An Efficient Metaheuristic algorithm for optimization for Location of Optimum Connectivity Services with Drones in Healthcare

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Abstract:

Drones are being extensively used for a variety of practical purposes, including providing medical care. For instance, giving vaccinations, healthcare equipment, and samples of blood to individuals in isolated locations as well as during calamities. This study examined an efficient metaheuristic algorithm called MAP-LOCS, which optimizes the location of optimal connectivity amenities using drones. The use of drones in relation to facility placement and navigation is the issue. Within certain drone range limits, it entails choosing drone launch spots to optimize patient care availability. This work develops a heuristic called Location of Optimal Connection Services. The algorithm's basic premise is to start by randomly selecting a few services to open from among those that are most capable of meeting patient requests. Following that, patients are matched with the nearest open facility that can accommodate them. In the end, patients get allocated a drone according to which one uses the smallest quantity of battery life when traveling between the patient and the facility. In a short amount of time, it was capable of handling a large number of patients (above 90% on average).

Key words: Drone in healthcare, Metaheuristic Algorithm, Crow Search Optimization Algorithm, Location, Time performance

1. Introduction:

Drones are multiplying so quickly that there are both potential and difficulties for several sectors and safety organizations. The demand for efficient anti-drone technologies grows as the frequency of events involving unapproved and possibly malevolent drones rises. Integrating machine learning (ML) and artificial intelligence (AI) algorithms into anti-drone systems is one potential strategy. This article looks into how AI and ML are improving drone detection, tracking, and mitigation capabilities, which is changing the practical use of anti-drone equipment. A key extension project in medicine is the delivery of life-saving medical care to patients in emergency and aftermath situations. Natural calamities have become more frequent in recent years. Examples of these include the Atlantic Hurricane Season in 2021 [1], the COVID-19 pandemic in the year 2020 [2], the North American Wildfire Season in 2021 [3], the Haiti Earthquake and Tropical Storm Grace in 2021 [2], the Australian bushfires in 2019 [4], Cyclone Idai struck the continent in 2019 [5], and an earthquake and tsunami struck Indonesia in 2018 [6]. India's 2014 Kashmir flooding was disastrous. India's Uttarakhand flooding in 2013. The 2007 flood tragedy in Bihar, India. Natural catastrophes present challenges to medical professionals trying to assist patients and victims with necessary therapies, which could worsen the propagation of diseases and raise the death toll. Injured people need to get medical attention fast in order to be rescued from crisis and post-disaster scenarios. These rescues can be carried out by placing patients in the care of the closest hospital, clinic, or social center and by delivering vital medical necessities, like blood and heart rate monitors, to the wounded individual's area.

The majority of the difficulties in determining a patient's location are due to geographic factors such as scattered islands, inadequate transit systems, and constrained mobility options. These issues are typically more serious in developing and rural nations alike. Furthermore, natural disasters frequently affect the nearby transportation infrastructure. For instance, bridges may break or highways can become impassable as a result of natural calamities [7, 8].

The use of effective strategies to serve patients is vital in order to get past these hurdles and offer the appropriate medical care for patients in emergencies and post-disaster scenarios. In a perfect world, infrastructure damage would not have an impact on transportation, and it would not be significantly more expensive than terrestrial transit. It is remarkable, then, that this is possible with unmanned aerial vehicles (UAVs) or drones. Additionally, there are a number of healthcare possibilities for drone utilization (Fig. 1- sample photos).

