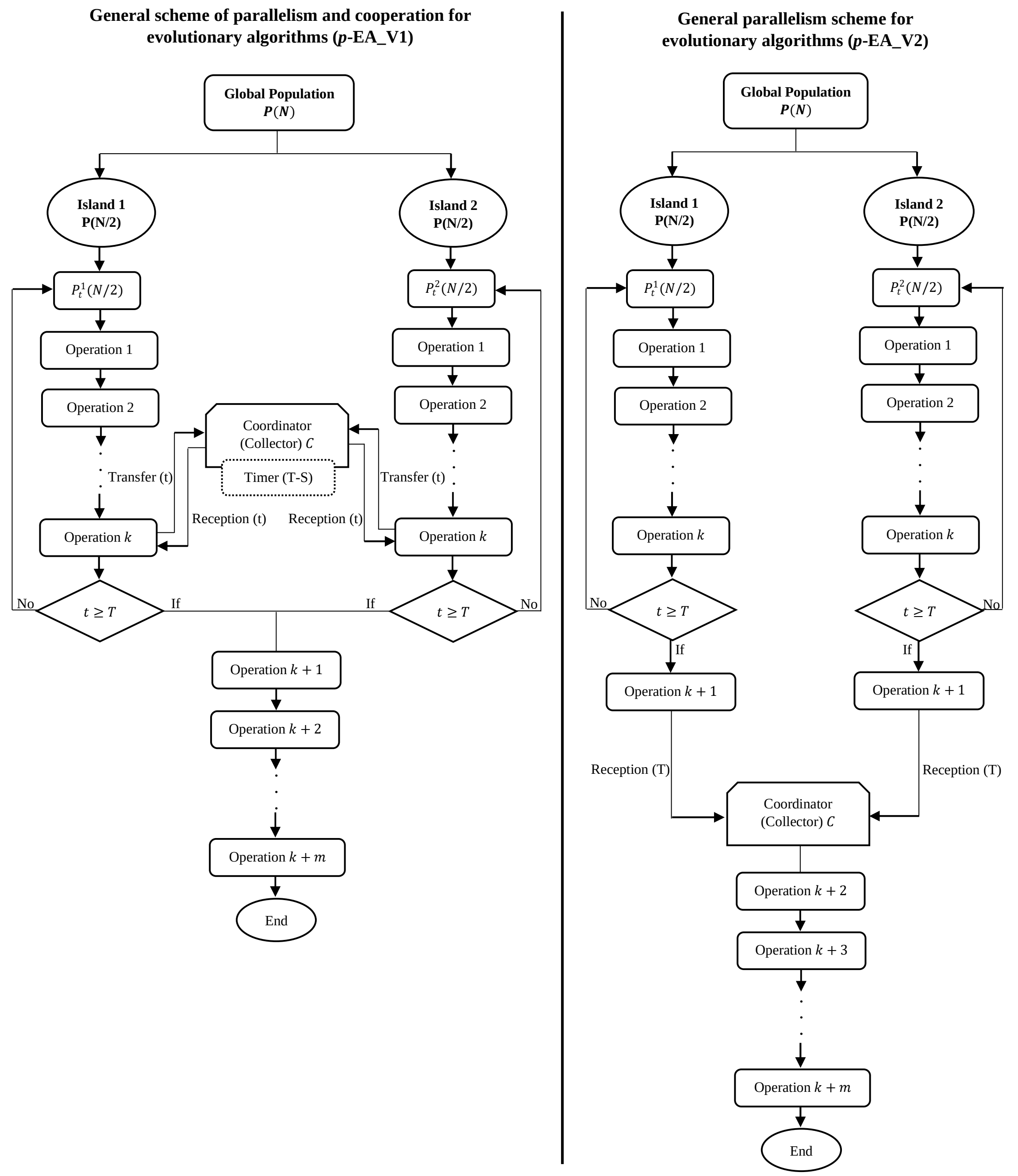

Fig 2 - General operation of parallel-cooperative and purely parallel evolutionary algorithms

5. EXPERIMENTATION

Once the solution techniques have been coded in the Python programming language, it is essential to validate them, in order to verify consistent outputs, depending on the problem addressed and the assumptions established.

To carry out this procedure, it was necessary to create a set of test instances (testbed), taking into account those designed by Albareda-Sambola et al. (2005) and Prodhon (2006), since there are currently no easily adaptable scenarios in the literature; these instances are consolidated under the nomenclature presented in Table 3.

