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A Hybrid Metaheuristic Algorithm for Stop Point Selection in Wireless Rechargeable Sensor Network

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Abstract

A wireless rechargeable sensor network (WRSN) enables charging of rechargeable sensor nodes (RSN) wirelessly through a mobile charging vehicle (MCV). Most existing works choose the MCV's stop point (SP) at random, the cluster's center, or the cluster head position, all without exploring the demand from RSNs. It results in a long charging delay, a low charging throughput, frequent MCV trips, and more dead nodes. To overcome these issues, this paper proposes a hybrid metaheuristic algorithm for stop point selection (HMA-SPS) that combines the techniques of the dragonfly algorithm (DA), firefly algorithm (FA), and gray wolf optimization (GWO) algorithms. Using FA and GWO techniques, DA predicts an ideal SP using the run-time metrics of RSNs, such as energy, delay, distance, and trust factors. The simulated results demonstrate faster convergence with low delay and highlight that more RSNs can be recharged with fewer MCV visits, further enhancing energy utilization, throughput, network lifetime, and trust factor.

Keywords: wireless rechargeable sensor network (WRSN), mobile charging vehicle (MCV), stop point (SP), optimization, hybrid algorithm

1. Introduction

A wireless sensor network (WSN) consists of a variety of sensors [1] that are interconnected through wireless technology and find applications in diverse fields such as field surveillance, agriculture, and environmental monitoring [2]. To fulfill their intended purpose, these small sensors are deployed across different locations. The sensor nodes wirelessly transmit data to the base station (BS) with the help of intermediary sensor nodes. In some cases, a sensor node can function as both a data router and a data originator. Conversely, a sink or BS collects data transmitted by the sensors. The collaborative nature of sensor nodes is a unique characteristic of WSN. Ensuring seamless data routing while extending the lifespan of a WSN is both crucial and challenging.

Due to recent advancements in wireless power transfer (WPT) technology [3], one of the variants of WSN, wireless rechargeable sensor network (WRSN) [4], has grabbed the interest of the research community as it enables the sensor nodes to work indefinitely. When a node's battery is exhausted in the WRSN, a mobile charging vehicle (MCV) with an energy transmitter is dispatched to charge the required nodes for a specific time. The MCV returns to the BS to recharge its battery to address future charging requests. With sufficient battery power, WRSN successfully supports long-lasting sensor serviceability, enabling the network to continue functioning until the end of time and facilitating a long lifespan by lowering the number of dead sensors. Assorted applications in the fields of engrained infrastructure sensing, motion detection, farming, military services, forest fire detection, etc., are also made possible by WRSN.

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The charging mode can be either single-node charging or multi-node charging. In single-node charging [5], the MCV goes to every node separately for charging, whereas in multi-node charging [6], the MCV collaboratively charges many nodes at an instance. Single-node charging suffers from charging delay and the increased number of dead nodes. The single-node charging scheme puts more strain on the MCV and is less scalable than multi-node charging. It also extends the time required to charge the sensor nodes. By maximizing the number of RSNs charged during each MCV trip, multi-node charging lowers the proportion of dead nodes in the WRSN and speeds up charging.

Due to this, the collaborative charging (multi-node charging) mode is preferred as it charges numerous nodes within the clusters. But, finding the stop point (SP) for the mobile charger within the cluster plays a vital role. Simply selecting the center point of the cluster will not help, as it does not consider the status of the neighborhood RSNs. Therefore, to cope with this, a dynamic selection of SPs is preferred to enhance the charging efficiency. If the cluster head (CH) selection is made dynamically based on the current network status, then the position of CH can be used as SP for the corresponding cluster. As a result, MCV goes to the CH position and charges the nearby sensor nodes. In addition, MCV collects the information from the CH and delivers it to BS. Consequently, MCV knows the up-to-date information about the cluster. Fig. 1 depicts the functioning of the WRSN environment.

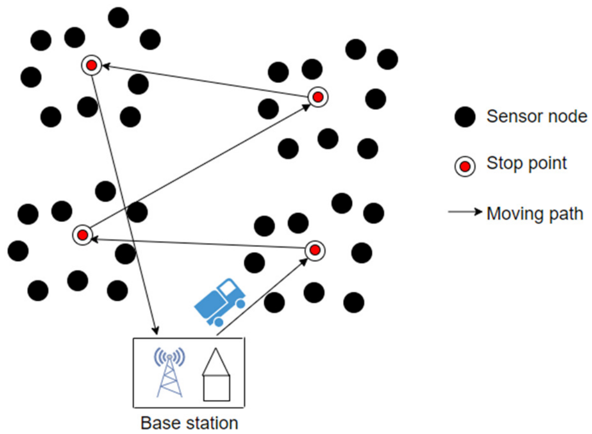


Fig. 1 Wireless rechargeable sensor network (WRSN)

The remainder of the paper is organized as follows: Section 2 briefs about the related work along with their summarization. The proposed hybrid HMA-SPS algorithm is presented in Section 3. Section 4 demonstrates the simulation results and comparisons, and the final section provides the paper’s conclusion.

