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PAPER

Optimizing Performance in Wireless Sensor Networks through a Multi-Objective Rendezvous Points Selection Algorithm

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ABSTRACT

Wireless sensor networks (WSNs) play a vital role in modern research and applications due to their potential to gather data from various environments. Because sensor nodes (SNs) within WSNs have limited battery life, those in close proximity to the sink often experience rapid power depletion, leading to the emergence of hotspot issues. To address this, the concept of a mobile sink (MS) has emerged as a potential solution, effectively mitigating power usage in SNs and thereby extending the network's overall lifespan. Furthermore, many sensor-based applications necessitate specific data collection timeframes, underscoring the necessity of effective strategies. Leveraging rendezvous points (RPs) to enhance network efficiency becomes imperative in enabling the MS to efficiently collect data from all SNs within designated time periods. A sophisticated cost function is employed to strategically determine RPs, considering multiple factors that influence the efficacy of each RP. This process culminates in the selection of RPs, optimizing for the longest path with minimal delays. Through the proposed hybrid mobile vehicle (HMV) method, compared against the prevailing MOOVor method, significant enhancements are observed in terms of sensor coverage and reduced hop count within the network.

KEYWORDS

wireless sensor networks (WSNs), hot points, sink, mobile sink (MS), sensors, network, rendezvous points (RPs), MOOVor, hybrid mobile vehicle (HMV)

1 INTRODUCTION

Wireless sensor networks (WSNs) consist of a significant number of field-deployed sensor nodes (SNs). Their diverse applications encompass weather [1, 2, 3], environmental monitoring [4, 5], and health [6]. Typically, they comprise a multitude of wireless devices (SNs) equipped with sensing, computing, and communication

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capabilities. These devices coalesce to form networks responsible for transmitting data to sinks [7, 8, 9, 10].

Given that SNs relay on batteries for power, conserving their energy stands out as one of the most crucial factors for extending the network's lifespan. In multi-hop communication, SNs situated in closest proximity to the sink node function as links between the sink and the rest of the nodes in the WSN [11, 12]. Consequently, the SNs transmitting data become overburdened as other SNs within the network route their data through them. This results in rapid battery power depletion and eventual node failure, leading to the challenge of network splits [13].

Scientists have suggested a potential resolution to this problem by introducing a mobile sink (MS) that moves through the network, gathers data from SNs, and then transmits the collected data to the central sink [14].

Mobile sinks play a crucial role in gathering data from distributed SNs across the network area. Several solutions have been proposed to address the challenge of determining the optimal path for a MS to collect data from SNs and efficiently transmit it back to the sink during its visits. This is necessary due to the inherent impracticality of a MS physically accessing every individual SN. Various approaches, such as random [15] or controlled [16, 17, 18] movement of the MS, have been explored. The unconstrained movement approach, outlined in reference [19], allows unrestricted mobility of the MS throughout the network area, potentially leading to increased data latency delays.

In WSNs, a random path selection algorithm can be employed to guide the MS along its route. Using this approach, the MS traverses the network in a somewhat random manner, making stops at various points to collect data before relaying it to the main sink. This technique not only facilitates exploration of new areas within the network but also ensures a more balanced distribution of energy consumption among the SNs, as it doesn't rely on predefined routes or algorithms. Despite its simplicity and decentralized decision-making, the random path selection method may have drawbacks such as suboptimal routes and increased transmission delays. Therefore, it's crucial to thoroughly consider the specific requirements and objectives of the network, weigh the trade-offs, and explore alternative path selection strategies to optimize data collection and energy efficiency.

A controlled path selection technique in WSNs involves deliberate decision-making to determine the optimal route for the MS as it traverses the network. This strategy takes into account factors such as node energy levels, data transmission requirements, network structure, and broader WSN objectives. By employing various algorithms and methodologies, this approach aims to identify the best path for the MS, considering parameters such as energy conservation, reduced wait times, and enhanced network longevity. Through meticulous route planning, this method seeks to optimize resource utilization, minimize resource depletion, and extend network lifespan. The potential benefits encompass improved data gathering efficiency, enhanced energy utilization, and elevated network performance. By adopting a controlled path selection strategy tailored to specific demands and employing suitable algorithms, WSNs can achieve significant enhancements.

Addressing these challenges necessitates the implementation of efficient algorithms and protocols to optimize network performance. Controlled mobility of the sink (MS) emerges as a strategy to enhance the effectiveness of WSNs. Some researchers propose that the MS can acquire data by visiting each SN in the network, thereby maintaining energy equilibrium among SNs and prolonging the network's lifespan. However, this approach results in longer data paths, leading to increased data delivery latency and decreased network throughput. For applications sensitive to delays, determining a route for the MS becomes intricate.

To addressing this challenge, researchers have proposed the use of rendezvous points (RPs) [20, 21]. These designated locations enable the MS to collect data from SNs via single- or multi-hop communication. However, reducing the number of RPs might result in uneven energy consumption and a shorter network lifespan. When designing the trajectory of the MS, considerations such as the number of RPs and route length are crucial to maintaining equilibrium. The selection of optimal RPs is an intricate problem. This paper aims to determine the most suitable set of RPs from a candidate pool, establishing a route for the MS to collect data within an acceptable time delay through one-hop or multi-hop transmission.

The selection of RPs holds particular significance, as it influences network longevity and minimizes the number of required hops. Random selection could result in excessive hops, causing rapid network demise, or elongated paths causing data arrival delays, both unfavorable outcomes. To address this, a cost function evaluates RP locations based on multiple parameters, aiming to reduce hop counts and the distance between RP locations and SNs. The proposed method aims to extend the sensor network's lifespan while enhancing its overall performance.

