

Performance Analysis On Uav Assisted Data Collection In Wsn

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ABSTRACT

Wireless Sensor Network (WSN) has no communications in huge number of wireless sensors which observe the abiotic or biotic conditions. Data collection is a basic problem in WSNs. During the data collection, the in SN is fed into sensed data from each sensor node and the base station (BS). The Unmanned Aerial Vehicle (UAV) collect the sensed data is transmitting to the BS. In WSNs, the aim of data collection is to gather the different number of data to improves the flexibility and reduce the data loss due to few amount of memory capacity of sensor nodes. The several researchers introduced to diverse data collection technique for gathering data. But, the WSN using UAV aids to data collection method overcome many obstacles because of energy boundaries and sensors. The current research provides comprehensive overview of data collection methods in WSN. Therefore, classification and optimization methods are used for performing resource efficient data collection in WSN with higher accuracy and minimum energy consumption.

Keywords: Wireless sensor network, environmental conditions, data collection, data loss, classification and optimization

Introduction

1. BACKGROUND

WSNs have gained to significant research momentum due to their versatile integration into different sectors such as healthcare, smart farming, and industrial automation. WSNs facilitate the transfer of detected data to centralized processing centers while minimizing power consumption to extend the overall duration of the network.

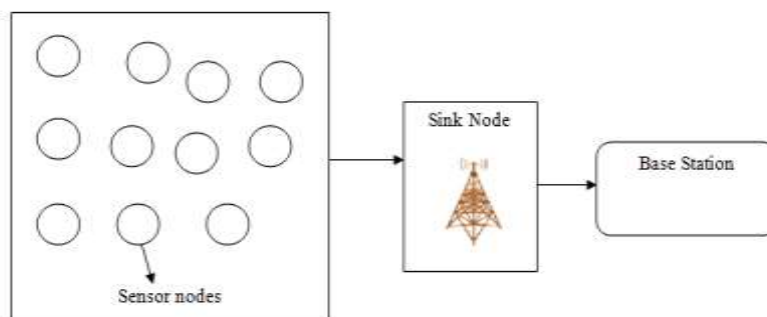


Figure 1 Structure of Wireless Sensor Network

In recent times, UAVs have involved big attention of examiner during wireless communication. It emerged as an effective remedy for extending connectivity to isolated and rural territories, either by operating as mobile BS or by facilitating data migration to remote cloud infrastructures. While WSNs often struggle to meet real-time requirements during data offloading, UAVs overcome these latency issues by utilizing

high-bandwidth communication technologies, such as millimeter-wave (mmWave) transmissions.

- To collect the sensed data from sensor nodes (SN) with UAV assistance at different locations with minimum time and higher accuracy
- To discuss different data collection methods for minimizing the energy consumption and error rate
- To compare the conventional data collection approach performance for attaining better results.

2. LITERATURE REVIEW

In [1], the method of energy-efficient multi-UAV data collection designed for WSNs. But, optimizing the UAV's flight speed and hovering locations remains an unaddressed challenge for future exploration. In [2], the RDCL charging UAV approach was introduced to address the complexities of gathering data. But, energy consumption was not taken into consideration by RDCL algorithm. An Energy Efficient (EE) deployment was carried out in [3] for Mobile Wireless Sensor Networks (MWSNs). A novel technique of multi-objective clustering was introduced in [4] to combine the sensor nodes. In [5], a data collection method was designed. In WSN, a DL based GMA was proposed in [6] to reduce power consumption. An efficient search method was introduced in [7] to search for optimal energy threshold. The UAVs enabled edge computing scheme was employed with [8] to form edge computing nodes. The GSDRL approach was investigated in [9] and to reduce the data packet loss using Deep deterministic policy gradient based maneuver control method described in [10]. An iterative algorithm was introduced in [11]. A new UAV-assisted IoT system was introduced in [12]. A hierarchical data collection scheme was introduced in [14] with UAV-aided industrial WSNs. In [15], a process of bi-level hybridization-based metaheuristic algorithm was designed to addressing data collection problem. An efficient routing protocol was introduced in [16] for UAV-WSN data collection. A singular unmanned aerial vehicle (UAV) was used in [17]. A UAV-assisted data gathering multi-objective optimization (UAVDGM0) was introduced in [18] to increase the data volume. A hybrid MAC was investigated in [19] to data gathering in UAV-WSN. IoT-UAVs design was introduced in [20]. In [21], a novel UAV-assisted data collection scheme was introduced. To achieve streamlined data collection, a buffer-aware dynamic UAV trajectory framework that considers buffer constraints was introduced within the study presented in [22]. In [23], NOMA-enabled UAV-assisted data collection method was designed with improved WSN performance like location, sensor grouping and power control. To address the dual challenges of node localization and information gathering, an efficient joint data collection and sensor positioning scheme was formulated in [24]. In [25], a Joint user scheduling and trajectory planning data collection is designed with minimum data loss by addressing non-convex optimization problem. The structure of blockchain-enhanced data collection with UAV-assisted WSNs using improved data security designed in [26]. An energy-saving architecture for data acquisition, facilitated by Unmanned Aerial Vehicles (UAVs), was detailed in [27]. In [28], the Gathering data Assisted by Multi-UAV with BALanced Clustering method was proposed to optimize information harvesting through coordinated aerial nodes. An efficient UAV-assisted data collection algorithm was introduced in [29] for reducing the power consumption in WSN. UAV Fuzzy Travel Path was introduced in [30] to perform efficient smooth path design.

