Data Collection Utility Maximization via Near Optimal Path Prediction for UAV and UGV

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Declaration

We certify that

1. The work contained in this report is original and has been done by ourselves and the general supervision of our supervisor.
2. The work has not been submitted for any project.
3. Whenever we have used materials (data, theoretical analysis, results) from other sources, we have given due credit to them by citing them in the text of the thesis and giving their details in the references.
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Abstract-In this paper, we address the problem of data collection maximization from a wireless sensor network using one Unmanned Aerial Vehicle (UAV) and one Unmanned Ground Vehicle (UGV) while minimizing the energy consumption of both (as they have limited energy capacity). There are sensors placed on the agricultural field which are storing sensor data. UAV and UGV are deployed from the data center (located at the center of the agricultural area) periodically to collect the data from these sensors. We show that this data collection problem can be reduced to the orienteering problem (OP), which is an NP-Hard problem. We used Greedy Randomised Adaptive Search Procedure (GRASP) algorithm to solve the addressed OP. The GRASP algorithm returns an optimal path, using that UAV and UGV can collect data subjected to their constraint.

Keywords-UAV-Unmanned Aerial Vehicle, UGV-Unmanned Ground Vehicle, OP-Orienteering Problem, GRASP- Greedy Randomized Adaptive Search Procedure.

1 INTRODUCTION

The Internet of Things (IoT), which has huge potential in numerous sectors such as wearables [1], [2], smart homes [3], and smart cities [4],[5],[6], has seen remarkable growth in the previous decade. Automation of agriculture through IoT can change the agriculture sector from being static and manual to dynamic and smart, which helps in increasing production and reducing human involvement. The main automation drivers in the agriculture domain are Precision Agriculture (PA) and Wireless Sensor Networks (WSN). PA use specialized sensors and algorithms to guarantee that the crops receive exactly what they require for maximum productivity and long-term viability. PA entails receiving realtime data from sensors in the field concerning soil, crop, and weather conditions. High-resolution photographs of crops are taken from satellites or manned or unmanned airborne vehicles, then processed to extract data for future decisions [7]. Wireless Sensor Networks (WSNs) are critical in the Internet of Things (IoT) because they provide a vast amount of data collected by omnipresent sensors [8]. As a result, data gathering becomes critical in order to feed new data into IoT services while preventing data overwriting due to IoT sensors' low storage capabilities [9],[10],[11],[12],[13],[14],[15]. Unmanned Aerial Vehicles (UAVs) have recently gained a lot of attention for data collecting because of their great agility, mobility, and versatility [16],[17],[18]. A variety of efforts have been made to explore UAV enabled WSNs. For example, in [19], hovering location positioning of UAV and the utility maximization of data collection was considered. In [20], UAVs were deployed to collect data from IOT devices while ensuring the 'freshness' of the data. In [21], the authors addressed the issue of ensuring synchronization among ground and aerial devices. Data collection via UGV has also been explored. For example, in [22], the authors proposed an algorithm that would allow sensor nodes to choose between multiple available UGVs, with the primary objective of reducing the network reconfiguration and signalling overhead.

This paper's primary contributions are summarised below.

1) We are using a single UAV and UGV for the data collection from different AIoT sensor devices in the agricultural field.

2) We use the utility associated with every AIoT sensor to optimize data collection by both UAV and UGV, where the data collection function and priority of that sensor contribute to the utility associated with that sensor.

3) We use the Greedy Randomised Adaptive Search Procedure (GRASP) algorithm to solve the data collection maximization problem as this problem can be reducible to the orienteering problem (OP).

4) The remaining paper is summarized as follows. All the related works of this paper in the Section 4, system model and problem formulation part in Section 5 (path prediction in Subsection 5.1, Delay analysis in Subsection 5.2 and problem statement in Subsection 5.3), algorithm for our problem in Section 6. The breakdown of the paper is as follows: Section 3 reviews relevant work. The system model and problem formulation is introduced in Section 4. The proposed framework and performance study are mentioned in sections **??** and **??** respectively. Section **??** offers conclusion and future research directions.

2 Related Works

The work in [19], maximized the data collection by optimizing the trajectory of the UAV through utility maximization. The authors introduced a utility function and maximized the utility through various potential hovering locations to get optimized trajectory for the UAV. However, the authors did not consider the deployment of UGV and thus, optimized the trajectory of UAV only. In [23], the authors described a sensor planning scheme based on the path of the UGV which they optimized by minimizing the cost function. However, they are not using both UAV and UGV to collect data. Rather, the UGV is carrying the UAV to different points and then the UAV is collecting the data. Thus, they are not considering the utility in the prediction of the trajectory. In [16] the authors are trying to optimize the trajectory of the UAV based on the number of IoT devices it can serve in the budget time T. They described a minimum amount of data that is to be uploaded to validate the presence of that IoT in the path and are keeping track of it through a binary variable. However, they are not considering the priority of the data and rather only focusing on the amount of the data collected in a particular tour. In [24] the authors are trying to minimize the combined distance of trajectory of the UAV and UGV to fit the energy budget of the UAV. They are not implementing any data collection task with the UGV and are using it only to serve the energy constraint of the UAV. They are considering UGV as a simple device capable of simple movements with enough energy to complete the mission.

