Hindawi
Journal of Optimization
Volume 2018, Article ID 3605298, 14 pages
https://doi.org/10.1155/2018/3605298

Research Article

Extended GRASP-Capacitated K-Means Clustering Algorithm to Establish Humanitarian Support Centers in Large Regions at Risk in Mexico

Santiago-Omar Caballero-Morales, Erika Barojas-Payan, Diana Sanchez-Partida, and Jose-Luis Martinez-Flores

Universidad Popular Autonoma del Estado de Puebla, A.C., Postgraduate Department of Logistics and Supply Chain Management, Puebla, Mexico

Correspondence should be addressed to Santiago-Omar Caballero-Morales; santiagoomar.caballero@upaep.mx

Received 9 July 2018; Revised 25 November 2018; Accepted 4 December 2018; Published 20 December 2018

Guest Editor: Morteza Ghobakhloo

Mexico is located within the so-called Fire Belt which makes it susceptible to earthquakes. In fact, two-thirds of the Mexican territory have a significant seismic risk. On the other hand, the country's location in the tropical zone makes it susceptible to hurricanes which are generated in both the Pacific and Atlantic Oceans. Due to these situations, each year many communities are affected by diverse natural disasters in Mexico and efficient logistic systems are required to provide prompt support. This work is aimed at providing an efficient metaheuristic to determine the most appropriate location for support centers in the State of Veracruz, which is one of the most affected regions in Mexico. The metaheuristic is based on the K-Means Clustering (KMC) algorithm which is extended to integrate (a) the associated capacity restrictions of the support centers, (b) a micro Genetic Algorithm μGA to estimate a search interval for the most suitable number of support centers, (c) variable number of assigned elements to centers in order to add flexibility to the assignation task, and (d) random-based decision model to further improve the final assignments. These extensions on the KMC algorithm led to the GRASP-Capacitated K-Means Clustering (GRASP-CKMC) algorithm which was able to provide very suitable solutions for the establishment of 260 support centers for 3837 communities at risk in Veracruz, Mexico. Validation of the GRASP-CKMC algorithm was performed with well-known test instances and metaheuristics. The validation supported its suitability as alternative to standard metaheuristics such as Capacitated K-Means (CKM), Genetic Algorithms (GA), and Variable Neighborhood Search (VNS).

1. Introduction

A *phenomenon* or *disturbing agent* is defined as an aggressive and potentially harmful physical event, natural or derived from human activity, which can cause loss of life or injury, material damage, serious disruption of social and economic life, or environmental degradation. Thus, these agents can have the following origins [1, 2]:

(a) Natural: geological, hydrometeorological, and astronomical.

(b) Anthropogenic: chemical-technological, health-ecological, and social-organizational.

Mexico is located within the so-called *Fire Belt* of the Pacific and within the tropical zone. This makes the country susceptible to a great variety of disturbing agents of natural origin [3]:

(a) Two-thirds of the country have significant seismic risks.

(b) Coastal regions are frequently affected by hurricanes which are generated in the Pacific and Atlantic Oceans.

Due to its geographical location, geological characteristics, and the complex morphology of its territory, the State of

Table 1: Declarations of natural disasters: 2014-2017 [5].

Year	Description	FONDEN (Mexican Pesos)
2014	01. Severe rain and fluvial flood in October 13-16	193,636,015.00
2015	01. Severe rain in March 11-12	1,610,707,729.00
	02. Severe rain in March 21-23 and severe rain and fluvial flood in March 25-27	
	03. Severe rain and fluvial flood in June 11-14	
	04. Hillside movement in July 9-13	
	05. Hillside movement in September 16-18	
	06. Severe rain and fluvial and rain flood in October 16-21	
	07. Severe rain and fluvial and rain flood in October 18-24	
2016	01. Hillside movement in August 5-7	860,195,408.00
	02. Severe rain and fluvial flood in August 5-7	
	03. Severe rain in September 27-28	
2017	01. An earthquake with magnitude 8.2 on September 7	496,947,819.20
	02. Hurricane "Katia" - severe rain and fluvial flood in September 8-12	
	03. Hillside movement from September 27 to October 9	
	04. Severe rain and fluvial flood from September 27 to October 9	
	05. Fluvial flood in October 11-15	
	06. Severe rain in October 11	
	Total	3,161,486,971.20

Veracruz in Mexico is exposed to natural phenomena such as earthquakes, volcanic eruptions, floods, and landslides. The presence of hydrometeorological phenomena is very common in Veracruz, which leads to frequent affectations. In response to the presence of disturbing natural phenomena, in Mexico the Natural Disasters Fund (FONDEN) was created. This is a financial instrument whose purpose is to provide relief supplies and assistance in emergency and disaster situations. In Veracruz, the rules of the Fund for the Prevention of Natural Disasters (FOPREDEN) are an instrument that aims to revitalize initiatives aimed at preventing disasters and seeks to optimize the use of available financial resources and magnify the results linked mainly to the preservation of the life and physical integrity of people, as well as that of public services and infrastructure and the environment [4].

As of 2017 FONDEN has authorized resources for more than three billion of Mexican pesos to support the road, educational sectors, forestry, hydraulic, naval, housing, and urban infrastructure in Veracruz due to the significant occurrence of natural disasters within the period 2014-2017. Table 1 presents an overview of the historical phenomena within this period and the resources provided.

Standard protocols to be performed before, during, and after a disaster involve different logistic processes. These are performed in the different phases of a disaster [6, 7]:

(1) Interdisaster phase: processes are performed in which the elaboration of the map of risks for the community is highlighted. Also the Plans of Emergency, which consist of inventory and location planning of resources, are performed.

(2) Pre-impact phase: warning to the population based on prediction mechanisms and implementation of mitigating measures are performed.

(3) Disaster impacts the community.

(4) Emergency phase: isolation, rescue, and external assistance are performed. It is often the phase in which local resources are overwhelmed and external aid is required to reduce the number of fatalities.

(5) Reconstruction phase: activities focused on recovering the normal duties of the community are performed.

Before the disaster occurs, it is important to have facilities with an optimal inventory of products of first necessity to support the survival of the people who will be affected. Also, after the disaster occurs, it is important to have the infrastructure to resupply the facilities and transport affected people to other facilities as needed.

Hence, among the most critical decisions and resources to provide relief to the affected communities in Veracruz, prepositioning of warehouses must be performed. This allows the protection of supplies and the efficient and timely supply of products to cover the basic needs of the people affected by the disturbing phenomenon. Within the activities to be performed in these warehouses or support centers, the following can be mentioned:

(1) Identification, labeling, and location of the necessary supplies to attend the emergency.

(2) Consolidation of load and change of means of transport.

(3) Delivery scheduling for the supplies.

Likewise, the warehouse must have an information and inventory control system which must be updated, through the control of inventories. The activation of a prepositioned warehouse is the responsibility of State Civil Protection with selection criteria for its allocation such as (a) being located outside the risk area, (b) having a solid and roofed construction in compliance with safety parameters, (c) being accessible through favorable conditions for transport loading and unloading, (d) being ventilated, illuminated, and without water seepage risk, (e) being located far away from flood-prone areas, (f) being free of pollution or plague, and (g) having space to facilitate the mobility, cleaning, and classification of products [8, 9]. Minimization of distance between the affected regions and the prepositioned warehouses is an important aspect of humanitarian relief planning because communities must be able to reach these centers within short periods of time and distances due to the severity of the disasters.

In this regard, humanitarian logistics (HL) formally addresses the "process of planning, implementing, and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information from point of consumption for the purpose of meeting the end beneficiary's requirements" [10, 11]. The need of HL for strategic planning has been recognized by important organizations such as the U.S. Federal Emergency Management Agency (FEMA) and the United Nations (UN) [11, 12]. In contrast to commercial logistics (CL), the main focus of HL is to save lives and provide beneficiaries with aid instead of maximizing profits. However, due to this characteristic, HL has disadvantages when compared to CL as it faces lower technology, challenging inventory control, unstable demand patterns, zero lead time, and unpredictable supply resources [13, 14].