The structure of the remaining paper is outlined as follows: In Section 2, a discussion of related work relevant to this paper will be presented. Section 3 will delve into preliminary work and lay down the fundamental assumptions. Section 4 will present the formulation and discussion of the problem, along with a flowchart, pseudo-code for the proposed approach, and explanations of key definitions utilized throughout the paper. Results will be reported, compared, and graphically represented. The concluding remarks can be found in Section 5.

2 LITERATURE REVIEW

Researchers have extensively investigated data gathering techniques in WSNs to enhance network performance, energy efficiency, and data accuracy. These techniques encompass a range of strategies, including single-hop and multi-hop communication, MSs, RPs, clustering, and data aggregation algorithms. The objective of the literature review is to delve into the existing knowledge base, highlight advancements, pinpoint research gaps, and provide insights into the efficacy of diverse data gathering strategies within wireless sensor networks.

Several published papers, such as [26, 27], have introduced the data gathering problem in WSNs. These authors approached the data gathering challenge in MS using two distinct implementations to address energy holes in WSNs. The first method, termed direct collection, involves the MS collecting data directly from all SNs to mitigate hotspot issues. However, data collection can sometimes experience slowdowns due to extended trajectory lengths caused by an excessive number of nodes. The second approach involves using cluster heads (CHs) to gather information from shared cluster nodes. While MS obtains data only from a set of CHs instead of all SNs, it can still address localized hotspots by frequently accessing these CHs. This approach capitalizes on the fact that only a small number of CHs provide data to the mobile sink.

In another study [13], researchers addressed the "hotspot" issue and proposed an approach utilizing MS to alleviate it. Expanding on the RPs concept, they devised an algorithm to create a path for the MS that optimizes both delay and energy efficiency. Their approach involved investigating Voronoi diagram vertices to identify potential candidates for RPs. Subsequently, they applied a cost function to optimize this group of RPs, considering various parameters that influence RP performance. The RPs were chosen based on their ascending order of respective cost functions, and the Traveling salesman problem (TSP) algorithm was utilized to find the most time-efficient route for the MS while adhering to delay constraints. Graphical representations illustrate comparison results across different scenarios, demonstrating the superior performance of their proposed approach compared to existing methods.

In a separate work [22], the authors introduced a RP selection method based on the squirrel search algorithm, known as SSA-RPS. This method aimed to select an optimal set of RPs for reliable data collection. The objective of SSA-RPS was to minimize the MS trajectory as it visited a selected set of optimal RPs, considering non-uniform data generation and the limited buffer capacity of SNs to ensure dependable data acquisition. SSA-RPS utilized an efficient encoding scheme to construct variable-dimension "squirrels," each representing a potential MS trajectory, with the dimensions indicating the number of RPs. Additionally, SSA-RPS incorporated a mechanism for reselecting RPs to maintain a balanced distribution of energy among SNs. Simulation results highlighted that SSA-RPS outperformed existing state-of-the-art methods in terms of dropped packets, data gathering ratio, energy consumption, and network lifetime.

In another study [23], the researchers conducted a thorough analysis of existing data acquisition methods based on RPs. These methods were categorized into two groups, aiming to balance energy consumption and data acquisition time: RP-based methods and RA-based methods. The paper extensively discussed design objectives and performance metrics, as well as the overall advantages and disadvantages associated with each approach.

In a different study [24], the authors introduced a multi-objective whale optimization algorithm (MOWOA) to determine the optimal number of sink nodes within the network. The primary goal of MOWOA was to reduce energy consumption and prolong the lifetime of low-sink wireless sensor networks (LSWSNs). To achieve these objectives, a lifetime fitness function was developed to maximize network longevity and minimize energy usage. Experimental results demonstrated that the proposed MOWOA outperformed four well-known optimization algorithms—the multi-objective grasshopper optimization algorithm, the multi-objective salp swarm algorithm, the multi-objective gray wolf optimization, and the multi-objective particle swarm optimization—by reducing total network power consumption by 26% across various network sizes.

In a different research work [25], the authors introduced a routing protocol for WSNs using the multi-objective cultural algorithm. In this proposed protocol, individual sensors assume the role of cluster centers. The fitness function was designed to maximize quality of service (QoS) objectives for each sensor, with the sensor having the highest fitness value being chosen as the cluster head within each sensor cluster in the study area. This cluster head was responsible for data packet transmission. Compared to previous protocols, the proposed protocol demonstrated lower average energy consumption and an extended lifetime. The protocol's enhanced energy efficiency and prolonged lifetime underscored a balanced energy usage approach and the sustained operation of SNs through precise clustering and the monitoring of essential network parameters.

In another study [26], the authors outlined an energy-conscious routing protocol based on a multi-objective particle swarm optimization approach. This method utilized the fitness function of the particle swarm optimization algorithm to select the optimal cluster head based on QoS requirements, including residual energy, link quality, end-to-end delay, and delivery rate. By effectively balancing these QoS criteria, the proposed strategy achieved reduced energy consumption while extending the network's lifespan.

3 PRELIMINARIES

3.1 Fundamental presuppositions

This paper presents a modified approach for selecting RPs within a mobile system, capable of efficiently and effectively addressing delay constraints within a working environment. The suggested approach considers the following environmental limitations:

- Data collection: As the mobile station (MS) approaches a relay point (RP), it initiates data retrieval by collecting information from SNs within its local vicinity. Each SN within the network possesses a spherical sensing range.
- Random deployment: Sensor nodes are often deployed in an arbitrary manner, often through methods such as aerial deployment. Once in place, these SNs are assumed to remain stationary, with their positions remaining unchanged.
- Centralized system: The centralized system takes charge of determining the route the MS will take to its destination. The proposed approach is employed to compute the path based on the available information.