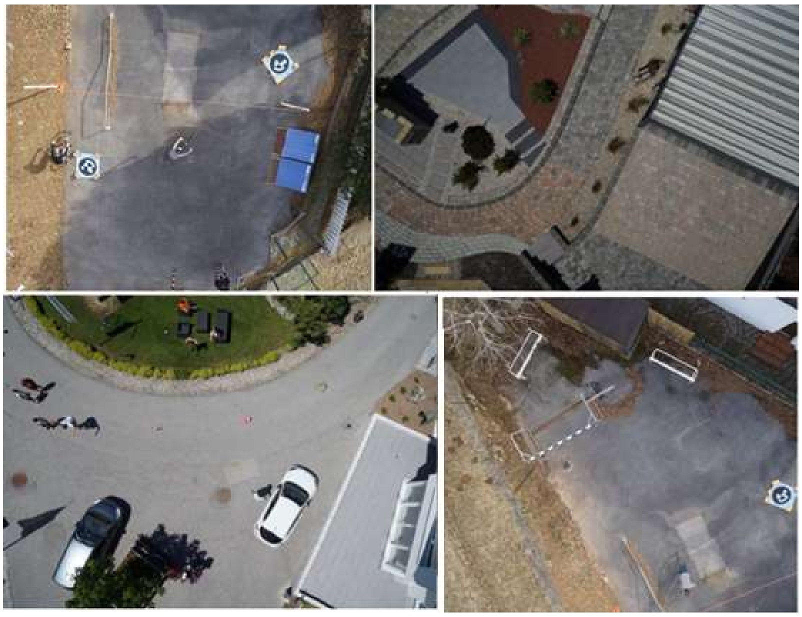

Fig. 1. Drone View Point

2. Drone in healthcare industry with AI

A few developments in the healthcare sector hold the potential to completely transform how clinical services are provided. Robots have progressed to the point where surgeons can now operate digitally on the skull and heart with such accuracy. AI performs a wide range of tasks, including patient diagnosis, documentation completion, research discovery, and accurate medical outcome prediction. The use of drones in healthcare applications is one such breakthrough and our main area of interest.

Often associated with aerial photography and package delivery, drones are set to revolutionize important parts of healthcare by improving availability, efficacy, rapid response times, and more. In certain situations, drones have already been utilized to quickly move medications, lifesaving healthcare supplies, and even tissue for transplantation over difficult terrain and crowded spaces. The prospect of effective large-scale deployment is immense, as it may potentially save countless lives. Just think of the opportunities.

Drones can be used to deliver supplies like drugs and healthcare tests, as well as healthcare services like blood components and vaccines. Drones started delivering COVID-19 tests as well as personal safety gear to hospitals in the United States during the outbreak. As of October 2020, the zip line had delivered over 70,000 medical supplies using drones.

The health care drone delivery market is growing rapidly as a result of the use of drones to transport blood donations, vaccines, drugs, anti-venom treatments, organ transplants, and other medical supplies. More than 30 businesses use drones to transport healthcare equipment, which is divided between drone service providers and business-internal solutions. The new Matternet location endorses the company's vision of shared, peer-to-peer drone transportation networks for urban areas by integrating with Matternet's self-governing M2 Drone and Cloud Platform as well. This integration enables hospitals and their supply collaborators to incorporate automatic drone deliveries for labs and pharmacies.

3. Related search

In this part, we examine and talk about cutting-edge approaches to solving the FLP for drone launch sites. Drone research on FLP and its variations has not been done much [9]. Actually, FLP has a lot of uses when it comes to drone use, especially in post-disaster scenarios or when trying to reach hard-to-reach places. Drone power supply, drone flight range, and additional factors are just a few of the many factors that need to be taken into account when choosing drone launch locations [10]. A quick medical reaction is made possible in the realm of healthcare by keeping a short distance between the patient's location and the drone's launch site [11]. This part reviews a few more earlier researchers attempt to solve the FLP and its variations for the purpose of choosing drone-launching locations. Three methods were applied to the issue described in [12, 13]: a several-stage heuristic (3SH), a unique greedy heuristic, and a mixed-integer computing solution. The researchers proposed the two algorithms, greedy and 3SH. The greedy heuristic first creates a weighted matrix in which the rows correspond to resources and the columns to need point objects. The proportion of the variation across a point's request weights and the amount of energy used to travel among the point and the location are used for filling every component. Locations are then opened, and a weighted matrix is used to allocate particular request points to each of them. The number of drones required for each facility (NDj) is then determined by dividing the overall battery consumption of the facility by the demands placed upon it, as well as the drone's battery capacity. Afterwards, the opened locations (J) are arranged based on (NDj). Every open site gets allocated a drone in turn based on the drones that are accessible. Ultimately, the drone's demand assignment is carried out based on the amount of battery used at each location and demand.