Hence, different strategies have been developed within the field of HL for the optimal operation of all the aspects of the supply chain (SC) for the delivery of goods to affected communities considering these disadvantages. In this context, humanitarian relief organizations (HRO) have been identified as the best suited organizations for preparedness and recovery when compared to commercial and military organizations [13]. An important aspect of preparedness is the prepositioning of inventories or warehouses for postdisaster relief. Among the most recent strategies, which are focused on transportation, planning, policies and procedures, and inventory/warehousing [15], the following can be mentioned:

(i) In [16], a stochastic model was developed to determine the location of Emergency Medical Service (EMS) systems. In order to solve this model, exact and approximate (metaheuristics) methods were proposed.

(ii) The facility location problem was also addressed by [17] that presented a multiobjective optimization model to solve a multidepot emergency facilities location-routing problem. Due to the inherent computational complexity of this model an approximate method based on the metaheuristic of Genetic Algorithms (GAs) was developed.

(iii) Prepositioning or relief assets was studied in [11] to optimize the transportation of affected people to relief centers. The proposed stochastic model considered optimization of resources such as personnel and vehicles to minimize casualties.

(iv) In [18] the aspect of considering containers as storage facilities was studied, and a mathematical model was proposed to determine the locations of supply points and the quantity of containers and relief supplies assigned to each supply point under the minimum distance criteria.

(v) A stochastic inventory control strategy was proposed in [19] for the uncertain requirements of goods for postdisaster conditions, in order to have the adequate stock to serve the vital needs of affected communities.

(vi) A conceptual model that integrated the aspect of agility in HL was presented in [20] to improve on the response of HL to disaster scenarios. While no mathematical model was presented or discussed, the roles of people, processes, and technology were identified as agility enablers for the success of general models within HL.

In general for the determination and location of facilities (i.e., support centers, warehouses, prepositioned inventory, etc.) the following mathematical models have been considered: the Capacitated p-Median Problem (CPMP) [21, 22] and the Capacitated Centered Clustering Problem (CCCP) [23, 24]. Both models are focused on determining the location of p facilities in order to minimize the total weighted distance from the facilities to all demand points (customers). A demand point cannot be assigned to more than one facility, and the points assigned to a facility cannot exceed its capacity. The main difference between both models is about the features of the locations of the p facilities. In the CPMP the location is determined at a median point while for the CCCP the location is determined at a centroid.

Both models are difficult to be solved to optimality due to their NP-hard computational complexity. Particularly for large problems, this has led to the development of metaheuristics to provide near-optimal solutions [25]. In the literature, metaheuristics based on Clustering Search (CS) have been reported as the most competitive methods for the CCCP [24]. However, in this work we focus on providing an alternative to standard methods which are commonly implemented for practical situations. In the case of humanitarian relief actions, fast implementation is required, and we are considering the situation of Veracruz in Mexico, where 3837 communities with 526,954 people are at risk.

Thus, in this work a metaheuristic based on the integration of the Greedy Randomized Adaptive Search Procedure

(GRASP) and the K-Means Clustering (KMC) algorithm is presented to provide a suitable location planning for the support centers (prepositioned warehouses) for these communities in Mexico. In order to provide more accurate solutions for large CCCP instances than those of standard methods, the proposed metaheuristic has the following features:

(a) capacity restrictions to the KMC algorithm for the assignation of communities to support centers (Capacitated K-Means Clustering, CKMC);

(b) micro Genetic Algorithm (μGA) that performs single executions of the CKMC to estimate a search interval for the most suitable number of support centers;

(c) variable number of assigned communities to centers in order to add flexibility to the assignation task through iterative executions of the CKMC;

(d) conditional decision process to perform insertion, deletion, and exchange of communities between centers for further improvement of the final assignments;

(e) Earth's arc length as distance metric to locate centers within measurable distance in kilometers.

The details of this metaheuristic, termed as GRASP-CKMC, are presented as follows: in Section 2 the technical details of the GRASP-CKMC and its validation are presented. Then, in Section 3 the results on the instance of Veracruz are presented and analyzed. Finally, our conclusions are presented in Section 4.

2. GRASP-CKMC

A Greedy Randomized Adaptive Search Procedure (GRASP) is a metaheuristic which consists of two main phases: (a) the Construction Phase which consists in providing a feasible solution by combining a greedy function with a method of random selection and (b) the Local Search Phase which consists in iteratively improving the feasible solution [26, 27].

As presented in Figure 1 the proposed GRASP manages three main algorithms for these phases:

(i) Constructive Phase: a μGA is performed to determine the lower and upper limits for the most suitable number of clusters. Random selection is performed for the creation of the initial population and the number of V nearest points to extend the KMC to comply with capacity restrictions (CKCM).

(ii) Local Search Phase: the CKMC is iteratively performed with uniform random variation in V and the number of clusters K restricted by the lower and upper limits identified in the previous phase.

(iii) Random decision process to exchange locations between capacity-complying assignments for further improvement of the final CCCP solution.

In the following sections the details of the main algorithms used for the phases of the GRASP are presented and discussed.

2.1. Capacitated KMC.

2.1. Capacitated KMC. K-Means is one of the basic unsupervised learning algorithms that solve the well-known clustering problem [28–30]. This model is similar to the also well-known K-Nearest Neighbor (KNN) search algorithm [31]. The KMC follows a simple procedure to classify a given data set through a certain number of clusters K [28, 32]. Within the context of the CCCP or CPMP the facility is located at the cluster's centroid or median point, respectively. For multiple facilities, the first problem to be solved is the consolidation of clusters (i.e., groups of points) and the second is the determination of the median point or centroid. Both problems can be addressed simultaneously by the K-Means Clustering (KMC) algorithm. Figure 2 presents the details of the standard KMC algorithm.

As presented in Figure 2 clustering involves the unique assignment of a point to the nearest cluster based on its center (defined as the median point or the centroid). The locations of the centers must be reestimated each time that new assignments are performed, and new assignments can be generated each time that the reestimation process is performed as they affect the closeness of the centers to the considered points.

For the purpose of determining the locations of the support centers and their assigned communities, the standard KMC algorithm must integrate capacity restrictions. However this adds complexity to the assignment task because not all nearest points to a certain center can comply with its capacity restriction (thus, not all nearest points can be assigned to this center).

Approaches have been proposed to address the capacitated task. In contrast to the circular regions shown in Figure 2, in [32] a rectangular region around the center was considered to determine the candidates for clustering. This reduces the number of points to be assigned to the cluster and thus reduces the likelihood of not complying with the capacity restriction. The points located outside the rectangular region are omitted by this initial assignment process. After this process is performed, a priority is assigned to the omitted points in order to be assigned to the clusters with available capacity in a final assignment process. Other approaches involve an average distance for the reassignment of points [33].

The assignment of close points and reassignment of omitted points are procedures which can be performed with some randomness to add flexibility to the local search process of KMC. Thus, the proposal to extend the KMC to perform the capacitated task consists in including a uniform random variable to control the ratio of acceptance for the KMC algorithm (and thus, of the V nearest locations). This proposal is similar to the Variable Neighborhood Search (VNS) principle [34].

Figure 3 presents the general structure of the proposed capacity-restricted KMC algorithm (CKMC). As presented in Figure 1, this CKMC algorithm is used in both phases of the GRASP-CKMC metaheuristic. This is the reason of the adjustments stated in Figure 3:

(i) In the Constructive Phase, the CKMC is executed only once for two random K values which will be used

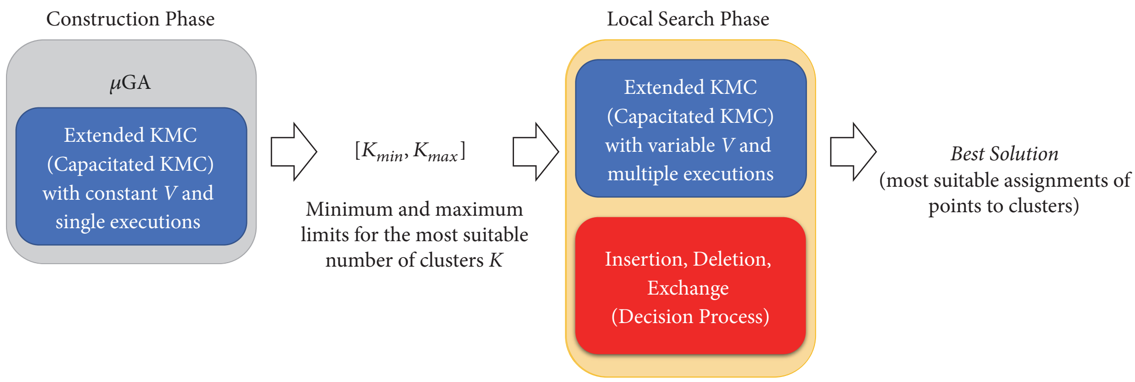


FIGURE 1: General structure of the GRASP-CKMC algorithm.