3 System Model and Problem Formulation

As illustrated in Fig. 1, we are considering combined Unmanned Aerial Vehicle (UAV) and Unmanned Ground Vehicle (UGV) model, each equipped with MEC server capable of data processing, caching and storage, a LoRa trans-receiver and a camera. Let $S = \{1, 2, \cdot\cdot\cdot, s, \cdot\cdot\cdot, S\}$, $G = \{1, 2, \cdot\cdot\cdot, g, \cdot\cdot\cdot, G\}$ and $A = S - G$ represent sets of all AIoT sensors placed in the field, AIoT sensors reachable by the UGV and AIoT sensors not reachable by the UGV respectively. We have uniform placement of sensors all over the field. All the sensors placed on the field are acquiring and storing a huge amount of data. Let D_s denote the volume of data at sensor $s \in S$. UAV and UGV move to different areas of field to collect data from AIoT sensors using near optimal path. UAV and UGV starts from data center placed in the center of field. Both follow the near optimal path to collect data from AIoT sensors placed uniformly across the field. AIoT sensors transmit data to the UAV (drone) and the UGV (ground robot). After collecting data UAV and UGV return to data center. A data collection tour of UAV is a closed tour starting from and ending at the data center itself. The tour is a sequence of overing locations, at altitude h, which UAV visits one after another for data collection. Since, it is not posssible to collect data in a single tour due to energy constraints, so the data is collected in multiple tours with near optimal path across fields and returns to the data center at the end of each tour.

TABLE 1: Summary of related works

Problem Focus	Prediction Path	Maximization Utility	UGV + UAV	LoRa
Utility Maximization [19]	✓	✓	×	×
Precision Agriculture [26]	×	×	×	✓
Orienteering Problem [25]	✓	×	×	×
GRASP [27]	✓	×	×	×
Sensor Planning [23]	✓	×	✓	×
Our approach	✓	✓	✓	✓

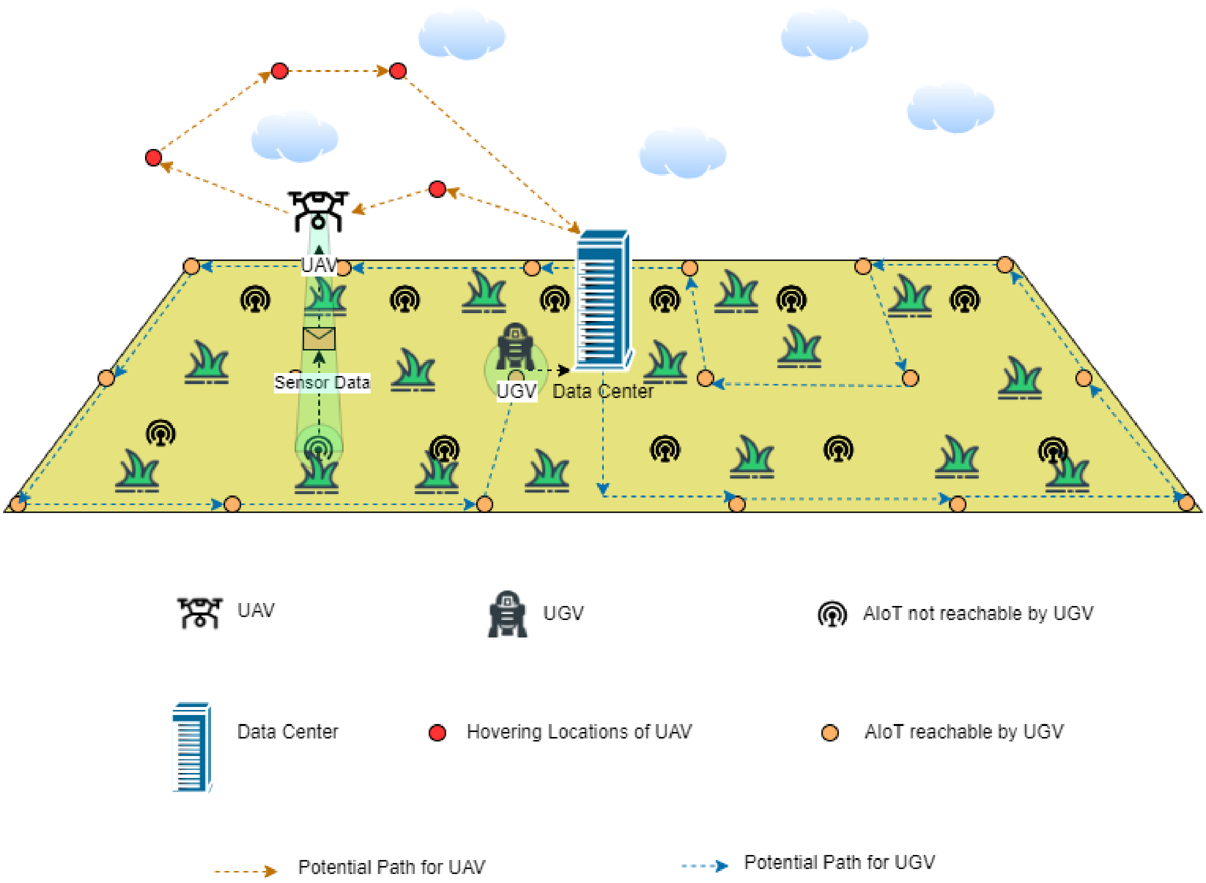


Fig. 1: Proposed model

3.1 Path Prediction

We are assuming data center to be at the center of the agricultural field and that it is deploying the UAV and UGV.

