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On Energy-Efficient UAV Route Scheduling to Offload Health Data from Under-Served Rural Communities

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***Abstract*—Digital connectivity in distant, under-served rural communities is regarded as a major barrier to improving healthcare services. To alleviate this issue, in this paper, we consider Unmanned Aerial Vehicles (UAV)-based health data offloading from the wireless terminals (WTs) of the inhabitants of a rural area that include user-smartphones, Internet of Things (IoT) devices, vital monitors, and so forth. However, serving a large area using the UAVs emerges as a challenging problem due to their limited energy resources. Therefore, the need for an energy-efficient route planning of the UAVs to maximize the offloaded health data from the WTs is discussed in this paper. This is then formulated as an optimization problem, which is identified to be computationally hard. To solve this problem, we first develop a randomized energy-efficient path selection scheme, and then improve its performance with a greedy heuristic. Next, we design a genetic algorithm-based technique to provide a much improved solution with a fast execution time when compared with commercial optimization solver for large scenarios. The effectiveness of our proposal is clearly demonstrated through extensive computer-based simulations for various scenarios.**

***Index Terms*—Energy-efficiency, rural healthcare, Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), genetic algorithm, route scheduling.**

I. Introduction

With the recent surge of the Internet of Things (IoT) and wearable devices, remote home monitoring to track various well-being indicators of patients and senior citizens has emerged as an important digital health technology to collect the much needed data for medical analytics. However, there is a large gap between urban and rural healthcare landscapes. The inhabitants of the rural areas (e.g., Northern Ontario in Canada and similar under-served regions in North America and the rest of the world) still suffer from intermittent or no connectivity. Laying out terrestrial networks is, indeed, difficult and expensive due to a number of barriers, including harsh weather conditions to inaccessible geographical terrains [1]. Broadband satellite connectivity is also subject to performance and cost issues in many of these remote areas [1]. In this paper, we address this challenge by investigating an alternate means of connectivity using Unmanned Aerial Vehicles (UAVs) to offload the health data of the rural users from various wireless terminals (WTs) such as smartphones, wearable devices, IoT sensors, biomedical monitors, and so forth.

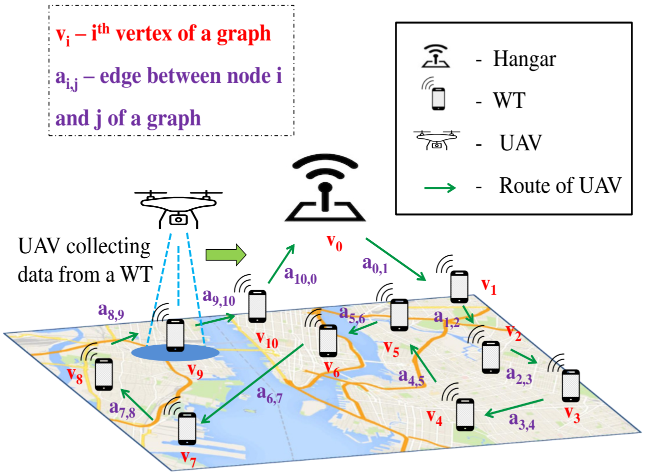

Fig. 1: Considered architecture of the UAV-based health data in a rural, under-served community.

Using several missions over the target community daily, the UAVs will bring the offloaded data to the corresponding community server for localized analytics to facilitate a community level, near-continuous health monitoring for the under-served population for tracking chronic diseases, such as diabetes, cardiac conditions, kidney disorders, mental heath conditions, post-surgery conditions, and so forth. Similar UAV missions, among the community servers, can then be carried out to offload the analyzed results to the nearest nursing station, which is assumed to have Internet gateway, through which the analyzed data can be securely shared with urban healthcare providers and relevant clinicians to facilitate needed medical appointments and interventions. Thus, the UAV-based connectivity can alleviate the digital gap between urban and rural, under-served users to improve their health monitoring conditions in an affordable and scalable manner.