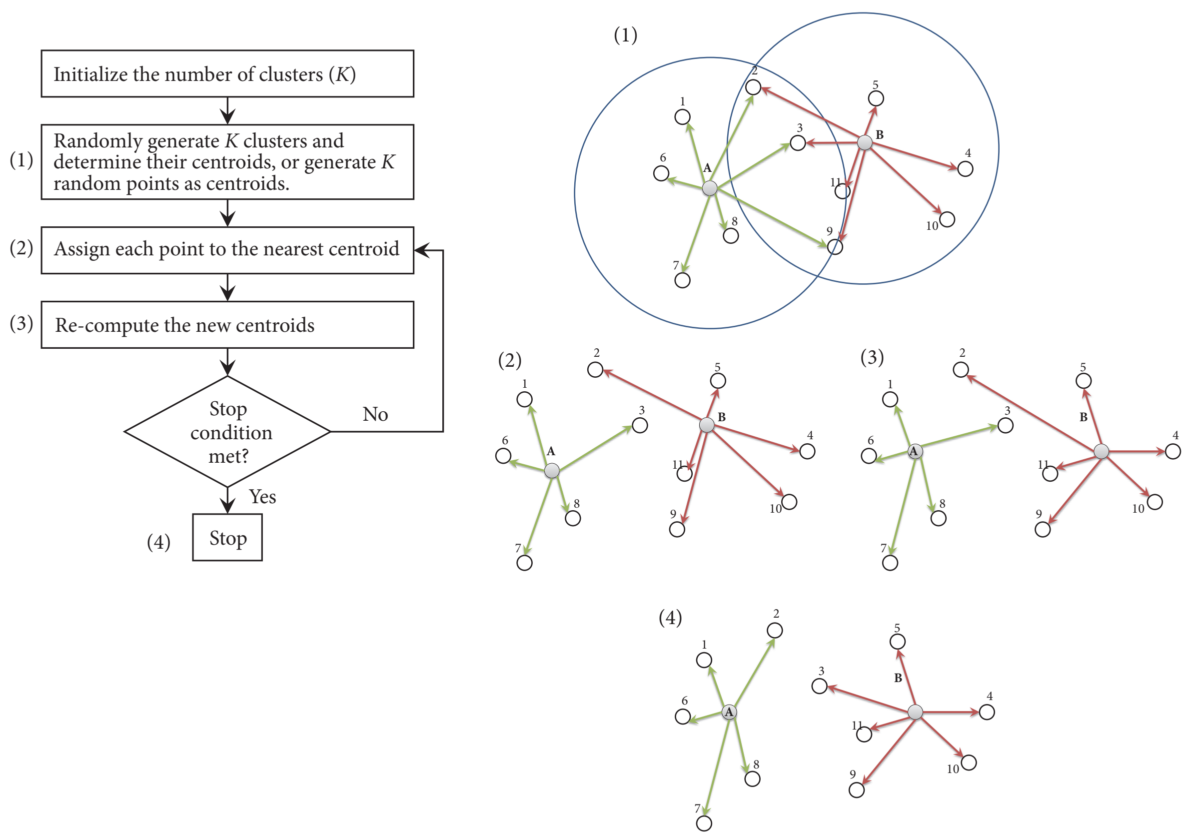


FIGURE 2: Structure of the standard K-Means Clustering (KMC) algorithm.

by the μGA to determine the lower and upper limits (K_{min}, K_{max}) for K. Also, the number of nearest points to each center (V) is constant given by X.

(ii) In the Local Search Phase, the CKMC is iterated P times, and at each iteration, different values of K (within K_{min} and K_{max}) and the ratio of acceptance V (which has an upper limit given by X) are considered. At each iteration, the best assignment of points (locations) to clusters (centroids) (as measured by its objective function value G) is saved. After the P iterations of the CKMC algorithm are executed, the best found solution is improved by means of insertion, deletion, and exchange operations which are controlled by a decision process.

2.2. μGA. The standard KMC algorithm considers that the quantity of clusters is known *a priori* [30]. Within the context of the CCCP, the minimization of the objective function (total distance from each cluster to each assigned point) depends on finding the most suitable number of clusters. Hence, the proposed GRASP-CKMC includes an evolutionary mechanism to determine the suitable range of clusters which can minimize the total distance to the affected communities.

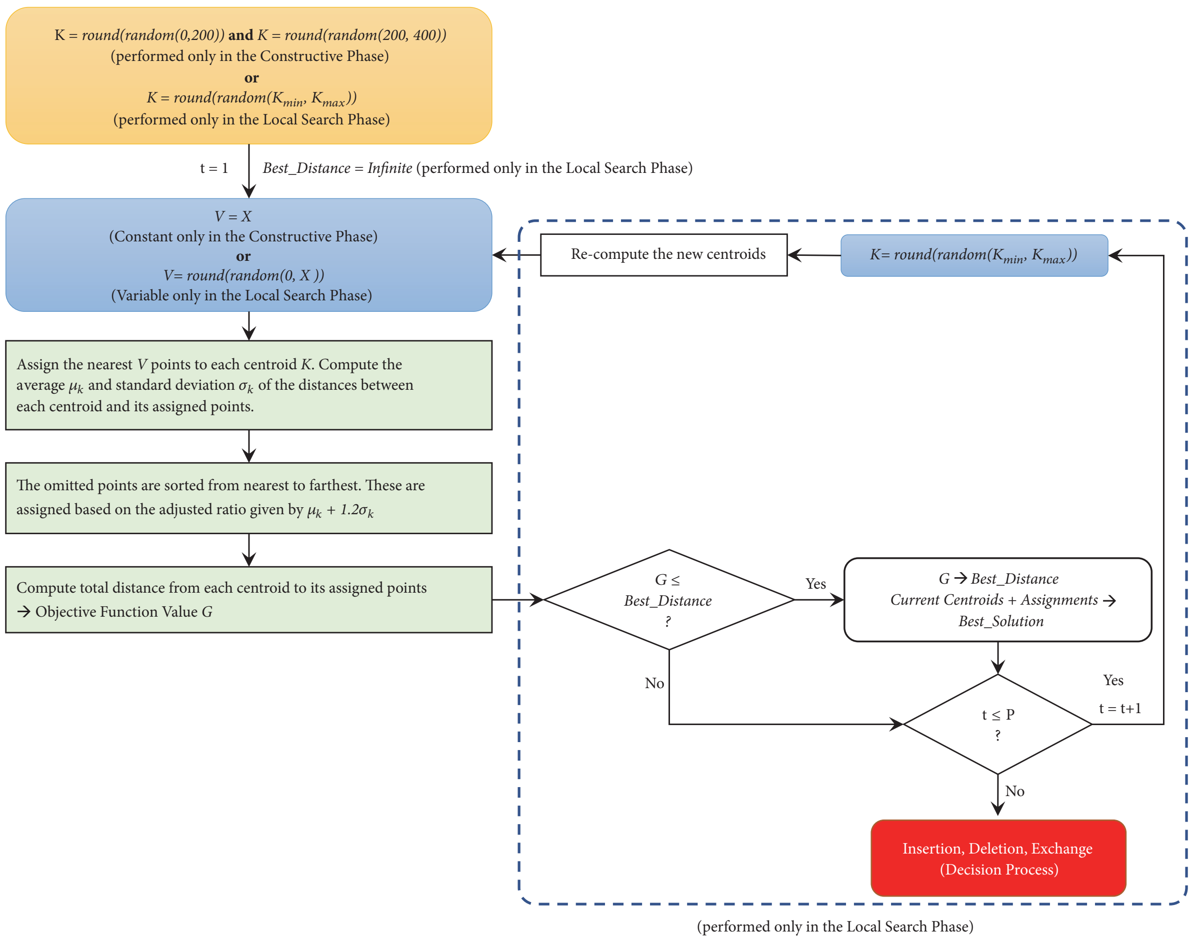


Figure 3: Structure of the proposed Capacitated K-Means Clustering (CKMC) algorithm.