1) We assume an initial path between the data center and a dummy data center with zero cost.
2) Other hovering locations are injected in the path one by one till the cost is under the budget.
3) Once a tour is found a randomised local search algorithm is initiated to ensure near optimal tour.
4) After getting a near optimal tour all the hovering locations in the tour is removed from the set of hovering locations to be visited by the device.

3.2 Data Collection Tour Model

A data collection tour is closed path starting from and ending on the data center. We are assuming our data center to be located at the center of the field. This point is assumed to be the origin.

3.2.1 UAV

For UAV, the tour is a sequence of hovering locations at altitude h. Let H be a set of hovering locations given by,

$H = \{(x_0, y_0, h), (x_1, y_1, h), \cdots, (x_a, y_a, h), \cdots, (x_H, y_H, h)\}$ where $(x_0, y_0, h) = (0, 0, h)$, h is the fixed hovering height above the ground and $(x_a, y_a, 0)$ is the coordinates of ath AIoT sensor. The total flight distance f_d for the UAV with total flight duration Γ traveling with speed v_{UAV} is given by

$$f_d = v_{UAV} \times \Gamma \qquad (1)$$

Thus, the UAV can travel to a point (x, y, h) and back to data center if

$$x^2 + y^2 + h^2 \le R^2 \qquad (2)$$

where,

$$R = f_d / 2 \qquad (3)$$

Let, the time taken to collect all the data from ath sensor be $t_d = D_a / B$, where B is the channel bandwidth[26] and the duty cycle of LoRa trans-receiver[26] be t_{DC}. Now, let Ψ_a be the hovering time for each hovering location, then it is given as:

$$\Psi_a = \mathrm{Min}(t_d, t_{DC}) \qquad (4)$$

The distance travelled by UAV from current location to the next hovering location is given as:

$$d_{c,a} = \{(x_a - x_c)^2 + (y_a - y_c)^2\}^{1/2} \qquad (5)$$

where (x_a, y_a) is the next hovering coordinates and (x_c, y_c) is the current coordinates.

Total time required to travel to ath hovering location and collect the data is given by

$$T_a = d_{c,a} / v_{UAV} + \Psi_a \qquad (6)$$

The UAV is unlikely to collect data from all sensors in one tour because of energy constraints. Thus, it should prioritize the more important hovering locations. Suppose the priority of all points in the set H is given by set

$P = \{P_0, P_1, \cdots, P_a, \cdots, P_H\}$ where P_a is the priority of hovering location (x_a, y_a, h).

3.2.2 UGV

For UGV, the tour is a sequence of transmition locations. Let N be a subset of G denoting the possible transmission locations is given by

$N = \{(x_0, y_0), (x_1, y_1), \cdots, (x_g, y_g), \cdots, (x_N, y_N)\}$

where $(x_0, y_0) = (0, 0)$ and (x_g, y_g) is the coordinates of gth AIoT sensor. Let UGV is travelling with the velocity of v_{UGV} and the required distance from current location (x_c, y_c) to the next location (x_g, y_g) is given as:

$$d_{c,g} = \{(x_g - x_c)^2 + (y_g - y_c)^2\}^{1/2} \qquad (7)$$

Let, $\Psi_{trans\ g}$ be the time required to sample the data at (x_g, y_g), then $\Psi_{trans\ g}$ is given as:

$$\Psi_{trans\ g} = D_g / B \qquad (8)$$

where, D_g is the data size and B is the channel bandwidth[26].

3.3 Data Collection Utility Model

The amount of data collected by UAV or UGV from a sensor is directly proportional to the amount of time it is stationary at the hovering or transmission location corresponding to that sensor. It increases with time and tends to maximum after a certain amount of time leading to an increasing function. Thus, as described in [19], let $F_s(t)$ be a function defining the amount of data collected in time t for sth sensor where,

1) $F_s(t) = 0$ if $t = 0$; $F_s(t) > 0$ if $0 < t \leq \Psi$; otherwise $F_i(t) = F_i(t_i)$ if $t > \Psi$.
2) $F_s(t)$ is a non-decreasing function, i.e. $F_s(t_1) \leq F_s(t_2)$ for $0 \leq t_1 < t_2$.
3) $F_s(t)$ is a submodular function, where $F_s(t_1 + \Delta) - F_s(t_1) > F_s(t_2 + \Delta) - F_s(t_2)$ for $0 \leq t_1 < t_2 \leq \Psi$ and $F_s(t_1 + \Delta) - F_s(t_1) = F_s(t_2 + \Delta) - F_s(t_2)$ for $\Psi \leq t_1 < t_2$. where $\Psi = \Psi_a$ if the above function is used for UAV and $\Psi = \Psi_g$ if the function is used for UGV.

