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Employing Grey Wolf Optimizer for Energy Sink Holes Avoidance in WSNs

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Abstract

Many efficient data gathering approaches have been proposed utilizing a mobile sink (MS). MS significantly alleviates the energy holes that result from multi-hop data dissemination near the stationary sink in wireless sensor networks (WSNs). However, most of those approaches design a predetermined MS trajectory that may encounter changes in sensor nodes status during the MS roaming. Thus, this paper proposed two MS methods called fuzzy *A*-star sink mobility (FASM) and grey wolf mobility (GWM). Both methods aim to alleviate the energy holes and data latency by considering the residual energy, sensor density, source sensors angle, and traffic load as guiding parameters for the next potential position. FASM uses a grid model with a fuzzy inference system, while GWM uses the grey wolf optimizer to explore the optimal MS position precisely. Both methods utilize fuzzy*A*-star routing protocol to run all sensors even if they were far from the MS to reduce the buffers overflow and provide a balanced energy consumption during data routing. The effectiveness of the proposed schemes for prolonging the WSNs lifetime is confirmed through strict simulations as they have been compared with two efficient existing protocols which are WRP and DBRkM.

Keywords WSNs · Grey wolf optimizer · Fuzzy inference system · Mobile sink · Routing protocol

1 Introduction

WSNs are large-scale ad hoc networks that consist of tiny, inexpensive, and battery-powered devices which densely distributed in the field for sensing the desired physical properties, aggregating data, and wirelessly transmitting it to a data collector center known as the sink [1–3]. WSNs have widespread applications in different fields such as natural disaster prediction, military monitoring systems, and healthcare [4].

Over the past few years, prolonging the network lifespan has revolutionized the state of the art, since the data throughputs are very low in wireless communication model, and conventionally, thousands of limited battery-powered sensor nodes (SNs) are distributed randomly over dangerous unreachable environments; therefore, it is hard to replace or recharge the dead battery of SNs [5]. In the context of power-saving, the communication distance plays an essential role in the energy consumption issues, where the quantity of energy depleted by the source SN increases super-linearly with the distance between the source SN and the destination [6].

In multi-hop data transmission techniques, SNs collaborate to deliver the packets hop by hop to a stationary sink which forces the SNs near the sink to take charge of transmitting the packets from the entire network to the sink, thus their energy is dissipated more quickly than any other SNs, due to a significant traffic overhead near the sink [7–9]. This problem was called "Energy sink-holes problem" [10], or "bottleneck problem" [1]. Hence, the nearest SNs are to the sink, the more their battery drains out, whereas those situated remote to the sink may preserve more than 90% of their initial energy [11]. As a result of such non-homogeneity in the energy consumption, if those overloaded SNs die, the sink would not be able to collect any data packets, although a tremendous number of away SNs still retain an abundant amount of energy, and will lead to forming a disconnected WSN that suffers from a bad coverage and connectivity [11, 12].

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A remarkable improvement in terms of energy hole avoidance has been attained by using MS due to the position-rotation of SNs to be MS neighbors [9]. Many studies have been conducted to create an MS trajectory for data gathering that takes into account both random [13] and controlled [14] mobility of the MS.

The uncontrollable behavior of MS and buffer overflow of SNs is the main disadvantage of random mobility. Alternatively, in early-proposed controllable mobility methods, MS approaches every SNs to capture their data [15–17]. In a large-scale sensing network, this behavior significantly overflows SNs buffers, hence increasing the data latency caused by the time longevity of MS tour, before returning to any SN at the next collecting tour [18]. However, it is still an effective roaming behavior over small-scale areas with a limited number of SNs [11].

The other controllable behavior of MS trajectory is accurately and optimally selecting a limited number of SNs (or positions), called rendezvous points (RPs) that should be visited by the MS for gathering data. If the RPs were SNs, they take on the mission of receiving the data from their neighbors and transmitting it to the MS once the MS reach their spots, while if they were positions, the MS will target those positions and all nearby SNs deliver their data directly to the MS once it reaches those positions [19, 20].

The RPs-based mobility mitigates the problem of MS path longevity and thereby reduces data delivery latency. However, designing the MS route is a difficult topic, since it affects data transmission, network coverage, and the lifetime of the network [21]. Artlessly, it is preferable to reduce the MS trajectory for rapid data gathering. However, constructing a short trajectory for MS would increase the count of hops in data dissemination which results in more energy consumption [22]. On the other hand, constructing a long MS trajectory would reduce the hop count, but increase the traffic load on SNs (i.e., stacking of the sensing data on the memory of SNs). As a result, while constructing the MS path, attention must be made to ensuring that there is a trade-off between the MS trajectory length and the hop count [23]. Avoiding the energy holes and limiting the data latency are the X factors for designing a good MS path.

Many MS great techniques that adopted a positional RPs, such as in [23], aimed to preselect a collection of RPs to be halting points for MS trajectory that aim to minimize the number of hops in such manner that the potential RP within the range of more number of SNs and less distance to them has the advantage to be selected as a target for MS in the current tour. When MS visits those RPs, the SNs deliver their data directly by the possible minimum number of hops (i.e., one-hop is better). This method has two drawbacks, one is the predetermination of RPs collection, and the other is the high data latency.

Regarding the first drawback, in the context of energy holes avoidance, to conserve more energy, the predetermination of RPs makes the MS not aware of the real energy status at those RPs as all the SNs run constantly during the MS roaming time. As an illustrative example, during the starting of each tour round, the energetic and traffic situation of SNs at the last RPs is not the same as it was when the MS start to target the first RP, or start its computation to build the trajectory. On the other hand, if the RPs-selecting method hardly enforces the MS to explore the RPs that ensure one-hop communication distance between the SNs and the MS, it may lead to high data latency since the SNs of the other RPs have to wait much more time till the arrival of MS to their one-hop away RP.

As a result and contribution, in our paper, we claimed that using an energy-efficient multi-hop transmission technique along with a non-predetermined RPs mobility method would significantly extend the network lifetime and reduce the data latency. Our contribution in this paper was to avoid the energy sink-holes problem through the proposal of two different approaches for sink localization that does not adopt a predetermined trajectory, one is based on a fuzzy inference system called Fuzzy*A*-star Sink Mobility (FASM), and the other is based on the grey wolf optimizer (GWO), and called grey wolf mobility (GWM).

In both approaches, to ensure higher energy conservation, it has been considered that MS should target the energy-rich areas with less traffic load. Furthermore, we also enforced the MS to attract to the position near the SNs that own the scheduling time to turn their radio on and transmit their data which will result in reducing the communication hops between SNs and the MS. On the other hand, for reducing the data latency, All SNs are allowed to send their data to the MS current location using a multi-hop transmission method. In both approaches, we have benefited from the fuzzy*A*-star routing protocol proposed in [24], which executes well in terms of balancing the selection of possible routing paths from the sender SN to the MS.

The first approach partitions the network area into a grid-like shape based on the transmission range of SN (TR) which will assist the MS to make a relocating decision from the current high traffic grid to the best nearby grid based on decision parameters. The second approach adopts a swarm intelligence algorithm, which is GWO, to discover the optimal position inside a specific search space outside the energy hole area as the next target. Primarily, The concealing of energy hole near the sink is a priority for both approaches.

The rest of this paper is organized as follows: A literature review of sink mobility approaches is discussed in Sect. 2. Section 3 presents some preliminaries of the system model that is required to implement the proposed approaches. Section 4 explains the two proposed approaches (i.e., FASM and GWM). Section 5 describes the simulation setup and analyzes the performance results, and finally, the conclusion is highlighted in Sect. 6.

2 Related Work

It was noted practically that utilizing an MS is one of the perfect techniques to extend the WSNs lifetime. Specifically for avoiding the energy holes near the sink [25, 26]. In mobile ad hoc networks, sink mobility management is a key challenge due to the repeated alteration in the topologies of the network communications. As a result, the continuous topological alteration might affect the data transmission efficiency positively or in contrast [27]. Furthermore, a long traveling distance of an MS inevitably raises the data latency leading to attrite the resources of SNs and reducing the performance of real-time applications [28].

