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MOBILE CLINICS ROUTING IN RESPONSE TO COVID-19 OUTBREAK: AN INTELLIGENT HYPERHEURISTIC APPROACH

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***Abstract*— In March 2020, the World Health Organization (WHO) announced the COIVD-19 as a global pandemic that caused thousands of deaths and brought the world to a standstill with a huge economic burden [1]. Health is an essential factor for sustaining a better life in a better world. Today, for different reasons, several districts in our countries would be deprived from the needed health support and thus, in such cases, we need to deliver health care to those regions. Despite its considerable cost, the mobile clinic remains one of the good solutions to deliver health care to critical areas in our countries. A recognized problem in this domain is minimizing the cost of mobile clinics route in a way that the number of served patients is maximized. This problem is known as the mobile clinics routing problem (MCRP). The purpose of this paper is to present a novel approach that, within the given limited resources, it minimizes the cost and the traveling distance of mobile clinics while maximizing the number of served patients as per priorities assigned according to the patients' medical status. This paper implements and tests an intelligent variable neighbourhood search algorithm for MCRP.**

Keywords— **Pandemic Management, Hyperheuristic, Machine Learning**

I. BACKGROUND OF THE STUDY

Today, several reasons prevent governments in different countries from providing suitable health care to their citizens. Some of these reasons are related to pandemics, natural disasters, or even to terrorist acts that hit health care centers, which might take a long time for governments to recover. Other reasons could be the distributions of the population in different geographic areas that lead to establishing health care centers in these areas becoming expensive and unfeasible projects. All these reasons forces governments to think about delivering health care to citizens instead of having them cross the long distance to acquire it. Mobile clinics were one of the feasible solutions to be considered.

Mobile clinic is defined as "a typical clinic with all needed machines and equipment which can move from one place to another to provide better service. It is a way of having all the equipment built into a moving vehicle to be ready for usage at any time and to reach long distances where there are no fixed clinics" [2]. Today, the need for mobile clinics is demanding to resolve the dilemma of an enormous number of people deprived from health care services. This fact is revealed in World Health Organization' report [1], the report clearly stated that 400 million people do not have access to essential health services due to the increase in natural disasters, epidemics, food shortage, refugee aid and military conflicts. The basic problem reported is the lack of or destroyed infrastructure, which hinders the performance or the reconstruction of clinics. The report further "recommend that countries pursuing universal health coverage should aim to achieve a minimum of 80% population coverage of essential health services", and that everyone everywhere should be protected from catastrophic and impoverishing health services.

The demand for universal health coverage is further asserted by the WHO [1], which requires the "health policies and programs focus on providing quality health services for the poorest people, women and children, people living in rural areas and those from minority groups". Further, in its report on health care services, the Rural Health Services Review Committee of Alberta [3] found that "some fixed clinics are closing in the rural area because of the declining population, economic recession, shortages of physicians and other health care professionals, a disproportionate number of elderly, poor, and underinsured residents, and high rates of chronic illness". Participants in the report claimed that it is difficult for them to find out a professional doctor or a trusted health care center in rural areas. Most of the citizens in the rural areas believed that the government should provide clinics in the rural areas other than sending people to other places and clinics.

At present, mobile clinics offer a feasible solution to the above dilemma. In addition to being equipped to respond to the COVID 19 outbreak, mobile clinics provide many programs and centers including the da Vinci® Surgical system, cancer services, diabetes, digestive health, emergency services, and many other health care services. In fact, such a variety of services offered by mobile clinics provides efficient health care, flexibility, accessibility to patients; still a major problem faces mobile clinics operators. The problem is to optimize the mobile clinics trip in a way that minimizes the cost and the traveling distance of the mobile clinics routes while maximizing the number of patients served as per priorities assigned according to the patients' medical status. Such a problem is very critical and hard since it incorporates vehicle routing and scheduling problems. This makes the mobile clinic routing problem (MCRP) a nondeterministic polynomial time (NP)-complete problem. Such problems may be too computationally-intensive to find their exact solution. In such cases, heuristic techniques can be effective. In fact, due to their random nature, heuristic techniques are not guaranteed to find an optimal solution for any problem, but they will find a good solution if one exists.