Type of Instance	**Nomenclature**							**Reference**
	C	**L**	**R**	**W**	**V**	**P**	**T**	
1	30	10	7	11	6	8	7	I1_30C-10L-7R-11W-6V-8P-7T
2	50	8	4	10	6	3	4	I2_50C-8L-4R-10W-6V-3P-4T
3	100	20	14	30	22	4	3	I3_100C-20L-14R-30W-22V-4P-3T
4	65	12	9	17	12	2	2	I4_65C-12L-9R-17W-12V-2P-2T
5	26	9	5	10	8	6	3	I5_26C-9L-5R-10W-8V-6P-3T
6	40	12	12	11	7	5	3	I6_40C-12L-12R-11W-7V-5P-3T
7	57	10	12	14	10	11	2	I7_57C-10L-12R-14W-10V-11P-2T
8	32	11	9	14	14	5	5	I8_32C-11L-9R-14W-14V-5P-5T
9	125	8	11	13	9	2	2	I9_125C-8L-11R-13W-9V-2P-2T
10	91	6	7	16	10	3	2	I10_91C-6L-7R-16W-10V-3P-2T
11	75	7	6	9	8	4	4	I11_75C-7L-6R-9W-8V-4P-4T
12	140	5	3	12	11	2	2	I12_140C-5L-3R-12W-11V-2P-2T
13	45	15	10	7	5	7	2	I13_45C-15L-10R-7W-5V-7P-2T
14	60	4	8	8	4	3	4	I14_60C-4L-8R-8W-4V-3P-4T
15	80	7	13	12	8	3	3	I15_80C-7L-13R-12W-8V-3P-3T
16	35	6	7	9	5	4	5	I16_35C-6L-7R-9W-5V-4P-5T
17	70	16	16	13	9	2	3	I17_70C-16L-16R-13W-9V-2P-3T
18	38	5	7	8	10	6	4	I18_38C-5L-7R-8W-10V-6P-4T
19	54	3	10	15	13	5	5	I19_54C-3L-10R-15W-13V-5P-5T
20	28	4	8	10	7	9	6	I20_28C-4L-8R-10W-7V-9P-6T

Table 3 - Set of instances for validation of AEs

Note. C= Number of clients, L= Potential local centers, R= Potential regional centers, W= Second tier vehicles, V= First tier vehicles, P= Products and T= Relief periods.

Once the errors have been corrected and the codes debugged, it is possible to move on to the calibration process, which consists of identifying the main variables influencing the performance (solution quality and computational time) of the algorithms (GA, *p*-GA_V1/V2 *p*-NSGA-II_V1/V2 and *p*-SPEA-II_V1);

Therefore, it is decided to use a 2^k factorial design (DOE), composed of the parameters of the evolutionary algorithms (factors), i.e., population size (PS), number of generations (NG) and mutation probability (MP); taking into account as response variables, the best solution found (BS), if the methodology is of the single-objective type, the number of non-dominated solutions (NDS), for multi-objective approaches and a variable common to both techniques, the computational time (CT) required. On the other hand, the configurations established for this experiment are shown in Table 4 and Table 5, where the levels or treatments were chosen based on the experimentation and the review of previous studies.

Factors	Levels	
	Low (-)	High (+)
PS	100	200
NG	150	300
MP	0,05	0,10

Table 4 - Factorial design for the single-objective techniques

Factors	Levels	
	Low (-)	High (+)
PS	240	480
NG	50	100
MP	0,05	0,10

Table 5. Factorial design for the multi-objective techniques

It is important to mention that the tests were performed on a laptop computer with a Core i5-1035G4 processor, 8 GB RAM memory and solid-state hard disk, using a total of 5 replicates for each of the possible combinations of the levels of the main factors; in addition, the hypotheses of significance for the BS and NDS variables were contrasted under a confidence level equivalent to 80% and for the case of CT, a level equal to 95% was taken into account.}

In order to choose the best configuration of levels for the evolutionary factors (initialization parameters) and to allow adequate outputs, taking into account the set of instances tested on each technique, it was decided to use the response optimizer that Minitab 19 has in the section: "DOE>Factorial>Optimizer". Once this tool has been executed, under the same level of importance between test scenarios, the structure shown in Table 6 is obtained, which will serve as a starting point when executing any test instance.