3. DATASET DESCRIPTION

At first, the proposed method using All Natural Disasters 1900-2021 / EOSDIS dataset is taken from <https://www.kaggle.com/datasets/brsdincer/all-natural-disasters-19002021-eosdis>. It involves climate change project / csv data. The global climate disaster creates their impact more felt day by day. The parameter recognition created by climate crisis is helpful in deciding the measures taken against it. The dataset comprised 45 features and 16126 instances. After that, we utilize the second dataset of Natural Disasters in India (1990 - 2021) dataset is taken as

<https://www.kaggle.com/datasets/vaibhavrmanekar/natural-disasters-in-india-1990-2021>. The dataset comprised Natural disasters that occurred in Indian subcontinent from 1990 to 2021. The geography of India is extremely different from the snowy mountains in North to Coastal Plains in the South. The dataset comprised the dense rain forests and Thar Desert. In worldwide, the India is second most populated country (1.3 billion people). The diversity brings different natural disasters from floods, earthquakes to hurricanes and cyclones. Different diseases spread quickly because of dense population. The dataset is collected from the Wikipedia. The text is extracted from the Wikipedia articles and then the text is cleaned, processed, and sorted according to the date. The dataset includes six features and 216 instances. The dataset comprised the features:

- Title: Title of the disaster
- Duration: It includes the day and month with intervals for disasters that lasted more than day
- Year: Year of disaster
- Disaster_Info: Information about disaster
- Date: Date in particular format
- More specific information is extracted from text with natural language processing methods.

The last dataset of global air pollution dataset is available on

<https://www.kaggle.com/datasets/hasibalmuzdadid/global-air-pollution-dataset>.

urban centers worldwide are monitored for various Air Quality Index (AQI) parameters. The air pollution represents the degradation of atmospheric integrity through physical, biological, or chemical contaminants. Primary contributors to this environmental crisis include industrial emissions, vehicular exhaust, domestic heating systems, and wildfires. Specifically, substances such as ozone, nitrogen dioxide, sulfur dioxide, carbon monoxide, and particulate matter pose the most significant risks to public health, frequently leading to chronic respiratory conditions in both indoor and outdoor setting. The air pollution is an essential one for providing morbidity and mortality. Dataset provides geo-located information about pollutants:

S. No	Attributes	Description
1.	Country	Name of country
2.	City	Name of the city
3.	AQI Value	AQI value of the city
4.	AQI Category	AQI category of city
5.	CO AQI Value	AQI value of carbon monoxide of city
6.	CO AQI Category	AQI category of carbon monoxide of the city
7.	Ozone AQI Value	AQI value of Ozone of city
8.	Ozone AQI Category	AQI category of Ozone of city
9.	NO2 AQI Value	AQI value of Nitrogen Dioxide of city
10.	NO2 AQI Category	AQI category of Nitrogen Dioxide of city

