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Energy-Efficient Data Gathering Framework-Based Clustering via Multiple UAVs in Deadline-Based WSN Applications

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ABSTRACT This paper proposes a new method for energy-efficient data gathering using multiple unmanned aerial vehicles (UAVs) in deadline-based wireless sensor networks (WSNs). This method collects WSN node data in minimum energy by providing the optimal position and trajectory of UAVs, the minimum travel time, and the minimum number of UAVs in a determined deadline. First, in order to minimize the energy consumption of WSN nodes and determine the positions of where to place UAVs for receiving network nodes data, this paper clusters the nodes in a distributed form and considers the centers of these clusters as a place to meet the UAVs. Then, beginning and ending virtual nodes are used for controlling the minimum number of UAVs. This paper attempts to complete the proposed solution and obtain the minimum travel time of UAV required for collecting data from the network. In order to find the optimal solution for this problem, a mixed integer linear programming mathematical model is presented, followed by normalizing and putting weights on each part of an objective function. Results obtained in the simulation step show that the presented model has an optimal performance in providing the position and optimal trajectory of UAVs, energy consumption, minimum travel time, and the number of UAVs used.

INDEX TERMS Data gathering, wireless sensor networks, unmanned aerial vehicles, mixed integer linear programming model, deadline, clustering.

I. INTRODUCTION

It is expected that millions of unmanned aerial vehicles (UAVs), which are also called a drones, shall become active in our daily life in the near future and provide wide services [1]. UAVs have numerous applications such as in deadline-based wireless sensor networks (WSNs), battlefield surveillance, forest monitoring, and animal tracking in a protected area [2]. Since these devices have small batteries, they usually cannot be ported in long distances due to energy limitations. UAVs can move toward WSN devices, collect WSN data, and transfer them to devices that are out of the communication domain of WSN devices.

Basic applications of UAVs can be divided into three classes [3]:

1. Total coverage in which UAVs are employed to help available communicative infrastructures to provide integrated wireless coverage in the desired area. In this case, UAVs usually act as fixed networks above a desired area in the form of base stations [4]. UAV-based wireless communication has its unique capabilities for quick, reliable, and affordable connections to areas that are weakly covered by ground networks [5].

2. Another promising application of UAVs is UAV-aided relaying where UAVs are sent for providing a reliable wireless connection between two or more distant users or group of users in an enemy environment, such as for communication between front lines and a base for emergency or military operations [6], [7].

3. Data gathering is another usage for UAV systems. This application is attractive especially for WSNs from which UAVs can collect data, in which case the operational power of sensors is decreased thus lengthening the lifetime of the network [8], [9].

Collecting data with UAVs not only features the flexibility of mobile datasets, which are suitable for WSNs on a large scale, but there are also the following advantages [10]:

First, collecting aerial data by UAVs can be directed automatically as a mobile data collection. There is no movement limitation in ground transfer and it can be used in specially protected areas where humans cannot access.

Second, aerial data collection is controlled by an aerial vehicle which is quicker than other modes of collection. Thus, it can raise the speed of searching for and meeting nodes and shorten the data collection life cycle when there is a sensor network on a large scale.

Third, aerial data collection usually faces less obstacles and has higher coverage for the wireless signal, which can decrease communication delay and increase bandwidth.

Animal tracking, pollution monitoring, forest monitoring, and battlefield surveillance in a protected area are examples of deadline-based WSN applications. In forest monitoring, for example, sensor nodes are installed for recognizing fire and smoke. A UAV flies regularly above the desired area to collect data from all sensor nodes in determined points, which are called virtual grid points. Collecting these data should be done based on the determined deadline (Figure1). One of the potential applications of UAVs is deadline-based WSN applications, which include monitoring a given area to assess danger. Accordingly, it is possible to have a beneficial collaboration between a UAV team and a smart city's security force for the monitoring of strategic sites [11].

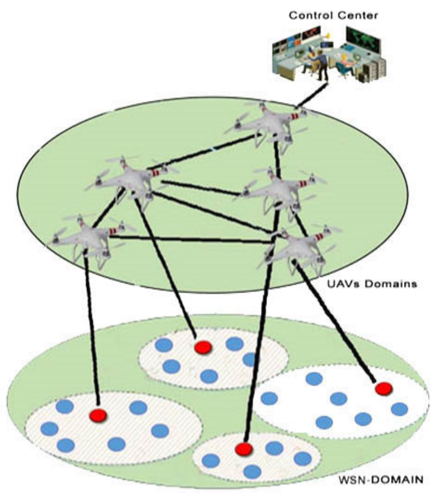

FIGURE 1. UAVs and WSN device communication.

A deadline for collecting WSN data is determined with regard to the type of application. For example, for many deadline-based WSN applications, data collection time is determined with regard to priority and the critical level of previously collected data. In this case, the distant user can ask different deadline times for data collection at the network level.

In terms of efficient and effective UAV and WSN energy consumption, the main problem in this paper is the optimal position and trajectory, minimum time required for collecting data, and the optimal number of UAVs to collect data at the network level within a predetermined deadline. In fact, these are Vehicle Routing Problems (VRP) with the requirement of data collection by a certain deadline added to the UAV routing problem; hence, the term Vehicle Routing Problem with Time Window (VRPTW) is presented. The present paper solves a mathematical formula for a multi-objective optimization model in which different objective functions are simultaneously optimized. Specifically, the proposed optimization model assumes three objectives: the minimization of all distances travelled by all UAVs, the minimization of the time required for data gathering at the network level, and the minimization of the number of UAVs required for data gathering. This problem produces the optimal position and movement of UAVs with the minimum time possible for data collection. Increasing the complexity of this problem, in its modeling and solving approach, also involves determining the optimal number of UAVs required for covering the desired area..

The contributions of this paper can be defined as follows:

1. By identifying the key challenges of the UAV in the WSN network, an accurate investigation of wireless communications is conducted using the UAV, which constitutes the main features of this paper.

2. A framework is provided for energy efficient data collection employing multiple UAVs in the WSNs and with regard to the deadline and energy of sensor nodes and UAVs.