3.3.1 UAV

For UAV, we define utility u_a of hovering location (x_a, y_a, h) as:

$$u_a = F_a(\Psi_a) \times P_a \qquad (9)$$

Thus, total utility U_{UAV} can be calculated by accumulating the utility u_a.

$$U_{UAV} = SUM_{(x_a,y_a,h) \in H}(u_a) \qquad (10)$$

Maximizing the utility functions gives us a set of possible tours $\tau = \{\tau_0, \tau_1, \cdots, \tau_m, \cdots, \tau_n\}$. For the cost of a UAV, let ΔE be the energy consumed by the UAV per unit time. Thus, the total energy consumed in travelling from current location (x_c, y_c, h) to (x_a, y_a, h) and hovering during collection of data from that location is given by: $\Delta E \times T_a$. Thus, we define the cost $c_{a,m}$ for ath hovering location in the tour τ_m as:

$$c_{a,m} = \Delta E \times T_a \qquad (11)$$

Thus, total cost for UAV is the accumulation of cost of each hovering location in the tour.

$$C_{UAV} = SUM_{(x_a,y_a,h) \in \tau_m}(c_{a,m}) \qquad (12)$$

3.3.2 UGV

For UGV, we define utility u_g of transmission location (x_g, y_g) as:

$$u_g = F_g(\Psi_g) \times P_g \qquad (13)$$

Thus, total utility U_{UGV} can be calculated by accumulating the utility u_g.

$$U_{UGV} = SUM_{(x_g,y_g) \in N}(u_g) \qquad (14)$$

For the cost of the UGV, let ΔE_1 be the energy consumed per unit time during travelling and ΔE_2 be the energy consumed per unit time during transmission. Thus, the total energy consumed in travelling to (x_g, y_g) and collecting data at that location is given by:

$$E_g = \Delta E_1 \times d_g / v_{UGV} + \Delta E_2 \times \Psi_{trans\ g} \qquad (15)$$

We define cost C_{UGV} as the accumulation of total energy required in the tour.

$$C_{UGV} = SUM_{(x_g,y_g) \in N}(E_g) \qquad (16)$$

3.4 Problem Statement

In WSNs, we propose the following formulation for a novel data collecting utility maximisation problem (UMP).

For UAV, consider the set A of sensors with a volume D_a of data to be collected, each sensor a in A has a data transmission bandwidth B and a data transmission range R. We take it for granted that each sensor's utility function $F_a(\Psi_a)$ is constant. For data collection, the UAV with a hovering duration budget Γ flies above the WSN at a fixed altitude h. The UMP must then devise a closed data collecting tour for the UAV (beginning and ending at the depot), consisting of a series of hovering sites and hovering durations at each one, with the goal of maximising the total utility and minimizing the total cost of the tour.

For UGV, consider the set G of sensors with a volume D_g of data to be collected, each sensor g in G has a data transmission bandwidth B and a data transmission range R. We take it for granted that each sensor's utility function $F_g(\Psi_g)$ is constant. For data collection, the UGV starts at the data center and collect the data from all the sensors while maximizing the utility and minimizing the cost of the path and then returns to the data center. Thus, The UMP must then devise a closed data collecting tour for the UGV (beginning and ending at the depot), consisting of a series of transmission sites and at each one, with the goal of maximising the total utility and minimizing the total cost of the tour.

Formally, the problem is formulated as:

P: $\quad$ **max** $\left(SUM_{(x_a,y_a,h) \in \tau_m} F_a(\Psi_a) \times P_a + SUM_{(x_g,y_g) \in N} F_g(\Psi_g) \times P_g \right)$ $\quad$ (17)

$\quad$ **min** $(C_{UAV} + C_{UGV})$ $\quad$ (18)

s.t. $\quad$ $\mathbf{SUM}_{a \in \tau_m} T_a \le \Gamma$ $\quad$ (17a)

$\quad$ $C_{UAV} < Th_{cost}$ $\quad$ (18a)

$\quad$ $C_{UGV} < Th_{energy}$ $\quad$ (18b)

Constraint 17a states that the total time for a tour must be less than the budget time, constraint (18a) states that total accumulation cost for UAV should not exceed threshold limit of Th_{cost}, constraint (18b) represents that total accumulation energy should be less than Th_{enrg}.