2. Literature Review

In general, many Metaheuristic algorithms [7] are used to solve a problem in the most efficient way possible. The use of metaheuristic algorithms in SP selection in WRSNs allows for flexibility and adaptability, as well as the handling of large and complex search spaces. In anchor point or CH selection, the metaheuristic algorithm should concentrate more on parameter selection to define the objective function. Ant colony optimization (ACO) [8] is a population-based metaheuristic approach for solving complex optimization problems. The simulated ants capture their positions and the efficiency of their solutions in the same way so that in subsequent iterations, more ants find better solutions. Particle swarm optimization (PSO) [9] is a bio-inspired algorithm that solves a problem by generating a population of possible solutions, which are referred to as particles. The movement of each particle is controlled by its local best-known position, which is then updated when other particles discover better positions.

The fruit fly optimization algorithm (FOA) [10] is a swarm intelligence optimization technique used to address continuous complicated optimization issues and determine optimal global solutions. The fruit fly outperforms other species in terms of smell and vision. The smell phase involves the software agents moving around the problem area using their sense of smell. In the vision phase, they employ their vision to advance toward the ideal resolution. Dragonfly algorithm (DA) [11] is one of the recent optimization algorithms. It originates from the static and dynamic swarming behaviors of dragonflies. DA has proved its persuasiveness and superiority over several well-known meta-heuristics algorithms [7]. In the exploration phase of DA, dragonflies form sub-swarms and fly over different places in a static swarm. Dragonflies fly in larger swarms in the exploitation phase which cause swarms to travel in a single direction as the static swarm.

The firefly algorithm (FA) [12] is a well-known swarm-based algorithm inspired by the flashing aspect of fireflies and their Levy flying movement, which has achieved prominence quickly. The unisexual fireflies will be attracted to another firefly, and their appeal is proportional to the brightness of light that they emit. As a result of the attraction, one firefly will be drawn to another that is brighter. If there isn't another firefly with a light brighter than it, it will move in a random direction. Choosing the CH, clustering nodes, and managing the power of sensor nodes are all common uses of FA in WSN.

Gray wolf optimization (GWO) [13-14] is a search-based optimization algorithm based on a wolf pack's hierarchy, hunting techniques, and social interactions. It is more adept at searching for the best solution simultaneously using numerous agents in less time. It creates circle-shaped surroundings around the solutions that can be expanded to higher dimensions to determine the location of the prey. These algorithms, along with other algorithms, are summarized in Table 1.

Table 1 Comparison of metaheuristic algorithms

Algorithm	Inspiration	Advantages	Disadvantages
ACO [8]	Ants are seeking a path between their colony and a source of food.	Global exploration is a strong suit.	In the process of exploitation, the results were unsatisfactory. Slow convergence speed and easy to premature
PSO [9]	Birds are flying and searching randomly for food.	Computational time and parameter tuning are less.	To some extent, the convergence velocity and searching precision are inadequate.
FOA [10]	Fruit flies search their prey.	Simple to implement and easily adaptable.	Easily falling into a local optimal solution, failing to traverse the problem domain.
DA [11]	Static and dynamic swarming of Dragonflies	Have better convergence time, as it eliminates looking in non-promising areas and locating into local optima.	Due to the high exploitation rate, DA is readily trapped in local optima.
FA [12]	Firefly's attraction to flashing light	Suitable for usage in nonlinear and high-dimensional problems.	It is challenging to arrive at an optimal solution in a fair amount of time.
GWO [13-14]	Leadership hierarchy and hunting mechanism of grey wolves	Fast-seeking speed, high search precision,	Inferior local searching

In general, an anchor node or CH is selected based on the residual energy to assure full connectivity and reliability of the WRSN. Existing solutions manage to elect the anchor node or CH, but it is not energy efficient in some cases due to irregular distribution of CH. Due to the constraints of WRSN, selecting a better anchor node for inter and intra-cluster communication faces several challenges. In WRSNs, choosing a stop-point necessitates choosing between increasing network coverage and reducing node energy consumption. Many of the existing studies, however, only take into account one side of this trade-off and neglect to take the impact of stop-point selection into account. The primary objective of the proposed work is to predict a better SP in each cluster, so the proposed algorithm does not focus on CH selection or its responsibilities.