Shavarani et al. [14] investigated an FLP in another effort to find the best way to locate drone launch sites and charging facilities. Their goal was to keep the system's overall cost as low as possible. After using and comparing a genetic algorithm and a hybrid genetic algorithm, it was discovered that the latter offered the best result. The final study of note is Kim et al. [12, 15], in which the authors presented a stochastic framework for disaster-affected areas. The structure attempts to solve the FLP by determining the ideal number of drone launch sites and their capabilities, taking into consideration the uncertainty of drone journey distances. The writers created a heuristic approach that yields excellent and effective results by utilizing Bender's decomposition and linear programming reduction.

Despite their potential to save lives and ease the load on medical institutions and patients alike, there has been little research done on the use of drones in the healthcare industry, according to the literature. The recent COVID-19 pandemic has highlighted the dearth of study in this field, despite the fact that drone technologies have greatly aided in the distribution of necessities to remote places at a lower cost and with greater safety and speed than conventional means of transportation. This literature study also shows that exact approaches are clearly not appropriate for tackling large datasets of FLP and its variants. Formal techniques take very extensive processing time to produce results because they are an NP-hard problem. As a result, the literature now in publication often employs heuristics and metaheuristics to find near-optimal (quality-wise) solutions with reasonable processing times for real-world situations with massive data sets.

4. Problem Formulation

The Facilities Location Problem has a version known as the Maximum Covering Facility Location Problem with Drones [16, 17]. In particular, the FLP uses a collection of facilities that can be selected or allotted from available locations to meet the needs of a group of clients. On the other hand, the OLP (Optimal Location Problem) in the ECSAOLC (Efficient Crow Search Algorithm for Optimization for Location of Optimum Connectivity) takes into account drone range limitations as well as drone-to-facility and demand-to-drone transportation. Because of these computationally demanding aspects, the ECSAOLC is more sophisticated than the traditional OLP. Implementing a solution to enhance the ECSAOLC results reported by Chauhan et al. was the goal of this work. [19,20] The ECSAOLC focuses in particular on determining the ideal or nearly ideal number of drone launch facility placements so that patient coverage is improved. The current centre locations must be used to select the drone locations.

5. Methodology

This work presents the development of a new ECSA-OLCS technique to tackle the Location of Optimal Interconnection problem. This ensures that every constraint listed in Table 1 is met. From the set of possible connectivity J, the procedure's first notion is to choose a set of optimum connectivity, or OC, to be opened with size p, $\sum_{i \in I}^{\infty} \sum_{j \in oc}^{\infty} Yj\ \ Cij\ \ Wi$ (Or, putting it another way, maximizing the total number of patients that can be served). Every prospective patient is then assigned by the system to the closest open location ($j \in OC$) with the capacity (uj). Drones that are accessible are then assigned to the opened location based on the highest weights of unused requests $\sum_{i \in I}^{\infty} Wi\ aij$, where $j \in OC$ and $a_{ij} = 1$. Lastly, patients are assigned to drones (in each opened location) based on the greatest demand weight W_i of all the unused patients of a particular open location j, which then follows by the lowest battery consumption b_{ij}. This way, for every drone K, the total number of batteries used by the drone to meet demand is fewer than the drone's total battery life. (that is, $\sum_{i \in I}^{\infty} bij \leq BK$, where $j \in OC$). Where J denotes the set of all potential facility locations ($j \in J$), K denotes the group of drone locations ($k \in K$), whereas I refers to the group of patient locations ($i \in I$).

5.1 Metaheuristic algorithm

A metaheuristic algorithm strikes a balance between worldwide research and local searches. A common technique to obtain a large range of solutions is randomization. One useful technique for moving from local to global search is randomization. Because of this, almost all metaheuristic algorithms can be used for worldwide optimization and nonlinear modeling. Using metaheuristics can help you solve complex problems in a fair amount of time by generating workable answers through trial and error. It is challenging to look for each prospective approach or solution due to the complexity of the issue at hand; instead, the objective is to find a decent, workable solution within a reasonable amount of time. Choosing the best answers is just one aspect of it. To ensure that the approaches converge to optimal performance, the most effective options are selected.