In this work, we propose a novel Variable Neighbourhood Search (VNS) metaheuristic for solving MCRP. The selection of the VNS metaheuristic was motivated by [4] perception which states that "it aims at solving very rapidly, very large instances, and increasing precision and reducing solution time for combinatorial optimization problems; further VNS uses strategies for search diversification and intensification that have proved effective in a variety of optimization problems". This paper presents and tests the VNS algorithm with randomly generated input that simulates actual data in MCRP with instances of 200 patients and 12 mobile clinics. The test case results clearly show a significant improvement in the cost of the objective function and the execution time.

The rest of this paper is organized as follows. The next section is devoted to the literature review. Section 3 presents the mathematical formulation. The Variable Neighbourhood Search metaheuristic is discussed in Section 4. Section 5 presents the empirical results. Finally, the conclusion is presented in Section 6.

II. LITERATURE REVIEW

Several researchers addressed the mobile clinics routing problem (MCRP). A number of researchers considered reducing the mobile clinics routes as the most important factor to optimize since the distance may sometimes hinder the usage of a medical service [5-11]. Literature also shows that many governments equip clinics with mobile healthcare facilities instead of building fixed healthcare centers [2, 12, 13]. Furthermore, other researchers studied the idea of building fixed healthcare centers that could be reached within a given walking distance instead, and thus aimed at finding the best location a healthcare center is suited, and how they should be staffed [14-17]. Most of the previous works dealt with the problem as either a tour planning distance reduction problem or as a fixed healthcare allocation problem. In addition to that, only a few articles addressed this problem in the past five years, at a time international healthcare organizations urged the need for further research in this area. All this motivated us to present our novel algorithm to solve this problem. To the best of our knowledge, none of the previously proposed solutions used VNS algorithm to solve the MCRP. Unlike other evolutionary methods, VNS uses strategies for diversification and intensification that have proved effective in a variety of optimization problems [4]. Interestingly our proposed solution was able to find very good results tested on large-sized problems with 200 patients and 12 mobile clinics within an acceptable running time.

III. PROBLEM STETEMENT

Disasters, such as pandemics, natural disasters, wars, etc., are intractable problems for humanity that lead to human losses that are not easy to recover. Routing of mobile clinics to cure victims in such environments is an important problem. The objective is to minimize the mobile clinic route time while taking into consideration other important parameters such as patients' priorities, road conditions, and clinics' capacities. To solve this problem, we propose a mathematical model and a hyper-heuristic solution method that comprises several low-level heuristics guided by a reinforcement learning heuristic.

IV. MOBILE CLINIC ROUTING PROBLEM

In the mobile clinic routing problem, mobile clinics are required to serve many patients living in a given spatial area. These patients are assigned priorities according to their medical status. Given a limited number of resources, a mobile clinic is required to serve the maximum possible number of patients, taking into consideration the patients' priorities. In this problem, it is assumed that there exists an overall time limiting the whole process, and that each mobile clinic can handle one operation at a time, where each operation is processed within an uninterrupted period. It is worth noting that failing to find a feasible assignment of a mobile clinic to patients would be very expensive in terms of wasting exceptional healthcare resources processed in unexpected time frames that would further lead to threatening patients' lives in some cases. The effect of such an assignment is illustrated in the following example. This example shows two different permutations to assign one mobile clinic to eight patients taking into consideration the operation time, traveling time and patient priorities. The first permutation is illustrated in Figure 1. In this permutation, the

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mobile clinic is assigned to the corresponding eight patients consecutively 1, 2, 3, 4, 5, 6, 7, 8.