This paper uses run time metrics such as distance, energy, trust factor, and delay to elect an anchor node whose position is considered an SP. This problem is well addressed with deterministic approaches in the literature. These approaches pave an efficient way to determine the best location for an anchor node or CH. To achieve improved accuracy and scalability than any one algorithm alone, hybrid algorithms can combine the strengths of various algorithms. Additionally, in WRSNs, hybrid algorithms can be created to conserve energy. The existing related work is briefly explained in section 2 which provides context, identifies research gaps, and demonstrates knowledge of the existing works.

From the above discussion, it is inferred that SP selection procedures in WRSNs typically confront two obstacles: (i) determining the best SP in each cluster for a given fitness function for enhancing the charging efficiency, (ii) building this fitness function with the dynamic and critical parameters by current network condition. To address this, the hybridization of metaheuristics algorithms [15] will be the better choice as it combines the benefits of different optimization algorithms by minimizing their limitations. It can be seen from Section 1.1 and Table 1 that DA, FA, and GWO will make better hybridization candidates. With these observations in hand, the following objectives are targeted in this paper.

(1) Developing an efficient SP selection technique for collaborative charging of RSNs with minimal charging delay and prolonged network lifetime.

(2) Designing an effective hybridization technique with DA, FA, and GWO and generating its fitness function for the hybrid technique with the aid of dynamic network parameters. This guarantees a better SP that minimizes charging delay with a few MCV trips.

(3) Simulating the proposed hybrid model and comparing its performance with other existing algorithms to show its efficiency in terms of convergence rate, charging throughput, delay, and network lifetime.

3. Related Work

This section discusses various approaches that have addressed the charging scheme, including a summary of these approaches in Table 2. Xie et al. [6] utilized the reformulation linearization technique to optimize the path and travel time of the mobile charger. The cell structure was divided into hexagonal cells, with the middle point of each cell designated as the SP. The charging vehicle would commence from the utility station (US) or BS, travel to the middle point of the cells, and collaboratively charge the sensors in the corresponding cells.

After completing the trip, the MCV would return to the US to recharge itself and remain idle until further requests are received. A joint optimization technique was employed to maximize the ratio of idle time to trip time. The proposed multi-node charging scheme has demonstrated improved charging efficiency and scalability. However, it does result in an increased number of SPs for a limited number of nodes.

Xie et al. [16] addressed the charging problem as a non-linear program (NLP) and recast it as a mixed integer linear program (MILP) using discretization. The network is taken as a 2D plane, and the charging space is divided into hexagonal cells. The middle point of the cell is considered SP, where the MCV travels through an optimal path to the SP for charging the RSNs. Even though a cell contains one energy-depleted node among very few RSNs, the charger needs to go to the middle of the cell to replenish that single RSN, thus increasing trip time.

He et al. [5] proposed an on-demand charging method that allocates a time slot for serving each node. Based on the geographical priority of RSNs, the charging trip is estimated. The SP is assumed as the nearest point of each energy-depleted node. However, estimating the better trip plan is a challenging task in a fair amount of time.

Han et al. [17] adopted the K-means clustering algorithm to divide the network into clusters. The US calculates the positions of the anchor nodes in each cluster based on the energy dispersion. Each cluster's anchor point is visited by two MCVs traveling in opposite directions with the shortest Hamiltonian cycle. After the current tours of two MCVs, a semi-Markov model for energy prediction is proposed for changing the anchor nodes for the next tour, which is quite complex.

Khelladi et al. [18] translated the SP calculation problem of MCV into a clique partition problem. During the clique formation, there is a good chance for overlapping their PRDs in a single point, which is considered an SP for that clique. It facilitates the MCV to charge all nodes in the clique. Though the number of SPs is reduced, overlapping SP regions results in inappropriate SP selection for certain RSNs.

Lin et al. [19] proposed a threshold-based on-demand charging scheme and tested it in a circular and square-shaped network. In the first case, MCV chooses a random SP in this circular area and charges all RSNs in its charging range at the same time. Whereas in the second case, the middle point of the square is considered as SP to charge all the RSNs in the square. The SP selection is unseemly poor in both cases, with increased SPs for limited RSNs. Han et al. [20] exhibited a collaborative charging algorithm and adopted a gradient descent optimization approach to select SP in each cluster. If there are more energy-depleted nodes, then the optimization approach models RSNs as discrete particles to choose MCV's good SP. The clustering of RSNs is enhanced through the use of an optimization algorithm. However, managing the MCV to locate the sub-MCVs presents significant challenges and complexity.