Some important challenges should be accurately considered to design an efficient MS approach such as the precise time at which the MS should leave the current position and the selection of the best next position. Hence, designing efficient MS approaches have piqued the curiosity of researchers in recent years.

Basagni et al. [29] proposed one of the earliest MS strategies by providing a mixed-integer linear programming model for constructing an MS trajectory method that extends the WSNs lifetime. They introduced three MS constraints which were the resident time of MS at a sojourn point (SJ), the MS maximum traveling distance from one SJ to another, and the cost of building a new MS trajectory. Then, they developed a distributed localized algorithm, called greedy maximum residual energy (GMRE), for determining the energy-rich position to act as SJs for MS. Motivated therefrom, the authors in [15] described this issue in the context of SNs buffers by addressing the mobile element scheduling problem, thus they proposed an MS path construction technique that aims to gather the data from the overloaded SNs before their buffers overflow, and they discussed this problem as an NP-hard with integer linear programming. However, unlike the typical travel salesman problem, MS may visit the same SN multiple times during the same round. Although the approach is efficient over a small-scale network, it suffers in large-scale networks due to high computations.

Marta and Cardei [30] have made substantial progress by proposing a sink mobility approach based on a hexagons partitioning model. They discussed the MS roaming in two situations, which are when the MS approaches the Hexagon's corners, and when it approaches multiple positions over the hexagon's perimeter. Then, they proposed a distributed localized method to detect the best energy-rich positions for multiple MS. They showed a great improvement in balancing energy consumption among SNs. Nevertheless, this method suffers from complex computation, and economically, employing multiple MSs at each hexagon is very costly. In [31], the authors proposed a clusters-based network with a centralized static sink and MS that moves over a grid system where each grid is embedded with a cluster. Each cluster head computes the distances to the centralized static sink and the regional MS and transmits the data to the nearest sink.

Salarian et al. [11] proposed a heuristic MS trajectory planning called weighted rendezvous planning (WRP) based on RPs. The MS in WRP roams through all RPs within a delay bound, thereby the SNs deliver their data to MS via their nearest RP considering the data packets size and the hop number from the tour. In [23], the authors proposed an MS path planning method called delay bound reduced k-means (DBRkM) which utilizes the k-means algorithm to design an RPs-based trajectory that detects the RPs collection that communicates with their neighboring SNs with one-hop distance.

On the other hand, evolutionary and swarm optimization algorithms also had their crucial rule in solving real-time problems. A. K. Srivastava et al. [32] forwarded the genetic algorithm (GA) to the march of sink mobility. GA designed an MS trajectory by detecting the optimum number of RPs based on three decision variables which were the minimum number of SNs that are tow-hops away from RP, the minimum traveling distance of MS, and traffic load at the RP. The author in [33] improved the artificial bee colony (ABC) with a cumulative factor that speeds up the convergence and improved the global search with a mutation operator. The authors formulated a problem based on the fact that a fewer number of hops between SNs and their RPs mean a low energy consumption in the network, and therefore, the improved ABC showed efficient energy conservation and a great performance in collecting the data in real-time.

Preeth et al. [34] proposed an integrated hybrid model utilizing the adaptive neuro-fuzzy system (ANFS) for cluster-head organization, and the emperor penguin optimizer (EPO) to design an efficient path for MS. EPO aims to discover the minimum number of RPs. They showed a great result; however, using a swarm intelligence algorithm along with the ANFS is computationally complex in large-scale areas. For effective data collection, Gupta et al. [35] designed a protocol for selecting the best set of cluster heads and constructing an optimal MS path for data gathering based on the blade eagle search (BES) and a hybrid system combining the seagull and slap swarm optimizations. BES aims to pick the best collection of nodes to act as CHs; meanwhile, the hybrid optimization takes the responsibility to construct an MS path for collecting the data from the selected CH.

The author in [36] presented a shift toward the implementation of machine learning paradigms by proposing an MS path planning called density-aware and energy-limited path construction algorithm for data collection (DEDC) to improve the network lifespan. DEDC was designed over two stages. First, the network is partitioned into grids to build a primary snake-like trajectory for MS. In the second stage, they used hierarchical clustering to classify each grid in the network into balanced and unbalanced classes, the predetermined MS path is then modified over both classes using a mathematical model. This proposal showed a great enhancement for avoiding the energy sink holes and prolonging the WSNs lifetime.

Several conclusions have been taken from the above review. The MS approach must be compatible with the physical specifications of SNs, roams with a moderate distance, have an acceptable computation, and fit well with various SNs densities. Moreover, the majority of the above works adopted neither a non-predetermined RPs nor combined the parameters of energy, traffic load, sensor density, and distance to the transmitting area.

To alleviate the energy sink holes problem around the sink and reduce the data latency, this paper proposed two integrated energy-efficient WSNs schemes, each comprised of fusing two methods which are an MS method, and a multi-hop routing method. Thus, the combination will result in extending the lifetime of WSNs.

3 System Model

In the proposed approaches, we assumed a homogeneous WSN having SNs that are deployed randomly over a regular size area. Those SNs transmit their data to a single energy-unlimited MS which is aware of its position and roaming in the network to gather the nearby SNs data. Both of the proposed approaches adopted a low-cost multi-hop routing technique to transmit the data from the SNs to the MS which will further help in avoiding uneven energy consumption problems. Furthermore, the following are some key assumptions about the WSN that the system model considers.

1. After the random scattering, every SN remains static in the area and has a unique ID number.
2. Since the WSN is homogeneous, all SNs have the same limited initial energy, communication range, and buffer size and are aware of their location coordinates by using a positioning system.
3. Every two SNs can communicate with each other over a shared radio channel if they were within the communication radius.
4. Each SN can automatically modify the transmission power based on the communication distance to its receiver.
5. Each SN can transmit the buffered data based on a time slot allocating method.
6. The packets that are buffered in SNs can be disseminated to the MS through a multi-hop routing technique.

The proposed approaches use the time-division multiple access (TDMA) system as a MAC protocol due to its effectiveness in terms of saving energy, since it changes the status of the radio transceiver of SN to the sleep mode for a long time. TDMA constructs a scheduling framework based on time slots that is each slot belongs to a specific SN. When the SN time slot is activated, the SN will be able to transmit the data stored at its buffer. In the proposed system, the sink initially broadcasts the time slot of the data collection schedule to each SNs in the geographical area. each slot contains a unique identification number of the related SN, thus the sensed data, which is stored in the node's buffer for further processing, can be forwarded to the next hop only if the time slot of that SN has come.

3.1 Radio Channel Model

SNs deplete energy during sensing, data processing, and communication. In this work, we only focused on the energy depletion that is occurred during communication. As demonstrated in Fig. 1, the power loss of sending k-bits of data by a node turns on the radio electronics along with the power amplifier, whereas the power loss of receiving the k-bits turns on the radio electronics only. This paper adopted the first-order radio model which was proposed by [37], and well simulated by [38]. In the model, the energy is dissipated based on the communication distance (d), which classifies the channel model into two model a "free propagation model" and "multi-path fading model." Therefore, when the communication distance between the transmitter and the receiver is lower than the attenuation threshold (d_0), the transmission model is free propagation, thus the power of transmission is attenuated by d^2 (d^2 power loss). In contrast, if the distance is greater than d_0, the transmission model is a multi-path fading, and the power of transmission is attenuated by d^4 (d^4 power loss). As a result, the energy consumed by the transmitter when sending K-bits of data by an SN is calculated as follows.

$$E_{\mathrm{Tx}}(k, d) = E_{\mathrm{Tx-elec}}(k) + E_{\mathrm{Tx-amp}}(k, d) = \begin{cases} kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{fs}}d^2, \ d < d_0 \\ kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{mp}}d^4, \ d \leq d_0 \end{cases} \quad (1)$$

The energy consumed for receiving a k-bits packet by an SN is calculated by Eq. (2).