Figure 4 presents the general structure of the μGA which was developed to address this task. The μGA is characterized by small populations which can lead to achieving faster convergence with less storing memory [35, 36]. In this case, the individuals of the population of the μGA consist only of pairs of values (K_{min}, K_{max}) that can define the lower and upper limits of a range that may contain the K value that can lead to a total minimum distance on a single execution of the CKMC algorithm. By using the random mutation and the linear crossover operators a diversification on these bounds is obtained to estimate an interval for the local search of K within the main GRASP-CKMC algorithm. An estimate for (K_{min}, k_{max}) is obtained after m generations (in this case, m = 100) of the μGA are executed, and within this range, K is randomly selected.

2.3. Insertion, Deletion, and Exchange. As presented in Figures 1 and 3, the best solution found by the CKMC in the Local Search Phase is improved by a decision algorithm which performs insertion, deletion, and exchange of points between clusters. A conditional decision process was designed to avoid unnecessary tasks due to the random selection of points which can be inserted, deleted, or exchanged. The description of this improvement process is presented in Figure 5.

Finally, the implementation of the metaheuristic was performed with Octave and MATLAB in a HP Workstation with Intel Zeon CPU at 3.40 GHz with 8 GB RAM.

2.4. Assessment. Before proceeding to obtaining a solution for our instance, we assessed the performance of the GRASP-CKMC metaheuristic with a selection of CCCP instances. Due to the size of the instance (3837 communities), we considered the following SJC and DONI instances [37, 38]: SJC1 (100 points), SJC2 (200 points), SJC3a (300 points), SJC4a (402 points), DONI1 (1000 points), DONI2 (2000 points), DONI3 (3000 points), DONI4 (4000 points), and DONI5 (5000 points) [39]. For comparison purposes, the performance of the GRASP-CKMC metaheuristic was compared to standard and most recent methods, including the latest best known solutions as follows:

(i) Best known solutions as reported in [24].

(ii) Best results obtained by CKM and GA as reported in [38].

(iii) Best results obtained by VNS as reported in [23].

(iv) Best results obtained by TS (Tabu Search) and CS (Clustering Search) as reported in [24].

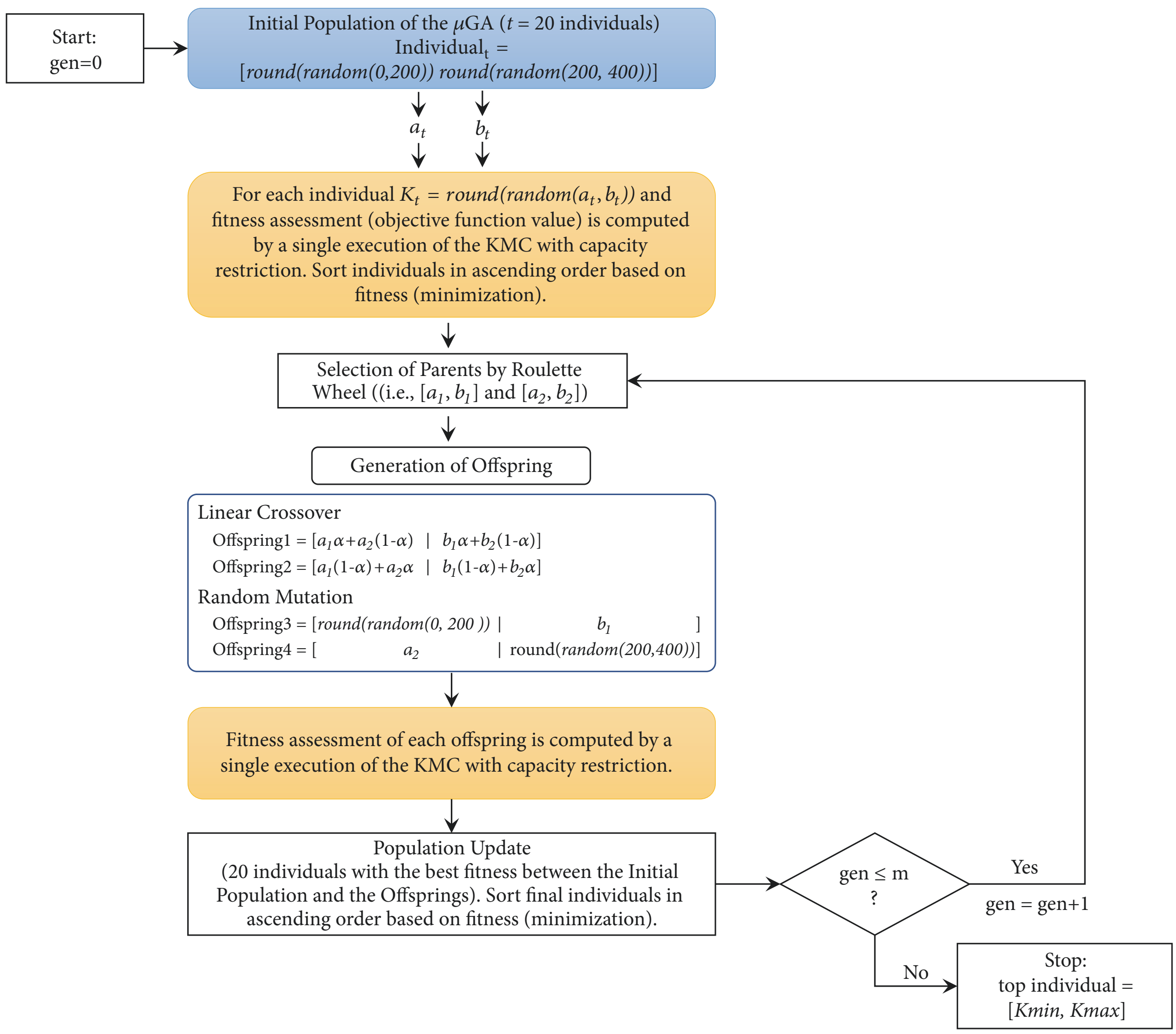


Figure 4: Structure of the μGA for initialization of K.

(v) Best results obtained by the latest method known as Adaptive Biased Random-Key Genetic Algorithm (A-BRKGA) as reported in [24].

Table 2 presents the parameters for the GRASP-CKMC algorithm. As mentioned in [24], metaheuristics have no optimal values of parameters. Thus, recommended ranges are usually considered for these cases. For the GRASP-CKMC algorithm it was considered to have a lean execution due to the size of the instance and the diverse algorithms which were developed. Thus, small values were considered for X (the upper limit for the number of nearest points to each cluster), the executions of the CKMC in the Local Search Phase (P) and the number of pairs of points to be considered for exchange, deletion, or insertion (Y). Regarding the Mersenne Twister random number generator, it was considered as recommended by the MATLAB documentation.

Table 3 presents the results obtained for 10 runs of the algorithm. It is observed that the average of the best results is 3.03% while the average of the worst results is 5.59%. Particularly for the instances DONI3 and DONI4, which have a similar number of points to the considered instance of 3837 communities, the GRASP-CKMC metaheuristic is able to obtain solutions with errors smaller than 5.0% (3.93% and 4.64%, respectively) within 10 runs.

Table 2: Parameters of the GRASP-CKMC.

Parameter	Value
X	10
P	50
Y	10000
Random Number Generator	Mersenne Twister

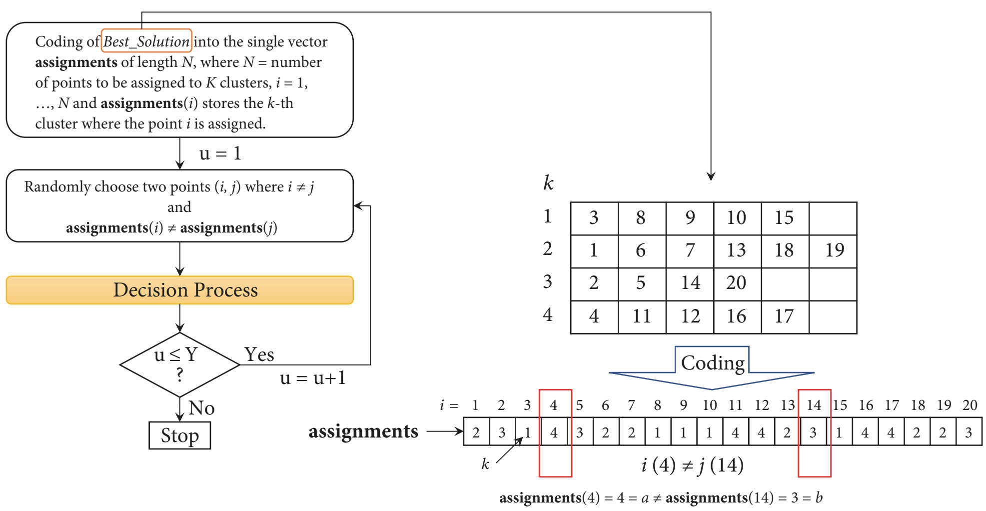
Table 4 presents the comparison of the best results obtained with the reviewed methods. When compared to CKM the proposed metaheuristic outperforms it in all instances. This is observed in the average error which is significantly higher for CKM in comparison to GRASP-CKMC (10.58% > 3.03%). The average performance of the GA is similar to the performance of CKM (10.27% ≈ 10.00%).

