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Dossier

Application of Operational Research in the Distribution of COVID-19-Related Resources

Aplicación de la investigación de operaciones a la distribución de recursos relacionados con la COVID-19

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ABSTRACT

Aim: To apply the vehicle routing model based on optimized decision-making for the distribution of medical resources to hospitalized patients, and patients with a possible COVID-19 diagnosis, in Camagüey, Cuba.

Methods: Heterogeneous vehicle routing problems with time windows were used in combination with optimization algorithms to cope with the distribution of supplies.

Main results: A total of 15 models were used in the experiment to study the behavior of the algorithms applied to the problem. The CVRP library was run in Matlab. Three metaheuristic models were utilized: EDA, SA, VNS. FSMVRPTW was solved according to the information modeled, through the EDA and VNS algorithms. The latter was included in the study for its open source code, in Excel.

Conclusions: Studies of vehicle routing problems have shown their usefulness in different complex scenarios, such as pandemics, to optimize the distribution of resources. The existence of optimum organization of transportation to distribute medical resources in COVID-19 times is a vital tool for decision-making in the province of Camagüey, which can be extended to the whole country.

Key words: vehicle routing; operations research; metaheuristic; COVID-19; decision-making.

RESUMEN

Objetivo: Aplicar el modelo de enrutamiento de vehículos combinado con algoritmos de optimización para la toma de decisiones en la distribución de insumos relacionados con el servicio asistencial a pacientes hospitalizados y sospechosos de la COVID-19 en Camagüey, Cuba.

Métodos: Se utilizaron los problemas de enrutamiento de vehículos heterogéneos con ventanas de tiempo, en combinación con algoritmos de optimización para solucionar la distribución de estos recursos.

Principales resultados: Se experimentó con un total de 15 modelos para el estudio del comportamiento de los algoritmos aplicados al problema, donde se utilizó la biblioteca CVRP, implementada en Matlab. Se implementaron tres de metaheurísticas: EDA, SA, VNS. A partir de la información modelada se procedió a la solución del problema FSMVRPTW a través de algoritmos EDA y VNS, utilizado este último por contar con una implementación de código abierto en Excel.

Conclusiones: Los estudios acerca del problema de enrutamiento de vehículos han demostrado su utilidad en diferentes situaciones complejas, como las pandemias, para optimizar la distribución de recursos. En tiempos de COVID-19, contar con una organización del transporte óptima para distribuir los recursos médicos, es una herramienta vital para la toma de decisiones en la provincia Camagüey, extensible a toda Cuba.

Palabras clave: enrutamiento de vehículos; investigación de operaciones; metaheurísticas; COVID-19; toma de decisiones.

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INTRODUCTION

In 2020, a pandemic outbreak posed an enormous challenge to humanity. The emergence of COVID-19 (Ludvigson and Ng, 2020), caused by the novel coronavirus SARS-CoV-2 has forced all affected countries to conduct efforts to stop the pandemic, and minimize the damage caused by its impact.

Coronaviruses (CoV) are a family of viruses that can cause diverse effects, from a common cold to the most severe diseases, as is the case with the coronavirus that caused the Middle East Respiratory Syndrome (MERS-CoV), and the one that caused the severe acute respiratory syndrome (SARS-CoV) (Wu, Wu, Liu & Yang, 2020). Coronaviruses can be transmitted from animals to people (zoonotic transmission). According to comprehensive studies in this respect, SARS-CoV was transmitted from civet-cats to humans, and transmission of MERS-CoV from dromedaries to humans has been observed. It is also known that other coronavirus types circulate among animals, which have not infected humans yet. These infections can cause fever and respiratory symptoms (cough and dyspnea or difficulty to breath). The most severe cases can develop pneumonia, severe acute respiratory syndrome, renal insufficiency, and even death (Simonnet *et al.*, 2020).

COVID-19 (*coronavirus disease* 2019) is an infectious condition caused by a recently discovered coronavirus (Walach & Hockertz, 2020), which is also known as coronavirus pneumonia. It is an infectious disease caused by virus SARS-CoV-2, which was first detected in late 2019. It produces similar symptoms to the flu, among which are fever, cough, dyspnea, myalgia, and asthenia. It can cause pneumonia, acute respiratory syndrome, sepsis, and septic shock that may lead to death. No specific treatment has been developed, and the main therapeutic measures consist in alleviating the symptoms and maintaining the vital functions.