$$E_{\mathrm{Rx}}(k) = E_{\mathrm{Rx-elec}}(k) = kE_{\mathrm{elec}} \quad (2)$$

where E_{Tx} and E_{Rx} represent the total amount of energy consumption at the transmitting and receiving circuits, respectively. E_{elec} represent the electronics energy that is dissipated for sending 1-bit of data.E_{elec} depends on some

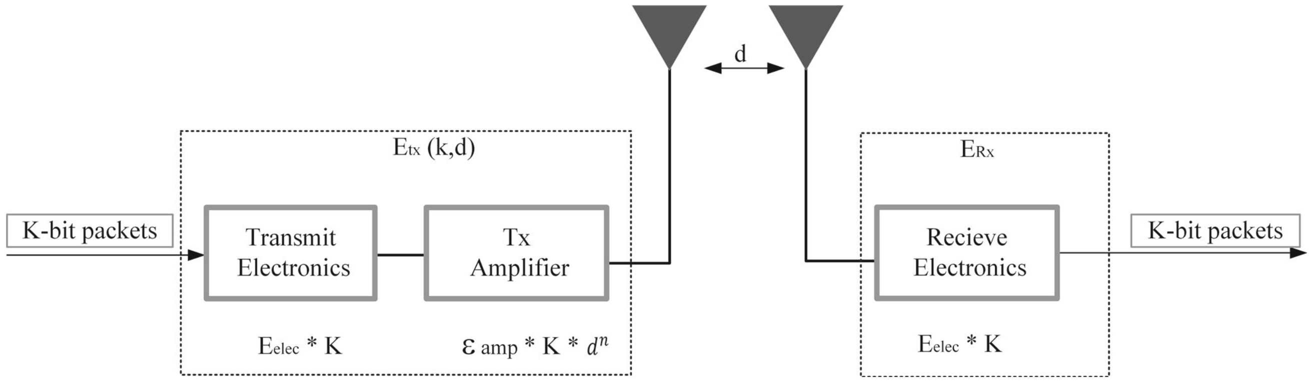


Fig.1 Radio energy model

factors such as modulation, digital coding, filtering, and signal spreading.ε_{fs} and ε_{mp} denoted to the energy dissipated by the amplifier under the free propagation model and the multi-path fading model, respectively, which is selected by the transmitter based on the communication distance. d_0 represent the attenuation threshold which can be calculated using Eq. (3).

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{3}$$

4 Proposed Work

In the proposed methods, new sink localization algorithms based on artificial intelligence are proposed to select the best next position. The first intelligence paradigm is a fuzzy inference system that controls the MS roaming based on a grid model, while the second model employs GWO to explore the optimal MS position. The forthcoming subsections describe the two approaches.

4.1 Fuzzy-Based Sink Mobility Model FASM

After the random deployment of SNs, the MS is placed at any position in the network to collect the data from SNs. In the proposed method, initially, the network area is virtually partitioned into an equal size square-shaped grid system as illustrated in Fig. 2. The MS starts moving and stabilizes at the center of the nearest grid and broadcasts the position coordination along with the scheduling frame to all SNs. In the grid model, determining the distance value of grid side length (l) is essential for circling the energy holes area, therefore Eq. (4) is utilized to calculate l. For better encirclement of energy holes area, the consideration is that l has a relationship with the radius of TR of SNs that is if the TR radius has a low distance value, l should have a higher value than TR.

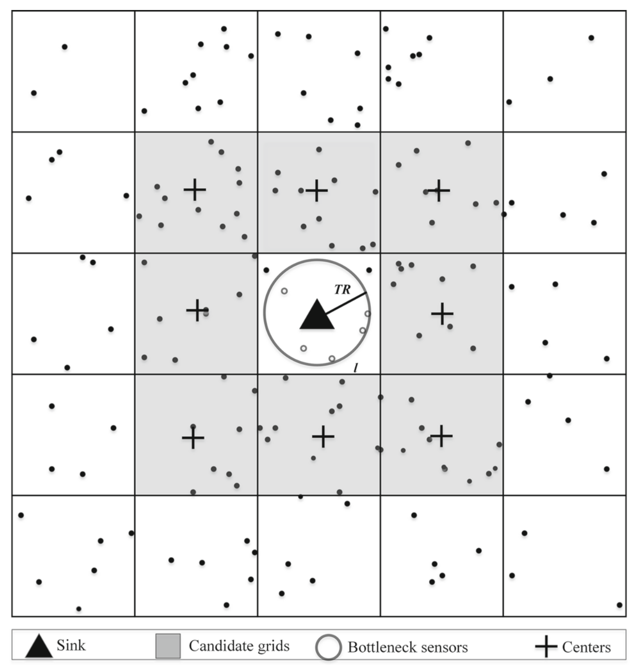


Fig. 2 Network model of FASM

In contrast, the higher TR radius of SNs, the more equal l to TR. As mentioned, the basic goal behind such a grid model is to confine the high overloaded SNs inside the MS grid.

$$l \geq \mathrm{TR} \tag{4}$$

Equation (4) has been formulated based on the center position of MS at any grid. Consequently, the majority of high traffic SNs which suffer rapid energy dissipation exist at the current MS grid within the TR radius. Those SNs are overloaded with traffic loads, energy consumption, and computations. Since MS should move restrictedly over an acceptable distance to alleviate the data latency and severe topological changes, the determination and confining of those

SNs help the MS to roam away from them at the next movement. Moreover, it also provides the MS the ability to evaluate the energy levels at the current grid to decide on the appropriate time to leave the current grid.

After the initialization of the network, the SNs transmit their data to the MS using the fuzzy$A$-star routing protocol, which is proposed in [24]. The data packets are forwarded from the source SNs to the intermediate SNs and reach the MS with balanced energy consumption; furthermore, the continuous energy-efficient data delivery would reduce the data latency. In the fuzzy A-star routing protocol, the fuzzy inference system and $A*$ heuristic are hybridized into a single paradigm to explore the low-cost path from the sender SNs to the MS based on three parameters that represent the status of the neighbors of the sender. The parameters are the remaining energy, traffic loads, and distance from sender to MS. The more energy, the more SN participates as an intermediate node. On the other hand, the traffic load is considered to prevent transmitting the data to the intermediate SNs with overflowed buffers. Lastly, to reduce the end-to-end delay, the minimum number of hops is considered by minimizing the distance between the candidate intermediate SN and the MS. Equation (5) represents the evaluation function of the candidate SNs that should be maximized to detect the best next hop.

$$f(n) = \mathrm{NC}(n) + \left(\frac{1}{\mathrm{MH}(n)}\right) \tag{5}$$

where n is the neighbor of the source node. $\mathrm{NC}(n)$ is the cost value of the candidate neighbor which is calculated by the fuzzy inference system.$\mathrm{MH}(n)$ is the distance from the candidate neighbor to the MS.

In short, the sender SN broadcasts a message to the SNs within a range of TR, and the SNs within the range send their information to the sender SN, which further adds them to an open list. After evaluating the SNs in the open list, the sender SN selects the SN with the best value, adds it to the close list, and removes it from the open list of the$A$-star algorithm. The currently selected intermediate SN performs the same process to the neighbors by adding them to the open list which is already containing the neighbors of the previously selected intermediate SN (or the sender) and selects the best next intermediate node. This process goes on until reaching the final destination which is the MS. After determining the path, the packet will be forwarded throughout this path, (close list path), from the source SN to the MS. Two advantages have benefited from utilizing this multi-hop routing technique. First, determining the area of the overloaded SNs surrounding MS. Second, balancing the energy consumption.