5.1.1 Crow Search Optimization Algorithm

The ability to think for yourself means collecting replies from various objects and then computing all of the responses together to determine the best answer to the given problem. This approach finds a more ideal solution for a particular problem, which is why CSA is used. To put it simply, a problem is solved by using the concept of collective behavior in distributed self-organization. The objective of this meta-heuristic is for a specific crow to be equipped to track other crow to its secret food source. During this process, the crow's location must be updated gradually. The crow also has to change where it is when food is taken.

Step 1: Drone random initialization in d-dimensional space.

Step 2: Every drone is assessed using a measure of fitness, and the result is set as the initial memory quantity. Every drone has a memory variable called M_i where it keeps its hidden place.

Step 3: The drone chooses an additional drone at random, X_j, and generates a random number to modify its position. In the event that this value exceeds probability, drone X_i will pursue X_j in order to determine M_j.

Step 4: The drone chooses another random crow, X_j, and follows it to determine M_j in order to revise its position. Afterward, fresh X_j is computed in this way:

$$Xi, iter + 1 = \begin{cases} -xi, iter, +riX & \\ (mj, iter - xi, iter) & rj \geq Pj, iter \end{cases} \quad (1)$$

Algorithm CSA: Crow Search Optimization Algorithm

Step 1: Input: No of Available Drones(K)

Procedure:

Step 2: iteration Maximum number of iterations.

Output:

Step 3: Optimal drone position

Step 4: Set the starting point's location.

Step 5: **while** iteration<$iteration_{max}$ **do**

Step 6: select a place at random.

Step 7: Find the probability P's value.

Step 8: Reload $x_{i,iteration+1}$ using Eq. (1)

Step 9: Verify the bounds of the solution.

Step 10: Identify the drone's location.

end while

end procedure

5.2 Location Coverage

An efficient way to address a complicated optimization problem that is challenging to solve for optimal performance is to use a metaheuristic algorithm. In this real-world word with finite resources (time and location), it is essential to develop a close to optimal solution based on faulty or incomplete knowledge. The fraction of total satisfied patient demand that is attributed to location coverage. The optimization approach provided the best time performance, according to the authors of [12, 18], despite having very little coverage when compared with the other techniques. The reason why the Bat algorithm (BA) performed the best among the three approaches in regard to coverage is that it takes an excessively long time to reach a workable solution. On the other hand, BA was also linked to the best time performance. On the other hand, the Cuckoo search algorithm (CuSA) achieves lower performance; on average, it takes just about 54.9 seconds when compared to the Bat Algorithm. Comparing the greatest coverage of the other two approaches and the MAP-LOCS (CSA) method, Fig. 1,2,3 groups the places that have been opened and the drones that are accessible to use. The number of places that have opened is shown on the x-axis, while the drones that are available are shown on the y-axis. The following was the median maximum coverage obtained for every method: MAP-LOCS (CSA) (90.06%), CuSA (74.74%), and BA (81.17%). The aim is to optimize coverage while reducing time by comparing the approaches of BA and CuSA. At 90.06%, MAP-LOCS (CSA) now attained ideal coverage. The average time performances of the BA are 53.5 s, CuSA 54.9 s, and CSA 49.9 s, as indicated in Table 1.