The proposed method aims to optimize RP selection to effectively accommodate delay constraints within the MS's operational environment. This objective will be achieved by considering the inherent environmental restrictions.

3.2 Definitions and statement of the problem

Below, we provide the terminology and notation necessary for comprehending the suggested algorithms:

Static SNs, referred to as the S set, are fundamental components of the wireless sensor network, deliberately positioned to monitor specific regions. It is assumed that these SNs transmit only one packet per cycle to the MS [27]. The MS traverses the target area with static speed, halting at RPs. At each RP, the MS employs single-hop or multi-hop communications to retrieve sensed data from the SNs.

In a Voronoi diagram, the vertices constitute a set of potential RPs that aid in our selection process. These vertices are subsequently optimized based on criteria such as distance and coverage of SNs.

By formulating the problem and establishing relevant terminologies, we lay the foundation for developing the proposed algorithms aimed at optimizing RP selection within the wireless sensor network.

Data transmission length (DTL): These measures how many SNs data traverses before reaching the MS. Data can be transmitted in a single hop, directly from an

SN to the MS, or in multiple hops, relayed by intermediate nodes. DTL quantifies the distance covered during data transmission.

Center target area (CTA): The MS moves towards SNs to gather data. To ensure efficient and accurate data collection, the MS adheres to a path dictated by the CTA. Determining the CTA's coordinates involves deriving the mean of SN positions within the target area, which can be calculated using Equation (1).

$$CTA_X = \frac{\sum_{i=}^{n}(x_i)}{n}, \quad CTA_Y = \frac{\sum_{i=}^{n}(y_i)}{n} \tag{1}$$

Subscribed edges of the target area (SETA): Sensor nodes are utilized for overseeing the designated objective zone, and their positional information plays a crucial role in specifying the designated area. The borders of this area are outlined by eight specific points, and these points' coordinates are calculated based on the positional data of the SNs. These eight points are symbolized as (max_x,max_y), (max_x,min_y), (max_x/2,Min_y), (max_x/2,max_y), (max_x,Max_y/2), (Min_x,Max/2),(Min_x,Min_y), and (Min_x,Max_y).

Direct communicating sensor nodes (DCSN): A DCSN is an SN that directly communicates with a RP using a single hop.

Optimal route radius (ORR): One of the challenges in delay-aware applications is determining an efficient path for the MS. If the chosen route exceeds the ORR, the total number of hops within the network will increase. This results in higher energy consumption for SNs and reduces the network's lifespan. To address this, a circular path is selected within the target area based on the CTA and the SETA. Calculating the ORR involves determining the farthest edge of the path, which is derived by averaging the distances between the CTA and the midpoint of SETA. Equation (2) provides a mathematical representation of the optimal route radius.

$$ORR = \frac{\sum_{n=1}^{8}\left(\frac{distance(CTA, SETA_n)}{2}\right)}{8} \tag{2}$$

Number of hops (HC): Due to the limitation in the number of selected RPs that do not encompass all sensors, certain sensors necessitate more than one hop to transmit data to the MS. This heightened energy consumption in sensors consequently diminishes the network's lifespan. Hence, the proposed development focuses on augmenting the total count of covered sensors while concurrently minimizing the overall number of hops. This approach aims to enhance network efficiency.

Covered sensor nodes (covered SNs): An SN is deemed "covered" if it can transmit data to the MS within a single hop when the MS halts at any of the rendezvous points.

Maximum tour length permitted (MTLP): For a given maximum allowed delay (MD), Equation (3) can be employed to determine the maximum allowable tour length (MTLP). This calculation utilizes the speed of the mobile sink (SMS).

$$MTLP = MD \times SMS \tag{3}$$

Traveling salesman problem: It is a function of code that accepts a set of coordinates as input and provides the shortest path connecting them as output.

4 PROPOSED ALGORITHM

4.1 Hybrid mobile vehicle method

In this approach, a random method is employed to determine the sensor placements, which are subsequently organized into a set denoted as S. The Voronoi algorithm is then utilized to identify recommended RPs based on the sensor locations. Following this, the MOOVor method is utilized to establish the CTA, which designates the location with the highest sensor concentration, as suggested. Subsequently, the computation of the SETA is undertaken.

Figure 1 illustrates instances where certain sensors are situated at considerable distances, occasionally leading to dispersion in the CTA value during the calculation of the ORR using Equation 2. The presence of these distant sensors is evident. To address this, a refinement is proposed involving the exclusion of the farthest 12% of sensors when computing the CTA equation. This new value is termed MCTA, which then serves as the basis for calculating a new ORR, denoted as MORR.

The optimal set of RPs is determined through the application of a cost function reliant on various factors. The calculation of the longest path within the permissible delay using the TSP is facilitated, resulting in the hybrid MOOVor (HMV) method.