Table 3: Results of 10 runs of the GRASP-CKMC metaheuristics on the SJC and DONI instances.

Instance	Best Known	Runs 1	2	3	4	5	6	7	8	9	10	Best	Worse	Average	Best Error(%)	Worst Error(%)	Average Error(%)
SJC1	17359.75	17807.73	18230.49	17742.19	18088.71	17791.75	18054.23	18169.28	17948.46	18132.05	17789.13	17742.19	18230.49	17975.40	2.20%	5.02%	3.55%
SJC2	33181.65	33810.48	34077.98	33568.98	33529.65	33673.30	33342.50	33745.19	33330.23	34084.06	33731.71	33330.23	34084.06	33689.41	0.45%	2.72%	1.53%
SJC3a	45356.35	46993.46	46165.69	46789.82	46503.93	46559.25	46459.06	46944.45	46697.09	46250.59	46030.70	46030.70	46993.46	46539.40	1.49%	3.61%	2.61%
SJC4a	61931.60	62774.78	62710.35	63064.16	62962.47	62844.49	62899.00	63000.86	63357.25	62926.63	63369.95	62710.35	63369.95	62990.99	1.26%	2.32%	1.71%
DONI1	3021.41	3088.71	3165.04	3104.18	3144.54	3169.48	3141.08	3095.66	3109.24	3157.25	3158.03	3088.71	3169.48	3133.32	2.23%	4.90%	3.70%
DONI2	6080.70	6487.85	6499.84	6498.32	6490.31	6459.86	6498.46	6487.18	6484.72	6483.75	6420.06	6420.06	6499.84	6481.04	5.58%	6.89%	6.58%
DONI3	8343.49	8706.45	8971.18	8953.30	8964.51	8677.99	8691.23	8894.92	8782.56	9010.17	8671.70	8671.70	9010.17	8832.40	3.93%	7.99%	5.86%
DONI4	10777.64	11540.02	11508.46	11704.86	11568.63	11541.06	11534.28	11702.91	11277.44	11392.09	11685.20	11277.44	11704.86	11545.49	4.64%	8.60%	7.12%
DONI5	11114.67	12016.16	11991.16	12034.59	11846.86	12022.82	11724.42	11934.19	11937.12	11938.20	11893.37	11724.42	12034.59	11933.89	5.49%	8.28%	7.37%
														Average =	3.03%	5.59%	4.45%

Table 4: Performance of CKM, GA, VNS, GRASP-CKMC, A-BRKGA, TS, and CS on the SJC and DONI instances when compared to best-known solutions.

Instance	Best-Known	CKM	GA	VNS	GRASP-CKMC	A-BRKGA	TS	CS
SJC1	17359.75	17.18%	0.02%	1.94%	2.20%	0.00%	0.00%	0.00%
SJC2	33181.65	6.12%	0.83%	0.73%	0.45%	0.00%	0.00%	0.00%
SJC3a	45356.35	11.54%	3.29%	5.80%	1.49%	0.00%	0.00%	0.00%
SJC4a	61931.60	11.87%	4.92%	7.68%	1.26%	0.00%	0.10%	0.00%
DONI1	3021.41	7.06%	3.88%	0.00%	2.23%	-0.13%	0.12%	0.21%
DONI2	6080.70	10.06%	14.88%	0.00%	5.58%	4.78%	5.00%	4.81%
DONI3	8343.49	17.42%	15.70%	5.10%	3.93%	0.41%	0.00%	1.14%
DONI4	10777.64	7.58%	23.66%	6.85%	4.64%	0.12%	0.00%	1.62%
DONI5	11114.67	6.42%	25.24%	4.68%	5.49%	0.54%	0.00%	0.86%
	Average =	10.58%	10.27%	3.64%	3.03%	0.64%	0.58%	0.96%



- Compute the distances between the points (i, j) and their centroids (a, b): $[d_{ia}\ d_{ib}\ d_{ja}\ d_{jb}]$

Decision Process

- If $d_{ia} < d_{ib}$ and $d_{jb} < d_{ja}$ → The current assignments of i-a and j-b are suitable, no need to change.
- If $d_{ia} > d_{ib}$ and $d_{jb} < d_{ja}$ → The current assignment j-b and the new assignment i-b are more suitable to minimize distance (*insertion* of point i to cluster b = *deletion* of point i from cluster a)
- If $d_{ia} > d_{ib}$ and $d_{jb} > d_{ja}$ → The new assignments j-a and i-b are more suitable to minimize distance (*exchange* of point j to cluster a, and point i to cluster b)
- If $d_{ia} < d_{ib}$ and $d_{jb} > d_{ja}$ → The current assignment i-a and the new assignment j-a are more suitable to minimize distance (*insertion* of point j to cluster a = *deletion* of point j from cluster b)
- *Best_Solution* and G are updated if the changes in the assignments of (i, j) comply with the capacity restriction.

Figure 5: Structure of the decision process of the GRASP algorithm.

However this is observed because the GA outperforms the CKM method for medium instances (SJC1-DONI1) while the CKM significantly outperforms the GA for large instances (DONI2-DONI5). Better performance is observed with the VNS method with an average error of 3.64%. Also, in two instances the VNS method obtained the best known solutions (error = 0.0%). Even though the GRASP-CKMC metaheuristic is not able to obtain the best known solution, overall performance is better than VNS (3.03% < 3.64%). Particularly for instances SJC3a, SJC4a, DONI3, and DONI4, the GRASP-CKMC metaheuristic outperforms the VNS, GA, and CKM methods.

When comparing the performance of the GRASP-CKMC with more updated metaheuristics such as TS, CS, and A-BRKGA, these reported a better performance with average errors smaller than 1.0%. This is expected as the proposed metaheuristic is based on the GRASP and KMC principles and as such, it is proposed as an alternative to similar metaheuristics such as GA, KMC, and VNS. In general terms, the GRASP-CKMC performs in the middle between the

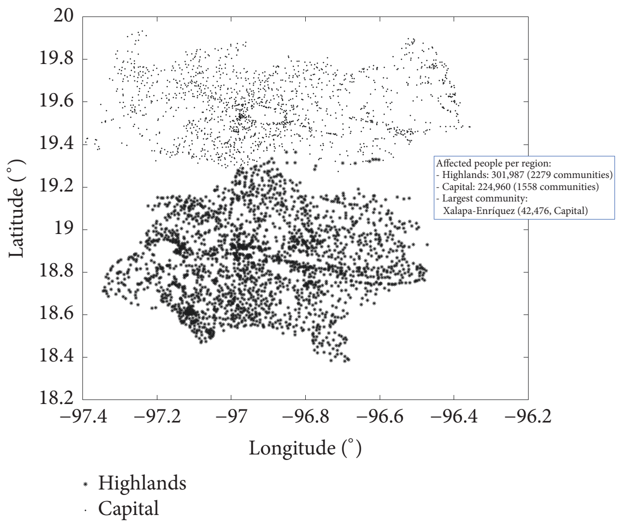


Figure 6: Affected communities in Veracruz: capital and highlands regions.