Algoritmo	Best combination of treatments associated with the response variable (Optimizer)					
	BS/NDS			CT		
	PS	NG	MP	PS	NG	MP
GA	200	300	0,05	100	150	0,10
p-GA_V1	200	300	0,05	100	150	0,10
p-NSGA-II_V1	480	50	0,10	240	50	0,10
p-SPEA-II_V1	480	50	0,10	240	50	0,10
p-NSGA-II_V2	480	50	0,10	240	50	0,10
p-GA_V2	200	300	0,05	100	150	0,10

Table 6 - Optimal combination of factors associated with AEs

Taking as reference the configuration of the evolutionary parameters obtained previously by means of the factorial design, the testbed is executed on each algorithm, with the purpose of obtaining sufficient data to verify the preliminary statements, associated to the performance; which is represented in the case of the mono-objective techniques, by the variable: best solution found (BS) and for the multi-objective approaches, the variable defined as: number of non-nominated solutions (NDS), taking into account in turn, the computational time (CT). To carry out this procedure, it was necessary to use a sample size equivalent to thirty (30) per instance tested and to apply the t-test statistic with joint equality of variances, for differences between two means. The results of each technique are presented in Table 7-10, using an algorithmic contrast or GAP.

Instance	**Algorithm**				**GAP**	
	***p*-NSGA-II_V1**		***p*-SPEA-II_V1**		**(*p*-NSGA-II_V1-*p*-SPEA-II_V1)**	
	NDS	**CT**	**NDS**	**CT**	**NDS**	**CT**
I1	6,100	399,550	5,900	477,034	0,200	-77,484
I2	8,567	223,042	8,167	299,973	0,400	-76,932
I3	5,867	348,650	6,967	421,611	-1,100	-72,961
I4	6,633	163,684	8,167	233,694	-1,533	-70,009
I5	8,867	117,551	9,633	188,416	-0,767	-70,865
I6	9,200	188,290	9,200	257,267	0,000	-68,977
I7	5,567	181,082	6,400	252,590	-0,833	-71,507
I8	8,167	230,756	9,600	296,181	-1,433	-65,425
I9	5,200	238,188	6,533	303,023	-1,333	-64,835
I10	8,900	178,006	8,867	250,924	0,033	-72,918
I11	8,533	294,992	8,400	361,875	0,133	-66,883
I12	9,767	211,720	10,800	281,523	-1,033	-69,803
I13	11,100	111,218	12,667	165,437	-1,567	-54,219
I14	6,533	228,217	7,233	271,475	-0,700	-43,258
I15	6,533	259,037	6,200	296,033	0,333	-36,996
I16	9,200	214,804	9,400	265,671	-0,200	-50,867
I17	6,067	263,645	6,500	308,835	-0,433	-45,190
I18	6,400	208,508	7,633	267,172	-1,233	-58,665
I19	6,300	287,443	7,233	348,707	-0,933	-61,264
I20	5,900	242,527	7,533	305,711	-1,633	-63,184

Table 7 - GAP between algorithms *p*-NSGA-II_V1 and *p*-SPEA-II_V1(n = 30)

Note. The results correspond to an average and the computational time (CT) is given in seconds.

Instance	Algorithm				GAP (*p*-GA_V1-GA)	
	p-GA_V1		GA			
	BS	CT	BS	CT	BS	CT
I1	-2608329,808	693,339	-2621485,630	620,700	13155,822	72,639
I2	-118843,322	402,573	-119472,111	343,335	628,789	59,239
I3	-2666872,956	585,832	-2687137,125	535,088	20264,169	50,744
I4	-3977960,852	276,149	-3986844,367	243,198	8883,515	32,951
I5	-1421596,543	204,778	-1422258,866	178,447	662,323	26,331
I6	-1598128,210	324,961	-1597821,753	285,487	-306,457	39,474
I7	-427842,676	315,004	-436876,559	281,402	9033,883	33,603
I8	-3020121,145	398,285	-3022902,409	355,207	2781,264	43,077
I9	-4452441,767	402,390	-4460707,077	352,999	8265,310	49,391
I10	-10437775,724	299,961	-10435912,098	269,714	-1863,626	30,248
I11	-5797773,828	499,006	-5800601,257	457,315	2827,429	41,691
I12	-9914707,692	374,540	-9921649,955	331,951	6942,263	42,589
I13	-1875211,244	172,358	-1876014,889	153,123	803,645	19,234
I14	-3081713,774	361,084	-3086399,139	325,763	4685,365	35,321
I15	-4233694,198	405,131	-4240697,709	367,707	7003,511	37,424
I16	-3571773,645	355,100	-3571430,187	317,716	-343,458	37,384
I17	-3975248,726	422,269	-3987212,763	385,487	11964,037	36,781
I18	-1418874,253	341,502	-1430756,336	311,764	11882,083	29,738
I19	-2936430,644	491,022	-2939044,696	455,393	2614,053	35,630
I20	-3442215,098	414,514	-3445306,281	382,268	3091,183	32,246

Table 8 - GAP between algorithms *p*-GA_V1 and GA (n = 30)

Note. The results correspond to an average and the computational time (CT) is given in seconds.