3. A problem is formulated as a Mixed Integer Linear programming (MILP) model.

4. The MILP is modeled by considering three parts of the objective as normalized, using a coefficient or weight for each part of the objective and examining its effect on output.

5. Comparing the output of the proposed model with a greedy method that selects the closest node for UAV movement in each step.

The remainder of this paper is as follows: In Section II, related work on using UAVs in WSNs is examined. Section III presents the limitations and assumptions of the network model. In Section IV, the steps of the proposed solution are described. In Section V, the proposed model is presented with normalization and a coefficient or weight for each part of the objective function is introduced to find optimal solutions to the problem. Section VI presents a simulation and performance evaluation of the proposed framework. Finally, results and future work are presented in Section VII.

II. RELATED WORKS

Despite several advantages and practical applications of UAVs as mobile collectors for WSNs, many technical challenges should be considered, such as optimal trajectory, optimal deployment, data routing, air channel to ground modeling, user association, flight time optimization, and efficient energy consumption of UAVs and WSN should be considered. The following first classifies related works with regard to previous challenges and then describes the strengths and weaknesses of each category [10]–[27].

Table 1 compares reviewed papers for UAV-based WSN connections based on deadline, optimal positioning, the optimal number of UAVs, mobile nodes, and minimum times required for collecting data from cluster heads. The table shows that available approaches have the following shortcomings:

TABLE 1. Comparing reviewed works.

Reference	Single/ Multiple UA/	Fixed/ mobile nodes	Optimal number of UAV	Optimal positioning of UAV	Predetermined points	Minimum travelled time of UAV	Deadline
Feng et al [12]	Multiple	Fixed	✓	×	✓	×	×
Zeng et al [13]	Single	Fixed	×	×	×	×	×
Yakichi [14]	Multiple	Fixed	×	×	✓	×	×
Ladosz et al [15]	Single	Fixed	×	✓	×	✓	×
Wang et al [10]	Single	Fixed	×	×	✓	×	×
Zorbas et al [19]	Single	Fixed	×	✓	✓	✓	×
Li et al [20]	Single	Fixed	×	×	✓	×	×
Jeong et al [21]	Single	Fixed	×	×	✓	×	×
Hen et al [9]	Single	Mobile	×	✓	✓	✓	×
Mozaffari et al [23]	Multiple	Mobile	×	✓	×	✓	×
Henchey [24]	Single	Fixed	×	×	×	×	×

- Deadline time has not been reviewed.
- The optimal deployment of UAVs has not been investigated.
- The optimal number of UAVs has not been provided.
- Multiple UAVs have not been considered.
- Mobile nodes have not been considered.
- UAV minimum time has not been considered.

III. ASSUMPTIONS AND LIMITATIONS

Assumptions and limitations considered in this paper are:

A. ASSUMPTIONS AND LIMITATIONS OF WSN NETWORK

To propose a method for optimizing data collection in UAV/WSN networks, assumptions and limitations of the network are determined as follows:

- **Distribution of WSN nodes in the network**: it is assumed that the sensors used are stationary and selected randomly in two-dimensional areas and that the distribution of WSN nodes is uniform.
- **Node division**: two roles are assumed for WSN nodes: cluster head (CH) and cluster member (CM). CHs and CMs are placed randomly in the network field. In this paper, the clustering plan is assumed to be optimal.
- **Ground to air communications**: each device usually has a LoS view to a certain UAV with a given probability. This LoS probability depends on the environment, device and UAV location, and the elevation angle between the sensor node and UAV.
- **The transfer rate of WSN nodes**: each WSN node can regulate its transfer rate as well as transfer radius.
- **Node location**: all nodes of the wireless sensor are aware of their geographical place based on Global Positioning Systems (GPS) and their locations are known to UAVs, and are used to find the optimal route for UAVs.

B. ASSUMPTIONS AND LIMITATIONS OF UAV NETWORK

- **•UAV mobility in the network model**: the random mobility model was assumed as a UAV mobility model in which the UAV can move around the WSN network and stop in certain places if required to collect data from sensor nodes.
- **Type of UAV**: the rotary wing UAV was used instead of a fixed wing UAV, since rotary wing UAV is more flexible than other types of UAV and can fly in any direction, vertically, horizontally, or in a fixed position.
- **UAV capacity**: the maximum distance that any UAV can travel is predetermined and should not be surpassed.
- **UAV energy**: the maximum energy that any UAV can consume is predetermined and the spent energy should not exceed this.
- **UAV buffer**: each type of UAV has its own buffer size. Data collected by cluster heads should not be more than the UAV buffer size.
- **Ability to move with a fixed velocity**: each UAV can move with a fixed velocity.
- **Ability to move at a constant flight altitude**: each UAV can move at a fixed altitude.
- **Obstacle-Free**: no obstacle has been assumed for UAV movement.
- **Collision-Free**: each UAV has been considered with the ability to move without collision.

IV. STEPS of PROPOSED METHOD

The following are the steps of the proposed solution to provide energy efficient data collection and optimal trajectory based on network assumptions and conditions:

STEP 1: CLUSTERING

First, the nodes are clustered in a distributed manner, so as to determine the place where UAVs receive data from network nodes. For efficient clustering in terms of WSN energy consumption for data transfer to the network, the proposed clustering minimizes the mean sent distance of cluster members while the WSN consumes the minimum possible energy when sending data to the cluster head. For this purpose, the threshold limit for the sent distance of WSN nodes is determined based on the network domain and by considering the energy parameter; then, each node can recognize its neighbors from this distance. Next, the threshold limit of the number of nodes in each cluster is determined based on network density, which is dependent on the number of nodes and the network area size. Neighborhoods having an equal or greater number of neighbor nodes than this threshold form clusters. In this case, the number of clusters required for an efficient sent of information by a WSN is determined and the centers of these clusters are considered as the UAV meeting place. After cluster formation and UAV placement in the center of each node, data are sent from the WSN to the UAV, which receives data from the cluster after a certain amount of time passes.

The problem in this step is the decrease in WSN energy consumption when the number of clusters is high. Because each UAV in the center of each cluster stops for a while to receive the cluster's data, more time is spent and thus the distance traveled by UAVs increases, which is contrary to the proposed model's objectives. In comparison, if the number of clusters is low, the UAV distance traveled is less and WSN energy consumption rises; WSN node energy use grows due to longer sent distances among these nodes. In fact, achieving a balance between these two conditions should always be considered in this step.