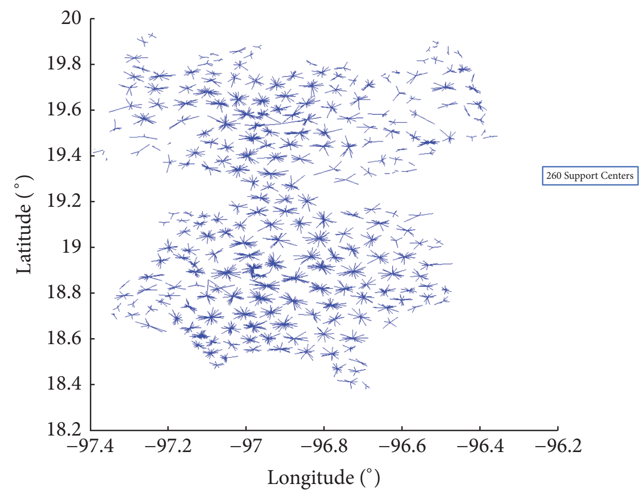


Figure 7: Affected communities in Veracruz: assignment of support centers.

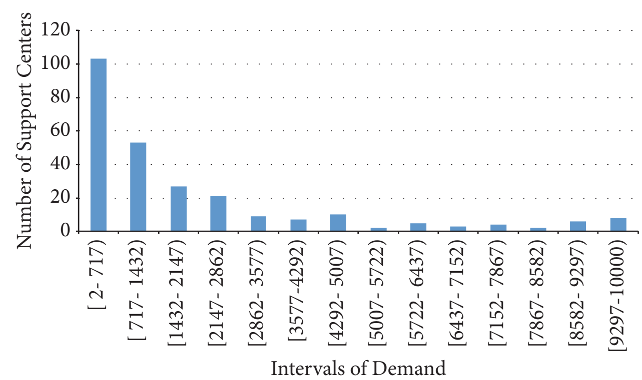


Figure 8: Affected communities in Veracruz: number of centers vs. intervals of demand.

standard and the most recent methods for the CCCP with an average best error of approximately 3.0%.

Due to these results, the proposed metaheuristic is considered suitable to address the location of the support centers or prepositioned warehouses for the communities of Veracruz.

3. Proposed Locations for Communities at Risk

Figure 6 presents general statistics regarding the people affected by disasters in the considered regions of Veracruz, Mexico. In total, in the capital and highlands regions, there are 526,947 people at risk throughout 3837 communities where the community of Xalapa-Enríquez has the largest amount with 42,476 people. Because support centers are considered to supply resources for a maximum of 10,000 people, larger communities (such as Xalapa-Enríquez) were segmented into equally-sized smaller communities. This led to a total of 3844 communities.

Due to the importance of minimizing the distance between the affected communities and the location of the centers, a reliable distance metric must be used. In this case, the geographic arc length metric is considered because it can provide accurate distances in kilometers based on the spherical model of Earth's surface which has a radius of R= 6,371 Km. With this metric, the arc length (distance) between two locations ($d_{i,j}$) with geographic coordinates (ϕ_i, θ_i) and (ϕ_j, θ_j), where ϕ is the latitude and θ is the longitude in radians, is estimated as follows [40]:

$$d_{i,j} = R \times \alpha_{i,j} = R \times \operatorname{Arccos}\left[\cos\phi_i \cos\phi_j \cos\left(\theta_i - \theta_j\right) + \sin\phi_i \sin\phi_j\right]. \quad (1)$$

With this data, the GRASP-CKMC metaheuristic determined a set of 260 centers to provide support to the 3837 communities (or extended 3844 communities) with minimum average total distance. The general results are presented in Table 5 while Figure 7 presents the visualization of the assignments.

Based on these results, it was determined that the mean distance that people at risk must travel from their community to its assigned center is approximately 2.08 Km with a standard deviation of 0.60 Km. In this case, humanitarian relief can be provided within a short period of time.

These results also provide information to determine the most suitable capacities for each center. Although the GRASP-CKMC imply the establishment of 260 centers to provide supplies to a maximum of 10,000 affected people, the people at risk within the communities assigned to each center can be considered to determine its most suitable capacity. Figure 8 presents a histogram that represents the number of centers assigned for each interval or range of people at risk. As observed, 103 centers serve communities with a minimum and maximum of 2 and 717 affected people, respectively. In contrast, just 8 centers serve communities with a minimum and maximum of 9297 and 10000 people, respectively. These results can be considered to make a better estimation of the capabilities of the prepositioned warehouses and, thus, of the necessary inventory.

Table 5: Affected communities in Veracruz: number of centers, number of locations (communities), and people at risk assigned to each center, total distance, and average distance from the locations to the assigned center.

Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance
1	12	2476	27.05	2.25	66	18	1927	44.33	2.46	131	9	1074	23.23	2.58	196	19	3227	53.64	2.82
2	5	68	8.38	1.68	67	12	656	29.48	2.46	132	11	926	20.38	1.85	197	19	320	46.62	2.45
3	10	4437	18.75	1.87	68	17	1034	39.65	2.33	133	15	713	37.88	2.53	198	12	741	28.42	2.37
4	15	602	44.27	2.95	69	13	1163	26.15	2.01	134	5	123	9.42	1.88	199	10	1924	25.27	2.53
5	3	167	5.16	1.72	70	25	9411	63.99	2.56	135	19	1995	45.68	2.40	200	21	2385	39.45	1.88
6	9	362	18.19	2.02	71	23	1269	54.62	2.37	136	17	312	50.70	2.98	201	5	460	9.81	1.96
7	23	3203	55.71	2.42	72	32	2259	78.58	2.46	137	8	175	18.37	2.30	202	4	81	4.22	1.05
8	14	213	25.19	1.80	73	41	8874	82.90	2.02	138	9	716	16.62	1.85	203	16	691	42.14	2.63
9	5	584	15.96	3.19	74	26	911	79.92	3.07	139	12	729	23.00	1.92	204	12	215	16.81	1.40
10	4	194	5.09	1.27	75	17	8374	30.90	1.82	140	13	2962	29.88	2.30	205	10	991	31.85	3.18
11	16	1410	34.09	2.13	76	33	4714	92.23	2.79	141	25	5207	55.78	2.23	206	3	198	4.01	1.34
12	2	137	1.19	0.59	77	14	2301	26.56	1.90	142	23	2576	39.97	1.74	207	3	62	5.03	1.68
13	2	88	3.03	1.52	78	7	639	13.16	1.88	143	6	213	9.57	1.59	208	11	911	20.30	1.85
14	19	4482	42.91	2.26	79	26	9941	50.56	1.94	144	4	544	5.23	1.31	209	23	3683	43.62	1.90
15	17	1561	41.25	2.43	80	3	14	3.58	1.19	145	7	185	6.71	0.96	210	15	920	32.07	2.14
16	10	267	23.04	2.30	81	5	70	8.30	1.66	146	18	2996	46.03	2.56	211	6	972	11.23	1.87
17	3	1233	2.46	0.82	82	19	1491	32.65	1.72	147	3	10	5.38	1.79	212	12	1711	21.40	1.78
18	7	584	24.53	3.50	83	16	828	38.64	2.42	148	41	5836	111.30	2.71	213	5	144	11.74	2.35
19	16	488	33.97	2.12	84	16	279	27.52	1.72	149	15	790	38.17	2.54	214	7	379	10.39	1.48
20	28	2371	71.08	2.54	85	6	263	6.15	1.02	150	4	76	3.58	0.89	215	28	150	50.60	1.81
21	6	921	7.91	1.32	86	17	434	36.45	2.14	151	3	157	1.93	0.64	216	14	585	27.98	2.00
22	4	242	5.73	1.43	87	14	1139	31.64	2.26	152	2	58	1.38	0.69	217	17	1270	31.63	1.86
23	15	1194	34.99	2.33	88	5	357	6.89	1.38	153	9	4179	19.71	2.19	218	17	1875	40.34	2.37
24	7	1105	11.96	1.71	89	23	1035	71.20	3.10	154	7	3404	19.11	2.73	219	3	585	4.06	1.35
25	17	321	29.46	1.73	90	24	1860	52.37	2.18	155	4	1235	14.53	3.63	220	12	627	26.54	2.21
26	5	326	8.13	1.63	91	9	258	15.56	1.73	156	10	756	20.69	2.07	221	6	174	11.57	1.93
27	6	779	14.21	2.37	92	21	4511	46.10	2.20	157	9	116	13.90	1.54	222	30	652	70.32	2.34
28	16	10000	52.02	3.25	93	3	804	9.60	3.20	158	8	1445	15.22	1.90	223	3	1508	1.91	0.64
29	24	2130	72.72	3.03	94	9	25	15.34	1.70	159	19	380	56.62	2.98	224	16	1250	36.62	2.29
30	29	1444	82.77	2.85	95	22	304	41.04	1.87	160	7	639	12.56	1.79	225	4	60	4.40	1.10
31	20	2256	36.76	1.84	96	16	1658	45.35	2.83	161	21	1564	41.40	1.97	226	23	9367	66.26	2.88
32	23	6639	53.35	2.32	97	4	385	7.06	1.77	162	27	9448	84.59	3.13	227	4	95	2.70	0.67
33	19	2312	42.10	2.22	98	23	9011	42.20	1.83	163	6	518	9.81	1.63	228	5	120	5.66	1.13

Table 5: Continued.

Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance	Center	Locations	People at Risk	Total Distance	Average Distance
34	17	2277	25.31	1.49	99	16	2071	41.36	2.59	164	2	2	2.12	1.06	229	8	306	12.83	1.60
35	39	8353	109.04	2.80	100	5	538	6.88	1.38	165	2	33	0.23	0.12	230	6	137	10.67	1.78
36	16	9118	30.44	1.90	101	4	249	7.08	1.77	166	7	388	15.00	2.14	231	6	362	15.15	2.52
37	8	1337	21.39	2.67	102	38	3314	99.33	2.61	167	6	88	15.03	2.51	232	13	2334	26.04	2.00
38	19	945	31.18	1.64	103	25	1519	53.60	2.14	168	7	9191	11.35	1.62	233	13	1960	35.09	2.70
39	12	2176	28.03	2.34	104	7	176	21.04	3.01	169	29	1399	72.16	2.49	234	19	476	51.24	2.70
40	14	878	39.35	2.81	105	13	2766	21.44	1.65	170	9	240	18.24	2.03	235	26	3872	61.26	2.36
41	12	810	26.20	2.18	106	3	225	1.51	0.50	171	4	137	4.48	1.12	236	4	162	4.63	1.16
42	5	661	11.09	2.22	107	22	6305	51.83	2.36	172	12	561	25.68	2.14	237	19	4613	52.11	2.74
43	10	1215	19.68	1.97	108	5	39	8.05	1.61	173	22	8947	54.23	2.46	238	44	9940	63.23	1.44
44	16	322	41.62	2.60	109	11	1172	36.57	3.32	174	28	7414	52.33	1.87	239	12	69	27.39	2.28
45	8	941	13.11	1.64	110	16	1271	39.64	2.48	175	11	1894	16.74	1.52	240	19	2173	39.79	2.09
46	4	404	5.87	1.47	111	15	1041	33.29	2.22	176	12	1187	17.39	1.45	241	15	4723	44.96	3.00
47	20	2326	49.74	2.49	112	22	1034	64.23	2.92	177	28	3846	81.85	2.92	242	28	2218	76.62	2.74
48	14	588	26.33	1.88	113	16	2714	39.87	2.49	178	5	226	6.91	1.38	243	7	244	16.24	2.32
49	10	1138	21.05	2.10	114	6	2319	11.74	1.96	179	19	2849	43.91	2.31	244	43	5216	87.43	2.03
50	24	1335	54.73	2.28	115	13	1285	29.71	2.29	180	18	1298	42.73	2.37	245	12	1646	27.97	2.33
51	9	1479	15.07	1.67	116	33	4990	88.85	2.69	181	11	44	17.58	1.60	246	6	355	16.88	2.81
52	8	243	14.90	1.86	117	60	7460	144.50	2.41	182	5	904	13.07	2.61	247	40	6829	105.91	2.65
53	38	4231	94.32	2.48	118	29	1599	67.88	2.34	183	4	19	2.76	0.69	248	34	7534	86.96	2.56
54	22	2053	48.93	2.22	119	51	1966	78.85	1.55	184	25	4846	79.86	3.19	249	24	5724	54.87	2.29
55	16	925	41.17	2.57	120	14	696	35.84	2.56	185	34	7175	83.06	2.44	250	19	2167	29.69	1.56
56	5	383	4.55	0.91	121	19	2926	26.93	1.42	186	18	2028	44.00	2.44	251	23	3379	46.16	2.01
57	35	4994	71.98	2.06	122	11	597	26.20	2.38	187	12	787	19.73	1.64	252	3	579	5.51	1.84
58	14	6182	27.62	1.97	123	15	1831	39.75	2.65	188	9	448	13.68	1.52	253	6	1300	18.06	3.01
59	5	292	9.44	1.89	124	15	663	38.52	2.57	189	24	2859	72.49	3.02	254	13	884	27.78	2.14
60	22	10000	35.81	1.63	125	21	9613	48.10	2.29	190	24	6301	55.37	2.31	255	20	3998	50.98	2.55
61	9	8725	16.34	1.82	126	6	13	8.60	1.43	191	14	1603	30.47	2.18	256	17	1281	29.53	1.74
62	23	1191	57.54	2.50	127	5	47	8.31	1.66	192	43	4528	100.74	2.34	257	27	3751	63.21	2.34
63	24	7015	37.22	1.55	128	7	441	13.20	1.89	193	20	2260	47.66	2.38	258	9	68	12.89	1.43
64	8	154	25.07	3.13	129	7	389	13.08	1.87	194	11	105	28.17	2.56	259	13	1273	24.20	1.86
65	8	853	9.31	1.16	130	12	2991	29.61	2.47	195	15	780	30.59	2.04	260	9	2005	18.30	2.03

4. Conclusions and Future Work

The present work addressed the location planning for prepositioned warehouses or support centers for communities at risk in Veracruz, Mexico. This was addressed by means of the Capacitated Centered Clustering Problem (CCCP) [23] because minimization of distances between the affected regions and the prepositioned warehouses is an important aspect of humanitarian relief planning.

Due to the large set of communities (3837) and people at risk (526,947), a metaheuristic was developed to provide a suitable solution for this problem. This metaheuristic integrated the principles of GRASP, GA, and KMC to provide more suitable solutions than those obtained by similar local search metaheuristics. When tested with well-known large facility location instances, the metaheuristic termed as GRASP-CKMC was able to obtain a mean best error of 3.03%. Although more complex algorithms such as CS and A-BRKGA reported better results with errors smaller than 1.00%, the performance of the GRASP-CKCM metaheuristic was more competitive when compared to standard methods such as GA, KMC, and VNS. Thus, the GRASP-CKCM can be considered as a more suitable strategy when compared to these methods.

When the GRASP-CKMC was applied on the real instance with 3837 communities, the metaheuristic determined a set of 260 centers to provide full coverage to all communities. These results also provided insights regarding the utilization of these centers considering the actual communities assigned to them. Based on these insights, it was determined that the facility location task could also support the decisions regarding the characteristics of the support centers by obtaining the estimation of the communities assigned to each one of them. Thus, smaller centers or prepositioned warehouses can be considered for some regions. This can optimize the use of resources and improve relief efforts.

Optimization of the supply chain for humanitarian relief efforts is an extensive field which requires continuous advances in the logistics and production planning processes. Thus, as future work, the following aspects are considered:

(i) Extending the CCCP model to consider heterogeneous capacities for the centers.

(ii) Integrating route planning on the facility location problem to optimize the two-echelon supply chain.

(iii) Multicriteria optimization to extend on the facility location problem.

(iv) Integrating the use of Artificial Neural Networks (ANNs) to dynamically determine the number of clusters to improve speed and convergence of the CKMC algorithm.

(v) Integrating the principles of the CS method to enhance the performance of the GRASP metaheuristic.

Data Availability

The databases used for the present work are publicly available in the referenced sources [39].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

Article Processing Charge (APC) was funded by Universidad Popular Autonoma del Estado de Puebla A.C.

References

[1] E. V. Arteaga-Vega and I. P. López-Delfín, *Gaceta Oficial: Ley Número 856 de Protección Civil y la Reducción del Riesgo de Desastres para el Estado de Veracruz*, Gobierno del Estado de Veracruz, 2013.

[2] V. E. R. Protección, *Instrumentos y Programas de Protección Civil*, Gobierno del Estado de Veracruz: Secretaría de Protección Civil, 2017.

[3] CENAPRED, *Diagnóstico de Peligros e Identificación de Riesgos de Desastres en México: Atlas Nacional de Riesgos de la República Mexicana*, Secretaría de Gobierno: Centro Nacional de Prevención de Desastres (CENAPRED), 2014.