Han et al. [21] addressed the energy replenishment problem in rechargeable sensor networks (RSNs) by formulating it as an optimization problem. Their objective was to identify optimal SPs while minimizing the number of non-functional nodes. The network is partitioned into clusters based on residual energy and distance criteria. The CH for each cluster is selected based on high energy levels and assigned as the SP for that cluster. Although this approach reduces the number of non-functional nodes, it may encounter SP selection challenges during periods of congestion.

Wang et al. [22] proposed an optimal scheduling scheme for the MCV to maximize its vacation time. The network is divided into clusters based on the distances between sensor nodes. The Floyd algorithm is employed to determine the shortest distance between each node, which is then designated as the SP for the MCV to charge the nodes within each cluster. This scheme is well-optimized for dynamic topology. However, it can be time-consuming due to the unnecessary movement of the MCV. A comparison of the related works is presented in Table 2.

Table 2 Related work

References	Network division	SP	Objectives	Disadvantages
He et al. [5]	No division	Near the point of each cell	Priority-based charging scheme.	Random increased number of SPs.
Xie et al. [6]	Hexagonal cells	Cell's middle point	Pathfinding between SPs using RLT.	Increased number of SPs for limited nodes.
Xie et al. [16]	Hexagonal cells	Cell's middle point	Averaging the energy transfer efficiencies is experimented. The traveling path is constructed.	Static clustering with an increased number of SPs for limited nodes.
Han et al. [17]	Clusters	The Anchor point of CHs	SPS selection in the 2D domain and Markov model for energy prediction have been constructed.	Extraneous MCV movement to charge a single-node of a cluster.
Khelladi et al. [18]	Clique	Overlapping point	To reduce SPs using clique algorithm.	Complex and inappropriate to include certain RSNs.
Lin et al. [19]	Circular region and square grids	Random points in circular regions and midpoints in square grids	On-demand charging path construction.	Random increased number of SPs for limited nodes.
Han et al. [20]	Cluster	Near the point of each cell or gravitational point	SPA using gradient optimization.	Complex gravitational SPs selection.
Han et al. [21]	Cluster	CH point	Uneven cluster-based SP selection and energy replenishment.	SP was selected based on only residual energy and distance factors.
Wang et al. [22]	Subnetwork as clusters	Center location	SP selection to maximize the vacation time of MCV.	Extraneous MCV movement to charge a single-node of a cluster.

From the above discussion, it is inferred that single-node and collaborative charging methods have their strengths and weaknesses. In single-node charging mode, the MCV movement is increased with increased charging time in the charging area. Whereas in collaborative charging, not all the energy-depleted RSNs are recharged due to improper selection of SPs.

Consequently, these issues trigger more MCV trips, charging delays, and lesser charging throughput, thus failing to prolong the network lifetime. To mitigate the problems described above and to address the objectives mentioned in Section 1.2, the following contributions are given by this paper.

(1) For predicting better SPs in each cluster, this paper proposes an efficient SPS for collaborative charging of on-demand RSNs with fewer charging tours.

(2) The proposed approach hybridizes three metaheuristic algorithms, DA, FA, and GWO, to elect an anchor node that becomes SP in that cluster. To enrich this selection, the fitness function of this hybrid approach considers the crucial run time metrics such as energy, delay, distance, and trust. This assists in identifying and recharging all energy-depleted RSNs before running out of energy.

(3) The hybrid algorithm is evaluated with 100 RSNs in a 100 × 100 charging area to show its performance over other traditional existing models.

4. Proposed Hybrid Metaheuristic Algorithm for Stop Point Selection (HMA-SPS)

For a better selection of SPs, a hybrid optimization algorithm is proposed to select an anchor node with the aid of run-time decision metrics. Its position will be the SP for MCV. The proposed HMA-SPS hybridizes the concept of FA, DA, and GWO algorithms. Though these algorithms possess many advantages individually, they suffer disadvantages like delayed convergence and curtailing internal memory. However, this hybridization achieves better convergence and increases the active nodes, as discussed in the following sections. Table 3 lists a few significant mathematical notations along with the descriptions that go with them.