STEP 2: DETERMINING VIRTUAL NODES

In this step, after clustering and determining meeting points of UAVs, the present work attempts to solve its main problem of the research. In this step, WSN nodes are assumed to be fixed in the network. In order to efficiently determine the route in the network efficiently, the network graph is formed as follows: By choosing the node centers selected in the previous step, the UAV meeting points are considered as network nodes. Moreover, determining the optimal number of UAVs for network coverage is among the goals of the present work. Such a solution should suggest some routes for UAV movement in these nodes, where UAVs simultaneously travel to these points and receive data. In order to control the number of these routes, 0 and n+1 virtual nodes are considered as initial and final nodes in the movement route of all UAVs. Therefore, by considering node 1 to node n as node centers, set N as network nodes is defined as follows:

The network graph for executing the route problem is defined as follows:

$$G = (N, E)$$
$$N = \{0, 1, 2, \ldots.., n, n+1\}$$

where E(i,j) is the Euclidean distance among nodes. Thus, the research problem is presented as follows: finding the shortest route (m) from node 0 to node n+1 with these conditions:

- Time distance of each route should be lower than the predetermined deadline.
- Routes do not have a shared edge and node, except the source and target nodes.
- Traveled routes should be the shortest routes possible.

The number of determined routes (m), which is in fact the number of UAVs, should be the least possible number. In this step, an efficient solution should be proposed for the problem. The current work determines that such solutions are based on MILP.

STEP 3: MINIMIZE TRAVELED TIME BY UAV

In previous steps, the deadline was determined by the network manager for collecting network data. The aim of this step is to spend the least possible time required for collecting data from the network. It should be noted that the minimum time for collecting network data and the minimum number of UAVs required for data collection are two of the present study's objectives. However, these two goals are dependent on each other such that by increasing the number of UAVs to a maximum number of clusters, the data collection time is minimized but the minimum number of UAVs is not. Therefore, by considering this dependency, assigning weights to the dual objectives, and analyzing different scenarios, this step attempts to propose a model that reaches a satisfactory balance between these two objectives.

V. PROPOSED MODEL

As mentioned earlier, to solve the present research's main problem, efficient clustering in the network is performed so as to minimize the energy consumption of sending WSN node data. This is followed by devising a network graph and utilizing MILP to arrive at a solution.

- **Problem:** Determining the optimal number of UAVs for collecting data for a determined deadline by spending minimum energy and minimum time required for collecting data.
- **Assumptions of the problem:**
  - UAVs are moving with a fixed velocity.
  - Nodes are fixed in the network.
  - Each UAV can travel a limited distance.
- **Objectives of the problem:**
  - Minimize energy use for WSN and UAVs when sending and collecting data.
  - Minimize the number of UAVs collecting data from the network.
  - Minimized the time required for data gathering.
- **Constraints of Problem:**
  - Network data should be collected by predetermined deadline.
  - Distance traveled by each UAV should not exceed the determined threshold for UAVs.

- **Parameters of problem:** In this section, definitions of symbols used in the MLIP formula are presented in Table 2.

TABLE 2. Symbols.

Symbol	Definition
$G = (N, E)$	Network graph
$N = \{0,1,2,\dots,n,n+1\}$	Set of network nodes including node 1 to node n as cluster centers and 0 and n+1 nodes as virtual initial and final nodes in the route of all UAVs.
v	UAV velocity
d_k	Maximum distance traveled by each UAV
M	Maximum number of UAVs
d_{ij}	Euclidian distance from node i to node j
τ	Data collection deadline
n	Number of clusters
t_i	Time required for receiving data by UAV in each cluster

- **Variables of Problem:** Variables are presented in Table 3.

TABLE 3. Variables of problem.

Variable	Definition
$x_{i,j}^k = \begin{cases} 1, & \text{if UAV k travel between i, j} \\ & 0, \text{else} \end{cases}$	Relating node i to node j by UAV with symbol k (which shows UAV movement with k number from node i to node j, where i and j are in fact centers of clusters)
m	Number of UAVs required (number of UAVs determined by the model)
T_k	Maximum movement time of the UAV
y_i	Integer free variable to examine the existence of subtour in route

It is of note that the maximum number of UAVs is determined by calculating the length of the route that should be traveled to collect data from the network. The time required for traveling this route based on UAV velocity is calculated and compared with the data collection deadline. The maximum number of UAVs is approximately determined for this purpose.

$$M = (((((max\,(E) + min\,(E))\,/2) * (n-1))\,/v)\,/\tau) \quad (1)$$

where M is the number of UAVs required for movement in this route. Assume that the route length is 200 and the deadline is 50. The maximum number of UAV is equal to 200 divided into 50; i.e., 4.

Mixed Integer Linear Programming Model:

$$min \sum_{k\in M} \sum_{i\in\{0,..,n\}} \sum_{j\in\{1,\dots,n+1\}} d_{ij} x_{ij}^k \quad (2)$$

$$min\ m \quad (3)$$

$$min \sum_{k\in M} T_k \quad (4)$$

Subjected to:

$$\sum_{k\in M} \sum_{j\in\{1,\dots n+1\}} x_{ij}^k = 1 \quad \forall i \in N - \{0, n+1\} \quad (5)$$

Constraint (5) ensures that each middle node should be connected only to an output node.

$$\sum_{k\in M} \sum_{j\in\{0,\dots,n\}} x_{ji}^k = 1 \quad \forall i \in N - \{0, n+1\} \quad (6)$$

Constraint (6) ensures that each middle node should be connected only to an input node.

$$\sum_{k\in M} \sum_{j\in\{1,\dots,n+1\}} x_{0j}^k = m \quad (7)$$

Constraint (7) ensures that the number of outputs of node 0 is equal to m.

$$\sum_{k\in M} \sum_{j\in\{0,\dots,n\}} x_{jn+1}^k = m \quad (8)$$

Constraint (8) ensures that the number of inputs of node n+1 is equal to m.