11.	PM2.5 AQI Value	AQI value of Particulate Matter with diameter of 2.5 micrometers or less of city
12.	PM2.5 AQI Category	AQI category of Particulate Matter with diameter of 2.5 micrometers or less of city

4. UAV-ASSISTED EFFICIENT DATA COLLECTION IN WSNS

UAV is determined as flying base station to give dependable forward and reverse link for sensors during freely unreliable their location and aerial posture depending on ground node deployment. In order to, collect the large amount of data over wide area in WSNs and it has limited longevity in sensor nodes. In WSNs, the data collection process classified by mobile sensor nodes, static sink approach and mobility based approach. The Mobility based approach is split into two sets is namely,

- Data Acquisition or Data collection using single mobile sink
- Data Acquisition using multiple mobile agents

In Data Acquisition, the multiple mobile agents are utilized to collect the data points. The mobility patterns are also constrained or random. The diagram of data collection process in WSN illustrated in below figure 2.

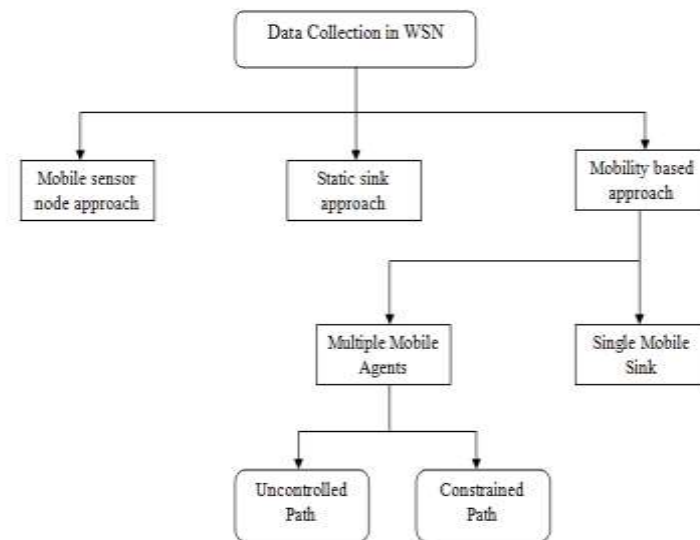


Figure 2 Data Collection Methods in WSN

In isolated environments, WSNs frequently encounter difficulties in transmitting aggregated data to centralized hubs due to insufficient network infrastructure. The UAVs are improving the network infrastructure to remote WSN by communicating with aggregator nodes to gather the data. It aids to data collection systems, the collected data efficiently improved by considering the UAV and WSN constraints.

4.1 Energy Optimization and Trajectory Planning

During WSNs, energy-efficient multi-UAV data collection method utilized with both optimized system cost and power consumption by less communication power, UAV mission time, and memory size. The position and several aggregators are utilized by triangulation-based K-means clustering with minimum number of aggregators usage and system cost. The gaining-sharing knowledge (GSK) optimization algorithm utilized by dock station position with less energy consumption. The optimum UAV trajectory for

every GSK applicant resolution is achieved by addressing the capacitated vehicle routing problem (CVRP) with heuristic and meta-heuristic methods.

4.2 Trajectory Optimization for UAV

UAV is determined in wireless aerial mobile BS for collecting data from the nodes. It is significant one for seamless services and improving the performance of data collection in future wireless networks. Inherent battery limitations essentially restrict the energy availability for UAV missions, necessitating efficient resource management. But, it failed to perform the data collection tasks for each sensor without energy replacement. The Real-time Data Collection with Laser (RDCL) -charging UAV challenges is highlight to collect the data from WSN. The major constraint of UAV is to gather the sensor data from WSN and sent to BS in outcome of flight trajectory of UAV. To guarantee time-critical network responsiveness, it provides a solution to underlying NP-hard complexities. In UAV, the Trajectory Optimization of Data Collection (TODC) and Charging Trajectory Optimization issue are resolved to classify the optimal flight plans correspondingly. In order to approximation algorithm, determined with constant factor.