Instance	Algorithm				GAP (*p*-NSGA-II_V2-*p*-SPEA-II_V1)	
	***p*-NSGA-II_V2**		***p*-SPEA-II_V1**			
	NDS	**CT**	**NDS**	**CT**	**NDS**	**CT**
I1	6,767	389,762	5,900	477,034	0,867	-87,272
I2	9,233	221,183	8,167	299,973	1,067	-78,791
I3	6,300	341,345	6,967	421,611	-0,667	-80,266
I4	6,667	159,942	8,167	233,694	-1,500	-73,752
I5	10,267	117,456	9,633	188,416	0,633	-70,960
I6	9,967	186,027	9,200	257,267	0,767	-71,240
I7	6,333	178,663	6,400	252,590	-0,067	-73,927
I8	8,967	223,228	9,600	296,181	-0,633	-72,953
I9	6,100	230,447	6,533	303,023	-0,433	-72,576
I10	8,933	176,165	8,867	250,924	0,067	-74,758
I11	9,533	291,936	8,400	361,875	1,133	-69,939
I12	11,067	215,053	10,800	281,523	0,267	-66,469
I13	13,267	100,823	12,667	165,437	0,600	-64,614
I14	7,467	206,141	7,233	271,475	0,233	-65,334
I15	7,767	234,765	6,200	296,033	1,567	-61,269
I16	10,500	204,194	9,400	265,671	1,100	-61,477
I17	6,500	247,296	6,500	308,835	0,000	-61,539
I18	8,100	197,680	7,633	267,172	0,467	-69,492
I19	7,400	281,774	7,233	348,707	0,167	-66,933
I20	8,533	234,325	7,533	305,711	1,000	-71,386

Table 9 - GAP between algorithms *p*-NSGA-II_V2 and *p*-SPEA-II_V1 (n = 30)

Note. The results correspond to an average and the computational time (CT) is given in seconds.

Instance	Algorithm				GAP (*p*-GA_V2-GA)	
	p-GA_V2		GA			
	BS	CT	BS	CT	BS	CT
I1	-2619906,796	679,429	-2621485,630	620,700	1578,834	58,729
I2	-119153,886	382,557	-119472,111	343,335	318,225	39,223
I3	-2679250,089	581,146	-2687137,125	535,088	7887,036	46,057
I4	-3985067,370	271,852	-3986844,367	243,198	1776,997	28,654
I5	-1423644,349	196,921	-1422258,866	178,447	-1385,483	18,474
I6	-1597800,833	314,473	-1597821,753	285,487	20,921	28,986
I7	-435757,645	315,684	-436876,559	281,402	1118,914	34,282
I8	-3020996,654	390,588	-3022902,409	355,207	1905,756	35,380
I9	-4457008,689	393,371	-4460707,077	352,999	3698,388	40,373
I10	-10437311,884	297,082	-10435912,098	269,714	-1399,786	27,368
I11	-5799699,320	504,373	-5800601,257	457,315	901,938	47,057
I12	-9918961,427	366,633	-9921649,955	331,951	2688,527	34,682
I13	-1875070,324	169,132	-1876014,889	153,123	944,566	16,009
I14	-3084389,255	360,077	-3086399,139	325,763	2009,884	34,314
I15	-4239894,080	390,638	-4240697,709	367,707	803,629	22,931
I16	-3572521,077	346,914	-3571430,187	317,716	-1090,890	29,198
I17	-3986816,770	418,637	-3987212,763	385,487	395,993	33,150
I18	-1421781,899	339,794	-1430756,336	311,764	8974,437	28,029
I19	-2937575,106	492,697	-2939044,696	455,393	1469,590	37,305
I20	-3445063,335	414,627	-3445306,281	382,268	242,946	32,359

Table 10 - GAP between algorithms *p*-GA_V2 and GA (n = 30)

Note. The results correspond to an average and the computational time (CT) is given in seconds.

6. DISCUSSION

The experimentation carried out points to the algorithms *p*-NSGA-II_V1 and *p*-NSGA-II_V2 as the best alternatives to solve the multi-objective 2E-LIRP problem applied to the humanitarian supply chain, because they obtain the highest average number of non-dominated solutions (NDS), allowing the decision maker to have a prudent set of possible solutions and also, the execution times (CT) are statistically lower than *p*-SPEA_V1.