$$\sum_{k\in M} \sum_{i\in\{0,\dots,n\}} x_{i0}^k = 0 \quad (9)$$

Constraints (9) ensure that the number of inputs of node 0 is 0.

$$\sum_{k\in M} \sum_{j\in\{1,\dots,n+1\}} x_{n+1j}^k = 0 \quad (10)$$

Constraint (10) ensures that the number of outputs of node n+1 is 0.

$$\sum_{i\in\{0,\dots,n\}} x_{ip}^k - \sum_{j\in\{1,\dots,n+1\}} x_{pj}^k = 0 \quad \forall p \in \{1,\dots,n\}, \quad \forall k \in M \quad (11)$$

Constraint (11) ensures that in each middle node, input flow is equal to output flow.

$$x_{ii}^k = 0, \quad \forall i\ \forall k \quad (12)$$

There is no loop in the node.

$$y_i - y_j + N.\sum_{k\in M} x_{i,j}^k \le N - 1 \quad \forall i, j \in \{1,\dots,n\},\ i \ne j \quad (13)$$

Constraint (13) ensures that there is no round in the route

$$\sum_{i\in\{0,..,n\}} \sum_{j\in\{1,\dots,n+1\}} X_{ij}^k d_{ij} \le d_k \forall k \in U \quad (14)$$

Constraint (14) ensures that maximum distance that any UAV can travel is predetermined and distance traveled should not exceed it

$$\sum_{i\in\{0,..,n\}} \sum_{j\in\{1,\dots,n+1\}} x_{ij}^k \left(\frac{d_{ij}}{v} + t_i\right) \le T_k \quad \forall k \in M \quad (15)$$

Constraint (15) ensures that traveled time on each route should not exceed the maximum movement time of the UAV.

$$T_k \le \tau \quad (16)$$

Constraint (16) ensures that maximum movement time (T_K) of UAV_K should not exceed a deadline (τ).

$$\sum_{k\in M} \sum_{j\in\{1,..,n+1\}} x_{0j}^k = m \quad (17)$$

$$m \le M \quad (18)$$

Constraints (17) and (18) ensure that The minimum number of active UAVs should be less than the maximum number of UAVs.

VI. SELECTING OBJECTIVE FUNCTION

Based on the suggested model, the objective function in the suggested model is in multi-objective form, which is considered as the following for solving the suggested model:

$$min\left(\sum_{k\in M}\sum_{i\in\{0,..,n\}}\sum_{j\in\{1,...,n+1\}} d_{ij}x_{ij}^{k} + m + \sum_{k\in M} T_k\right)$$

Different approaches have been proposed to solve such problems [28]. Before solving the proposed model, the following two steps should be taken:

- ***Normalizing the Objective***: To have a balanced objective, three parts of the objective are approximately normalized to make them close to the constraints of numerical value by calculating the total traveled paths by M UAV at the network level:

  $$maxtotalpaths = ((max\,(E) + min\,(E))\,/2) * (N - M)$$

  If all n nodes are met by one UAV, the path length is an n-1 edge. If all n nodes are met by the n-1 edge with M UAV, $M - 1$ edge is eliminated. Thus, $N - M$ edge remains, which should be simultaneously traveled by M drones.

  This part of the objective is normalized by considering the optimal travel value by the UAV to this maximum value in objective ratio and the resulting number is within [0,1]. For normalization in the second part, the determined optimal number M is divided by the value of m. For this purpose, for normalization in the third part, the maximum travel time by the UAV is divided by deadline value τ.

  $$\min\left(\left(\frac{\sum_{k\in M}\sum_{i\in\{0,..,n\}}\sum_{j\in\{1,...,n+1\}} d_{ij}.x_{ij}^{k}}{maxtotalpaths}\right) + \left(\frac{m}{M}\right) + \left(\frac{\sum_{k\in M} T_k}{\tau}\right)\right)$$

- ***Weighting Coefficients***: To weigh each part of the objective, coefficients α, β, and γ are defined and valued as important weights of each part of the objective.

  Based on the above discussions, the objective of the proposed model is considered as follows:

  $$min\left(\alpha\left(\frac{\sum_{k\in M}\sum_{i\in\{0,..,n\}}\sum_{j\in\{1,...,n+1\}} d_{ij}x_{ij}^{k}}{maxtotalpaths}\right) + \beta\left(\frac{m}{M}\right) + \gamma\left(\frac{\sum_{k\in M} T_k}{\tau}\right)\right)$$

  MILP modeling is minimized by considering the number of UAVs, minimum traveling time by UAV, and minimum energy consumption. Here, these three objectives are considered by normalizing them, assigning coefficients α, β, and γ to them and prioritizing them. For example, if energy is in priority, the number of UAVs increases. If the number of UAVs is the priority, energy reaches a reasonable value, but the UAV number is not released from the constraints.

TABLE 4. Effect of selecting coefficients α, β, and γ in a suggested solution with |N| = 10.

N	τ	α	β	γ	M	m	m_{ch}	m_{trj}	Path Len.	Total Time
10	50	**0.8**	0.1	0.1	6	6	4	2	39	41
		0.1	**0.8**	0.1	6	4	1	3	95	32
		0.1	0.1	**0.8**	6	6	4	2	33	18
	70	**0.8**	0.1	0.1	4	4	1	3	94	43
		0.1	**0.8**	0.1	4	3	0	3	124	60
		0.1	0.1	**0.8**	4	4	1	3	77	35
	90	**0.8**	0.1	0.1	2	2	1	1	103	70
		0.1	**0.8**	0.1	2	1	0	1	174	64
		0.1	0.1	**0.8**	2	2	1	1	108	49

Table 4 presents the effect of selecting coefficients α, β, and γ for suggested solutions in three different scenarios with |N| = 10 and different deadline values (τ = 50, 70, and 90).

In this table, by considering m_{ch} and m_{trj}, which are respectively the number of UAVs that move in the network and the number of UAVs that are assigned only to a cluster, the current paper attempts to minimize the traveled path by assigning UAV to each cluster in scenarios where the coefficient of the minimum energy objective is the dominant value. However, the number of UAVs assigned to each cluster decreases in conditions in which the coefficient of the minimum UAV objective is dominant. Thus, UAVs try to cover all clusters and collect data with the traveling path. If the coefficient of the least UAV movement time is dominant, then the UAV travel time decreases and UAVs attempt to cover all clusters and gather data with the traveling path.