Table 1. The average time performances of the BA

		BA		CuSA		CSA	
Opened Location	Available drones	Time	Coverage (%)	Time	Coverage (%)	Time	Coverage (%)
5	20	14.7	56.4	9.7	50.4	11.1	71.23
5	23	15.9	61.9	17.7	55.9	12.3	72.76
5	30	19.3	67.8	19.5	61.8	15.7	73.67
10	35	25.67	69.4	25.67	63.4	22.07	74.5
12	36	34.65	72.56	45.6	66.56	31.05	75.78
10	40	39	75.89	48.7	69.89	35.4	94.23

15	42	45.56	80.34	50.6	74.34	41.96	95.89
15	45	50.45	85.3	55.56	72.9	46.85	96.78
16	50	60.35	89.8	60.67	83.8	56.75	98.4
20	55	65.78	90.5	65.78	84.5	62.18	98.8
20	60	78.56	91.56	73.56	85.56	74.96	99.45
21	65	80.45	92.45	80.34	86.45	76.85	99.7
24	70	85.69	93.28	85.69	87.28	82.09	99.8
25	75	90.34	94.67	91.4	88.67	86.74	99.89
25	80	95.4	95.7	93.5	89.7	91.8	99.99
Average		53.5	81.17	54.9	74.74	49.9	90.06

5.3 Time performance:

Since maximizing coverage is the goal, we contrasted the Cuckoo Search Algorithm and Bat Algorithm techniques. The average time performances of the BA are 53.5 s, CuSA 54.9 s, and CSA 49.9 s, as indicated in Figs 1, 2 and 3. Despite the fact that the tests were carried out on various machines, it is still evident that the MAP-LOCS approach is significantly quicker than the others. Moreover, this even more confirms the exceptional time performance of the MAP-LOCS (CSA) considering that the hardware specifications of the computer used to test the MAP-LOCS were less than those of the apparatus used to test the BA and CuSA methods. The CSA actually moves very quickly—less than 1 m on average.