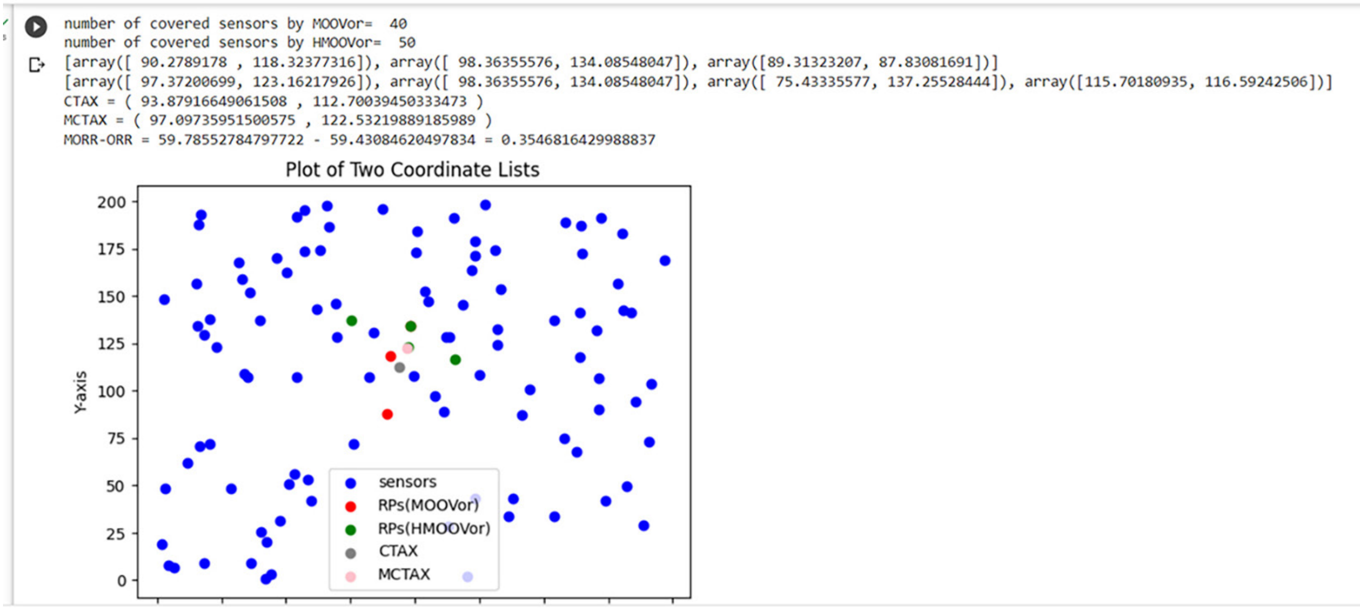

Fig. 1. Sensors, RPs, and CTA coordinates

The cost function for each RP takes into account the following factors:

1. Number of directly communicating sensor nodes (DCSN): The selection of a RP considers several factors, among which is the parameter DCSN. A higher DCSN value indicates a more favorable RP. In other words, a higher number of sensors that can send their data in a single hop contributes to a lower cost for that RP. This relationship between DCSN and cost is inversely proportional, as depicted in Equation (4).

$$\mathrm{Cost}_i \propto \frac{1}{\mathrm{DCSN}_i} \tag{4}$$

2. Distance from optimal route radius ($DORR_i$): In our proposed strategy, the primary aim is to select reference points (RPs) with the least possible number of hops. This approach aims to minimize multi-hop communication, conserve energy, and extend the network's operational lifetime. Consequently, the placement of RPs is thoughtfully strategized to avoid being excessively close to or far from the ORR. Ideally, RPs would be positioned in close proximity to the ORR. To visually demonstrate this concept, the cost function assigns the RP a minimized value when it is situated at the point closest to the ORR. The cost function increases as the distance between the RP point and ORR increases. This concept is captured by Equation (5).

$$\mathrm{Cost}_i \propto \mathrm{DORR}_i \tag{5}$$

3. Number of handled sensor nodes (SNH_i): The optimal selection of RPs entails choosing those with the fewest occurrences of multiple hops. This approach prioritizes RPs with a minimum of multi-hops, ensuring efficient data transfer. Equation (6) illustrates how a RP that can accommodate more sensors within a smaller number of multi-hops results in a lower overall cost.

$$\mathrm{Cost}_i \propto \frac{1}{\mathrm{SNH}_i} \tag{6}$$

4. Average data transmission length (DTL): As the number of hops required to transmit data increases with greater distances between sensors and RPs, higher energy consumption becomes inevitable. Consequently, an increase in the average distance between them results in an inversely proportional impact on the cost. This relationship is captured by Equation (7).

$$\mathrm{Cost}_i \propto \mathrm{AVG}\,(\mathrm{DTL}_i) \tag{7}$$

In order to create a unified cost function, it is necessary to combine all of the parameters mentioned in equations (4), (5), (6), and (7). In addition, since each of these metrics has a unique range, it is necessary to normalize them. When normalizing, the metrics are scaled to a range of 0 to 1. The value is described in a professional manner by Equations (8), (9), (10), and (11).

$$\mathrm{DCSN}'_i = \left(\frac{|\mathrm{DCSN}_i|}{\mathrm{maximum}(|\mathrm{DCSN}|)}\right) \tag{8}$$

$$\mathrm{AVG}'\,(\mathrm{DTL}_i) = \left(\frac{\mathrm{AVG}(\mathrm{DTL}_i)}{\mathrm{maximum}(\mathrm{AVG}(\mathrm{DTL}))}\right) \tag{9}$$

$$\mathrm{DORR}'_i = \left(\frac{\mathrm{DORR}_i}{\mathrm{maximum}(\mathrm{DORR})}\right) \tag{10}$$

$$\mathrm{SNH}'_i = \left(\frac{\mathrm{SNH}_i}{\mathrm{maximum}(\mathrm{SNH})}\right) \tag{11}$$