3.5 Formulation as a Graph Problem

The problem of both UAV and UGV can be formulated as graph problems as described below:

3.5.1 UAV

Let, $G_{UAV} = (V_{UAV}, E_{UAV})$ be a graph where V_{UAV} is the set of hovering locations of the UAV denoted by H and E_{UAV} is defined as

$$E_{UAV} = \{(u, v) : \forall u, v \in V_{UAV}\} \quad (19)$$

The cost of edge between vertex u and vertex v is given as

$$c_{u,v} = (t_u + t_{v)} / 2 + d_{u,v} / v_{UAV} \quad (20)$$

Now, in this graph we can consider the utility u_a of a_{th} sensor as the reward for visiting a_{th} node in the graph.

3.5.2 UGV

Let, $G_{UGV} = (V_{UGV}, E_{UGV})$ be a graph where V_{UGV} is the set of potential sampling locations of the UGV denoted by N and E_{UGV} is defined as:

$$E_{UGV} = \{(u, v)\} \quad (21)$$

where $u, v \in V_{UGV}$ and both are accessible to each other.

The cost of edge between vertex u and vertex v is given as

$$c_{u,v} = (t_{samp\ u} + t_{samp\ v})/2 + d_{u,v} / v_{UGV} \quad (22)$$

Now, in this graph we can consider the utility u_g of g_{th} sensor as the reward for visiting g_{th} node in the graph. Now, our goal is to find a tour that maximizes the rewards for both UAV and UGV.

3.6 NP Hardness of the Problem Statement

Our problem as formulated above can be reduced to the orienteering problem (OP) which is an NP Hard problem. The Orienteering Problem (OP) can be defined with the aid of a graph $G_{OP} = (V,E)$ where $V = \{v_i : i = 1, 2, 3, \ldots, N\}$ is the vertex set and E is the arc set. In this definition the non-negative score S_i is associated with each vertex $v_i \in V$ and the cost $c_{i,j}$ is associated with each arc $e_{i,j} \in E$. The OP consists of determining a Hamiltonian path G' over a subset of V, including preset start (v_1) and end (v_N) vertex, and having total cost of all edges in the path not exceeding the maximum limit C_{max}, in order to maximise the total collected score[25].

Theorem. Our Problem Statement is NP-hard.

Proof. We map the graph G_{OP} to the formulated problem statement. We consider the starting and ending point of the path as the location of data center. We map the Orienteering Problem as follows:

- Map the set of V vertices to A vertices of AIoT sensors for UAV and G vertices of AIoT sensors for UGV.
- Map the set of E edges to the defined edges for UAV and UGV.
- Map the reward to the utility.
- Map maximum cost limit to the travel budget.

As formulated in Section 3.5 by considering the utility of each vertex as the reward for visiting said vertex, our problem reduces to the Orienteering Problem (OP). In conclusion, the problem of maximizing the utility is a NP Hard Problem[25].

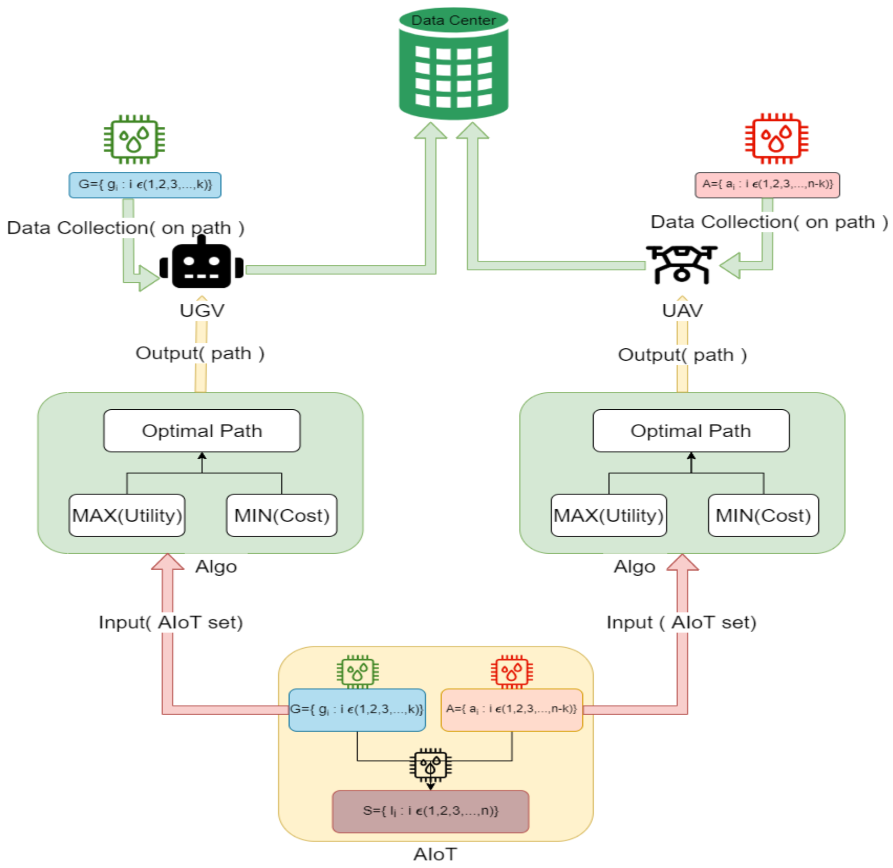
4 ALGORITHM

In Proposed algorithm 1, lines 1 and 2 show the number of inputs taken and near optimal path as output, respectively. Lines 3 to 4 calculates utility value for each vertices in set of vertices V. Line 5 to 6 calculates the edge cost for each edge in set of edges E. An auxiliary graph is constructed with a dummy data center d_o. The auxiliary graph is then provided as input for the GRASP algorithm 2. The GRASP algorithm return a path and sequence of visits. A near optimal closed tour is then derived from the returned path. In GRASP Algorithm 2, lines 1 and 2 show the number of inputs taken, path and sequence of visits as output, respectively. Lines 3 and 4 initializes the path and edge(from data center