Most people with COVID-19 experience mild to moderate symptoms, and recover without a special treatment; hence they must be taken to isolation facilities or hospitals for timely treatment. This is a characteristic of the Cuban protocol to treat the disease; it relies on the identification of the greatest possible number of contacts and sick people, and isolate them from the healthy population. These temporary isolation facilities and hospitals should receive all necessary resources in due time, including medication, and medical and non-medical supplies.

In Cuba, the distribution of medical supplies is made by the Wholesale Medication Distributing Company (EMCOMED), the Medical Supplies Company (EMSUME), and the Company for Supplying and Providing Services to Education (EPASE), for which they possess their own transportation means, and whose routes should be optimized to offer quality service. Therefore, proper transportation planning is fundamental to provide the necessary resources to confirmed and suspicious patients, based on a resource-saving approach, and efficient use of the available means (López, González, and Campos, 2020; Lozano, Marmolejo, and Rodríguez, 2020).

Planning transportation routes (VRP or vehicle routing problem), is one of the most important widely studied optimization issues with applications in real scenarios, in terms of distribution and transportation logistics (Toth & Vigo, 2002). This is critical for decision-making by executives.

Since it came into existence, by Dantzig and Ramser, in 1959 —who for the first time stated this problem, for application of fuel distribution—, VRP has generated numerous research studies, and various papers have been published on the various variants of the problem (Dantzig and Ramser 1959).

The objective is to minimize the total distance run by a set of vehicles that depart from a central warehouse, to meet the demands of a particular group of customers. Each customer has a known demand, and every vehicle serves a single route during the planning period. It must start and end in the central warehouse. This problem is a generalization of the Traveling Salesman Problem (Hatamlou, 2018).

In practice, a fleet of vehicles is rarely homogeneous, since the need to supply different market segments recommends that companies have vehicles that adapt to the typology of the goods transported. Similarly, having vehicles capable of transporting different payloads allows for better adaptation to the demands (Yepes and Medina, 2002). Accordingly, a study of this variant of VRP has been conducted, in which the number of vehicles available to meet customer demands is limited.

The literature shows different versions of classic VRP, in order to approach true contexts of different issues (Golden, Assad, Levy, and Gheysens, 1984). These variants are stated by including variables and additional restrictions to the original problem.

The VRP variant for heterogeneous fleets (HFVRP) is present when the different vehicles in the fleet differ in terms of equipment, capacity, age, cost structure or even emission levels, if considered (Golden *et al.* 1984).

The first instances of HFVRP derived from fleet size and mix problems (FSM), suggested by Golden *et al*. (1984). These authors recommended two heuristics, one based on the saving algorithm by Clarke & Wright (1964), and the other relying on a huge route scheme (Beasley, 1983). This author stated 20 problems that later were used as reference by many scholars to present the results of their algorithms for heterogeneous fleets.

Other HFVRP variants were issues with a limited number of HVRP vehicles, initially introduced by Taillard (1999), who presented a heuristic method based on the generation of columns. It starts with the solution to the homogeneous VRP for every type of vehicle, and uses a tabu search algorithm.

HFVRPs are a special classic VRP case; therefore, they are part of the NP-Complete, where the computing time grows exponentially with the size of the problem. Hence, several authors suggest heuristics or meta-heuristics to address these problems, since they are adequate methods to provide quality solutions within a reasonable calculation time (Taillard, 1999).

The literature shows several variants of HFVRP, which consider whether the fleet is limited or limitless, as well as the type of cost considered. The diverse variants are found below:

- Fixed fleet heterogeneous VRP, with route-dependent variable costs (HVRPD).
- Fixed fleet heterogeneous VRP, with fixed and variable costs (HVRPFD).
- Heterogeneous VRP, with limitless fleet and variable costs (FSMD)
- Heterogeneous VRP, with limitless fleet and fixed costs (FSMF).
- Heterogeneous VRP, with limitless fleet and fixed and variable costs (FSMFD).

Moreover, the variants considering time window (TW) restrictions are added.

Therefore, the aim of this paper is the application of capacitated vehicle routing problem (CVRP), combined with optimization algorithms in medical supply distribution to assist hospitalized and suspicious patients of COVID-19.