5. By combining Equations (8), (9), (10), and (11), we obtain Equation (12).

$$\mathrm{Cost}_i \propto \frac{\mathrm{DORR}'_i * \mathrm{AVG}'(\mathrm{DTL}_i)}{\mathrm{SNH}'_i * \mathrm{DCSN}'_i} \tag{12}$$

$$\mathrm{Cost}_i = \mathrm{C}\,\frac{\mathrm{DORR}'_i * \mathrm{AVG}'(\mathrm{DTL}_i)}{\mathrm{SNH}'_i * \mathrm{DCSN}'_i} \tag{13}$$

In Equation (13), "c" is the proportionality constant that has been omitted since the matter at hand is purely comparative, and there is no requirement to calculate the actual value. So, the Equation (14) was obtained.

$$\mathrm{Cost}_i = \frac{\mathrm{DORR}'_i * \mathrm{AVG}'(\mathrm{DTL}_i)}{\mathrm{SNH}'_i * \mathrm{DCSN}'_i} \tag{14}$$

Figure 2 illustrates the flowchart representing this concept. The proposed algorithm is delineated in pseudo-code format within Algorithm 1. It employs a cost function to select RPs aimed at minimizing the path length of the MS. This cost function incorporates several criteria governing the process of RP selection.

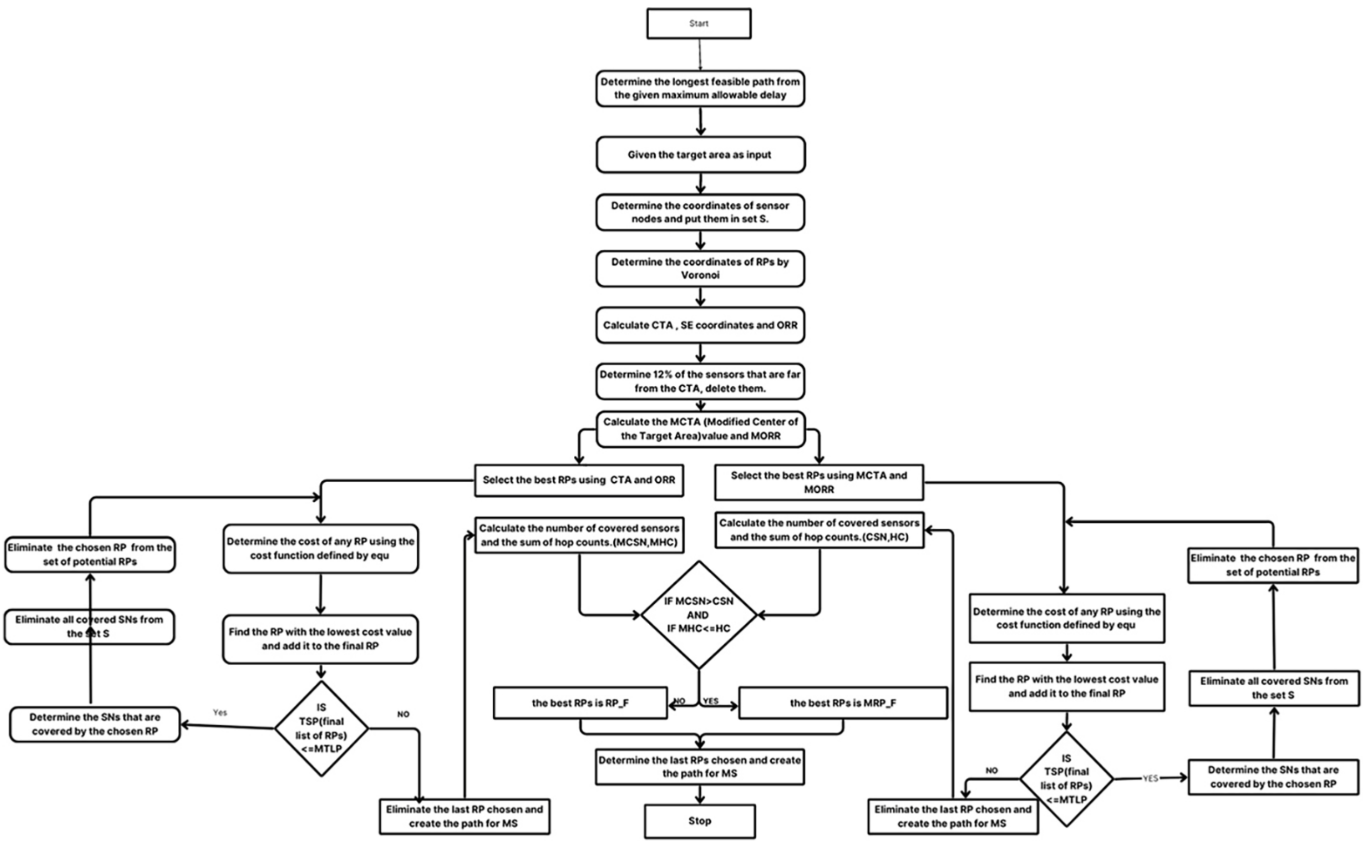

Fig. 2. Proposed flowchart

The algorithm involves defining the target area, determining the number of sensor devices, and placing them randomly within the target region. Next, RPs is determined using the Voronoi algorithm. The calculation of a CTA point involves an equation, which then determines the values of SE and ORR. Afterwards, the sensors that are the furthest 12% of the CTA are identified. A new set of sensors is developed, excluding a specific percentage, and a new central point (MCTA) is computed. The calculation of MORR is then performed. The cost of RPs is calculated using a cost equation that takes into account various factors. These factors include the proximity to MORR, the number of sensors covered by the RP within one hop, and the average distance between sensors and RPs. The cost of RPs is assessed, and the one with the lowest cost is included in the final set of RPs. The calculation determines the time it takes for the MS to travel between these points. If the specified time is shorter than the Maximum Tour Length Permit (MTLP), the algorithm will continue to repeat. If the time exceeds MTLP, the most recent RP is either removed (if it exceeds) or included (if it matches) in the final set of RPs. Therefore, if the total sum of hop counts determines the set of final RPs, these will be regarded as the optimal RPs for this network. Nevertheless, when the overall hop count is increased, the algorithm will take into account the set of final RPs generated by the algorithm without excluding any of the sensors.