to dummy data center). In line 5 to 7 we inject the edge points in the initial path using the AddLocation algorithm 25 until we get a path. AddLocation algorithm returns the updated path and sequence including the injected edge points. In line 8 we improve the returned path using the LocalSearch 14 algorithm. Finally we return the improved path and sequence in line 9.
In AddLocation Algorithm 25 we take the current path and sequence as input and output the updated path after adding a location to the. Lines 3 initializes the CandidateList to φ. From line 5 for every vertex in V if it is not in the current path we perform the insertion of the vertex in the path and sequence if the cost of the upadted path doesn't exceed the budget cost. Finally we return the updated path and sequence in line 9.
In LocalSearch Algorithm 14 After the examination of all locations from V in the AddLocation procedure, the final candidate list CL is created by the restrict operator defined in Eq. (4) for the particular iteration of the CP. CL then contains paths with associated utility that is greater than or equal to x% of maximum utility among the solutions found so far. Following [27] and further based on the empirical evaluations, the value of x is set to 20 . After getting CL′ , the path (P,) is chosen randomly from the restricted candidate list CL. The construction phase terminates when CL is empty, which means that no better solution has been found. Finally, after the initial construction of the solution (P,), the solution is improved in the localSearch procedure. The operator remove, is utilized to iteratively remove a location at the position j. For each path with the removed location, the GRASP-SR uses the 2- Opt optimization heuristic[28] to eliminate possible crossing segments by a local exchange of the particular sequence part. Once a location is removed from the path, a new attempt to insert not yet visited location is performed by AddLocation procedure. If such an attempt on the path ρ′ improves the collected rewards or it has the same rewards but length(ρ, P) < length(ρ, P), the path (, P) replaces (ρ, P).