DEVELOPMENT

CVRP is recommended when the sum of demands from all customers exceeds the capacity of a vehicle, (Baldacci, Battarra, & Vigo, 2008). As for most VRPs, CVRP is NP-complete. It is so because the number of possible solutions grows exponentially with the number of nodes in the graph (customers or stepping points), quickly surpassing the calculating capacities of the most powerful computers.

CVRP is considered a fixed and heterogeneous fleet of vehicles stationed in a central warehouse, to meet the demands of known customers. CVRP consists in a design of a set of lower cost Hamiltonian routes, so that each customer must be visited a single time by a single vehicle, and all the vehicle routes should start and end in the warehouse.

The basic CVRP is aimed to determine k routes of vehicles with a C_k capacity, which depart from a common origin, and must go through a number of places of interest (customers) to distribute or pick up goods, according to the demand d_i, then return to the origin. The total distance run (used time or cost) by the set of vehicles should be the minimum possible. The simplest form of the problem does not take into consideration the delivery or pick up times in all the places of interest (time window) (Baldacci *et al.*, 2008).

Because of its relevance, the vehicle routing problem with a time window (VRPTW) is the variant with the highest attention in the literature. Time windows are produced when the customers demand that their delivery or pick up service be produced within a specific time frame, which is determined by an early time, and a late time of service. Similarly, a total time limit in vehicle service can be included due to existing regulations in driver contracts.

The literature reviewed shows a distinction between hard and soft time windows. In the former, if a vehicle is too early for delivery it is allowed to wait for the customer until they are ready, though arriving later than the agreed time is not allowed. In the latter, customer hours may be changed at the expense of penalties in the objective function.

Heterogeneous fleet size and mix vehicle routing problem with time-windows

FSMVRPTW (*fleet size and mix vehicle routing problem with time-windows*) is defined as follows (Baldacci *et al.*, 2008):

- Being G= (V, E) a directed graph, where $V = N \cup \{0\}$ is the set of nodes (customers), and $E = \{(i, j) : i, j \in V\}$ is the set of arcs, where node 0 denotes the deposit.
- For each arc $(i, j) \in E$, denotation will be done with d_{ij} as the minimum time to travel from node i to node j.
- Each customer $i \in N$ is associated with a non-negative demand q_i (out of convenience in the notation, a demand is assigned to the deposit $q_0 = 0$).
- To load/unload the amount q_i some service time is needed s_i, as well as a time window (a_i, b_i).
- Customer service i, must start between a_i y b_i; that is, in any feasible solution, the vehicle servicing the customer i must arrive in a time instant $t \in [a_i, b_i]$ or time instant $t < a_i$, so they must wait $a_i - t$ time units before starting the service.

- To make this simpler, all time windows are assumed within a given time horizon (a day, for instance). This means that $a_i \leq b_i$ for each customer $i \in N$.
- The fleet is made of H different types of vehicles, in which each vehicle $h\ (h = 1, \cdots, H)$ has a Q^h has a Q^h capacity, and F^h fixed cost.

The objective of FSMVRPTW is to determine the optimum amount of heterogeneous vehicles, and their associated routes, to minimize the sum of fixed costs of routes subjected to these restrictions:

1. Each route starts and ends in the deposit.
2. Each route is assigned just one vehicle.
3. The total demand from customers served in a route cannot exceed the capacity of the vehicle assigned to the route.
4. Each customer is visited just once, and service starts within the time window agreed.

Without losing generality, the types of vehicles are assumed to be numbered in a non-decreasing order regarding the fixed cost value F^h, and that of every customer u, there is, at least, one type of vehicle h so $Q^{h'} > Q^h$. Otherwise, vehicles type h' can be taken away from the instance under any feasible solution, vehicles type h' may be replaced by vehicle type h, without increasing the cost of the solution.