In this proposition, the category of MS method adopts the controllability-based behavior, where the MS can control the path considering a set of parameters belonging to the current and the next potential grids. As previously declared, initially, the MS is situated at the center of a grid. At each transmission round k, the MS evaluates the current grid to gain knowledge about the situation inside that grid. Such an evaluation process is performed considering the average residual energy of the overloaded SNs ($\overline{\mathrm{RE}}_{\mathrm{BTS}}$) inside the current grid. Those SNs are called "bottleneck sensors" (BTS). The BTS that are involved in the evaluations are those who are one-hop away and can communicate directly with the MS. In other words, the distance from BTS to the MS is less than or equal to the radius of TR. Equation (6) states that If $\overline{\mathrm{RE}}_{\mathrm{BTS}}$ exceeds a mobility threshold (τ), the MS should leave the current grid and select another nearby grid to prevent the possible occurrence of energy holes at the current grid.

$$\overline{\mathrm{RE}}_{\mathrm{BTS}_k} \leq \tau \tag{6}$$

$$\tau = \overline{\mathrm{RE}}_{\mathrm{initial(BTS)}} * \alpha \tag{7}$$

where $\overline{\mathrm{RE}}_{\mathrm{BTS}_k}$ is the average residual energy of BTS at a transmission round $k{\cdot}\tau$ represents the mobility threshold which is calculated using Eq. (7). $\overline{\mathrm{RE}}_{\mathrm{initial(BTS)}}$ is the average residual energy of BTS at the beginning of MS arrival to a grid; α is the percentage value that represents the desired energy threshold which defines the time duration of MS residence at a grid.α is inversely proportional to the SNs density at the network. By using Eq. (6), the MS continuously monitors $\overline{\mathrm{RE}}_{\mathrm{BTS}}$ at each round k, if the condition is satisfied, the MS ends the resident time at the current grid and moves toward the best nearby grid using the fuzzy system.

The mobility technique of MS is a very critical approach. As the MS starts roaming over the network, the communication topologies of SNs may be subjected to major disruption and rises the data loss problems. Furthermore, a long MS path significantly extends the data latency in the network. To overcome those issues, the traveling distance of MS will be shortened to either diagonally or parallel to one of the maximum 8 surrounding grids. As illustrated in Fig. 3, MS uses the fuzzy inference system to analyze the information of a maximum 8 surrounding grids. The MS then evaluate the output of each grid and head to the best next target grid.

The fuzzy inference system is a paradigm to solve decision-making problems under incomplete information and uncertainty [39]. Figure 4 illustrates the basic structure of the MS fuzzy system which is built based on Mamdani model. The use of a fuzzy system in the sink mobility is to select the best grid out of a maximum of 8 grids. The fuzzy system receives four input parameters derived from the information at each surrounding grid and outputs one value representing the grid chance SC to be selected as the next target. The fuzzy inputs are described as follows.

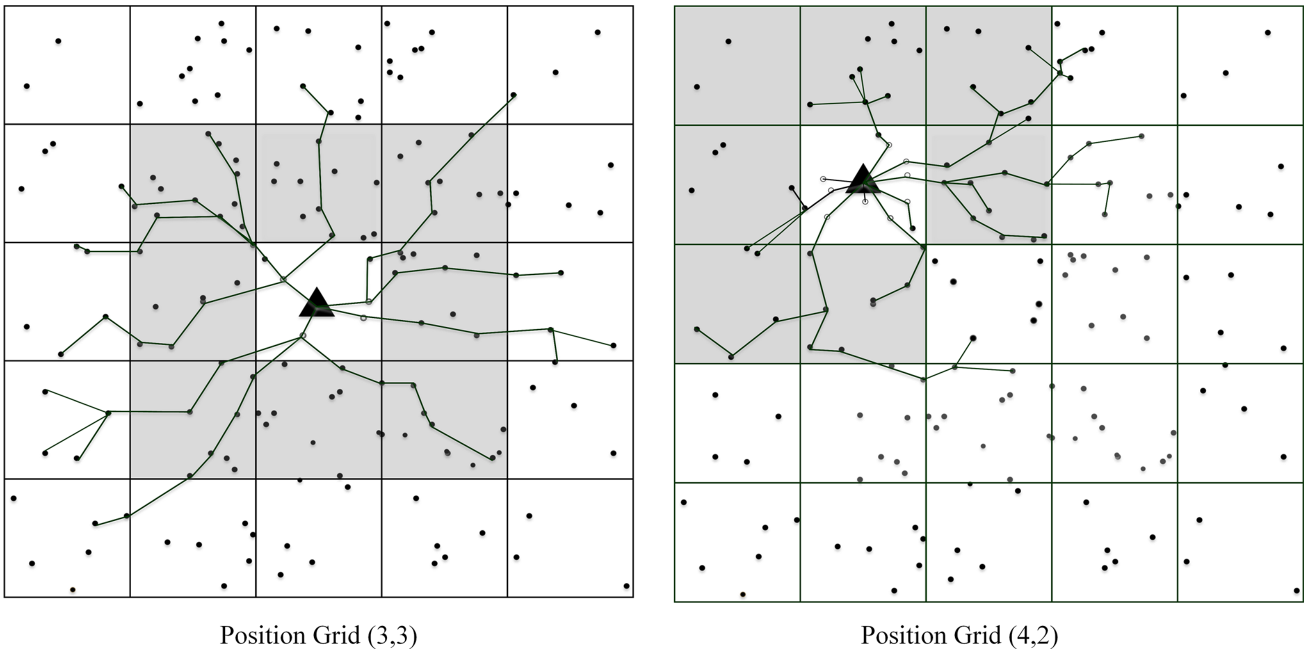


Fig. 3 The moving scheme of FASM

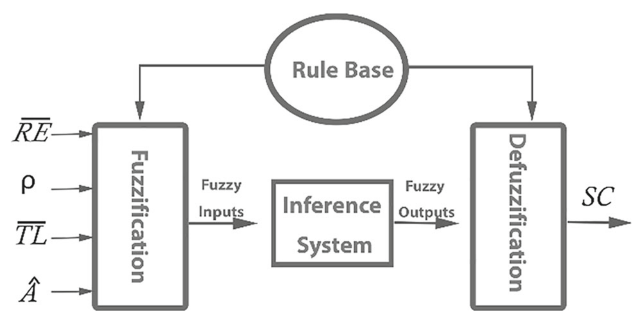


Fig. 4 The structure of the fuzzy system

4.1.1 *Average Residual Energy* ($\overline{\mathbf{RE}}$)

In various strategies of WNs lifetime enhancement, the residual energy of SNs is an essential feature to be considered. Thus, the grid that owns the SNs with the highest average residual energy has the opportunity to be selected as the next target for MS. The rule base system considers this feature with nearly 40% importance.

4.1.2 Sensors Density (ρ)

A grid that owns the highest SNs density has a better chance to host the MS. The density denotes the number of SNs that are located in a grid. A grid area that has more dense SNs is an energy-rich grid; nonetheless, this statement is not always correct because there might be a disparity in the sensing intensity in various regions of the environment. In the environment, there may exist a high-density region that would have a high traffic load which rapidly depletes the SN energy, at the same time, there is a low-density region with a very low traffic load that results in consuming very low energy. The rule base system considers this feature with nearly 20% importance.

4.1.3 Average Traffic Load ($\overline{\mathbf{TL}}$)

The traffic load represents the data processing levels inside the SNs buffers at a specific grid. Therefore, a grid that owns SNs with the lowest traffic load is expected to deplete less energy, since a low number of data packets wait for their turn inside the overall SNs buffers of that grid. The rule base system considers this feature with nearly 20% importance.