The flowchart comprises the following phases:

1. Inputs include the number of sensors, the target area, and the MS constant speed (2 m/s).
2. Equation (3) is utilized to determine the allowable maximum path length.
3. A collection of sensors is formed by randomly selecting sensors within the specified area.
4. The Voronoi algorithm identifies potential RPs, with their coordinates being calculated and saved in the RP set.
5. The CTA value is computed using sensor values in set "s" and Equation (1). SETA is determined by extracting the minimum and maximum x and y values from sensor coordinates and applying the method described earlier. The ORR is determined using the formula in Equation (2).
6. The distance law between two locations determines sensor distances from the CTA. The farthest 12% sensors from CTA are selected, forming a new set "Sc."
7. MCTA is calculated using sensor values in set "Sc" and Equation (1). MORR is determined using the formula in Equation (2).
8. Steps 9 are executed twice: first with parameters (S, RPs, ORR, CTA), and then with parameters (S, RPs, MORR, MCTA).
9. The best set of RPs is determined using parameters (S, RPs, radius, center):
   - The cost of each potential RP is computed using Equation (10).
   - Rendezvous points resulting in the lowest cost are selected.
   - A chosen RP is added to the final set.
   - Path length is computed using the TSP algorithm, checking if latency falls within acceptable limits.
   - If yes, covered sensors are identified and removed from set "S." Selected RP is also removed from RPs, and the process returns to step 1.
   - If no, the specific RP is eliminated from the final set, and the final RPs and radius are returned. Proceed to step 10.
10. Covered sensors are determined by comparing sensor-RP distances to the radius. The total number of hops required for sensors to transmit data to the MS is also computed.
11. Comparison of covered sensors and hops: if MCSN > CSN and MHC ≤ HC, the selected group is MRP_F; otherwise, it's RP_F.
12. The travelling salesman problem is applied to identify the shortest path from the chosen set of rendezvous points.

Algorithm 1: Proposed HMV to select the best RPs

INPUT: *TA, MD, SMS ,n.*
OUTPUT: *RP_F and path for MS*
1: *Using Equation 3, to calculate MTLP using SMS, MD*
2: *S = sensor coordinates that determine randomly by calling calculate_sensor_nodes(n)*
3: *RPs = vor(S) * Calling function to determine Voronoi diagram taking input as S and the returned RPs coordinates as list*
4: *Using Equation 5, to calculate SE using S*
5: *Using Equation 5, to calculate CTA using S*
6: *Using Equation 5, to calculate ORR using S*
C = a copy of the S
7: *Determine 12% of the sensors that are far from the CTA, delete them from C.*
8: *Using Equation 5, to calculate MCTA and MORR using C*
9: *RPs_f = select_RPS(S,RPs,CTA,ORR) * Calling function select_RPS ttat taking input as S,RPs,CTA and ORR, and the returned RPs_F*
10: *MRPs_f = select_RPS(S,RPs,MCTA,MORR) * Calling function select_RPS that taking input as S,RPs,MCTA and MORR, and the returned RPs_F*
11: *Calculate the number of covered sensors and the sum of hop counts (CSNs,HC) using RPs_f and stored CSNs,HC*
12: *Calculate the number of covered sensors and the sum of hop counts (CSNs,HC) using MRPs_f and stored MCSNs,MHC*
13: *If(MCSNs >= CSNs and MHC >= HC)*
14: *RP_F = MRPs_f*
15: *Else RP_F = RPs_f*
16: *Call TSP(RP_F) : To get the final path*

4.2 Simulation setup

The simulation of the proposed and existing approaches was executed using Anaconda (win64) on the Windows 10 platform. This computer is equipped with 16 GB of RAM, a 1.8 GHz processor, and an Intel Core i7-8565U CPU. The simulation results of the proposed algorithm were compared with those of the MOOVor algorithm in the proposed work.

Table 1. Simulation parameters

Parameters	Values
TA	100*100 m^2, 200*200 m^2, 300*300 m^2, 400*400 m^2
Number of SNs in the TA	100–250
MS one Communication range of SNs	R
MS constant speed	2 m/s
Route length constraint	200 meters

The proposed approach was evaluated on a 40,000 m^2 network, and multiple tests were conducted with varying numbers of sensors (100 times for each sensor count). This can be illustrated in Figure 3.