Mathematical formulation of FSMVRPTW

Defining the set of K different vehicles obtained by the definition of n vehicle type h for every $h \in H$. In every $k \in K$, being $\bar{Q}^k$ and $\bar{F}^k$, they denote the capacity and cost of vehicle k, respectively. This is a generalization of the formulation with three VRP indexes (Toth & Vigo, 2002). The routing part of the problem is modeled through two sets of binary variables: (i) variables x_{ij}^k take the value of 1 if the arc (i, j) is crossed over by vehicle k; (ii) variables y_i^k take the value of 1 if client i is served by vehicle k. To choose the appropriate set of vehicles, a binary variable Z^k, is introduced which takes the value of 1 if the vehicle $k \in K$ is used, and the value of 0 if otherwise.

Managing time windows and the duration of routes requires the definition of the following sets of variables: (i) variables t_i^k indicate the minimum time instant in which the vehicle k can arrive at each node $i \subset V$; (ii) variables τ_i to indicate the minimum time moment in which customer service i can start; (iii) variables π^k to determine the moment when the vehicle k, if used, starts the route. Notice that for every vehicle k, the start and end times of routes is given by variables π^k and t_0^k .

From the use of these variables, and a huge positive constant (a value $\max_{i \in N}\{b_i + s_i\} + \max_{(i,j) \in E} d_{ij}$ is assigned), FSMVRPTW can be formulated as follows:

$\min \sum_{k \in K}(\tilde{F}^k z^k + t_0^k - \pi^k) - \sum_{i \in N} s_i$ (1)

Subjected to:

$\sum_{k \in K} y_i^k = 1, \quad i \in N$ (2)

$y_i^k = \sum_{j \in V:(j,i) \in E} x_{ji}^k, \quad i \in N, k \in K$ (3)

$y_i^k = \sum_{j \in V:(i,j) \in E} x_{ij}^k, \quad i \in N, k \in K$ (4)

$\sum_{i \in V} q_i y_i^k \leq \tilde{Q}^k z^k, \quad k \in K$ (5)

$\sum_{i \in S} \sum_{j \notin S} x_{ij}^k \geq y_l^k, \quad S \subseteq N, l \in S, k \in K$ (6)

$t_j^k \geq \tau_i + s_i + d_{ij} - M(1 - x_{ij}^k), \quad (i,j) \in E: i \epsilon N, k \in K$ (7)

$t_j^k \geq \pi^k + d_{0j} - M(1 - x_{0j}^k), \quad k \in K, j \in N$ (8)

$t_0^k \geq \pi^k, \quad k \in K$ (9)

$\tau_i \geq t_i^k, \quad i \in N, k \in K$ (10)

$a_i \leq \tau_i \leq b_i, \quad i \in N$ (11)

$x_{ij}^k \in \{0,1\}, \quad (i,j) \in E, k \in K$ (12)

$y_i^k \in \{0,1\}, \quad i \in N, k \in K$ (13)

$z^k \in \{0,1\}, \quad k \in K$ (14)

$t_i^k \geq 0, \quad i \in V, k \in K$ (15)

$\tau_i \geq 0, \quad i \in N$ (16)

$\pi^k \geq 0, \quad k \in K$ (17)

Restriction **¡Error! No se encuentra el origen de la referencia.** suggests that every customer should be visited by a vehicle, exactly, whereas restrictions **¡Error! No se encuentra el origen de la referencia.** and **¡Error! No se encuentra el origen de la referencia.** suggest that if the customer i is visited by vehicle k, it must enter and exit the associated node, respectively. Inequality **¡Error! No se encuentra el origen de la referencia.** is related capacity restriction of every vehicle $k \in K$, and inequality **¡Error! No se encuentra el origen de la referencia.** considers the connectivity requirement of each route. Restrictions **¡Error! No se encuentra el origen de la referencia.**, **¡Error! No se encuentra el origen de la referencia.**, and **¡Error! No se encuentra el origen de la referencia.** define the moment of time to service every customer i, and sets time window restrictions. Moreover, restriction **¡Error! No se encuentra el origen de la referencia.** defines the instant of time when each vehicle $k \in K$ starts the route. Note that when vehicle k is not used, variables π^k and t_0^k have no restrictions, but **¡Error! No se encuentra el origen de la referencia.** establishes that $t_0^k - \pi^k \geq 0$, and the object function will place them within a common value for any optimum solution.

The large quantity of variables in the model **¡Error! No se encuentra el origen de la referencia.** - **¡Error! No se encuentra el origen de la referencia.**, and the presence in value restrictions of very large M, makes it impossible (or extremely complex) to obtain an accurate solution to the problem.