Despite the appealing features of UAVs to collect health data of rural users, their limited flight time due to energy/battery constraints poses a significant challenge to improve coverage area and maximize offloaded data from WTs. Therefore, it is crucial to design energy-efficient route scheduling for the UAVs to best utilize their available energy resources. To achieve this, each UAV must take an optimal path which yields a greater throughput with the minimum energy consumption. Therefore, in this paper, we formulate a Capacitated Vehicle Routing Problem with Profit (CVRPP) whereby each UAV needs to minimize its energy consumption while maximizing offloading throughput in all possible scenarios to find the most favorable path for an efficient health data collection system in underserved rural areas as depicted in Fig. 1. Since the optimization problem is NP-hard, for large number of UAVs and locations to visit, we propose several solutions based on randomized path selection, greedy heuristic, and a genetic algorithm to obtain a sub-optimal solutions. Based on both theoretical analysis and various simulation scenarios considering practical assumptions, we evaluate the performance of our proposed approaches and compare with the reference solution to the original optimization problem.

The remainder of the paper is organized as follows. A summary of relevant research work is provided in section II. The considered system model is described in section III. Our formal problem formulation is presented in section IV. Next, section V contains our proposed heuristics and the genetic algorithm-based solution. The performance of our proposal is evaluated in section VI. Finally, section VII concludes the paper.

II. Related Work

The rural communities, in general, lack adequate broadband connectivity, required for improved telemedicine, remote home monitoring, continuous/regular vital monitoring, and other electronic health (eHealth) services [1], [2]. In this vein, several researchers proposed the usage of UAVs to establish a smoother connection with the rural areas for better medical facilities by collecting health data, distributing medicines, collecting blood samples and test kits, keeping track of chronic diseases, and so forth [3]. One such important example includes the UAVs developed by Matternet [4] that are used to deliver medications and test kits in remote areas which lack access to roads by using global positioning system (GPS) and sensors to navigate between ground base-stations. The UAVs have also been used as relay nodes to enable communication between IoT devices and cloud [5]. However, the optimization solver used in the work was unable to always provide ideal solution for an increasing number of decision variables. Moreover, various path planning algorithms were proposed to construct efficient routes for UAVs [6], [7]. In addition, researchers focused on developing various heuristics to compute sub-optimal solutions to various problems at the expense of lower computation time compared to that taken by optimization solvers. In [8], the an energy-efficient data collection framework using UAVs was proposed for disaster-affected areas. This was ensured by minimizing the energy consumption as well as the path lengths of the UAVs. On the other hand, to find the optimized route plan of UAVs, a multi-chromosome genetic algorithm was developed in [9] by minimizing the route cost for each UAV in a multiple travelling salesmane problem (TSP) setting.

III. Proposed System Model: UAV-aided data collection technique

In this section, we describe our UAV-aided system model for collecting health data of users in rural, under-served areas. The system model consists of the mapping of the UAVs and WTs in a remote area network as follows. To construct a feasible model to collect data from the WTs, a set of WTs, W, is assumed within a fixed area. A UAV, also referred to as a drone, is expected to collect data from a maximum number WTs, $w \epsilon W$, that is allowed by its capacity. Traditionally, the UAVs are capacitated by their energy; hence, the desired output of visiting all the WTs, w, in an area and collecting data might not be achievable. Thus, the path should be constructed to collect the maximum amount of data within its capacity. The data offloaded by the UAV from the WTs of users are assumed to be health-related data, generated by IoT health devices including digital thermometer, blood pressure monitors, portable electrocardiogram (ECG) monitors, diabetes screening kits, at-home DNA health test kit, microbiome health device, smart weight-scales, and various other devices. Using the geographical map of the target area, the system model is presented the x & y coordinates of w in an area and the size of data, d_w, that are needed to be collected from w as inputs. Based on these inputs, with appropriate techniques/algorithms to be designed later in the paper, the system model is supposed to provide an optimal path of the UAV for health data collection. In order to calculate the energy consumption of each UAV, d_w and the distance from w_i to w_j, where $\{w_i, w_j\} \epsilon W$, should be tracked, since it is the main source of energy consumption of the UAV.