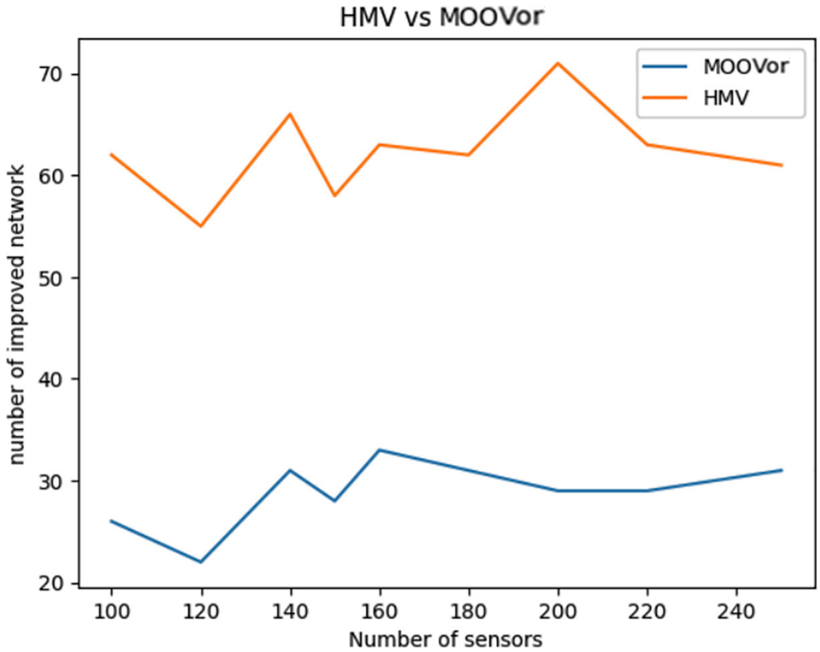

Fig. 3. Comparison of HMV and MOOVor based on the number of sensors

The Table 2 presents the outcomes of an experimental analysis that contrasts two methods, MOOVor and HMV, in relation to the number of sensors employed within a WSN and the resulting enhancement in network performance. The analysis encompasses various scenarios involving different quantities of sensors. Each sensor count is evaluated across 100 networks, highlighting the enhancements observed for each network with respect to the covered sensor count and the number of hops.

Table 2. Relationship between the number of sensors in the WSN and the corresponding enhanced network performance achieved by the MOOVor and HMV methods

Number of Sensors	MOOVor	HMV
100	36	62
120	33	55
140	35	66
150	30	58
160	30	63
180	31	62
200	42	71
220	34	63
250	30	61

The Table 2 illustrates the correlation between the number of sensors within the WSN and the corresponding improvement in network performance achieved by the MOOVor and HMV methods. Each cell in the table signifies the specific performance metric attained for a given number of sensors using the respective method. For instance, with 100 sensors, the HMV approach enhanced the performance of

62 networks, whereas the MOOVor approach improved 36 networks. These improvements were realized through the expansion of covered sensors or the reduction of required hops. Similarly, for 120 sensors, MOOVor and HMV yielded gains of 33 and 55 percentage points, respectively.

The proposed approach was evaluated on a network with one hundred sensors, conducting the experiment across various regions (one thousand trials for each region). The results demonstrated the superiority of the HMV method over MOOVor, as illustrated in Figure 4.

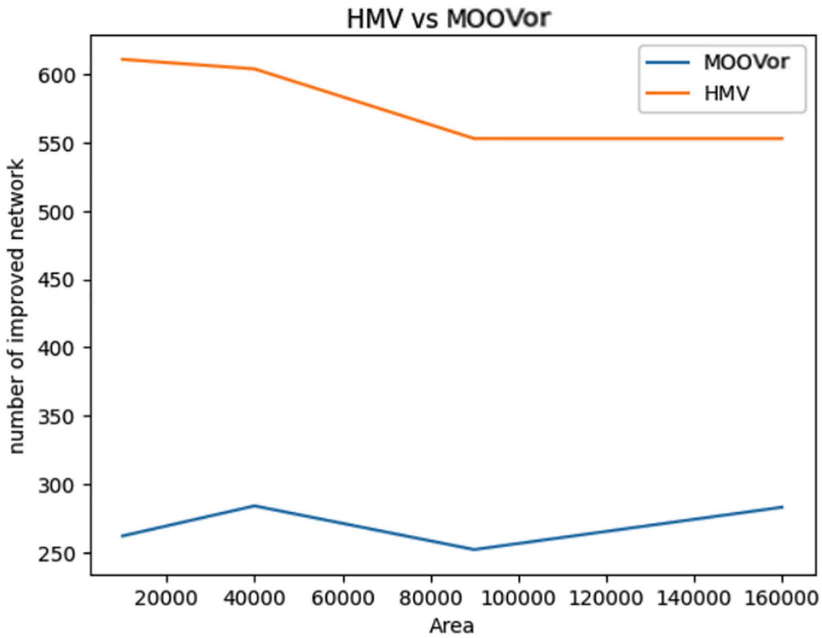

Fig. 4. Comparison of HMV and MOOVor based on area

Table 3. Results of an experimental analysis comparing two methods, MOOVor and HMV

Area	MOOVor	HMV
100*100 m^2	262	611
200*200 m^2	284	604
300*300 m^2	252	553
400*400 m^2	283	553

The Table 3 presents the outcomes of an experimental analysis that contrasts two methods, MOOVor and HMV, in relation to the area utilized within a WSN and the corresponding improvement in network performance. The analysis encompasses various scenarios involving different network areas, each of which is tested across 1000 networks. The observation pertains to the improvements observed in each network concerning the number of covered sensors and the number of hops.

The Table 3 illustrates the correlation between the network area and the corresponding enhancement in network performance achieved by the MOOVor and HMV methods. For instance, with a network area of 100×100 m^2, the MOOVor method enhanced 262 networks, while the HMV method achieved an enhancement of 611. Similarly, for a network area of 200×200 m^2, MOOVor and HMV resulted in enhancements of 284 and 604, respectively.