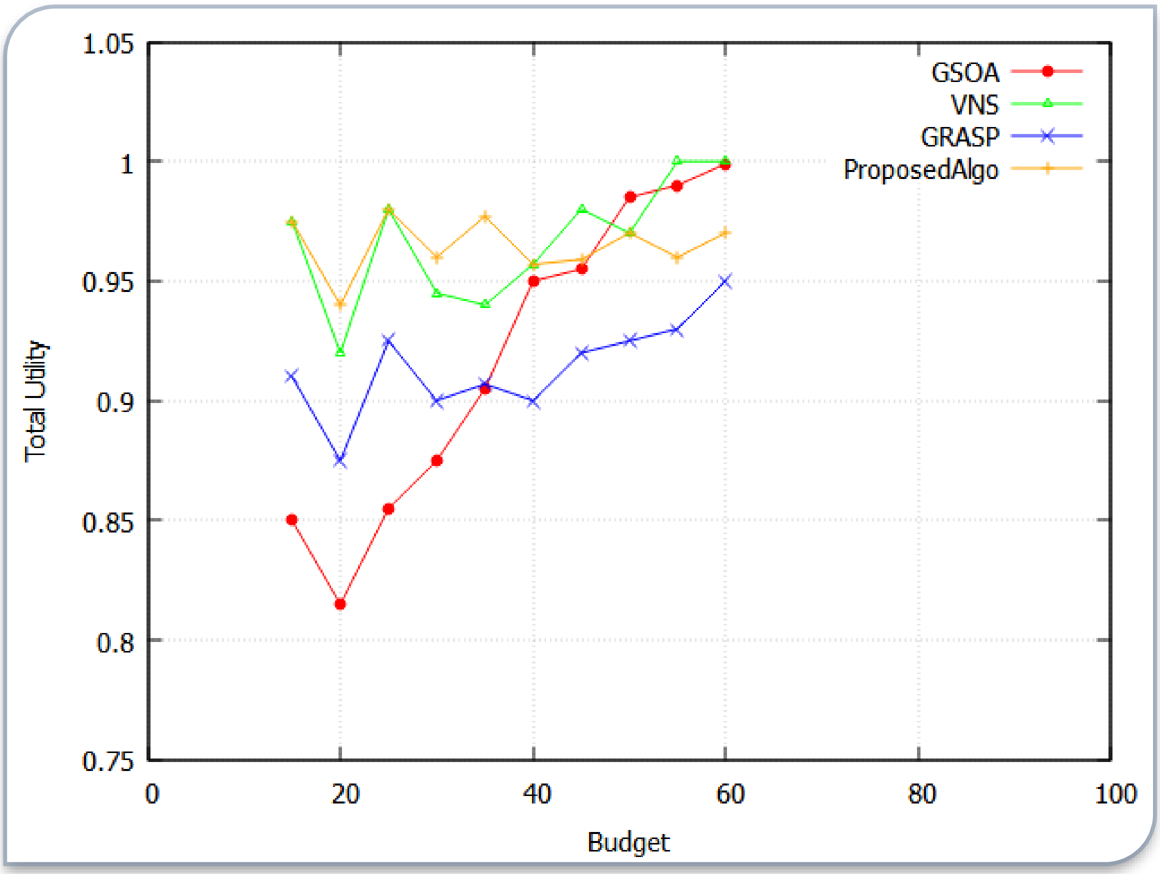
5 FLOWCHART

The flow-chart is given as follows:



5.1 Simulation And Result

For a particular set, the instance of the Proposed Algorithm is defined by the travel budget Γ selected from a particular set of values. Two existing approaches to the three CEOP are considered in the herein reported evaluation results. The first approach GSOA [29] uses unsupervised learning, the second approach is a combinatorial heuristic based on the VNS [30] that is considered with eight samples per each disk neighborhood and with the termination condition of the 1000 iterations or 200 iterations without improvement and the third one is the GRASP approach to CEOP [27]. Based on the reported results, the proposed GRASP-based method for the CEOP provides solutions with the competitive solution quality to the solutions provided by the evaluated existing methods, the GSOA, VNS and unmodified GRASP. In several cases, especially for relatively large instances, the proposed GRASP-based method provides the best results among the evaluated trials. The optimization in the local search phase significantly improves the solution quality. In few cases, VNS provides better results than the Proposed Algorithm because of the explicit discretization of the disk-shaped neighborhood, which is avoided by the heuristic determination of the waypoint location in the Proposed Algorithm, GRASP and GSOA Although the proposed enhancements are straightforward and easy to implement, the developed GRASP-based algorithm outperforms the existing approaches to the CEOP in terms of the solution quality (in comparison to the GSOA) and computational requirements (in comparison to the VNS). Thus, the proposed approach is a vital method to address combinatorial routing problems that also include continuous optimization.



The above graph is a side by side performance analysis of the evaluated approaches along with the Proposed Algorithm. We have plotted the total utility of all the tours taken by the UAV and UGV, in case of Proposed Algorithm and UAV, in case of other evaluated approaches against the total budget provided. As mentioned earlier, the Proposed Algorithm provided most optimal results majority of the time.

6 Conclusion

Although the proposed enhancements are straightforward and easy to implement, the developed GRASP-based algorithm outperforms the existing approaches to the CEOP in terms of the solution quality (in comparison to the GSOA) and computational requirements (in comparison to the VNS). Thus, the proposed approach is a vital method to address combinatorial routing problems that also include continuous optimization.

7 References

[1] A. Ometov, P. Masek, L. Malina, R. Florea, J. Hosek, S. Andreev, J. Hajny, J. Niutanen, and Y. Koucheryavy, “Feasibility characterization of cryptographic primitives for constrained (wearable) iot devices,” in 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), pp. 1–6, IEEE, 2016.

[2] F. Gu, J. Niu, S. K. Das, Z. He, and X. Jin, “Detecting breathing frequency and maintaining a proper running rhythm,” Pervasive and Mobile Computing, vol. 42, pp. 498–512, 2017.

[3] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, “Blockchain for iot security and privacy: The case study of a smart home,” in 2017 IEEE international conference on pervasive computing and communications workshops (PerCom workshops), pp. 618–623, IEEE, 2017.