4.1.4 Source Nodes Angle ($\widehat{A}$)

Based on the TDMA protocol, the source SNs is a set of nodes located at a specific region in the environment, whose own the time slots of TDMA to forward their packets. As a fuzzy input, it represents the distance between the center of the candidate grid and the center of the source SNs and can be calculated using the Euclidean distance formula. Consequently, the nearer grid to those SNs, the higher chances it has. The goal of utilizing such a feature is to reduce the number of transmission hops to gain an effective data transmission with no data loss and less energy consumption. By using this parameter, the MS would prefer to approach the SNs region that has the transmission time, thus decreasing the number of transmission hops which leads to reducing the

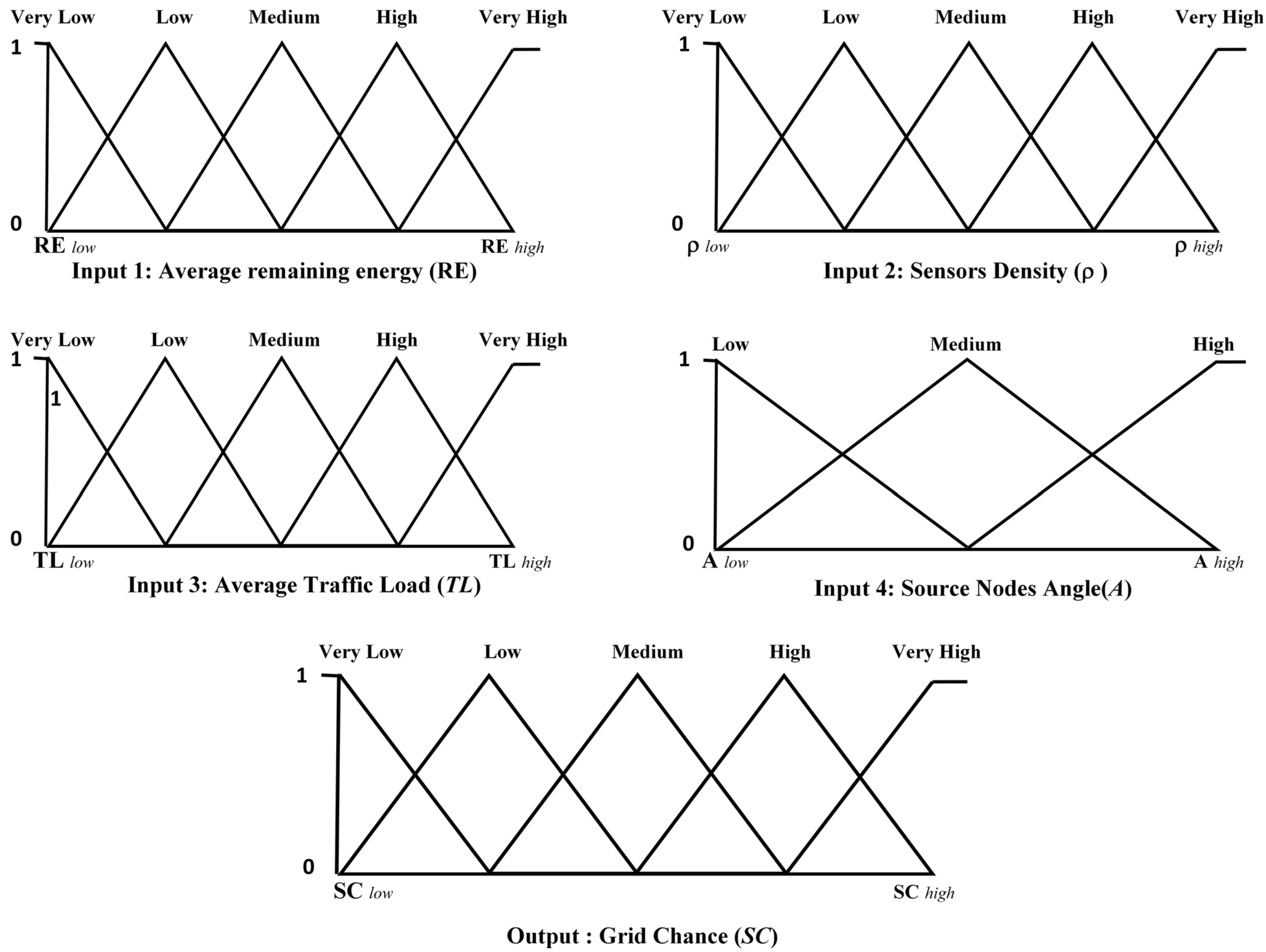


Fig.5 Inputs and output of the fuzzy system

overall energy consumption in the network. The rule base system considers this feature with nearly 20% importance.

By using the If–Then rules, the fuzzy output is mapped with the inputs. The fuzzy rule base set contains a total of 375 If–Then rules to cover all possible implications. The output SC is defuzzified based on the center of gravity formula. The MS head to the center of the grid that owns the highest *SC*. The MS then broadcast the new position to all SNs in the network. Figure 5 shows the membership functions of the inputs and output in the fuzzy system.

4.2 Grey Wolf Mobility Model GWM

GWO is a meta-heuristic algorithm proposed by Mirjalili et al. [40]. GWO is inspired by grey wolves called Canis Lupus. The GWO algorithm impersonates the grey wolves hunting style in nature along with the hierarchy of leadership in their community. Grey wolves have a very rigorous social hierarchy consisting of four categories of wolves which are alpha, beta, delta, and omega. The main rule of high-class alpha wolves is decision-making about sleeping location, hunting, and wake-up time. The beta grey wolves are the second level in the hierarchy which are subordinate wolves that help the alphas in their decision-making by sending commands to the lowest classes. The third class is the delta wolves which contain sentinels, scouts, elders, and hunters. The lowest class is the omegas which keep the disputes out of the herd or be a babysitter.

Encircling the prey is the first behavior of grey wolves through which the prey is encircled by wolves. The following equations mimic such behavior.

$$\overrightarrow{D} = \left| \overrightarrow{C} \cdot \overrightarrow{X_p}(t) - \overrightarrow{X}(t) \right| \tag{8}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) - \overrightarrow{A} \cdot \overrightarrow{D} \tag{9}$$

where t is the current iteration; $\overrightarrow{X_p}$ is the prey's position vector; $\overrightarrow{X}$ represents a grey wolf's position vector. The vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are coefficient vectors that can be calculated using

(10) and (11), respectively.

$$\overrightarrow{A} = 2\overrightarrow{a} \cdot \overrightarrow{r_1} - \overrightarrow{a} \tag{10}$$

$$\overrightarrow{C} = 2 \cdot \overrightarrow{r_2} \tag{11}$$

where r_1, r_2 are random vectors in [0,1]. The components of $\overrightarrow{a}$ are decreased linearly with the iteration courses from 2 to 0. The other behavior is the hunting behavior which is guided by the best three alpha, beta, and delta which have a better sense of the prey's position. Consequently, those best three solutions should be saved and force the entire solutions to update their position based on them. The following equations are used in the matter.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \overrightarrow{X}\right|,$$
$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \overrightarrow{X}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\beta} - \overrightarrow{X}\right| \tag{12}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \cdot \overrightarrow{D_\alpha}, \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \overrightarrow{D_\beta}, \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \cdot \overrightarrow{D_\delta} \tag{13}$$

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{14}$$

Initially, the sink is placed in the topographical area randomly. There are some common steps between this method and the fuzzy sink mobility method. The SNs start to send their data, based on TDMA, to MS using fuzzy*A*-star routing protocol. The SNs that are TR radius away from the sink are considered an overloaded SNs or bottleneck SNs BTS. Besides, the area that contains these SNs is considered as a critical area that might be converted to an energy hole, if the sink remains static.

Moreover, at each transmission round, MS performs an evaluating process inside the critical area based on its average remaining energy. Same as in the fuzzy mobility method, this method uses (6) and (7) to make the movement decision. If the average residual energy of BTS exceeds a specific threshold, the sink will decide to hold the data gathering process and head to another position found by GWO.