4.3 Mobile Wireless Sensor Network (MWSNs) using Optimized UAV-based data collection

Energy Efficient (EE) consumption is a significant one for MWSNs. It includes the multiple clusters of sensor nodes, one mobile sink and UAV. The UAV is utilized to wirelessly aggregate data from mobile sinks, subsequently relaying the collected data to IoT-enabled user devices. EE deployment model using optimization carried with less energy consumption and network lifetime improvement. The utilization of exact MWSN is mesh topology with different sensors. The several static nodes and mobile sink node proceed with cluster restrictions to collect the sensed data from nearby static nodes. To verify each mobile sink, the remaining power of another sensor node and charge every time requisite. The use of EE model achieved to enhanced packet delivery ratio and network lifetime.

4.4 Multi-Objective Clustering and DL method

Precision agriculture is the developing one to improve the agriculture with minimum waste through advanced technology. Optimizing energy consumption is a critical challenge for the sustainable implementation of smart farming technologies. Due to the energy-intensive nature of precision agriculture, optimizing power management has become a vital consideration for the successful deployment of smart farming systems. A novel multi-objective clustering method is designed for combine the sensor nodes of WSNs. By integrating the Aquila Optimizer (AO) with the Election based Optimization Algorithm (EBOA), a novel hybrid optimization technique termed EAO is formulated to address multi-objective clustering. The designed approach performed with CH selection process to distinguish the best CH and this method utilized to optimization technique with CNN with improved clustering precision, training and testing accuracy. It achieves enhance the classification accuracy, throughput, and packet delivery ratio and network lifetime in crop recommendation.

4.5 Adaptive Data Collection

To prevent the emergence of hotspots and enhance network connectivity, this study introduces a clustering methodology that dynamically regulates data transmission speeds within the WSN. UAV traversed along specified Trajectory and offload the energy to sensor nodes by WPT. To optimize network structure, the quantity of cluster heads is derived from the nodal distribution at each hop level, facilitating peak information

transfer within existing power constraints. The few amount of data to reduce the relay load on middle in sensor nodes. It considered the different transferred data by upstream nodes in hotspot and number of downstream nodes. By traversing a specified sink node; the mobile sink aggregates data from cluster heads and facilitates wireless energy transfer to bolster their remaining power reserves. The amount of energy is utilized by determine the numerous cluster heads. The hotspot nodes are prohibited from lack of energy.

4.6 Deep Learning based Grouping

WSNs are considered for efficient data acquisition and monitoring potential across several applications. The partial sensor nodes resource gives a main issue in improving the network life-time. In WSNs, the deep Learning based Grouping Model Approach (DL-GMA) is designed to enhance the energy utilization. It used RNN with LSTM provide develop the energy efficiency by efficient cluster structure, CH selection and maintenance. The designed DL-GMA carried to increased energy optimization and network performance. The designed method improve the WSN life-time and effective data transmission. It progress in energy optimization for overcome the energy resource needs and for increasing data transmission efficiency.

4.7 UAV-assisted data collection with dynamic working modes

As a hub element of IoT model, WSNs facilitate critical data-sensing capabilities across various industrial and commercial domains. The sensor nodes have diverse RE and dynamic working modes are employed by their RE and energy threshold to defend the sensor nodes with minimum RE. The UAV executes data harvesting from a heterogeneous WSN architecture. By implementing an energy threshold beside optimized node operational states, the system minimizes the joint energy expenditure of both WSN and the UAV, while severely adhering to data acquisition rate requirements. To identify the optimal power-level threshold, an enhanced search mechanism is integrated into the system. Cluster head designation is managed via a successive convex approximation algorithm featuring penalty-based constraints. Furthermore, the multi-objective optimization challenges are tackled through an iterative procedure characterized by low computational overhead. The designed approach reduced power consumption of sensor nodes with less RE for WSN.

4.8 Deep Reinforcement Learning (DRL) Approach

The Guided Search Deep Reinforcement Learning (GSDRL) algorithm is formulated to enable UAVs with non-uniform initial placements to successfully execute their information harvesting and transmission missions. The data acquisition process is modeled as a sequential decision-making framework, aimed at minimizing the average Age of Information (AoI) while maximizing node coverage within dynamic environments. By leveraging the GSDRL algorithm, the UAV attains the autonomous navigation and intelligent decision-making capabilities necessary to execute complex missions with high efficiency. Furthermore, the inherent robustness of the GSDRL scheme ensures strong adaptability to adverse conditions, providing an optimal strategy for both information harvesting and data relaying