[4] S. Roy, N. Ghosh, and S. K. Das, “biosmartsense: A bio-inspired data collection framework for energy-efficient, qoi-aware smart city applications,” in 2019 IEEE International Conference on Pervasive Computing and Communications (PerCom, pp. 1–10, IEEE, 2019. [5] S. Roy, N. Ghosh, and S. K. Das, “biosmartsense+: A bio-inspired probabilistic data collection framework for priority-based event reporting in iot environments,” Pervasive and Mobile Computing, vol. 67, p. 101179, 2020.
[6] C. Cabrera, A. Palade, G. White, and S. Clarke, “An urban-driven service request management model,” in 2020 IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 1–7, IEEE, 2020.
[7] U. Shafi, R. Mumtaz, J. Garc´ıa-Nieto, S. A. Hassan, S. A. R. Zaidi, and N. Iqbal, “Precision agriculture techniques and practices: From considerations to applications,” Sensors, vol. 19, no. 17, p. 3796, 2019.
[8] A. Ghosal, S. Halder, and S. K. Das, “Distributed on-demand clustering algorithm for lifetime optimization in wireless sensor networks,” Journal of Parallel and Distributed Computing, vol. 141, pp. 129–142, 2020.
[9] W. Choi, G. Ghidini, and S. K. Das, “A novel framework for energy-efficient data gathering with random coverage in wireless sensor networks,” ACM Transactions on Sensor Networks (ToSN), vol. 8, no. 4, pp. 1–30, 2012.
[10] M. Di Francesco, S. K. Das, and G. Anastasi, “Data collection in wireless sensor networks with mobile elements: A survey,” ACM Transactions on Sensor Networks (TOSN), vol. 8, no. 1, pp. 1–31, 2011.
[11] S. Gao, H . Zhang, and S. K. Das, “Efficient data collection in wireless sensor networks with path-constrained mobile sinks,” IEEE Transactions on mobile computing, vol. 10, no. 4, pp. 592–608, 2010.
[12] J. Wang, Y. Liu, and S. K. Das, “Energy-efficient data gathering in wireless sensor networks with asynchronous sampling,” ACM Transactions on Sensor Networks (TOSN), vol. 6, no. 3, pp. 1–37, 2010.
[13] A. Navarra, C. M. Pinotti, M. Di Francesco, and S. K. Das, “Interference-free scheduling with minimum latency in clusterbased wireless sensor networks,” Wireless Networks, vol. 21, no. 7, pp. 2395–2411, 2015.
[14] S. K. A. Imon, A. Khan, M. Di Francesco, and S. K. Das, “Energyefficient randomized switching for maximizing lifetime in treebased wireless sensor networks,” IEEE/ACM transactions on networking, vol. 23, no. 5, pp. 1401–1415, 2014.
[15] M. Chen, W. Liang, and J. Li, “Energy-efficient data collection maximization for uav-assisted wireless sensor networks,” in 2021 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–7, IEEE, 2021.
[16] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, “Uav trajectory planning for data collection from time-constrained iot devices,” IEEE Transactions on Wireless Communications, vol. 19, no. 1, pp. 34–46, 2019.
[17] Y. Liang, W. Xu, W. Liang, J. Peng, X. Jia, Y. Zhou, and L. Duan, “Nonredundant information collection in rescue applications via an energy-constrained uav,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 2945–2958, 2018.
[18] A. Khochare, Y. Simmhan, F. B. Sorbelli, and S. K. Das, “Heuristic algorithms for co-scheduling of edge analytics and routes for uav fleet missions,” in IEEE INFOCOM 2021-IEEE Conference on Computer Communications, pp. 1–10, IEEE, 2021.
[19] M. Chen, W. Liang, and S. K. Das, “Data collection utility maximization in wireless sensor networks via efficient determination of uav hovering locations,” in 2021 IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 1–10, IEEE, 2021.
[20] J. Zhang, Z. Li, W. Xu, J. Peng, W. Liang, Z. Xu, X. Ren, and X. Jia, “Minimizing the number of deployed uavs for delay-bounded data collection of iot devices,” in IEEE INFOCOM 2021 – IEEE Conference on Computer Communications, pp. 1–10, 2021.
[21] A. Trotta, M. di Felice, L. Bononi, E. Natalizio, L. Perilli, E. F. Scarselli, T. S. Cinotti, and R. Canegallo, “Bee-drones: Energyefficient data collection on wake-up radio-based wireless sensor networks,” in IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 547–553, 2019.
[22] O. Aldabbas, A. Abuarqoub, M. Hammoudeh, U. Raza, and A. Bounceur, “Unmanned ground vehicle for data collection in wireless sensor networks: Mobility-aware sink selection,” The Open Automation and Control Systems Journal, vol. 8, pp. 35–46, 07 2016.
[23] P. Tokekar, J. Vander Hook, D. Mulla, and V. Isler, “Sensor planning for a symbiotic uav and ugv system for precision agriculture,” IEEE Transactions on Robotics, vol. 32, no. 6, pp. 1498–1511, 2016.
[24] F. Ropero, P. Mu˜ noz, and M. D. R-Moreno, “Terra: A path planning algorithm for cooperative ugv–uav exploration,” Engineering Applications of Artificial Intelligence, vol. 78, pp. 260–272, 2019. [25] P. Vansteenwegen, W. Souffriau, and D. Van Oudheusden, “The orienteering problem: A survey,” European Journal of Operational Research, vol. 209, no. 1, pp. 1–10, 2011.
[26] A. Caruso, S. Chessa, S. Escolar, J. Barba, and J. C. L´opez, “Collection of data with drones in precision agriculture: Analytical model and lora case study,” IEEE Internet of Things Journal, vol. 8, no. 22, pp. 16692–16704, 2021.

[27] P. ˇStefan´ıkov´a, P. V´aˇ na, and J. Faigl, “Greedy randomized adaptive search procedure for close enough orienteering problem,” in Proceedings of the 35th Annual ACM Symposium on Applied Computing, pp. 808–814, 2020.
[28] G. A. Croes, “A method for solving traveling-salesman problems,” Operations research, vol. 6, no. 6, pp. 791–812, 1958.
[29] J. Faigl, “Data collection path planning with spatially correlated measurements using growing self-organizing array,” Applied Soft Computing, vol. 75, pp. 130–147, 2019. 8
[30] R. Pˇeniˇcka, J. Faigl, P. V´aˇ na, and M. Saska, “Dubins orienteering problem,” IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 1210–1217, 2017.