VII. SIMULATION AND PERFORMANCE EVALUATION

Using different scenarios, this section compares the suggested method with the greedy method. Two metrics evaluate the performance of the proposed method. The first metric is the maximum traveled distance, which is defined as the mean length of tour used by all UAVs to finish a round. The second metric is total travel time, which is defined as the mean of maximum travel time in UAVs to end a round. Simulation settings and results of the evaluation are presented in the following.

A. SIMULATION SETTINGS

In this simulation, network size is 600*600 m^2. The evaluation was performed with the Python software as an exploratory implementation platform in Pulp Library. To implement the MILP optimization objective, a system with Core i5-2410M 2.30 GHz central processing unit and 4 gigabytes basic memory was utilized. Other parameters of the simulation are presented in Table 5.

TABLE 5. Simulation parameters.

Parameter	Value
Area size	600×600 m^2
No. of sensors	300
No. of CHs	7 10 13 15
No. of UAV	2 3 4 6 7 8 9
Speeds of UAV	20 m/s
Heights of UAV	70 m
Deadline Times τ	50 70 90 s
Sojourn Times t_i	4 s
Transmission range	40 m
UAV Elevation Angles	45 deg
Transmission bit rate f	200 kbps
Initial energy E_0	0.1 J
Packet size	2000 bit
d_{max}	200 km

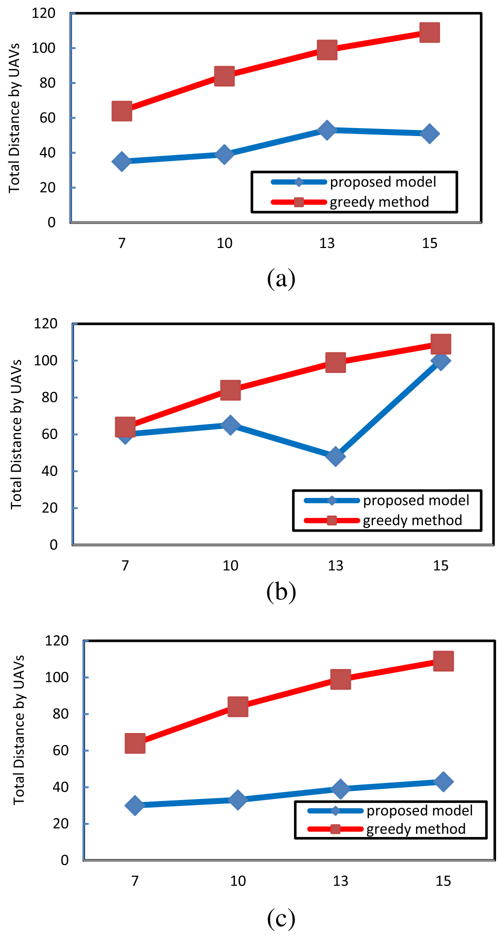

FIGURE 2. **Comparing the travel distance in the suggested method and greedy method with $\tau = 50$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

B. COMPARING THE PROPOSED METHOD WITH THE GREEDY METHOD

A greedy algorithm is an algorithmic paradigm that follows the problem of solving heuristic of making a locally optimal choice at each stage [29] with the intent of finding a global optimum. The main idea behind a greedy algorithm is local optimization. That is, the algorithm picks what seems

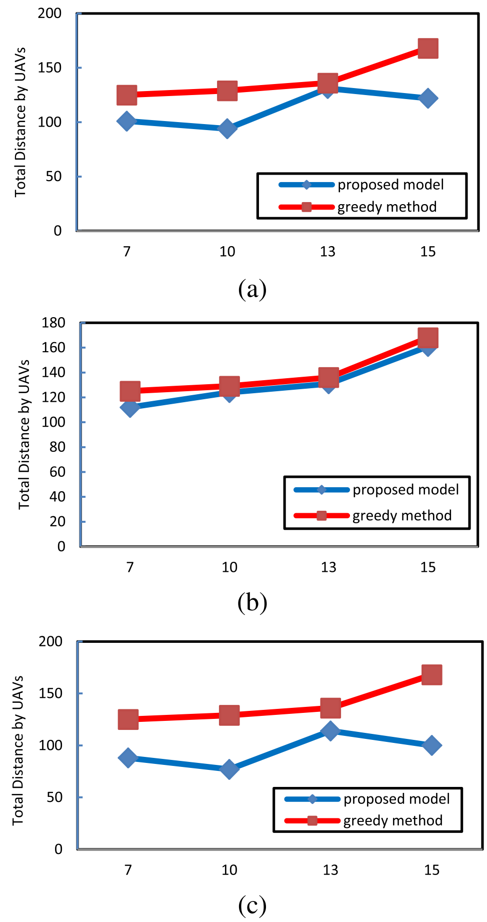

FIGURE 3. **Comparison of travel distance in the suggested method and the greedy method with $\tau = 70$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

to be the best thing to do at a particular time, instead of considering the global situation [30]. In many problems, a greedy strategy does not usually produce an optimal solution, but nonetheless a greedy heuristic may yield locally optimal solutions that approximate a globally optimal solution in a reasonable amount of time. This heuristic does not intend to find the best solution, but it terminates in a reasonable number of steps; finding an optimal solution to such a complex problem typically requires unreasonably many steps. Greedy algorithms mostly (but not always) fail to find the globally optimal solution because they usually do not operate exhaustively on all the data. For example, all known greedy coloring algorithms for the graph coloring problem and all other NP-complete problems do not consistently find optimum solutions. Nevertheless, they are useful because they are quick to think up and often give good approximations to the optimum. Greedy algorithms appear in network routing as well. Using greedy routing, a message is forwarded to the neighboring node which is "closest" to the destination. A greedy strategy for our problem (which is of a high computational complexity) is the following heuristic: "At each step of the tour, visit the nearest unvisited cluster head".