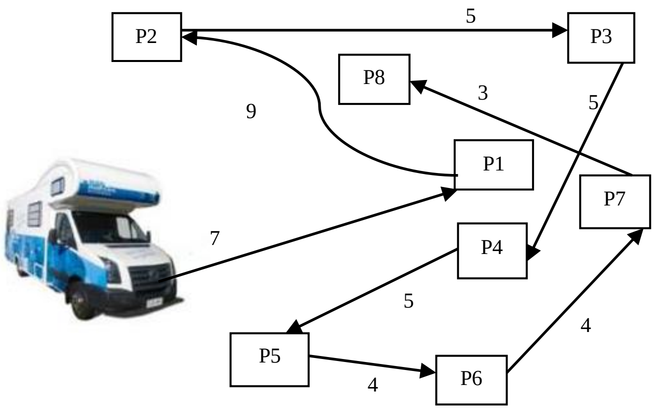

Fig. 1. Mobile clinic assignment – First permutation

Figure 1 clearly shows the path traversed by the mobile clinic to serve the eight patients. The numbers on the arrows represent the time taken to travel from one patient to another. For example, the time needed to reach patient 1 is 7, and to reach patient 2 from patient 1 we need 9 units of time. The cost of such a permutation would be calculated as follows (this formula will be verified in the following section): ∑(ti + tij) * PRi, = (5+7)*1+ (5+9)*2+ (7+6)*1+ (5+5)*1+ (8+5)*1+ (5+4)*1+ (5+4)*1+ (7+3)*1 = 104, where ti is the operation time at patient i, and tij is the time from patient i to patient j, and PRi is the priority of patient i.

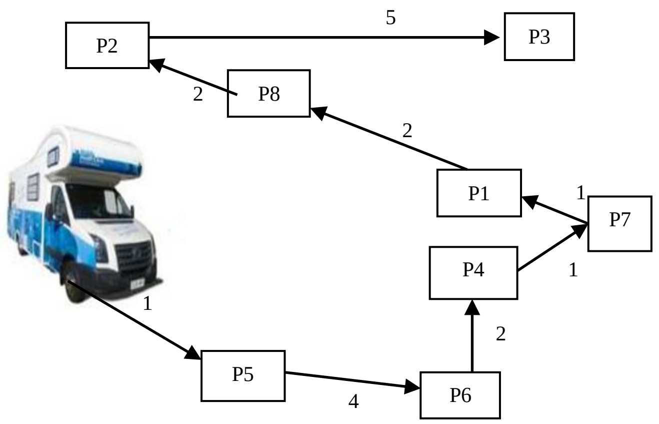

Fig. 2. Mobile clinic assignment – Second permutation

Obviously, the combination of the time and priority between patients has a tremendous effect on the total cost. Therefore, it is rational to assume that if we assigned the mobile clinic to patients with lower traveling time, we would get an optimized solution. To explain this concept further, consider Figure 2, which represents a different permutation from that given in Figure 1 where the mobile clinic is assigned to patients in a different sequence. The cost of such a permutation would be calculated as follows (this formula will be verified again in the following section): ∑(ti + tij) * PRi, = (8+1)*1+ (5+4)*1+ (5+2)*1+ (5+1)*1+ (5+1)*1+ (7+2)*2+ (5+2)*1+ (7+5)*1 = 72, where ti is the operation time at patient i, and tij is the time from patient i to patient j, and PRi is the priority of patient i. This clearly proves that reaching patients in different sequences may affect the total cost.

V. MATHMATICAL FORMILATION

Assignment problems can be represented by graphs [18]. Let G (VG, EG) be a graph in which vertex vi ∈ VG represents a patient, and |VG| = A is the total number of patients to be assigned to mobile clinics. Vertex weight PRi represents the priority that patient vi holds; further it also holds the time ti taken by each operation at patient vi. Edge e ∈ EG joining two vertices vi and vj represents the existence of a flow between patient vi and patient vj; the weight of edge e, tij, represents the travel time between the two patients vi and vj.