In the system model, we consider the origin of the UAV to be the hanger, collocated with the community server. The reason for choosing the community server as the hangar is to use the community technicians, who can also be trained to have drone license, to oversee the UAV missions for health data offloading. In the considered system model, two types of drone missions are considered, i.e., (i) UAVs offloading health data from WTs to the community server and (ii) UAVs offloading the analyzed data from the community server to the nearest nursing station and bringing back relevant lists of medical appointments and intervention recommendations. Note that for the first type of mission, the UAV is assumed to be able to deliver medical appointment/recommendation notifications (if any) to the WTs of the corresponding patients or users. Since both mission types follow similar steps, for brevity, we describe only the first type of UAV mission in the remainder of the section. At first, the UAV starts from the hangar, and traverses to the next WT according to the computed route, where it collects health data and moves to the next WT along the route. Thus, the UAV collects data from a number of WTs in the rural, under-served area, and finally returns to the hangar where it is recharged to be redeployed for the subsequent mission. The complete scenario in our considered system model is depicted in Fig. 1. Here, the UAVs, WTs, and the hangar are distributed in a two-dimensional (2D) region. Each $w \epsilon W$ attempts to send

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its data to the nearest UAV. While constructing a route for the UAV, it is important to guarantee that the energy consumption of the UAV remains within its energy capacity Q. If the UAV is in the verge of exceeding Q, it will return to the hangar. The total energy consumed, E_T, by the UAV for a particular w depends greatly on the energy consumed during travelling the path denoted by E_P, and the energy spent on collecting the data represented by E_D. Then, the total energy can be calculated as $E_T(= E_P + E_D)$. For the sake of simplicity, the IoT communication energy is considered to be constant throughout all our calculations, since the path of the UAV is pre-determined. Based on this considered system model, we describe our research problem in the following section.

IV. Problem Formulation

In this section, an optimization formulation of the UAV-aided data collection system is formally presented, and then the problem in deriving optimal solution for intractable scenarios is revealed.

For the optimization formulation, let the system be represented as a graph $G(V, A)$ where the WTs and the hangar are the vertices denoted by V while the paths connecting two WTs are the edges of the graph represented by A. With each edge $a \in A$, a non-negative cost is associated which is the amount of energy consumed by the UAV (E_P) to travel from one node to another. The energy $E_{P(v_i,v_j)}$ is calculated for each edge according to the distance between v_i and v_j where $\{v_i, v_j\} \in V$. The graph is represented in Fig. 1. The solid green lines represent the edges (or paths) $a_{i,j}$, and the set of nodes (i.e., the WTs and the hangar) are represented by v_i. The nodes $v_1, v_2, ..., v_n$ represent the various WTs in the scenario while the node v_0 indicates the hangar where $\{v_0, v_1, v_2...v_n\} \in V$. The x and y coordinates of v_n along with the data to be collected at each WT are pre-determined from the map of the area. Then, our research objective is to maximize the difference between the throughput θ_{v_j} and energy consumption by the UAV, $E_{P(v_i,v_j)}$, while travelling from v_i to v_j. While constructing the path, it is important to ascertain that the UAV is within its energy capacity Q. Therefore, the problem can be formulated as follows:

$$Max\ \alpha \sum_{i\in V} \theta_i y_i - \sum_{i,j\in A} x_{ij} E \tag{1a}$$

$$Subject\ to\ x_{i,j}\ \in\ \{0,1\} \quad i,j \in A \tag{1b}$$

$$\sum_{i\in V, i\neq j} x_{ij} = y_i \quad j \in W \tag{1c}$$

$$\sum_{j\in V, i\neq j} x_{ij} = y_i \quad i \in W \tag{1d}$$

$$\sum_{i\in V} \theta y_i \geq p_{min} \tag{1e}$$

$$u_i + E_{T(j)} = u_j \quad \forall x_{i,j} = 1, j \neq 0, i \neq 0 \tag{1f}$$

$$E_{T(i)} \leq u_i \leq Q \quad i \in V \tag{1g}$$

$$\sum_{j\in V} x_{0j} = \sum_{i\in V} x_{i0}, \tag{1h}$$

where the objective function states that the difference between the total throughput, θ, and total energy consumption of UAVs to traverse from i to j should be maximized to ensure a higher throughput and a lower energy consumption subject to some specific constraints. Here, the binomial decision variable $x_{i,j} = 1/0$ indicates if the path exists between WT i and j. If the path exists between them, the value is 1, otherwise 0.