[4] Instituto Nacional de Ecología y Cambio Climático, *Vulnerabilidad al cambio climático*, Secretaría de Gobierno: Instituto Nacional de Ecología y Cambio Climático, 2016, https://www.gob.mx/inecc/acciones-y-programas/vulnerabilidad-al-cambio-climatico-80125.

[5] Coordinación Nacional de Protección Civil, *Declaratorias de Desastre Natural: Fideicomiso No. 2003 FONDEN*, Coordinación Nacional de Protección Civil: Dirección General para la Gestión de Riesgos, 2018, http://www.proteccioncivil.gob.mx/work/models/ProteccionCivil/Resource/36/26/images/DGGR-RA2017-27MAR2018.pdf.

[6] P. I. Arcos González, R. Castro Delgado, and F. Del-Busto Prado, "Desastres y salud pública: Un abordaje desde el marco teórico de la epidemiología," *Revista Española de Salud Pública*, vol. 76, no. 2, pp. 121–132, 2002.

[7] A. Cozzolino, S. Rossi, and A. Conforti, "Agile and lean principles in the humanitarian supply chain: The case of the United Nations World Food Programme," *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 2, no. 1, pp. 16–33, 2012.

[8] Sistema Nacional de Protección Civil, *Centro de Acopio*, Sistema Nacional de Protección Civil (SINAPROC), 2012, http://sismos.gob.mx/en/sismos/Centro_de_acopio.

[9] Sistema Nacional para el Desarrollo Integral de la Familia, *Manual Operativo, Atención a la Población en Riesgo o Condición de Emergencia APCE*, Sistema Nacional para el Desarrollo Integral de la Familia (SNDIF): Unidad de Atención a la Población Vulnerable, Dirección General de Alimentación y Desarrollo Comunitario, 2011, http://www.dif.gob.mx/dgadc/media/Manual%20de%20Operaci%C3%B3n%20APCE%202011.pdf.

[10] A. Thomas and M. Mizushima, "Logistics training: Necessity or luxury?" *Forced Migration Review*, vol. 22, pp. 60-61, 2005.

[11] J. Salmerón and A. Apte, "Stochastic optimization for natural disaster asset prepositioning," *Production Engineering Research and Development*, vol. 19, no. 5, pp. 561–574, 2010.

[12] A. Cozzolino, "Humanitarian logistics and supply chain management," in *Springer Briefs in Business: Humanitarian Logistics*, pp. 5–16, Springer, Berlin, Heidelberg, 2012.

[13] T. E. Fernandez and N. Suthikarnnarunai, "Control aspects in humanitarian logistics," *International Journal of Logistics Systems and Management*, vol. 28, no. 3, pp. 267–286, 2017.

[14] G. Kovács and K. Spens, "Identifying challenges in humanitarian logistics," *International Journal of Physical Distribution and Logistics Management*, vol. 39, no. 6, pp. 506–528, 2009.

[15] R. E. Overstreet, D. Hall, J. B. Hanna, and R. Kelly Rainer, "Research in humanitarian logistics," *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 1, no. 2, pp. 114–131, 2011.

[16] P. Beraldi and M. E. Bruni, "A probabilistic model applied to emergency service vehicle location," *European Journal of Operational Research*, vol. 196, no. 1, pp. 323–331, 2009.

[17] B. Zhang, H. Li, S. Li, and J. Peng, "Sustainable multi-depot emergency facilities location-routing problem with uncertain information," *Applied Mathematics and Computation*, vol. 333, pp. 506–520, 2018.

[18] A. Şahin, M. Alp Ertem, and E. Emür, "Using containers as storage facilities in humanitarian logistics," *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 4, no. 2, pp. 286–307, 2014.

[19] K. Ozbay and E. E. Ozguven, "Stochastic humanitarian inventory control model for disaster planning," *Transportation Research Record*, vol. 2022, no. 1, pp. 63–75, 2007.

[20] C. L'Hermitte, M. Bowles, P. Tatham, and B. Brooks, "An integrated approach to agility in humanitarian logistics," *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 5, no. 2, pp. 209–233, 2015.

[21] B. Goldengorin, D. Krushinsky, and P. M. Pardalos, "The p-Median Problem," in *Cell Formation in Industrial Engineering: Theory, Algorithms and Experiments*, pp. 25–73, Springer, 2013.

[22] F. Stefanello, O. de-Araújo, and F. Müller, "Matheuristics for the capacitated p-median problem," *International Transactions in Operational Research*, 2014.

[23] M. Negreiros and A. Palhano, "The capacitated centred clustering problem," *Computers & Operations Research*, vol. 33, no. 6, pp. 1639–1663, 2006.

[24] A. A. Chaves and L. A. Nogueira Lorena, "Hybrid evolutionary algorithm for the Capacitated Centered Clustering Problem," *Expert Systems with Applications*, vol. 38, no. 5, pp. 5013–5018, 2011.

[25] A. Martínez-Gavara, D. Landa-Silva, V. Campos, and R. Martí, "Randomized heuristics for the Capacitated Clustering Problem," *Information Sciences*, vol. 417, pp. 154–168, 2017.

[26] R. Interian and C. C. Ribeiro, "A GRASP heuristic using path-relinking and restarts for the Steiner traveling salesman problem," *International Transactions in Operational Research*, vol. 24, no. 6, pp. 1307–1323, 2017.

[27] R. Dias, B. Guazzelli, and P. Henrique, "A GRASP heuristic in the choice of clusterheads for wireless sensor networks provided as a service," in *Proceedings of the International Conference on High Performance Computing & Simulation*, pp. 160–167, IEEE, 2017.

[28] M. C. Hung, J. Wu, J. H. Chang, and D. L. Yang, "An efficient k-means clustering algorithm using simple partitioning," *Journal of Information Science and Engineering*, vol. 21, pp. 1157–1177, 2005.

[29] K. Liao and D. Guo, "A Clustering-based approach to the capacitated facility location problem," *Transactions in GIS*, vol. 12, no. 3, pp. 323–339, 2008.

[30] M. Javadi and J. Shahrabi, "New spatial clustering-based models for optimal urban facility location considering geographical obstacles," *Journal of Industrial Engineering International*, vol. 10, no. 54, pp. 10–12, 2014.

[31] C.-M. Pintea and P. C. Pop, "An improved hybrid algorithm for capacitated fixed-charge transportation problem," *Logic Journal of the IGPL. Interest Group in Pure and Applied Logics*, vol. 23, no. 3, pp. 369–378, 2015.

[32] R. Sahraeian and P. Kaveh, "Solving capacitated p-median problem by hybrid k-means clustering and fixed neighborhood search algorithm," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 1–6, 2010.

[33] G. R. Sutanto, S. Kim, D. Kim, and H. Sutanto, "A heuristic approach to handle capacitated facility location problem evaluated using clustering internal evaluation," *IOP Conference Series: Materials Science and Engineering*, vol. 332, no. 332, Article ID 012023, pp. 1–9, 2018.

[34] J. Brimberg, P. Hansen, N. Mladenoviċ, and E. Taillard, "Improvements and comparison of heuristics for solving the multisource weber problem," Technical Report IDSIA-33-97, 1997.

[35] R. Batres, "Generation of operating procedures for a mixing tank with a micro genetic algorithm," *Computers & Chemical Engineering*, vol. 57, pp. 112–121, 2013.

[36] P. C. Ribas, L. Yamamoto, H. L. Polli, L. Arruda, and F. Neves-Jr, "A micro-genetic algorithm for multi-objective scheduling of a real world pipeline network," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 1, pp. 302–313, 2013.

[37] A. Palhano, M. Negreiros, and G. Laporte, "A constrained k-median procedure for the capacitated centered clustering problem," in *Proceedings of the XIV Congreso Latino Ibero Americano de Investigacion de Operaciones (CLAIO '08)*, 2008.

[38] A. Chaves, J. Goncalves, and L. Nogueira, "Adaptive biased random-key genetic algorithm with local search for the capacitated centered clustering problem," *Computers & Industrial Engineering*, vol. 124, pp. 331–346, 2018.

[39] L. Nogueira, *Problem Instances*, INPE-Instituto Nacional de Pesquisas Espaciais, http://www.lac.inpe.br/lorena/instancias.html, last accessed on July 9th 2018.

[40] L. Cazabal-Valencia, S.-O. Caballero-Morales, and J.-L. Martínez-Flores, "Logistic model for the facility location problem on ellipsoids," *International Journal of Engineering Business Management*, vol. 8, pp. 1–9, 2016.