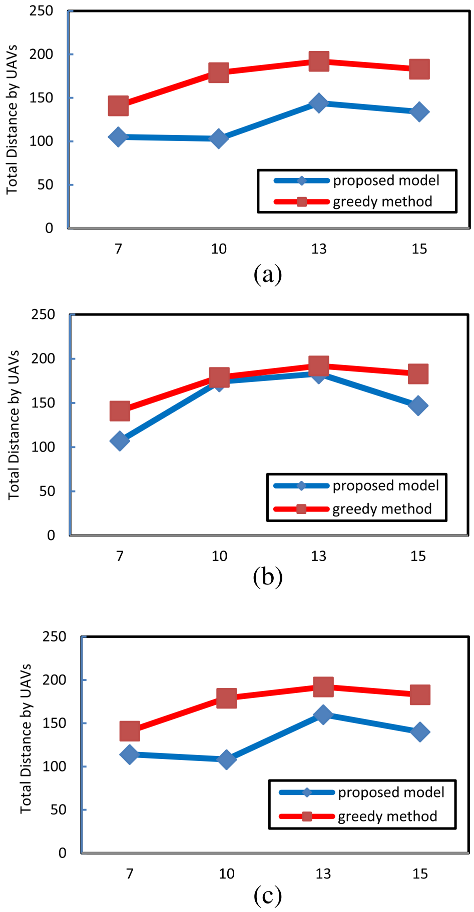

FIGURE 4. **Comparison of travel distance in the suggested method and greedy method with $\tau = 90$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

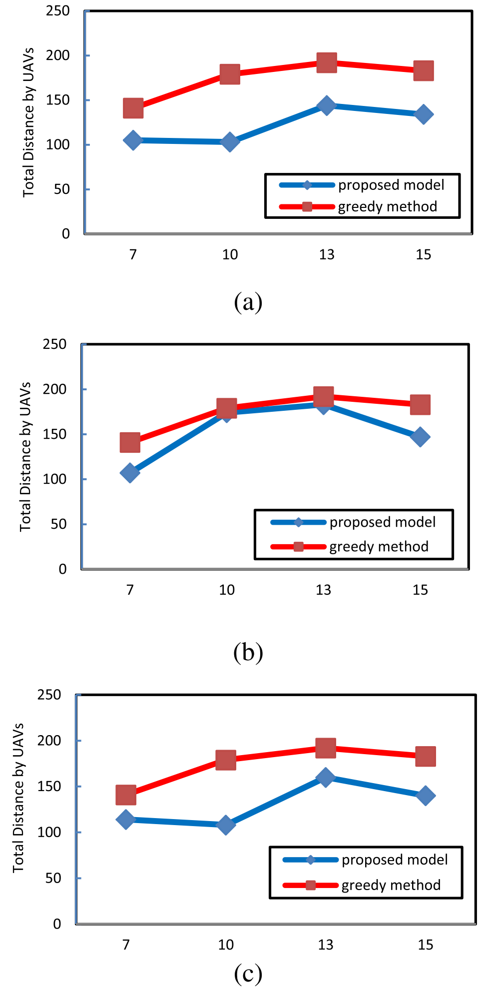

FIGURE 5. **Comparison of travel time by UAVs in the suggested method and the greedy method with $\tau = 50$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

According to the greedy approach, the UAV always pursues the closest cluster in its movement. In other words, the UAV always flies to a neighboring cluster with the closest distance. Also, in the greedy approach, the Greedy-UAV continues to visit the same neighboring clusters whose cluster heads the Greedy-UAV found the previous time. In other words, the greedy approach is trapped in the local minima and cannot adapt itself based on UAV movements [31].

To evaluate the efficiency of the proposed model in terms of energy consumption, the model output is compared with the method that selects the closest node in each UAV movement step. The proposed model and the greedy method are compared in different scenarios from the perspective of energy use. It is observed that energy consumption is directly proportional to distance. Hence, minimizing energy is equivalent to minimizing distance [32]. It should be mentioned that, since energy use depends directly on the travel distance, this distance can be used as a scale for energy comparisons.

In the $|N| = 7$ scenario with different deadlines, the UAV travel distance in the proposed method is compared with that of the greedy method and the results show a different number of UAVs. As mentioned earlier, in the greedy method, a longer distance is traveled due to the random selection of nodes for starting a movement. In contrast, the proposed model attempts to select a suitable place for the initial nodes. Previously stated in the section on selecting an objective, the effect of different values for coefficients α, β, and γ on the proposed model's output can be observed in a similar scenario.

Figure 2 shows a comparison of travel distance by UAVs in the suggested method and the greedy method in scenarios $N = 7$, 10, 13, and 15 in $\tau = 50$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$. In scenarios where the coefficient of minimum energy objective is the dominant value (Figure 2(a)), the maximum travel distance in the greedy method shows the highest value. In comparison, this distance is the lowest in the suggested method, because as the number of cluster heads increases, the maximum travel distance also increases. As seen in Figure 2(b) that the gap between traveled distance of the greedy method and our proposed method is greater when the number of cluster heads varies between 13 and 15. For example, when the number of cluster heads is 13, the total travel distance under the proposed method is 48

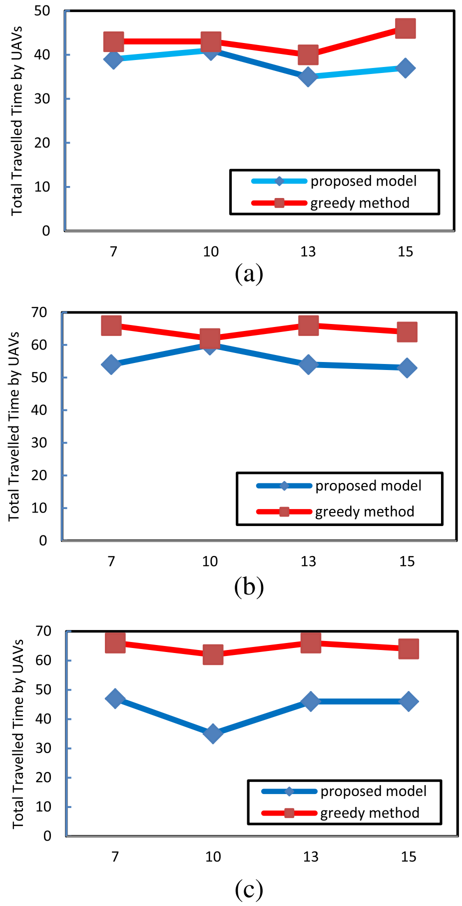

FIGURE 6. **Comparison of travel time of UAVs in the suggested method and the greedy method with $\tau = 70$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