Additionally, the other binomial variable $y_i = 1/0$ determines whether vertex i is visited or not, while α denotes a constant. The second and third constraints specify that each visited vertex, y_i, can have only one incoming and one outgoing edge, respectively. The third constraint states that the sum of throughput must be greater than or equal to the minimum throughput, p_{min}. The next constraint indicates that, if the path between i and j is active, the cumulative energy up to j, denoted by u_j, can be calculated by adding the cumulative energy upto the predecessor node, u_i, to the total energy consumption ($E_{T(j)}$) at j. The last constraint states that, at any point, i, the cumulative energy up to that point, u_i, must be greater than the total energy requirement of i, i.e., $E_{T(i)}$, and less than the total energy capacity, Q. Finally, the final constraint states that the UAV must return to the hangar once the constructed path has been visited.

The mathematical model formulated in eq. ((1)) to collect health data from WTs using UAVs is NP-hard, as it shares similar properties with the CVRPP problem [10] while constructing routes for η constrained vehicles.

Theorem IV.1. *The energy-efficient route assignment problem for the UAVs to collect data is NP-hard.*

Proof. For an instance of the considered system model sharing properties with the original CVRPP [10], let B be the set of capacitated vehicles and Ω be a set of to be served η WTs. The UAVs are all assumed to have the same capacity θ and the demand of each WT, $\omega \epsilon \Omega$, is ξ_ω. Each UAV, $\beta \epsilon B$, is restricted by its limited energy, which is similar to the load limitation of the capacitated vehicles. The UAVs will require ξ_ω amount of energy to collect data from a WT ω, which is considered as the cost of the route. Therefore, the main objective of the UAV route scheduling problem for optimal data collection is to compute such a route capable of minimizing the energy of the UAV while collecting data from the maximum number of WTs, i.e., maximizing the throughput. Since the energy consumed by the UAVs while collecting data is constant, regardless of the situation, the cost of the route depends on the energy consumed while travelling from one WT to another that corresponds to the demand of the customers in CVRPP. Therefore, for any instance, the energy required by the UAV to collect data can be only minimized if the corresponding cost of the vehicles is minimized in a capacitated vehicle routing problem. □

V. Proposed Energy-Efficient Route Scheduling for UAVs to Offload Health Data

Since there is a tradeoff between the optimal solution to the formulated problem in the earlier section and the computation time, in this section, we propose several heuristics to relax the original problem and find sub-optimal solutions to systematically approximate a near-optimal solution based on

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several heuristics. To obtain an optimal solution for smaller instances of the scenario in Fig. 1, optimizer solvers such as Gurobi [11] is employed. The solver aims to find the optimal solution from the optimization problem (1). However, with an increasing number of WTs in the scenario, the number of variables of the solver increases, which increasing the complexity of the solver. Therefore, designing a heuristic to compute the paths for the UAVs for collecting data requires scalability. In this vein, we propose three approaches, namely a randomized scheduling, a greedy heuristic, and a genetic algorithm-based energy-efficient route scheduling method for the UAVs. These approaches are described in detail in the remainder of this section.

A. Randomized Scheduling

The randomized scheduling of UAVs is considered as a naive, yet important reference heuristic, that is used in various studies to obtain an optimized solution [12]. In this approach, the routes are computed randomly for the UAVs, if the x & y coordinates of the WTs are provided. The randomized scheduling will keep on selecting a new WT arbitrarily as long as the UAV does not exceed the energy limit. While simple and easy to implement in various scenarios and large number of UAVs to offload health data from numerous WTs, the randomized scheduling does not account for the energy required to travel from one WT to another. Hence, the route computed might not always be sub-optimally energy-efficient because the UAVs will spend a major portion of their energy in travelling rather than collecting data optimally. Therefore, we require a more compact solution to address the problem in terms of energy consumption of the UAV.