The objective function of this problem presented in the following equation, it minimizes the total routes taking into consideration each patient's priority

$$\boldsymbol{Minimize\ \sum_{i,j\neq i}^{A}\left(t_i + t_{ji}\right).PR_i}$$

Given a fixed number of patients and mobile clinics distributed in the whole country. Distances between all mobile clinics and patients, in addition to distances between patients themselves are given as well. Each patient must be served exactly by one mobile clinic. Each mobile clinic can serve exactly one patient at a given time. Each mobile clinic takes an operation time for each patient.

VI. VARIABLE NEIGHBORHOOD SEARCH (VNS)

Variable neighborhood search (VNS), proposed by Mladenović and Hansen [19], is another kind of metaheuristics to solve combinatorial optimization problems. It explores neighborhoods found in one solution space, and moves from there to a new one randomly or intelligently if and only if an improvement was made. VNS includes two main phases: 1) the shaking phase and 2) the local search phase. The first one aims to diversify the search space in order to escape from local optima, while the objective of the second phase is to intensify the search around the current solution in order to improve it. Figure 3 illustrates how the implementation of the VNS phases avoids local optimum and helps to explore and exploit the search space in order to achieve a near optimal solution. Each phase of the VNS applies more than one heuristic; further

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description of the heuristics selection method is found in the below subsections.

In fact, VNS is used by several researchers to solve scheduling problems. In their work, Remde, Cowling [20] proposed a VNS in order to solve workforce scheduling problem where it proved to be a powerful tool compared with the solution quality resulting from by a genetic algorithm. Further, Hsiao, Chiang [21] propose a VSN based hyperheuristic method to solve more than one problem such as job shop scheduling, and bin packing problems.

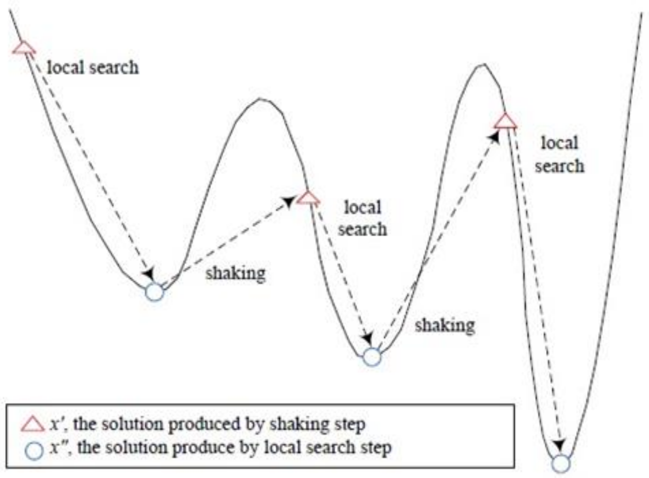

Fig. 3. A general schema of the VNS algorithm

In this work, the proposed VNS constructs a feasible solution as an initial step before moving to the shaking and the local search phases. In the shaking phase, the Tabu search method is used. It selects a low level heuristic from the set of perturbation heuristic. In the local search phase, a random cycle of the existing predefined improvement heuristics is formed. It applies an improvement heuristic while it is still improving the solution and switches to the next one in the cycle in case it stops improving the solution. As illustrated in Figure 4, this process keeps repeating until n consecutive non-improving solutions are reached. The proposed low level-heuristic is classified as constructive, improvement, and perturbation.

In our study, the constructive algorithm is applied only once at the beginning of the assignment problem to build the initial solution. Constructive heuristics build a solution from scratch based on several predefined rules. Thus, taking into consideration the overall (task length) time allocated to each mobile clinic, the proposed constructive method of this study, CS1, schedules for each mobile clinic the corresponding adequate patients.