For GWM, a set of search agents (solutions) are generated randomly in which each search agent represents a wolf. Each agent is defined as an array of coordinate vectors where each coordinate vector (x, y), which is a real encoding, represents the next potential position of MS. As declared in (15), $\boldsymbol{N}$ of random solutions n with length s is generated outside the critical area in the search space which is the bigger circle that is demonstrated in Fig. 6, The search space can be defined as the area that contains the next potential position, thereby it hosts the search agents and can be considered as the solution boundary. The distance between any two points

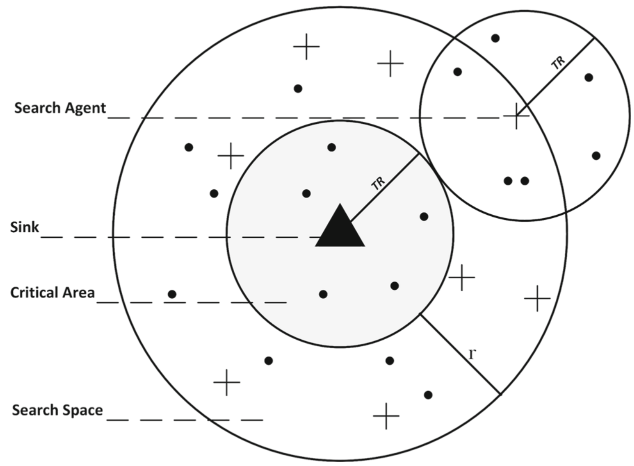


Fig. 6 Search space of GWM

in the perimeter of the search space circle and that of the critical area circle is r. Later on, the search agents continuously update their position to discover the optimal location for MS which will exist inside the search space circle and outside the critical area. Any coordinate vector (x_{ns}, y_{ns}) is associated with related characteristics that belong to that position. The related characteristic can be defined as a set of parameters embedded at a position (x_{ns}, y_{ns}) with the intent to evaluate the fitness of that position using those parameters as will be seen in the forthcoming step.

$$N = \begin{bmatrix} (x_{11}, y_{11}) & (x_{12}, y_{12,}) & \cdots & (x_{1s}, y_{1s}) \\ (x_{21}, y_{21}) & (x_{22}, y_{22,}) & \cdots & (x_{2s}, y_{2s}) \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ (x_{n1}, y_{n1}) & (x_{n2}, y_{n2,}) & \cdots & (x_{ns}, y_{ns}) \end{bmatrix} \tag{15}$$

It is to be noted that in (15), the population can suffice with one potential position in each search agent; however, defining more potential positions in each agent is efficient in terms of strengthening the relationship and communication between search agents by which the next optimal position will be more accurate and more reassuring, especially if the search space has a large area with a large number of SNs.

The fitness function is calculated based on a variety of parameters. It should be emphasized that the more important a parameter has, the more optimized value will be obtained. In the proposed model, the fitness parameters attempt to minimize energy depletion while rendering an extended lifetime to the network. The fitness value describes the suitability of any search agent for owning the optimal next location for MS. Thus, in GWM, each potential position (x, y) in the search space is associated with four parameters that describe the situations around that position within a range of TR. As shown in (16), the parameters that are involved in the fitness calculation are the same as that of the FASM approach which was the average residual energy, sensor nodes density, traffic load, and the distance to the source SNs (or source SNs Angle).

$$(x,\ y) \to \left[\mathrm{RE},\ \rho,\ \mathrm{TL},\ \widehat{A}\right] \tag{16}$$

where RE, TL represent the residual energy and the traffic load of each SN that is located within the search range of the position vector, respectively. ρ is SNs density within the potential position's range. $\widehat{A}$ is the distance between the source SNs and the potential position coordination which is calculated using the Euclidean distance formula. As a result, the fitness function of each search agent is calculated by using the following fitness sub-functions.

$$f_1 = \left(\frac{\sum_{i=1}^{s}(\sum_{j=1}^{\rho} RE)}{\sum_{i=1}^{s} \rho}\right)/s \tag{17}$$

$$f_2 = \left(\sum_{i=1}^{s} \rho\right)/s \tag{18}$$

$$f_3 = \left(\frac{\sum_{i=1}^{s}(\sum_{j=1}^{\rho} TL)}{\sum_{i=1}^{s} \rho}\right)/s \tag{19}$$

$$f_4 = \left(\sum_{i=1}^{s} \widehat{\mathrm{A}}\right)/s \tag{20}$$

where the first sub-function f_1 is for calculating the SNs average residual energy in each potential position (*x, y*) within a range of *TR*, this factor should be maximized to enforce the search agent converge at the energy spots. f_2 is the second sub-function which represents the average of neighbor SNs inside the potential position range. The more SNs in the vicinity of position, the more chance it has to be as MS next position, thereby this factor should be maximized. f_3 is the third factor which represents the average of the SNs traffic load in the potential position range. This factor should be minimized to pull the sink toward the areas with less traffic load. The last factor f_4 represents the average distance between the potential position coordination and the source SNs, and thus, it has to be minimized to pull the sink toward the SNs that capture the time slot to transmit their data. s is the dimension of the search agents.

After normalizing each fitness sub-function, Eq. (21) fitness function which should be maximized is used to evaluate each search agent.

$$\begin{gathered}\mathrm{Fit}_{\mathrm{solution}} = (c_1 * f_1) + (c_2 * f_2) - (c_3 * f_3) - (c_4 f_4) \\ |c_1| + |c_2| + |c_3| + |c_4| = 1\end{gathered} \tag{21}$$

To summarize the process sequentially, after initialization of search agents, a, A, and C, each search agent is evaluated using the above equations, and the best three wolves ($X\alpha$, $X\beta$, $X\delta$) are determined as the leaders of the optimal convergence process. Each search agent in the population is repeatedly updated based on the best three predetermined wolves using (14) until the termination condition is reached. Finally, the alpha agent and its fitness will be considered as the optimal solution and one of its (*x, y*) positions is considered as the optimal target location for MS. It is important to draw attention to the fact that all potential positions in the final alpha solution will have the same coordination. The flowchart in Fig. 7 describes the entire GWM procedure.

5 Performance Evaluation

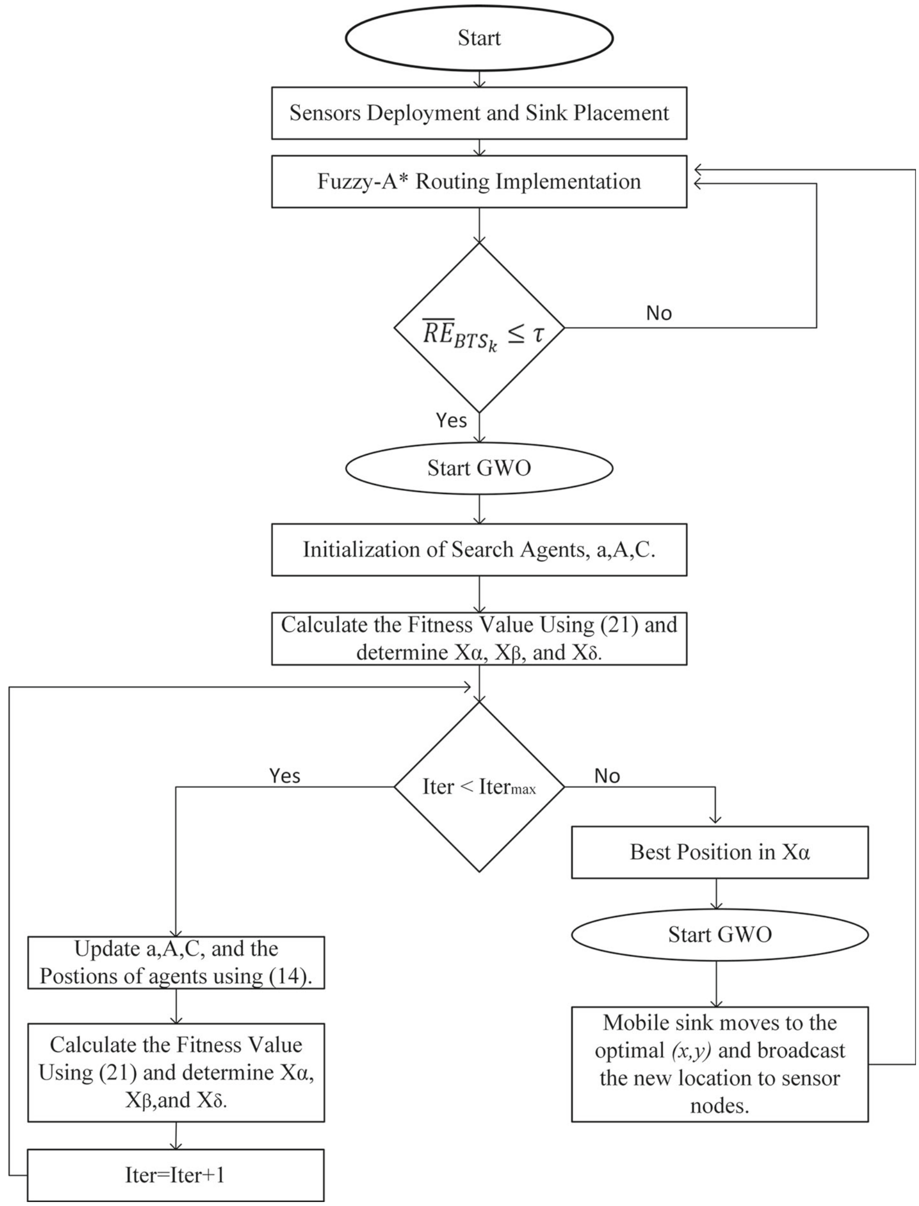
The performance of our proposed sink mobility methods in homogeneous WSNs was evaluated by comparing them with two of the most efficient algorithms in the field of sink localization (i.e., WRP and DBRkM).