B. Greedy Heuristic

To alleviate the shortcoming of the randomized scheduling, we present a greedy heuristic-based UAV route scheduling by computing the locally optimal solution while seeking for the global solution [13]. In our case, we consider the energy consumed of the UAV while travelling as the cost of the route. Each UAV starts from hangar and while the UAV is within its energy limit, it finds the least energy consuming an unvisited WT at each turn and adds to the list of routes. This heuristic works best when the problem has an optimal substructure. However, this condition may not hold in various scenarios, rendering a global solution impossible. In addition, the greedy heuristic may not be able to construct an optimal solution even when an optimal solution actually exists.

Theorem V.1. *The greedy heuristic does not guarantee an optimal solution even when a solution exist.*

Proof. In an instance of our UAV data collection from the WTs scheduling model, suppose we have one UAV, u, which will offload health data from the area containing four WTs, w_1, w_2, w_3, and w_4. The coordinates of the WTs are (4,9), (7,9), (9,11), and (14,8); and in each WT, the amount of data that needs to be collected are 2 bits, 1 bit, 3 bits, and 3 bits, respectively. If the total energy capacity of u is 10Wh and the energy required to collect 1 bit of data and travel a distance of 1km both requires 0.1Wh of energy, the greedy algorithm is unable to create a route that will be able to collect data from all the WTs. However, if the optimal solution is calculated, we can see that a solution exists that will cover all the WTs for data collection as shown in Table I. The constructed paths are shown in Fig. 2. □

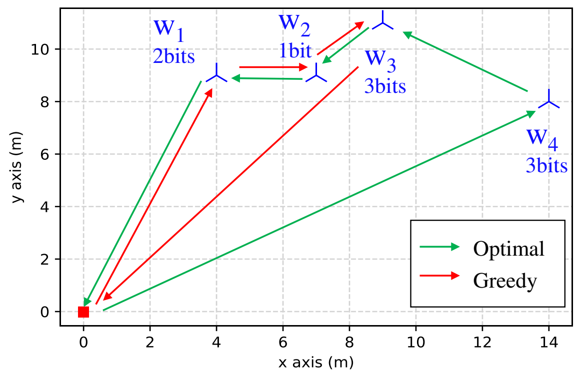

Fig. 2: Paths constructed by the optimal and greedy approaches using an instance to illustrate Theorem V.1.

TABLE I: Illustration in support of Theorem V.1.

Greedy	Optimal
$u: w_1, w_2, w_3$	$u: w_4, w_3, w_2, w_1$
w_4 is not visited by the UAV	All WTs are visited

C. Customized Genetic Algorithm-based Energy-efficient UAV-Scheduling

To obtain quality solutions compared to both the randomized approach and greedy heuristics, and approximate the optimal solution from the solver at a much lower computation time, we need to design a more energy-efficient route scheduling technique for the health data offloading UAVs. In this vein, we propose a genetic algorithm-based solution in the remainder of this section since similar use of genetic algorithms have been known to solve efficient yet fast solutions to various tradeoff problems previously [14]. The steps of our customized genetic algorithm-based process are shown in Algorithm 1. The x and y coordinates of the WTs, denoted by c_x and c_y, respectively, are used as inputs to the algorithm. At first, the population length (L_p), generations (G), elite size (L_e), and mutation rate (r_m) are initialized. Then a population (pop) is initialized by the algorithm containing various possible routes, or genes, for the UAV using the $generatePath$ function. The fitness function, δ, of all the members in the population is then calculated to evaluate the efficacy of each route. The fintess values are later ranked. Then, the fittest individuals are selected to create a mating pool, pop_{mp}, containing various fit parent genes. In the mating pool, crossover is applied, where a chunk of each parent gene among two parents are taken to create a new gene. The final step of the algorithm

Algorithm 1: Genetic algorithm-based scheduling.