5. EXPERIMENTAL SETUP AND PERFORMANCE METRICS

The experimental analysis of existing methods is carried out using four different parameters, namely energy consumption, processing time, error rate, data collection accuracy. The processing time refers to the time consumed for collecting the disaster data points in WSN. Processing time ' P_{time} ' is computed by product of number of data

points ' D_i ' and the actual time consumed for collecting one disaster data point. It is computed in milliseconds (ms). The error rate ' ER ' is the numbers of disaster data are inaccurately collected ' DD_{NPA} ' to total number of data points ' D_i '. It is measured in percentage (%). Energy consumption is product of number of sensor nodes utilized for data collection and energy consumed by one sensor node and it is calculated in Joules (J). The data collection accuracy is ratio of number of data points which are accurately collected ' DD_{AC} ' to total number of data points. It is measured in percentage (%). The formulation of the performance parameters are given in table 1.

Table 1 Performance Metrics

P_{time}	$\sum_{i=1}^m DD_i * Time \text{ (collecting one disaster data)}$
ER	$\sum_{i=1}^m \frac{DD_{NPA}}{D_i}$
DC_{acc}	$\sum_{i=1}^m \frac{DD_{AP}}{D_i}$
E_{consum}	$\sum_{j=1}^n SN_j * Energy \text{ consumed by one SN}$

6. RESULT AND DISCUSSION

The result depending on UAV-assisted in WSN based on data collection from different sensor nodes. Performance evaluation metrics are used to calculate the effectiveness and performance of data collection. The performance of existing methods is discussed with graphs.

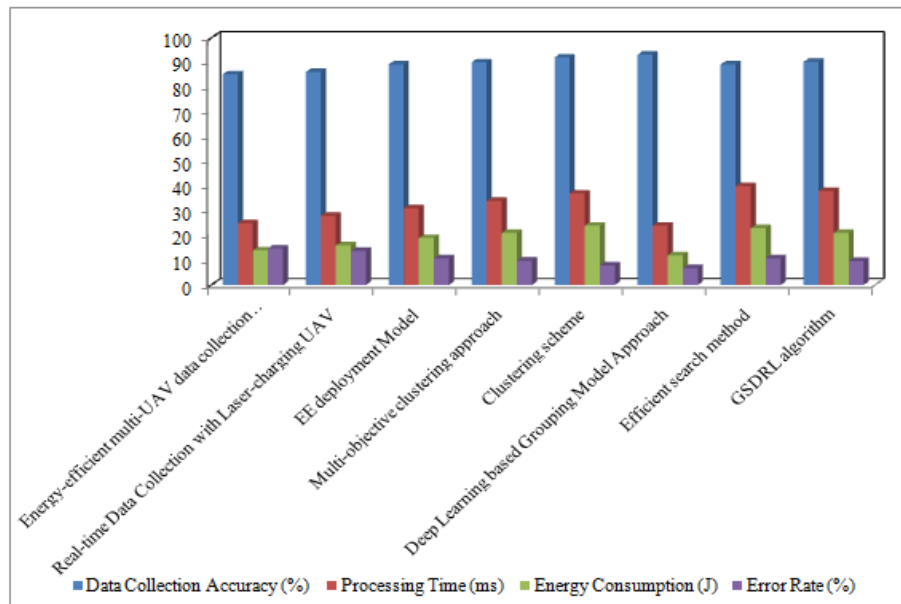


Figure 3 Measurement of Data Collection Accuracy, Processing Time, Energy Consumption and Error Rate for All Natural Disasters 1900-2021 / EOSDIS Dataset