In WRP [11], the MS roams in the network based on a preselected halting points trajectory that adopted a heuristic search algorithm to select the optimal collection of RPs in such a way that reduces the path length of MS. This goal has been achieved by assigning weights to each SN in the network based on the number of hops from the source SNs to the MS and the number of data packets delivered to the RP. In DBRkM [23], the MS path is guided by RPs which can be selected by employing the *k*-means clustering. DBRkM also uses a weight function to examine the possibility of a potential position to act as RP meanwhile, the path plan of MS could be designed by using the Christofides heuristic.

WRP and DBRkM aim to minimize the number of RPs along with the reduction of the number of hops from SNs to RPs. Even though those approaches extend the network lifetime, further development can be achieved. In all of their parameters, both algorithms have not considered the parameter of SNs energy of the targeted area. Furthermore, since those approaches also try their best to implement a single-hop pattern for delivering the data to the MS, they assumed a fixed multi-hop routing protocol when the approach fails to construct the single-hop RPs-data delivery, which does not guarantee energy balancing during data dissemination, and thus, this could be a serious problem in the large-scale networks that are suffering severe random deployment.

As a result, we have considered the parameters like average energy, average traffic load, sensor density, and source nodes angle to pull the MS toward the energy-rich, low traffic, high-density, and low hop count positions in the topographical areas.

Fig. 7 Flowchart of GWM



5.1 Simulation Setup

In order to analyze the efficiency of the proposed approaches to balancing the energy consumption and extending the network lifespan, the comparison parameters that have been considered are the number of dead SNs, average remaining energy, the standard deviation of energy consumption, and the execution time. The proposed protocol fuzzy-based sink mobility model is called FASM, and the other method is called GWM. The simulation of the environment for all methods has been programmed using Python 3.8.6 with Spyder IDE on the Anaconda environment. Packages such as Numpy, Pandas, and Math were also utilized for network preparation.

The simulation parameters and their values are shown in Table 1, which are identical to those used in [37]. A homogenous WSN has been simulated where 150 SNs have identical characteristics were deployed randomly over a (200 × 200 m) square area. Each SN is equipped with a 2 Joule battery and a radio that can communicate to other SNs within a range of 40 m. Furthermore, the traffic load that is continuously stacked in the buffers of SNs has been generated randomly during the network operating time with a range of 0–10 buffer sizes in each SN.

The network area of FASM is partitioned into grids based on the transmission range of SNs which is a low range considering a (200 × 200) area, therefore, it is better to have a grid size higher than (25 m). The grid size length was (l = 50 m). Thus, the MS can move to the center of the optimal grid (vertically/horizontally) about (50 m) or diagonally (70.5 m).

Table 1 Simulation parameters

Parameter	Value
Region size (m)	200 × 200 m
Node deployment	Random
No. of sensor nodes	150
FASM no. of grids	16
GWM population size	40
GWM iterations	300
GWM agent size	4
Search space distance r (m)	50 m
Transmission range (m)	40 m
Initial energy of each sensor (J)	2 J
α (%)	90%
Control packet length (bits)	4000 bit
No. transmissions (round)	10,000
Maximum traffic in each sensor's queue	10
E_{elec}	50 NJ/bit
ε_{mp}	0.0013 PJ/bit/m^4
ε_{fs}	10 PJ/bit/m^2
Mobile sink speed	2 m/s

In the GWM population, 40 search agents each with 4 potential positions (dimension) were initialized in every movement decision. It is to be noted that if there is a desire to get the most optimal position or the environment is a large-scale area, the search agents and their positions should be increased. However, the dimension of the search agent is reduced in the simulation to accomplish an acceptable computation complexity and less simulation time. Besides, for fear comparison, the search space distance r was equal to (50 m) which is the same as the vertical movement of the sink in the fuzzy model.

According to the radio model that is described in the preliminaries, the energy consumption model in the simulations is carried out using the values 50 nJ/bit and 10 PJ/bit/m^2, and 0.0013 PJ/bit/m^4 for E_{elec},ε_{fs}, and ε_{mp}, respectively.

5.2 Simulation Result

The majority of proposed works define the lifetime of WSNs as the period at which the energy of the (first/last) SN is fully dissipated. Figure 8 shows the number of SNs that are still active versus the number of transmission rounds (or network lifetime). Since GWM has the highest load and energy balancing among SNs, it owns the highest number of active SNs; moreover, the death of the last SNs in GWM occurs at a late round than the FASM, WRP, and DBRkM. FASM performed well in terms of latent the first SN death than WRP and DBRkM; however, it fails to keep such performance till the end.

On the other hand, many researches claimed that the network lifetime can be determined from the beginning of network actions to the period at which the first SN runs out of energy. Thus, Fig. 9 shows the death of the first SN in WSNs with diverse densities ranging from 200 to 700 SNs, where GWM dominates the other approaches in all densities as the first SN depletes the full energy after a long period. Regardless of the lifetime of FASM in terms of last SN death, FASM outperformed the WRP and DBRkM when the lifetime is taken from the first SN death perspective.

The network energy consumption is an essential factor that clarifies the energy depletion of the network during the rounds. The method with the lowest consumption has a priority to gain a better lifetime. This is due to the availability of an adequate energy amount that can be used for a longer period. The plot of the network energy consumption is shown in Fig. 10, where the GWM conserved more amount of energy as the rounds progressed. FASM and DBRkM also conserved an acceptable amount of energy at different rounds.

The standard deviation (SD) of energy consumption, which is expressed by Eq. (22), is an important factor for measuring the energy balancing levels at various rounds. The algorithm with less SD value has more balancing of energy consumption due to the low differences in energy levels among SNs. In Fig. 11, which shows the SD of all approaches, SD of GWM has a more balancing level than FASM, WRP, and DBRkM.

$$\text{SD} = \sqrt{\frac{\sum_{i=1}^{n} \left(E_{\text{cons}(i)} - \overline{E}\right)^2}{n}} \tag{22}$$

where $E_{\text{cons}(i)}$ represents the energy consumed by an SN at each transmission round. $\overline{E}$ denotes the overall average energy consumption.

Running time is an essential indicator of an approach's computational complexity levels. Moreover, it also provides some hints about the data latency resulting from the time which is consumed during the sink movement and data dissemination. FASM executes two procedures, which are the detection of a low-cost routing path, and a fuzzy inference system to find a new position for MS. GWO is a swarm intelligence optimization algorithm that runs for 300 iterations for every movement decision made by the MS. The running time of all protocols is shown in Fig. 12 in which GWM has a high time complexity compared with WRP and FASM. However, taking into consideration the efficiency GWM for extending the lifetime of the network, we can assume that there is a trade-off between time complexity and energy conservation efficiency, thus such complexity could be ignored.