Despite an approximately equal performance in terms of computational time (CT) or solution quality (BS), by genetic algorithms (GA) programmed in parallel under a cooperative environment or simply with a parallel approach, compared to their sequential counterpart, it is important to mention that there are some considerable improvements for the variable BS, using the *p*-GA_V1 and *p*-GA_V2 techniques, which are valued at 45% and 50% respectively, taking as a reference the testbed, i.e., the *p*-GA_V1 algorithm improves the solutions for 45% of the tested instances, while the *p*-GA_V2 allows to obtain a global improvement, equivalent to 50%.

On the other hand, the algorithms designed under the mono-objective and multi-objective approaches, taking into account sequential, parallel and cooperative characteristics, generally present a reasonable processing time (5 to 10 minutes approximately), thus becoming valid and efficient tools that support integral decision making for the management of the humanitarian supply chain, whose main objective is to attend the areas affected by a disaster in the shortest possible time, thus saving as many lives as possible.

Finally, the results obtained in each of the solution approaches indicate that the present study has fulfilled the general purpose, related to the development of a multi-objective optimization model for the two-echelon location, routing and inventory problem (2E-LIRP) and, consequently, to the design of a set of computational tools (Python code), which allow solving specific instances, providing relevant information to the decision-maker and designing the humanitarian logistics network.

7. CONCLUSIONS

One of the most significant contributions provided by this research is the development of a multi-objective model for the problem of location, inventory and multi-echelon routing, considering dynamic demand, heterogeneous fleet, multiple periods and products, which takes into account the optimization of social costs, due to its humanitarian context and the new approaches in the area of disasters that seek to mediate between private and humanitarian costs, despised so far in much of the existing literature, because they use adaptations of commercial logistics; in other words, the objectives of the mathematical model constructed are to minimize traditional logistics costs (location, inventory and routing) and, at the same time, to maximize the welfare of the affected areas, using a function that represents the impact on the distribution strategy and the time of deprivation experienced.

The parallel-cooperative or purely parallel scheme, acts favorably when constructing solution techniques that follow the methodology proposed by NSGA-II, thus allowing a higher performance, if compared to the SPEA-II algorithm, designed under identical conditions, using as metrics, the computational time (CT) and the number of non-dominated solutions (NDS). Moreover, it is important to mention how the *p*-NSGA-II_V1 and *p*-NSGA-II_V2 algorithms have strictly lower computational times for 100% of the executed instances and at the same time, the number of non-dominated solutions are at least equal or higher than those of *p*-SPEA-II_V1.

The experimentation carried out showed that using parallel programming under the cooperative paradigm or simply the parallel approach, in the design of a single-objective genetic algorithm (*p*-GA_V1 or *p*-GA_V2), for the solution of the 2E-LIRP, allows obtaining at the inferential level solution methods approximately equal, in terms of the variable, best solution found (MS), than its sequential counterpart, the genetic algorithm

(GA). However, it is important to mention that for a set of replicates (sample level), the *p*-GA_V1 and *p*-GA_V2 algorithms significantly improve the solutions obtained by the GA technique, finding approximately 45% (parallel-cooperative algorithm) and 50% (parallel algorithm) of the best global solutions in the testbed executed.

In spite of the effort made to build a parallel-cooperative genetic algorithm that would present an improvement in terms of computational time (CT), the experimentation allows inferring that under the scheme used (distributed system or islands), this purpose is impossible to achieve, since in most of the instances used, the performance obtained was inferior with respect to its sequential counterpart, This is due to two very important aspects, the first, the need to synchronize the two threads (islands) at the time of the transfer of genetic information and the second, the additional operations that it needs to perform in the collector (communication mechanism), to finally obtain a solution (better individual).

The evolutionary techniques used in the present study offered excellent performance (global range between 5 and 10 minutes) when solving the problem addressed, given the computational complexity that demanded the use of adequate tools to obtain good solutions in reasonable computational times. Each proposed technique was validated by applying a testbed, composed of twenty test instances, where the consistency and validity of the outputs were two very important aspects that were evaluated, with the purpose of offering the decision-maker useful tools to support the management of the humanitarian supply chain, taking into account the needs (location, inventory and routing) from an integral viewpoint, the multi-objective approach, which provides a set of possible solutions, which according to some criteria or specific technique, lead to the selection of an alternative, and the mono-objective approach, which allows to mediate or combine the interests under conflict, by applying a level of importance or weight, in order to obtain a single answer.

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