Input : c_x, c_y
Output: path ρ

Function `generatePath` ($wtList$):
  $e_t \leftarrow 0$, $path \leftarrow \emptyset$
  for $wt \in wtList$ **do**
    $e_t \leftarrow e_t + E_T(loc)$
    if $e_t \leq E_{max}$ **then**
      Append wt to $path$
  return $path$

Initialize L_p, G, L_e, r_m
$wtList \leftarrow [c_x, c_y]$
for i in L_p **do**
  $pop \leftarrow generatePath(wtList)$
for g in n_g **do**
  Calculate δ for each path in population
  $rankedPop \leftarrow$ Rank population based on δ
  $pop_{mp} \leftarrow$ select L_e routes from $rankedPop$
   $children \leftarrow$ perform crossover on pop_{mp}
  $pop \leftarrow$ Mutate $children$ by randomly swapping two locations in a path using r_m
$rankedPop \leftarrow$ Rank final pop in descending order based on δ
$\rho \leftarrow$ First route in $rankedPop$
return ρ

includes performing mutation on the newly created genes with r_m, where a particular WT in the route is exchanged with another WT in the same route. The fitness function of each route states the energy consumption of the route. Our proposed algorithm finally returns the least energy consuming path among all the routes.

VI. Performance Evaluation

In this section, we evaluate the performances of the methods proposed in section V by generating a synthetic dataset for various scenarios. Several practical assumptions were made while constructing all the scenarios containing multiple numbers of WTs in a 100×100 m^2 area. The data to be collected from each WT was considered in the range of 1 to 20 bytes. The energy required to collect each byte, e_d was 0.1 Watt hour (Wh) and the energy required to travel per metre, e_p was was 0.2Wh. Using these values, five scenarios, were constructed containing 10, 25, 50, 75, 100 WTs, respectively. As for the drone's battery, URUAV GRAPHENE 6S with 22.2V 6000mAh 100C Lipo Battery XT90 was considered with a battery capacity of 133.2Wh [15]. This drone-type is considered due to its sturdy frame required to explore a larger area and collect data from multiple WTs efficiently. While simulating in a smaller area, we assigned the maximum energy capacity of the drone to 50% of the total energy (i.e., 66.6Wh in this case), to ensure that the drone returns to the base station safely with the remaining energy budget.

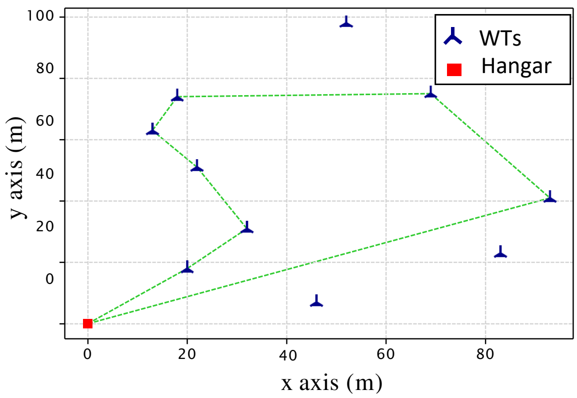

Fig. 3: Optimal route constructed by the optimization solver for a scenario incorporating 10 WTs.

With the aforementioned assumptions, we evaluated the proposed methods and compared them with the results obtained from the optimization solver, i.e., Gurobi. For the scenarios, a bounded time of 5000s was used. The optimal route constructed by the Gurobi solver for 10 WTs is shown in Fig. 3, where the WTs were chosen in such a way that yielded the highest throughput while minimizing the energy consumption of the UAV. On the other hand, the parameters for the genetic algorithm-based scheduling included $L_p = 300$, $G = 500$, $L_e = 20\%$ and $r_m = 0.01$. A fixed random seed of value 32 was used to produce random values. The solver, randomized, greedy, and genetic algorithm-based scheduling methods were incorporated for a single drone to demonstrate our proof-of-concept. The total energy consumed, E_T, the total distance travelled by the drone, and the throughput, $theta$, of the drone in each scenario are represented in Figs. 4, 5, and 6, respectively. It can be seen that for the solver, the UAV consumed the lowest energy and travelled a comparatively smaller distance, while having higher throughput. Additionally, the genetic algorithm performed the second best with slightly higher energy consumption and distance, and lower throughput. However, even in some cases where the randomized method exhibited lower energy consumption and travelled distance of the UAV, the throughput was significantly low. Since the solver and the genetic algorithm performed the optimal and near-optimal results, we computed the implementation time of these two algorithms. The solver was able to find the optimal result in a bounded time for number of WTs = 10 in about 16.82s. However, in the other scenarios, it was unable to find an optimal result in a bounded time. Additionally, the genetic algorithm took 289.9s, 300.5s, 317.7s, 340.6s, and 388.5s, respectively for the scenarios having WT values of 10, 25, 50, 75, and 100. It can be concluded that, even though the genetic algorithm took a higher time for the first scenario, it was still able to compute the tasks in a reasonable time. On the other hand, for the solver, finding an optimal solution became more and more time consuming with scenarios having larger numbers of WTs. Therefore, the genetic algorithm emerges as the most viable technique that achieves the best balance between energy-efficiency and computation time.