VRP solution

Estimation distribution of algorithms (EDA) are a group of evolutionary algorithms (EA) thaw allow for model fitting to the structure of a particular problem, which are made by estimating the distribution of probabilities from chosen solutions (Larrañaga, Lozano, and Mühlenbein, 2003). The model is a distribution of probability. These algorithms are based on the substitution of crossover operators and mutation of genetic algorithms by estimation, and later sampling of a distribution of probability, which is learned from individuals chosen in a population (Martínez, Madera, and Leguen, 2016; Martínez *et al.* 2019, Martínez, Madera, Rodríguez, and Barigye, 2019; Martínez *et al.*, 2020).

Simulated annealing (SA) (simulated overcooking, simulated crystallization or simulated cooling) is a metaheuristic algorithm used for global optimization problems; the general aim of this type of algorithm is to find proper approximation to the optimal value of a function in a large search space. This optimal value is named optimum overall. The name and inspiration comes from a process of steel and ceramic overcooking, a technique that consists in heating first, and then cooling down slowly to change the physical properties of a material. Heat causes atoms to increase their energy, and be able to move from their initial positions (a local minimum of energy); slow cooling provides greater chances of re-crystallizing in configurations with less energy than the initial (global minimal) (Van Laarhoven & Aarts, 1987).

The variable neighboring search (VNS) suggested by Mladenović & Hansen (1997), is a metaheuristic method to solve a group of problems of combining optimization. It explores neighbors with distant solutions, and changes to new values from there, and only if there was an improvement to the current solution. The local search method is repeatedly applied to find solutions in the neighborhoods to local optimal. VNS was designed to approximate solutions to discreet and continuous optimization problems; it focuses on solving problems of linear programing, problems of whole number programing, problems of mixed whole numbers, and problems of non-linear programing (Mladenović & Hansen, 1997)

Experimental results

The CVRP library (Mostapha, 2015) was used to conduct the following experiment, run in MATLAB 19a, and the three previously analyzed metaheuristics (EDA, SA, and VNS). A total of 15 models were used in the experiment (number of nodes x number of available resources) to study the behavior of these algorithms applied to the problem.

As can be seen in

, metaheuristics have similar behaviors in the evaluating efficiency for different model configurations (number of nodes x number of available resources), which converge in the optimum solution. Both VNS and EDA algorithms showed better behaviors than SA, though the number of iterations to find the optimal were similar. These experiments allowed for an analysis of the behavior of different meta-heuristics, to later choose the one to solve different problems in decision-making.

Based on the previous study, a tool that relies on variant VNS (Erdogan, 2017) to conduct two study cases in the province of Camagüey, Cuba, in decision-making, by executives in the transportation organization in times of COVID-19, was selected

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Table 1 Comparison of three metaheuristics analyzed in the CVRP library

Model	EDA		SA		VNS	
	Iteration	Cost value	Iteration	Cost value	Iteration	Cost value
8x3	16	220.1634	55	220.1634	21	220.1634

9x2	60	327.7324	75	327.7324	78	327.7324
10x3	164	284.9794	128	284.9794	161	284.9794
12x4	196	206.9034	197	206.9034	196	206.9034
14x4	145	275.5251	150	275,6516	142	275.5648
20x4	240	339.4230	293	334.2565	264	354.6740
25x5	189	324.9167	285	329.1888	220	325.4408
30x5	543	344.5186	697	349.2090	653	366.5209
36x5	660	322.3306	725	321.9128	634	321.9128
40x6	609	356.8877	640	356,743	607	356.7430
50x7	520	358.0239	584	357.9469	676	390.3850
60x7	1 097	378.2754	1 081	386.7325	1 080	378.2754
70x8	1 100	390.6932	1 133	383.2930	1 145	435.0010

Implementation of FSMVRPTW in EPASE Company, in Camagüey

FSMVRPTW was implemented in the province of Camagüey after modeling. Most companies that carry merchandise related to public health (EMCOMED, EMSUME, and EPASE) have a central warehouse in the municipality of Camagüey. When merchandise exits the warehouse, it is carried/distributed to the other 12 municipalities in the province. Transportation, merchandise, service hours, etc., were characterized according to information provided by these companies. Then, the distribution of a possible cargo was simulated, considering all the parameters for this type of problem. The distances among different municipalities in the province were calculated with Microsoft *BingMaps.* Note that the distances are symmetrical, representing a triangle matrix.