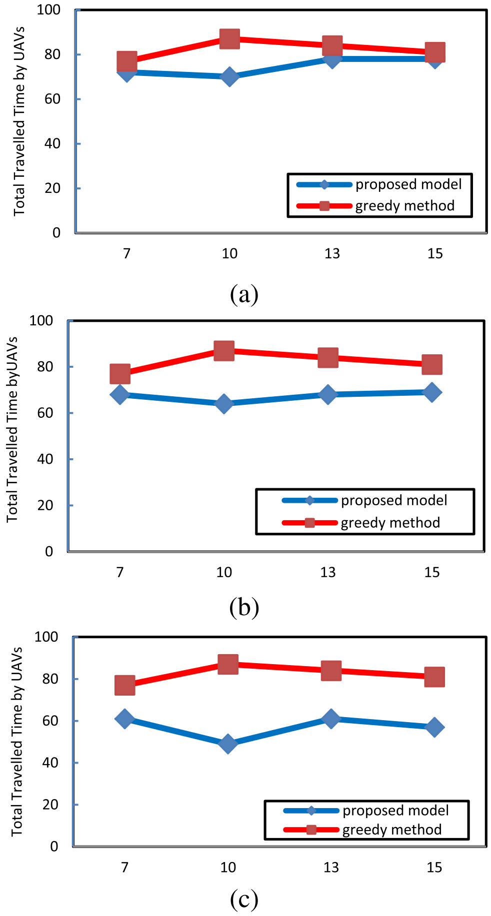

FIGURE 7. **Comparison of travel time by UAVs in the suggested method and the greedy method with $\tau = 90$. (a) $\alpha = 0.8$. (b) $\beta = 0.8$. (c) $\gamma = 0.8$.**

km, which is much lower than that of the greedy method (99 km), since the greedy method randomly selects the cluster heads for starting a movement with a longer travel distance. Although the coefficient of the least movement time of the UAV objective is dominant, Figure 2(c) shows that the total travel distance in the greedy method is more than in the suggested method.

Figure 3 compares the travel distance by UAVs in the proposed method with the greedy method's in a scenario with N = 7, 10, 13, and 15 in $\tau = 70$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$. This network shows the longest travel distance belongs to the greedy method, while the shortest travel distance is by the proposed method. Although the coefficient of the least travel distance by a UAV objective is dominant ($\alpha = 0.8$), Figure 3(a) reports the maximum distance, which is the highest in the greedy method and the lowest in the proposed method. The maximum travel distance grows with an increase in the number of cluster heads. As shown in Figure 3(b), although the coefficient of the least number of UAVs is dominant ($\beta = 0.8$), the total travel length increases when the number of cluster heads rises. The maximum travel distance of the proposed method is shorter than that of the greedy method. In Figure 3(c), while the coefficient of the least UAV movement time is dominant ($\gamma = 0.8$), the total travel distance has the highest value with the greedy method in contrast to the lowest total travel time of the proposed method.

Figure 4 compares the travel distance by UAVs in the proposed method and the greedy method in a scenario with N = 7, 10, 13, and 15 in $\tau = 50$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$. In Figure 4(a), even though the target coefficient is the least energy dominant ($\alpha = 0.8$), the proposed model shows the lowest UAV travel distance while the greedy method has the highest UAV travel distance. As presented in Figure 4(b), while the target coefficient is the minimum number of UAV domains ($\beta = 0.8$), the maximum travel distance in the greedy model rises with an increase in the number of clusters as opposed to the proposed model's lowest distance traveled. In Figure 4, with the scenario of the target's minimum traveled time for UAV dominant ($\gamma = 0.8$), the total travel distance is the highest in the greedy method while it is the lowest in the proposed method.

Figure 5 compares the distance traveled by UAVs in the proposed method and the greedy method by employing a scenario with N = 7, 10, 13, and 15 in $\tau = 50$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$. Although the coefficient of the

TABLE 6. Comparison of the travel distance and time by UAVs in the suggested method and the greedy method with τ = 50, 70, and 90 and N = 7, 10, 13, and 15.

N	τ	α	β	γ	M	m	m_{ch}	m_{trj}	Path Len.	Total Time	Method
7	**50**	0.8	0.1	0.1	3	3	2	1	35	39	Prop. model
		0.1	**0.8**	0.1	3	2	1	1	60	20	Prop. model
		0.1	0.1	**0.8**	3	3	0	2	30	14	Prop. model
		-	-	-	-	3	1	2	64	43	Greedy meth.
	70	**0.8**	0.1	0.1	2	2	0	2	101	59	Prop. model
		0.1	**0.8**	0.1	2	1	0	1	101	54	Prop. model
		0.1	0.1	**0.8**	2	2	0	2	88	47	Prop. model
		-	-	-	-	2	0	2	125	66	Greedy meth.
	90	**0.8**	0.1	0.1	1	1	0	1	131	72	Prop. model
		0.1	**0.8**	0.1	1	1	0	1	131	68	Prop. model
		0.1	0.1	**0.8**	1	1	0	1	114	61	Prop. model
		-	-	-	-	1	0	1	141	77	Greedy meth.
10	**50**	**0.8**	0.1	0.1	6	6	4	2	39	41	Prop. model
		0.1	**0.8**	0.1	6	4	1	3	95	32	Prop. model
		0.1	0.1	**0.8**	6	6	4	2	33	18	Prop. model
		-	-	-	-	6	4	2	84	43	Greedy meth.
	70	**0.8**	0.1	0.1	4	4	1	3	94	43	Prop. model
		0.1	**0.8**	0.1	4	3	0	3	124	60	Prop. model
		0.1	0.1	**0.8**	4	4	1	3	77	35	Prop. model
		-	-	-	-	4	0	4	129	62	Greedy meth.
	90	**0.8**	0.1	0.1	2	2	1	1	103	70	Prop. model
		0.1	**0.8**	0.1	2	1	0	1	174	64	Prop. model
		0.1	0.1	**0.8**	2	2	1	1	108	49	Prop. model
		-	-	-	-	2	0	2	179	87	Greedy meth.
13	**50**	0.8	0.1	0.1	8	8	6	2	46	35	Prop. model
		0.1	**0.8**	0.1	8	6	4	2	48	27	Prop. model
		0.1	0.1	**0.8**	8	8	0	8	39	18	Prop. model
		-	-	-	-	8	2	6	53	40	Greedy meth.
	70	**0.8**	0.1	0.1	6	6	0	6	131	60	Prop. model
		0.1	**0.8**	0.1	6	4	0	3	131	54	Prop. model
		0.1	0.1	**0.8**	6	6	0	6	114	46	Prop. model
		-	-	-	-	2	0	2	163	66	Greedy meth.
	90	**0.8**	0.1	0.1	4	4	2	2	144	78	Prop. model
		0.1	**0.8**	0.1	4	2	1	1	183	68	Prop. model
		0.1	0.1	**0.8**	4	4	0	4	160	61	Prop. model
		-	-	-	-	4	1	3	192	84	Greedy meth.