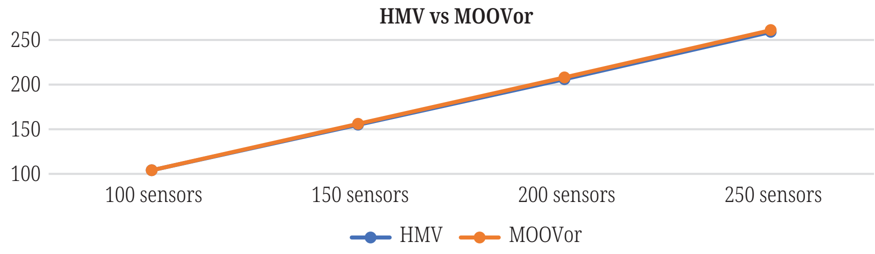

Fig. 5. Hop counts for two algorithms with varying numbers of SNs with area $(100)^2$

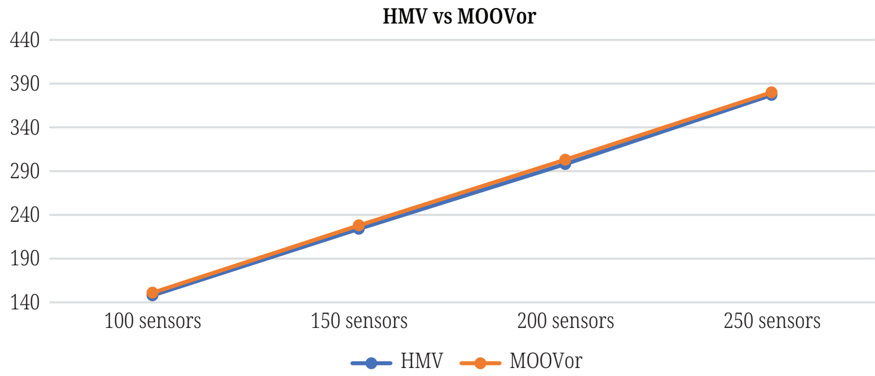

Fig. 6. Hop counts for two algorithms with varying numbers of SNs with area $(200)^2$

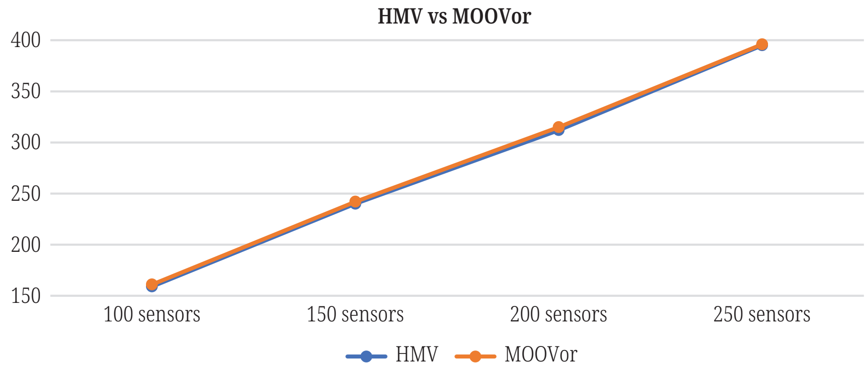

Fig. 7. Hop counts for two algorithms with varying numbers of SNs with area $(300)^2$

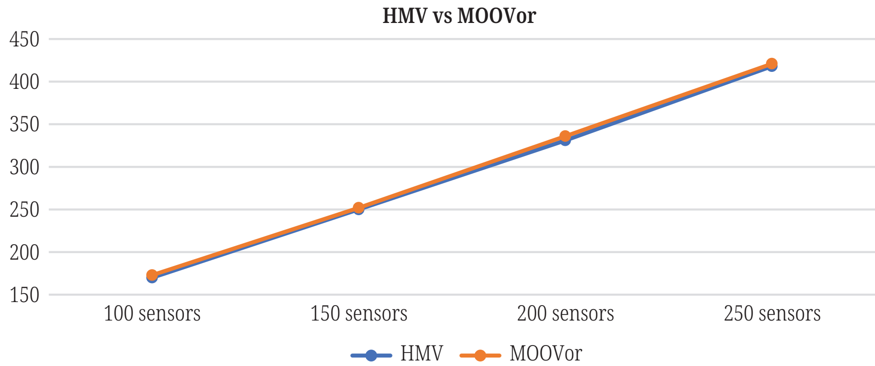

Fig. 8. Hop counts for two algorithms with varying numbers of SNs with area $(400)^2$

According to the findings shown in Figures 5–8, the decreased number of hops is a contributing factor to the enhancement of the performance of the network.

5 CONCLUSION

In conclusion, the intricate interplay between WSNs and the challenges posed by the limited energy resources of SNs has spurred innovative solutions aimed at optimizing network performance. This study has navigated this dynamic landscape by delving into the intricacies of the MS concept, a potent strategy that counteracts energy imbalances among SNs and prolongs the overall network lifespan.

The imperative for time-sensitive data collection in sensor-based applications underscores the importance of strategic RP selection for network efficiency. This research has underscored the paramount significance of leveraging RPs to facilitate effective data aggregation by the MS within predefined temporal constraints. A nuanced cost function, tailored to encompass a spectrum of influential factors, guides the selection of these RPs, ensuring their strategic placement.

The culmination of this systematic approach results in the identification of RPs that optimize for a longer path with minimal latency. The newly proposed hybrid mobile vehicle (HMV) method emerges as a remarkable advancement, rivaling the established MOOVor method. Through meticulous experimentation and evaluation, the HMV method has showcased substantial improvements in terms of both sensor coverage and a reduced hop count within the network.

As the realm of WSNs continues to evolve, this research underscores the pivotal role of dynamic strategies such as the MS concept and RP selection in shaping efficient and robust networks. By addressing energy disparities, temporal constraints, and network coverage, this study contributes valuable insights to the ever-evolving landscape of WSNs, enriching the possibilities for enhanced data collection and network performance.

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