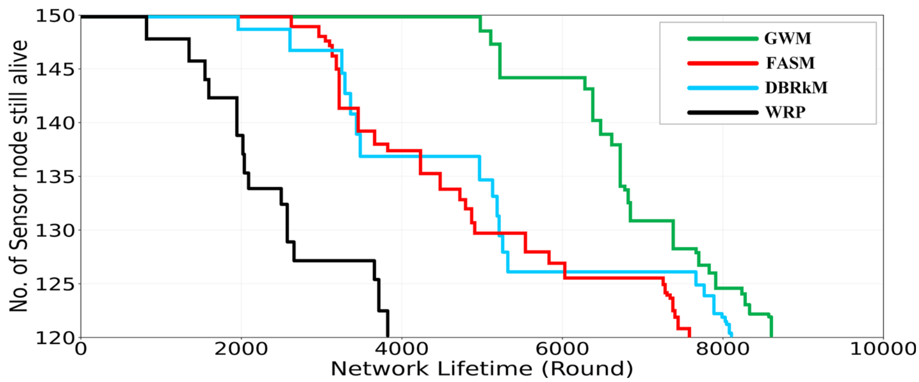


Fig. 8 Number of sensor nodes that still alive

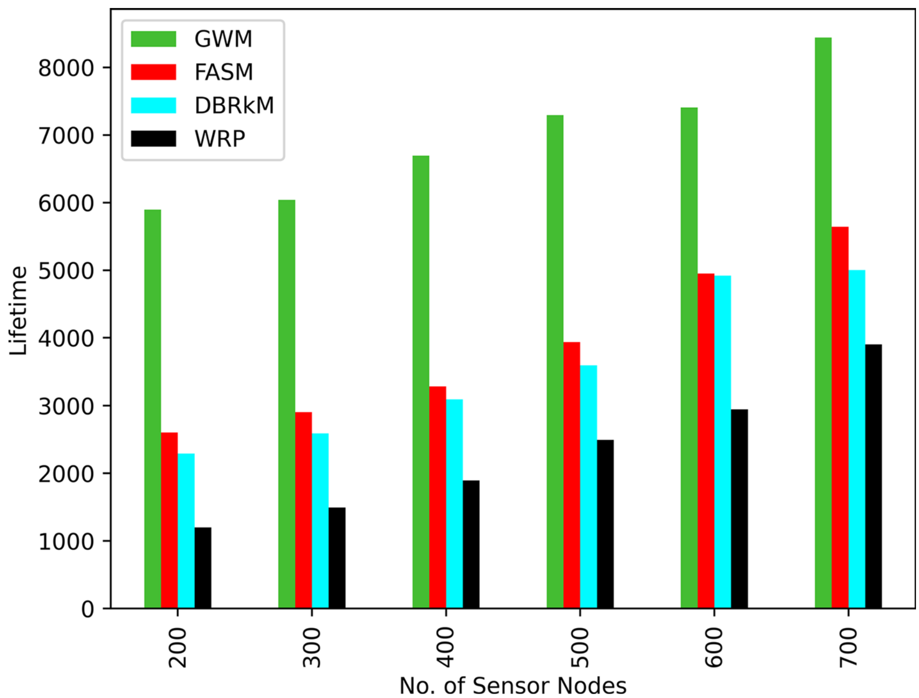


Fig. 9 First sensor node that exhausts the total energy

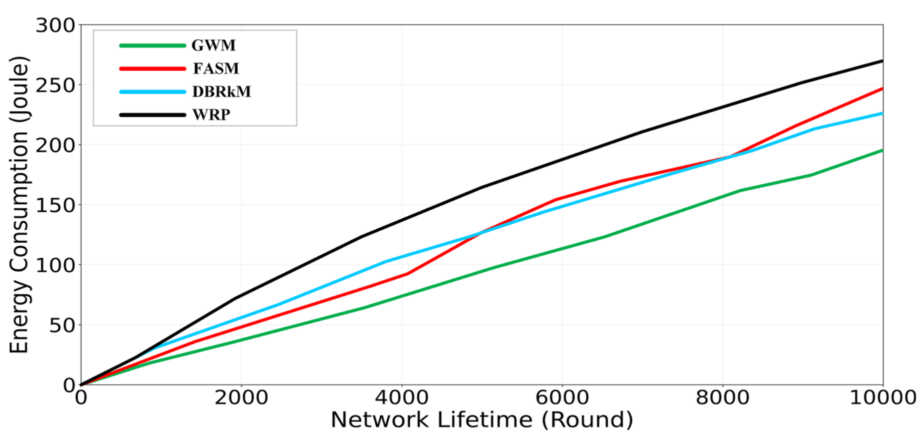


Fig. 10 Network energy consumption at each round

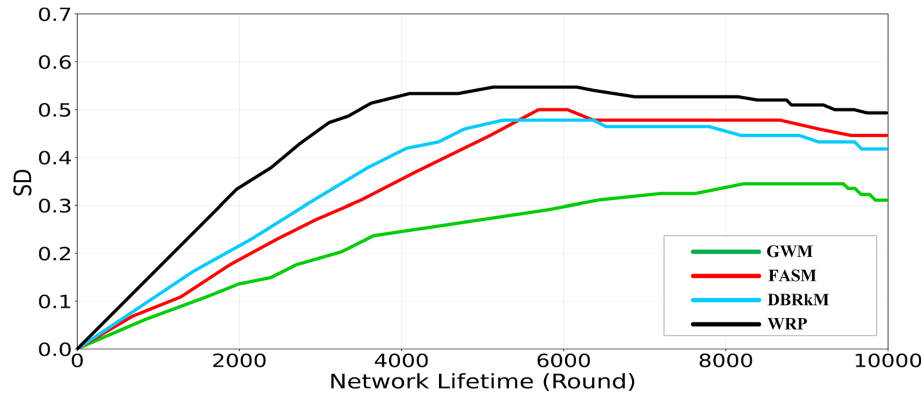


Fig. 11 Standard deviation of energy consumption

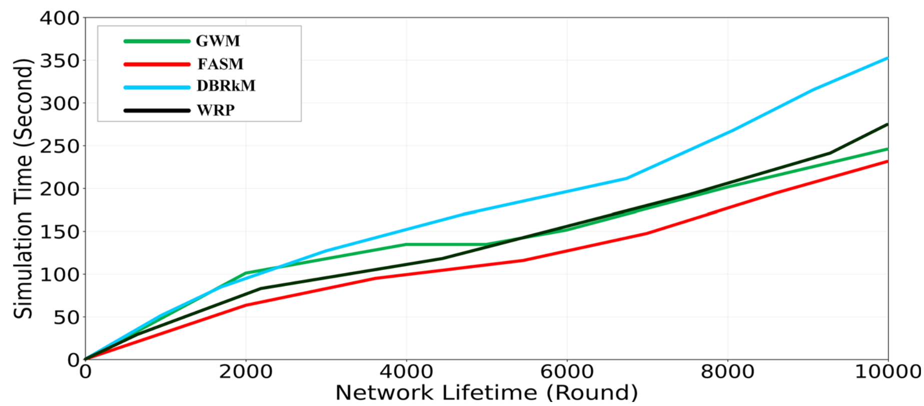


Fig. 12 Simulation time

6 Conclusion

In real-time WSNs application, sensor nodes state such as energy, traffic load, and computations change momentarily. Thus, in large-scale WSNs, an MS with a predetermined path may suffer SN information changes during the roaming time. Motivated therefrom, this paper has proposed two methods, called FASM and GWM for selecting the optimal next position for MS based on a threshold value that controls the sojourn time at each position. Both methods take into consideration four parameters that define the SN status of the targeted area which are the average remaining energy, average traffic load, SNs densities, and the source nodes angle. Both methods adopted a multi-hop routing method called fuzzy-A* protocol for collaborative data gathering. FASM partitions the network to a grid model and uses a fuzzy inference system to select the best grid for hosting the MS at the center. GWM employs the grey wolf optimizer algorithm to detect the optimal next position from MS. We build a fitness function to evaluate each solution based on the already mentioned parameters to converge at a designated search space that differentiates the area of potential position and the energy holes area. Finally, we have compared the proposed methods with two existing techniques, namely WRP and DBRkm to show their superiority. The simulation result confirmed that the proposed method outperformed WRP and DBRkM in terms of the number of remaining active SNs, the amount of energy exhausted, the standard deviation of energy consumption, and network lifetime with various SNs densities. The limitations of our proposed and the existing algorithms are that we have assumed that the SNs consume energy only by the radio transceiver during the transmitting and receiving of the data nevertheless, the SNs deplete some energy during data processing such as noise elimination and data aggregation. We will address such issues in the future.

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