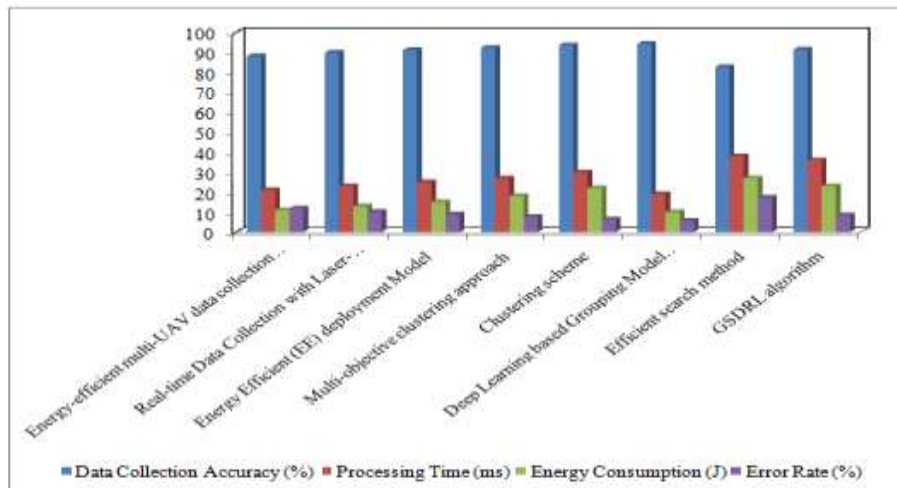


Figure 4 Measurement of Data Collection Accuracy, Processing Time, Energy Consumption and Error Rate for Natural Disasters in India (1990 - 2021)

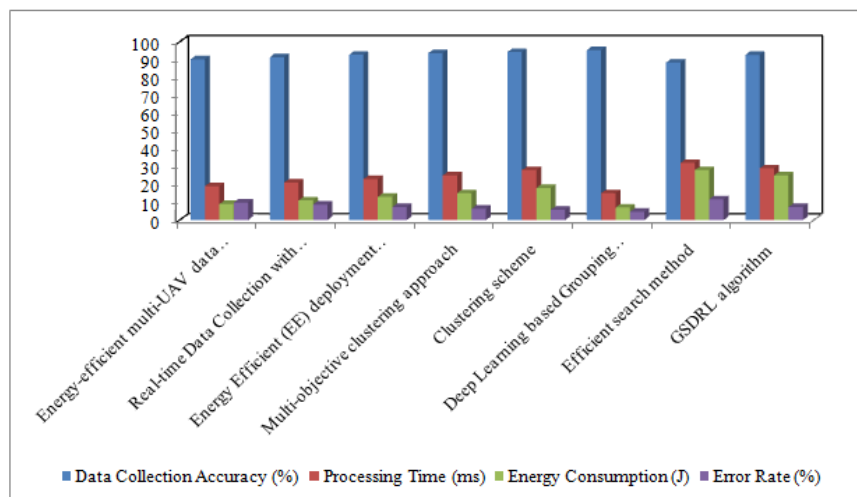


Figure 5 Measurement of Data Collection Accuracy, Processing Time, Energy Consumption and Error Rate for Global Air Pollution Dataset

The performance metric comparison of eight different existing methods for three different datasets described in above Figure 3, figure 4 and figure 5. From the graphical analysis, it clear that performance of DL based grouping model approach is better than any different techniques for three datasets. This is because of the application of RNN with LSTM to enhance the energy efficiency. It performed by cluster formation, CH selection, and maintenance. DL-GMA carried out efficient energy optimization and improved network performance and develops the WSN life-time and data transmission efficiency. For All Natural Disasters 1900-2021 / EOSDIS Dataset, DL based grouping model approach enhance the data collection accuracy by 5%, processing time by 26%, energy consumption by 37% and error rate by 37% when compared to other conventional techniques. For Natural Disasters in India (1990 - 2021), deep learning based grouping model approach attained data collection accuracy by 5%, processing time by 31%, energy consumption by 41% and error rate by 38% when compared to

other existing methods. For Global Air Pollution Dataset, deep learning based grouping model approach improved data collection accuracy by 4%, processing time by 39%, energy consumption by 52% and error rate by 39% when compared to other state-of-the-art methods.

7. CONCLUSION AND FUTURE WORK

In this study, introduce a UAV-assisted data collection in WSN is performed with disaster and pollution datasets using diverse techniques. Different performance metrics are used to analyze the data collection results with help of sensor nodes. When the outcomes are compared with a different study, data collection with deep learning method has attained improved results. In this approach, DL based grouping model method achieved by better accuracy with data collection in WSN for three different datasets. DL method attains maximum accuracy result than the other different existing methods. In future, these studies robustly recommend DL with AI concepts are designed for efficient data collection in WSN instead of the other conventional methods discussed in existing studies.

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