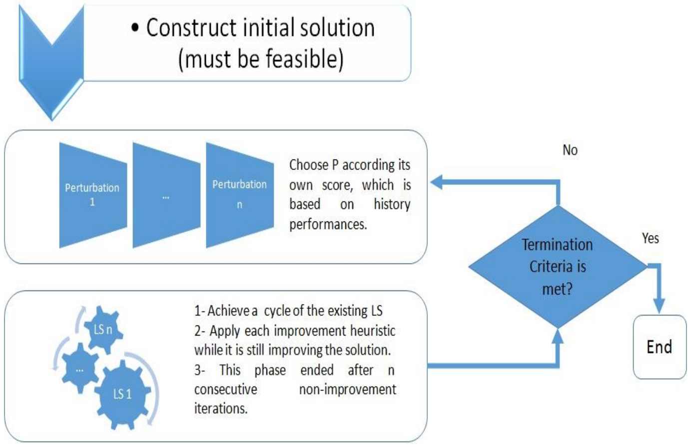

Fig. 4. The process of the proposed VNS Hyperheuristic

On the other hand, Improvement heuristics start from a complete solution and apply some moves to improve the objective function value. In our study, different improvement heuristics are proposed:

1. Better-sequence-on-the-same-mobile-clinic: for a given mobile clinic, we reorder (one task per time) the sequence of allocated patients to be served by this mobile clinic and among the improving solution found, we move to the best found feasible solution in a greedy manner. The pseudocode for local search (LS1) is described in Algorithm 1 in Figure 5. We note that Q(Hs) represents patients assigned to mobile clinic s.
2. Inset/drop-between-two-different-mobile-clinic: aiming at making a balanced utilization and fair distribution of tasks among mobile clinics, for two randomly chosen mobile clinics ri,rj(i $\neq$ j), we consider the following moves: 1) move one tasks from mobile clinic ri to mobile clinic rj (i$\neq$j) such that the difference between the objective functions of mobile clinic ri and mobile clinic rj, Δ = (OF(ri)−OF(rj)), is minimized. 2) removing a patient from the list of patients being served by a given mobile clinic and insert it in a proper place within the sequence of patients being served by the mobile clinic with the least objective function.

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Algorithm 1 LS1

```
procedure LS1(S) .                      INPUT: Clinics Queues
    for s = 1,...,m do                  ∀s = 1,...,m, (m = |H|)
        Queue temp;
    for i = 1,...,n do                  ∀i = 1,...,n, (n = |Q(H_s)|
        MinimumOF;
        CurrentPatient;
       if then MinimumOF > OF(P_i,H_s)
            MinimumOF = ← OF(P_i,H_s);
            CurrentPatient ← P_i;
        end if
        tabu ← P_i; |
        H_s ← P_i;
    end for
    end for
    return H;
end procedure
```

Fig. 5. Local Search algorithm

Perturbation heuristics start with a complete solution and do some changes in order to inject some diversification. It consists of exploring the search space step in order to escape from a local optimum. In this study, we implement two perturbation heuristics as follows:

1. Re-Construct: consists of destroy a part of the current solution and rebuild it using the proposed constructive heuristic.
2. SW1: consists of swapping two patients between two clinics if they can offer these patients their needed medical services.
3. Crossover: consists of swapping of 'genetic material' is made with the mobile clinic (part of the chromosome), while in the mutation operator is made with two mobile clinics, one in each chromosome.
4. Remove/Insert: removes a patient from a clinic queue and re-insert it to another one.

The pseudocode for SW1 is described in Algorithm 2 in Figure 6.