Case I

1. The company has a fleet of four vehicles, all of the same type ($H=1$), and the same capacity ($Q^h=100$), interpreted as boxes with the same sizes).
2. Each vehicle trip has a fixed cost of $ 100 CUP, and $ 10 CUP per km.
3. Each vehicle can run 400 km tops, and drivers are not allowed to drive for over 9 hours.

4. The average speed of the vehicles if 50 km/h, depending on the conditions of roads, and the technical conditions of vehicles.
5. Number of customers $N = 12$, represents all the 12 municipalities in the province of Camagüey.
6. The distances among municipalities represent the arc-weight in the graph.
7. The load time window in the central warehouse $(6{:}00, 8{:}00)$, indicating that vehicles must start loading in that lapse; the vehicle servicing time is 55 minutes.
8. The modeled time window for customers $(8{:}00, 16{:}00)$, indicating that all unloading from vehicles must start after 8:00 am and before 4:00 pm.
9. The unloading time in the municipalities is the same, equaling 20 minutes.

Besides, the number of containers to be transported to the municipalities; that is, the municipal demand, were defined.

Based on the information modeled, FSMVRPTW was solved using a VNS algorithm (variable neighborhood search), with an optimum solution shown in

Fig.. Note that the solution has four routes, which requires the utilization of four vehicles.

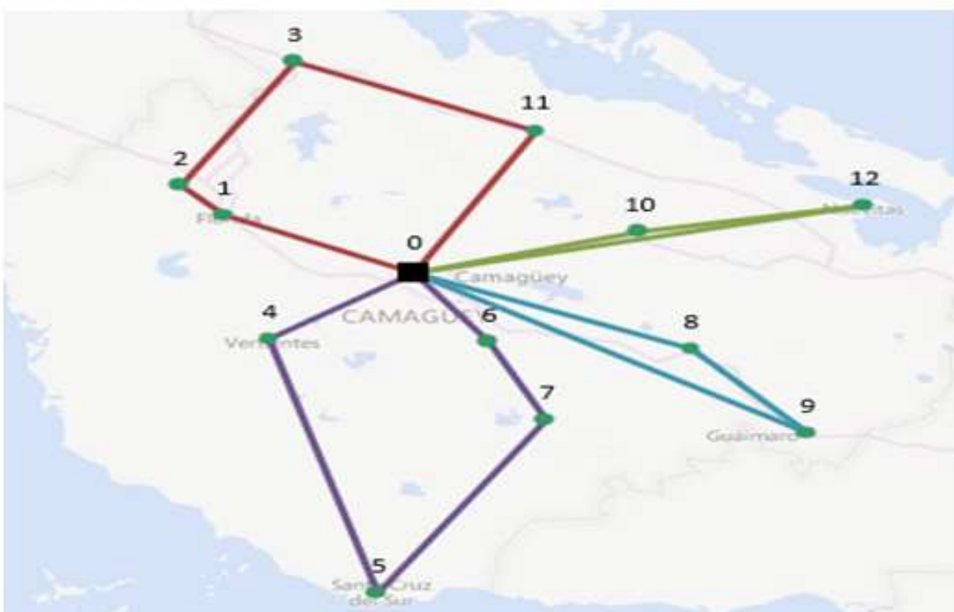

Fig.1. Optimum solution to FSMVRTW for transportation of COVID-19 supplies by EPASE company in the province of Camagüey

All the vehicles started from the central warehouse located in the city of Camagüey. The first vehicle goes to municipalities Sierra de Cubitas, Esmeralda, Cespedes, and Florida, in that order; then it goes back to base. This 180.6 km trip is done in 2 hours and 43 minutes. The second vehicle goes to Minas and Nuevitas, in 2 hours and 34 minutes, running a distance of 162.1 km. The third vehicle goes to Jimaguayu, Najasa, Santa Cruz, and Vertientes, in 3 hours and 15 minutes, through 226.25 km. The last vehicle goes to Sibanicu and Guaimaro in 2 hours and 29 minutes, covering a distance of 166.29 km.