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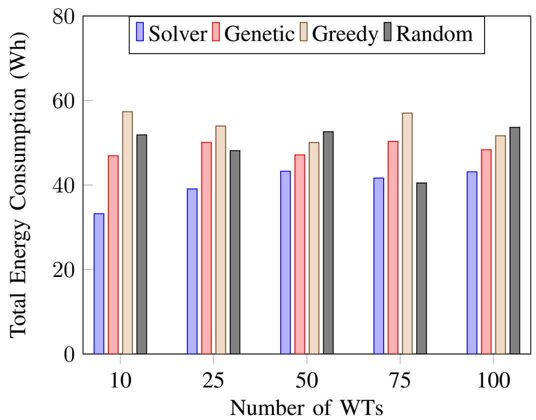

Fig. 4: Total energy consumed by the UAV in various scenarios using different techniques.

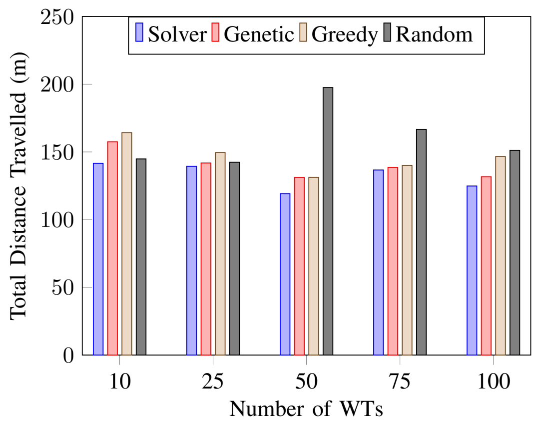

Fig. 5: The total distance travelled by the UAV in various scenarios using different techniques.

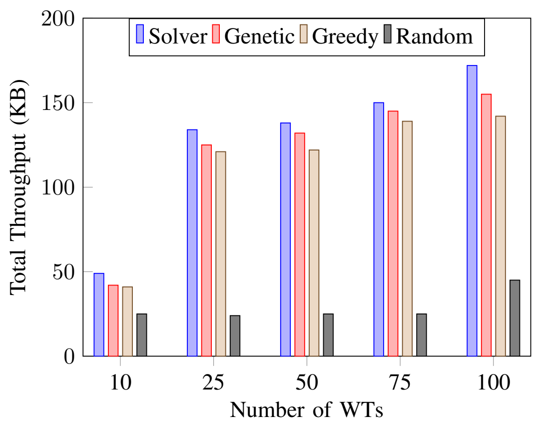

Fig. 6: The total throughput of the constructed routes in various scenarios using different techniques.

VII. Conclusion

In this paper, we considered UAVs to facilitate health data offloading from rural, under-served communities. We focused on the energy-efficient requirement of UAV route scheduling and presented the relevant research problem, which was shown to be computationally hard. To address the tradeoff between obtaining a high quality solution and the computation time for large number of WTs to be visited by the UAVs, we systematically developed several heuristics, i.e., randomized and greedy scheduling approaches followed by a genetic algorithm-based search for improving the quality of the derived solutions. In particular, our proposed genetic algorithm-based method was able to schedule an energy-efficient route for the UAVs for offloading the health data by demonstrating near-optimal performances for various tractable scenarios while requiring low computation time.

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