Algorithm 2 SW1

```
procedure SW1(S) .                          INPUT: Clinics Queues
    Random R1 ∈ 1,...,m                     (m = |H|)
    Random R2 ∈ 1,...,m−R1                  (m = |H|)
    RandomPosition1 P1 ∈ l,...,l            (l = |Q(HR1)|)
    RandomPosition1 P2 ∈ l,...,k            (k = |Q(HR2)|)
    Swap(H_R1(P1), H_R2(P2))
    return S;
end procedure
```

Fig. 6. Algorithm for swapping patients in perturbation heuristic

VII. Experimental Results

In this section, the results of VNS algorithm are presented. This algorithm is tested on a set of 33 test cases; each of these test cases has a different number of patients and mobile clinics with different timing to reach neighbor patients. Since real data are not available to evaluate the performance of the proposed algorithms, we generated synthetic data. The test cases are illustrated in TABLE I. This table shows several parameters: the test case number, the number of patients, and the number of used mobile clinics. In these 33 test cases we wanted to test how the performance is affected for different combinations of patients assigned to mobile clinics. Thus, in some test cases, (eg.TC1-TC3), we varied the number of patients and kept the number of mobile clinics fixed; in other test cases, the number of patients is fixed and the number of mobile clinics is varied. Further, different test cases scaled up in size to test our algorithm on small, medium, and large sized-problems.

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Table -1 Initial, Best solution and execution time results

TestCase #	Number of Patients	Number of MH	TestCase #	Number of Patients	Number of MH
TC1	8	1	TC18	50	10
TC2	10	3	TC19	75	7
TC3	15	3	TC20	75	9
TC4	15	5	TC21	75	10
TC5	20	5	TC22	100	7
TC6	25	3	TC23	100	9
TC7	25	5	TC24	100	10
TC8	25	7	TC25	100	12
TC9	30	3	TC26	150	7
TC10	30	5	TC27	150	9
TC11	30	7	TC28	150	10
TC12	35	3	TC29	150	12
TC13	35	5	TC30	200	7
TC14	35	7	TC31	200	9
TC15	50	5	TC32	200	10
TC16	50	7	TC33	200	12
TC17	50	9			

VIII. RESULTS AND DISCUSSION

Table 2 summarizes the best results of the VNS algorithms applied on the 33 test cases TC1-TC33. The VNS algorithm is implemented using Java language. Furthermore, the tests were carried out on a Pentium(R), dual-core CPU T4300- 2.10 GHz, and 2 GB RAM with Windows Vista SP1.

Table -2 Initial, Best solution and execution time results

Instance #	Number of Patients	Number of MH	Initial Objective Function (OF)	Best Objective Function	Execution Time
TC1	8	1	104	72	2.001
TC2	10	3	472	440	4.001
TC3	15	3	868	799	4.024
TC4	15	5	547	513	3.119
TC5	20	5	942	705	6.014
TC6	25	3	2375	2198	5.030
TC7	25	5	1475	1409	3.441
TC8	25	7	1093	1083	5.887
TC9	30	3	3413	3204	7.303
TC10	30	5	2089	1955	5.414
TC11	30	7	1586	1475	7.011
TC12	35	3	4340	4049	8.007
TC13	35	5	2665	2498	6.800
TC14	35	7	1980	1780	7.100
TC15	50	5	5772	5299	6.004
TC16	50	7	4116	3822	5.009
TC17	50	9	3312	3112	6.474

TC18	50	10	3002	2825	6.506
TC19	75	7	9556	8680	6.714
TC20	75	9	7502	6866	7.303
TC21	75	10	6752	6233	6.410
TC22	100	7	18557	17541	5.004
TC23	100	9	17373	16185	6.074
TC24	100	10	14245	13148	6.095
TC25	100	12	12216	11170	6.147
TC26	150	7	49165	45330	5.542
TC27	150	9	49056	46121	4.685
TC28	150	10	38394	35708	7.420
TC29	150	12	33388	30773	8.146
TC30	200	7	83511	76447	7.305
TC31	200	9	76780	68330	7.415
TC32	200	10	64016	57008	6.001
TC33	200	12	57662	52003	6.099

In Table 2, for each instance several parameters are shown such as the total time of the initial objective function value, the best value of the objective function found by the VNS, and the execution time taken to run the proposed algorithm. The results in Table 2 are further illustrated in figure 7. Figure 7 shows the percentage of objective functions improvement using the VNS algorithm. It is worth noting the VNS algorithm was able to improve the solution by at least 5% in less than 10 seconds. As for the significant improvement in TC1 and TC5 and the minor improvement in TC8, it is mainly affected by the traversal time from one patient to another and the priority assigned to every patient. This is clarified in the example shown in Tables 3-a and Table 3-b.