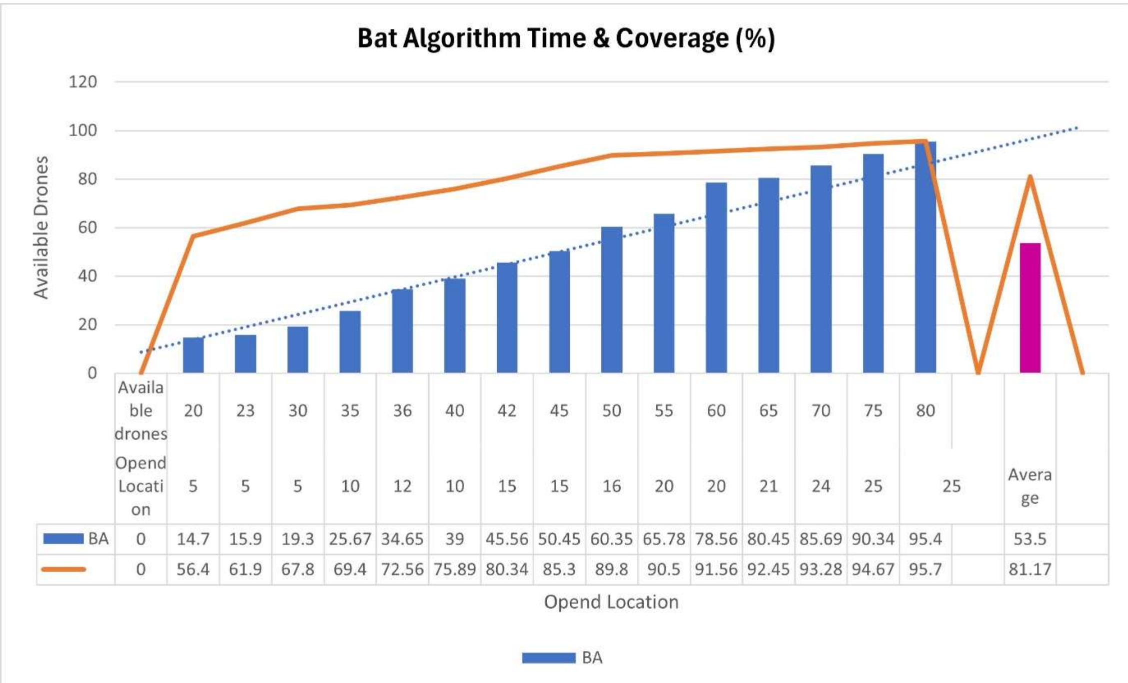

Fig. 2. Time and Location Coverage of Bat Algorithm

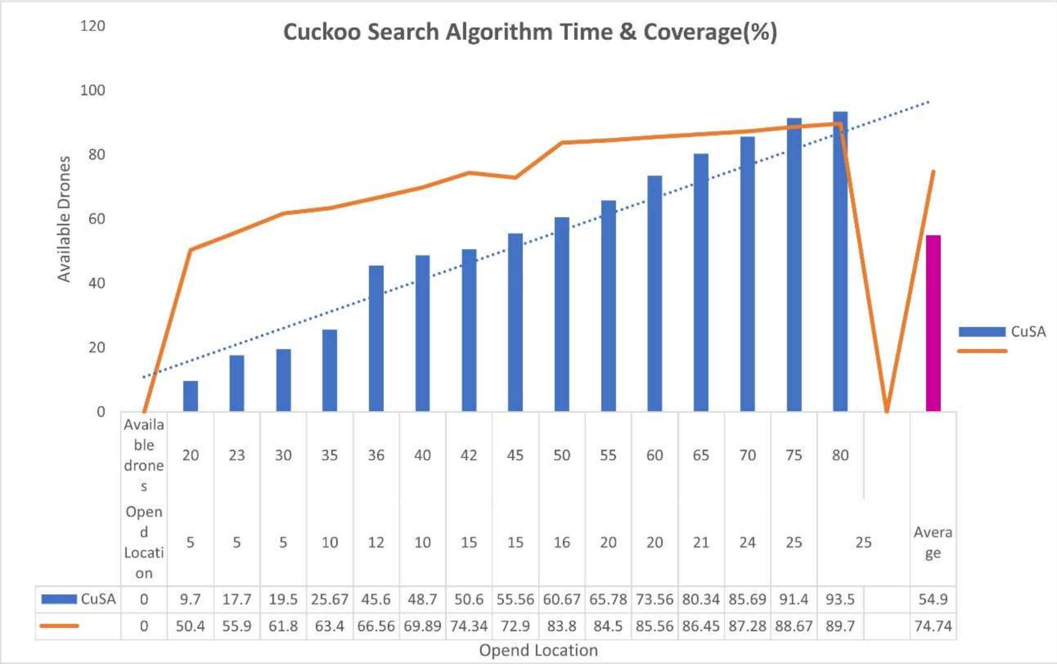

Fig. 3. Time and Location Coverage of Cuckoo Search Algorithm

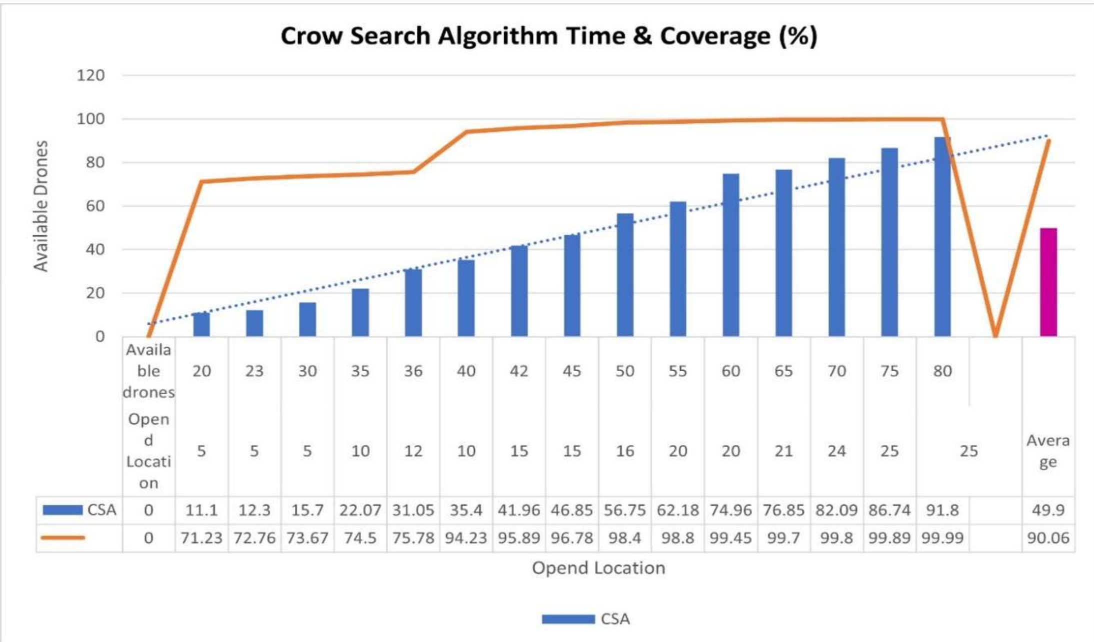

Fig. 4. Time and Location Coverage of Crow Search Algorithm

Figure 5 illustrations an evaluation of the maximum coverage of the Crow Search Algorithm and the other two methods, grouped by the number of opened locations. The x-axis denotes the various methods, while the y-axis denotes the average of time and location coverage [19]. The average maximum coverage attained using each method was as follows: time and coverage of the BAT method (53.5, 81.17%), Cuckoo Method (54.9, 74.74%), and the Crow Search method (49.9, 90.06%). The objective is to save time and maximize the coverage, a comparison between the BA, CuSA, and CSA methods is considered.

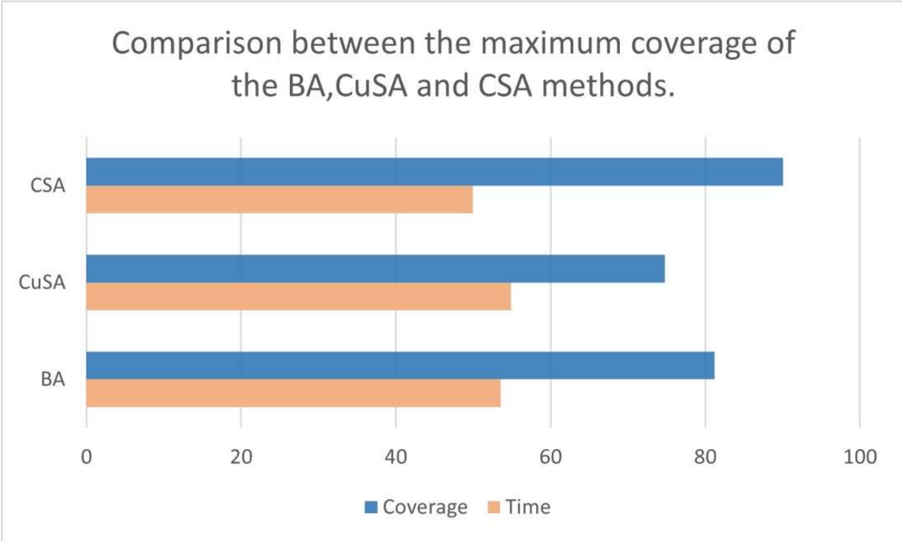

Fig. 5. Comparison between the maximum coverage of the BA, CuSA and CSA methods.

6. Conclusion:

Drones can be used to distribute medications and assist patients, both of which can greatly enhance healthcare services. The efficient metaheuristic algorithm for optimization for the location of optimum connectivity services with drones (MAP-LOCS) is more difficult than the conventional location of facilities problem, and the goal of this work is to produce effective solutions for it in an acceptable amount of time. Modern techniques have been put forth in the field to address this issue; a meta heuristic, which is incredibly quick but achieves high coverage in comparison to different methods, provides acceptable quality solutions in terms of coverage but has an unacceptably lengthy duration to find a possible solution. The following was the median maximum coverage attained with each method: MAP-LOCS (CSA) (90.06%), CuSA (74.74%), and BA (81.17%). The aim is to optimize coverage while reducing time by comparing the approaches of BA and CuSA. At 90.06%, MAP-LOCS(CSA) now attained ideal coverage.

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