TABLE 6. ***(Continued.)*** **Comparison of the travel distance and time by UAVs in the suggested method and the greedy method with τ = 50, 70, and 90 and N = 7, 10, 13, and 15.**

15	50	**0.8**	0.1	0.1	9	9	6	3	51	37	Prop. model
		0.1	**0.8**	0.1	9	6	2	4	124	35	Prop. model
		0.1	0.1	**0.8**	9	9	6	3	43	23	Prop. model
		-	-	-	-	9	6	3	109	46	Greedy meth.
	70	**0.8**	0.1	0.1	7	7	2	5	122	57	Prop. model
		0.1	**0.8**	0.1	7	5	1	4	161	53	Prop. model
		0.1	0.1	**0.8**	7	7	2	5	100	46	Prop. model
		-	-	-	-	7	0	7	168	64	Greedy meth.
	90	**0.8**	0.1	0.1	5	5	3	2	134	78	Prop. model
		0.1	**0.8**	0.1	5	3	1	2	147	69	Prop. model
		0.1	0.1	**0.8**	5	5	3	2	140	57	Prop. model
		-	-	-	-	5	2	3	183	81	Greedy meth.

least travel distance by a UAV objective is dominant ($\alpha = 0.8$), the total UAV travel time lengthens when the number of cluster heads increases. The total UAV travel time is the greatest in the greedy method and the lowest in the proposed method. As shown in Figure 5(b), although the coefficient of the least number of UAVs is dominant ($\beta = 0.8$), the total travel time is longer in the greedy method when compared to the proposed method and the total UAV travel time lengthens when the number of cluster heads increases. As shown in Figure 5(c), while the coefficient of the least UAV movement time is dominant ($\gamma = 0.8$), the total travel distance decreases when the number of cluster heads is higher. For most traveled times, this framework achieves a higher level in the proposed method in comparison to the greedy method.

In a scenario with N = 7, 10, 13, and 15 in $\tau = 70$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$, Figure 6 compares the UAV travel time of the proposed method with that of the greedy method. As shown in Figure 6(a), although the coefficient of the least energy objective is dominant ($\alpha = 0.8$), the total UAV travel time increases as the number of cluster heads rise. Moreover, while the coefficient of the least number of UAVs is dominant ($\beta = 0.8$), Figure 6(b) shows that the total travel time is longer in the greedy method when compared to the suggested method. In addition, the total UAV travel time lengthens when the number of cluster heads increases. In Figure 6(c), while the coefficient of the least UAV travel time is dominant ($\gamma = 0.8$), the total travel time increases when the number of cluster heads rises. The greedy method has a longer total travel time than that of the proposed method.

Figure 7 compares the time traveled by UAVs in the proposed method and the greedy method in a scenario with N = 7, 10, 13, 15 in $\tau = 90$ with $\alpha = 0.8$, $\beta = 0.8$, and $\gamma = 0.8$. Although the coefficient of the least UAV travel distance objective is dominant ($\alpha = 0.8$), Figure 7(a) shows that the proposed method has a lower total travel time than that of the greedy method. Although the coefficient of the least travel distance by UAVs is dominant ($\beta = 0.8$), Figure 7(b) indicates that the greedy method's total UAV travel time grows with an increase in the number of cluster heads. The proposed method provides the lowest total travel time. In Figure 7(c), while the coefficient of the least UAV travel time is dominant ($\gamma = 0.8$), the total travel time of the proposed method is shorter than that of the greedy method.

Table 6 presents the effect of selecting parameters α, β, and γ on the proposed model on three different deadline scenarios (τ = 50, 70, and 90) and with different numbers of cluster heads (N = 7, 10, 13, and 15).

VIII. CONCLUSIONS

The current paper presents a new framework to increase efficiency in data collection with a deadline in a WSN and multiple UAVs. To minimize the total travel distance, UAV travel time, and network energy consumption, the network is first divided into a set of clusters. Each of the clusters has a head and their centers are considered as a place for UAVs. Then, the initial and final virtual nodes are considered for controlling the minimum number of UAVs. Next, the present work attempts to complete the suggested solution and achieve the least UAV movement time required for collecting data. This problem is formulated as a MILP model, normalized, and then some weighing coefficients are added to find the optimal UAV routes in regard to energy constraints and the deadline related to the basic application's critical level.

The simulation was done in different scenarios to compare the performance of the MILP method with the greedy method. Results show that the suggested framework can provide efficient data collection while meeting the limitations of energy and deadlines, which are dependent on the critical level of application.

Three interesting directions are recommended for future research. The first recommendation is applying the distributed algorithm to achieve an optimal route planning for UAVs based on cluster heads. The second direction is extending the suggested framework for supporting mobile WSN. The third area is employing the suggested framework to support real-time applications.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this article.

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