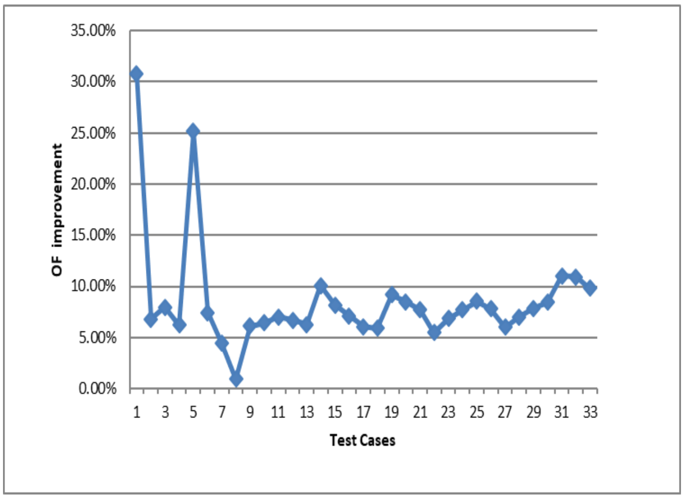

Fig. 7. Percentage of objective function improvement by VNS algorithm

Table 3 shows details related only to TC1. The parameters shown in the Table are the patient number, operation time taken at every patient location ti, the traversal time from patient i to patient j tij, the priority assigned to every patient PRi and the objective function OF.

Table - 3 Priorities and traversal time between patients in TC1.

(a)

Patient#	**t_i**	**t_{ij}**	**PR_i**	**OF**
1	5	7	1	12
2	5	9	2	28
3	7	6	1	13
4	5	5	1	10
5	8	5	1	13
6	5	4	1	9
7	5	4	1	9
8	7	3	1	10
Objective Function				104

(b)

Patient#	**t_i**	**t_{ij}**	**PR_i**	**OF**
5	8	1	1	9
6	5	4	1	9
4	5	1	1	6
7	5	1	1	6
1	5	1	1	6
8	7	2	2	18
2	5	1	1	6
3	7	5	1	12
Best Objective Function				72

In Table 3-a, the mobile clinic path to serve all patients was sequential from 1 till 8 with almost all patients had low priorities with initial objective function equals to 104. The value of the objective function is improved to 72 as shown in Table 3-b by simply changing the order of reaching patients. It should be clear from this example that as patients don't have competing priorities and there exist a chance to find neighbor patients living close to each other, there is a chance of a significant improvement in the objective function.

IX. CONCLUSION

In this paper, we presented our vision to solve the mobile clinic routing problem. The problem entails the assignment of a maximum number of patients with priorities to mobile clinics in such a way as to reduce the total mobile clinics traversal time. We presented a variable neighborhood search (VNS) algorithm for the MCRP. VNS is a metaheuristic that we were the first to utilize to solve the assignment problem in the mobile clinic routing problem. The methods of the VNS have been enhanced to solve this problem. One contribution of this work is proposing and testing a unique algorithm (VNS) that has not been used before for solving the MCRP problem. The results indicate that our VNS algorithm was able to improve the solution in at least 5% in less than 10 seconds. This is due to the VNS nature that focuses on the Diversification and then intensification methods. A unique constructive method has been used to boost the quality of the initial population. Clearly, this process affected the final results as it aided in yielding the best known solution at earlier stages of the iterations giving an edge when compared to other related work and research that did not focus on generating such enhanced solutions. Additionally, the improvement and heuristic improvement methods have been also reinforced to give better results.

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