Case II

1. The company has a fleet of five vehicles, all the same type$(H=1)$, and same capacity $(Q^h=100)$, interpreted as boxes of equal dimensions).
2. Each vehicle trip has a fixed cost of $ 100 CUP, and $ 10 CUP per km.
3. Each vehicle can run 400 km tops, and drivers are not allowed to drive for over 9 hours.
4. The average speed of the vehicles is 50 km/h, depending on the conditions of roads, and the technical conditions of vehicles.
5. Number of customers $N=36$, represents all the 12 municipalities in the province of Camagüey, hospitals, and isolation facilities.
6. The distances among municipalities represent the arc-weight in the graph.
7. The load time window in the central warehouse is (6:00,8:00), indicating that vehicles must start loading in that time; the vehicle servicing time is 55 minutes.
8. The modeled time window for customers is (8:00,16:00), indicating that all unloading from vehicles must start after 8:00 am and before 4:00 pm.
9. The unloading time in the municipalities is the same, equaling 20 minutes (Fig. 2).

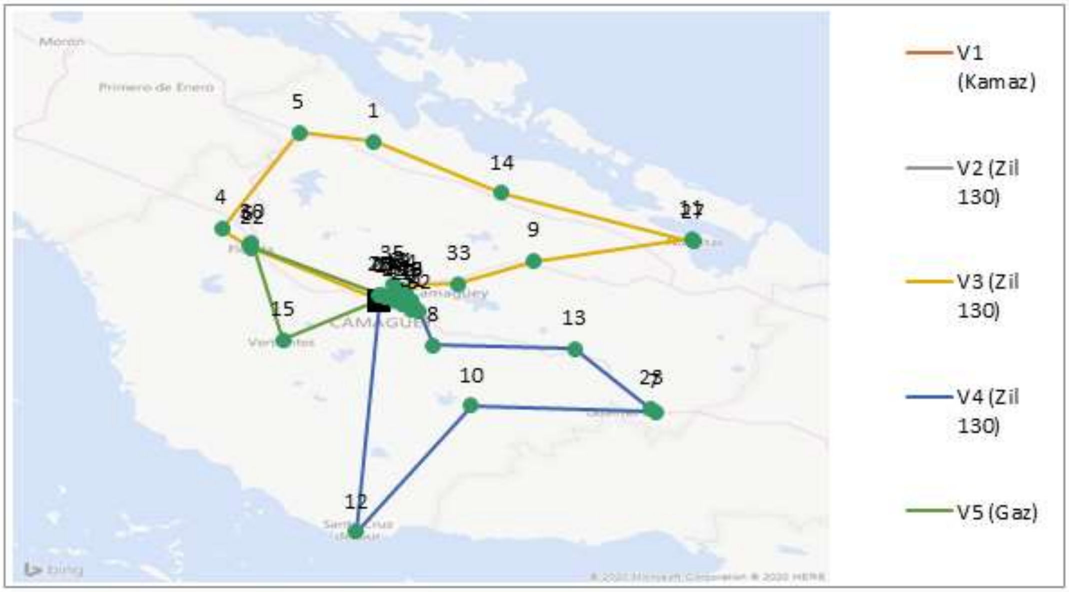

Fig.2. Optimum solution to FSMVRTW for transportation of COVID-19 merchandise in the province of Camagüey

CONCLUSIONS

Operations research is a powerful tool for planning resources in the fight against pandemics.

The utilization of IO tools demands interest and political will of government authorities, demonstrated in the emphasis placed by the Cuban government in the implementation of mathematical research in the fight against COVID-19.

Linear programing and transportation problems constitute useful tools for efficient utilization of resources to fight COVID-19.

The application of variable search and distribution estimation variables to VRP provides optimum solutions, in which cargo carrier routes are minimized.

Reducing the minimum distances and the number of vehicles allotted also reduces the amount of fuel needed, and therefore, produces savings, and less impact on the environment by decreasing CO_2 emissions.

Optimum organization of medical resources transport is required to fight COVID-19, which influences on decision-making by local executives.

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Conflicts of interest and conflict of ethics statement

The authors declare that this manuscript is original, and it has not been submitted to another journal. The authors are responsible for the contents of this article, adding that it contains no plagiarism, conflicts of interest or conflicts of ethics.

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