Table 3 Mathematical notation

Notation	Explanation
C_{Ar}	Charging range
O_{fn}	Objective function
R_p	P^{th} Sensor node (RSN)
$E(R_p)$	Energy of P^{th} (RSN)
BS	Base station
CH_c	Anchor node
L	Total number of clusters
R_{ser}	Packet service rate

4.1. WRSN system model

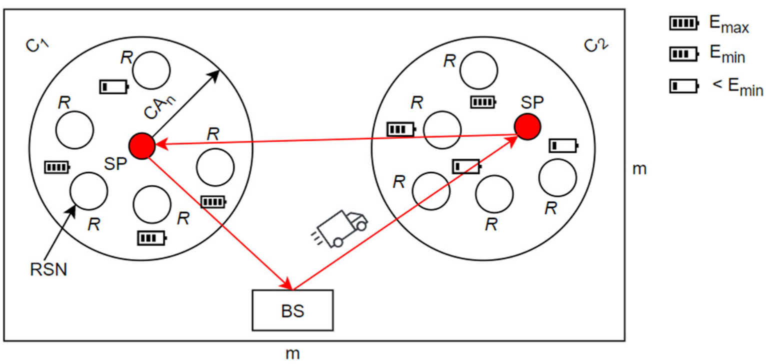


Fig. 2 WRSN system model

WRSN comprises a certain number of RSNs randomly deployed over an m × m dimensional area. These RSNs are distributed among C_1, C_2, …, and C_n clusters. The proposed algorithm predicts the SP for each C_i intending to charge more energy-exhausted RSNs during a visit. The estimated SPs need not be in the center of the cluster, and they may be anywhere in the cluster based on the requirement. E_{max} is the maximum residual energy of each RSN (R). The RSNs with the minimum energy E_{min} send the charging request to MCV through their corresponding anchor nodes. After receiving the requests, MCV gathers the information in terms of energy, distance, trust, and delay for each of the RSNs. With this information, MCV predicts the SP for each cluster and starts the trip. Once the MCV reaches SP, it collaboratively charges RSNs within its charging range CA_n. When the journey is over or the MCV itself runs out of energy, it returns to BS. The MCV's journey and scheduling play a significant role in the RSNs' timely charging, which prolongs their battery life [23-24]. The recharged MCV becomes idle in BS until it receives further requests. The Fig. 2 depicts the WRSN system model.

4.2. Constructing objective function for the proposed HMA-SPS

Most of the existing work considered the residual energy of RSNs and distance factors for SP selection [25]. The proposed algorithm seeks to forecast SPs more precisely to increase charging throughput. For that, additional parameters are taken into account to construct an objective function.

$$O_{fn} = \tau f_m + (1-\tau) f_n \tag{1}$$

Eq. (1) gives the minimized objective proposed function with additional parameters, such as trust factor (for assessing the dependability of RSNs) and delay (for slowing down faster data transmission).

$$f_n = \frac{1}{n}\sum_{p=1}^{n}\left\|R_p - BS\right\| \tag{2}$$

where τ is a mathematical constant and f_n calculates the summation of distance from each sensor node R_p to the BS as in Eq. (2).

The parameter f_m calculates the weighted sum value with the better values of distance, energy, delay, and trust values of RSN,

$$f_m = C1\times OPT_{dis} + C2\times OPT_{energy} + C3\times OPT_{delay} + C4\times OPT_{trust} \tag{3}$$

$$C1+C2+C3+C4=1 \tag{4}$$

In Eq. (3), each of the decision metrics OPT_{dis}, OPT_{energy}, OPT_{delay}, and OPT_{trust} is multiplied with their corresponding constant parameters $C1$, $C2$, $C3$, and $C4$, respectively, and they are estimated by satisfying the following Eq. (4). By altering weights, the optimization process considers these parameters' significance. In the subsequent subsections, the effects of the decision metrics and their estimations are covered.

4.2.1. Energy (OPT_{energy})

As the energy factor directly influences the network lifetime, it is considered a primary and inevitable metric in most processes. If the SP is selected nearer to more energy-depleted RSNs, the MCV moves to this SP and charges these nodes first and faster. The other 2-hop RSNs within CA_r will be recharged with some extra time due to the distance between RSNs and MCV. The proposed HMA-SPS algorithm implements the first-order radio model [26] for their energy dissipation calculations.

The objective function of the energy factor is calculated by

$$OPT_{energy} = \frac{OPT_{m-energy}}{OPT_{n-energy}} \tag{5}$$

where $OPT_{m-energy}$ and $OPT_{n-energy}$ denote the cluster's residual and deleted energy, respectively. If $OPT_{m-energy}$ and $OPT_{n-energy}$ of Eq. (5) [25] attain more CH and energy, then the value of OPT_{energy} will be higher than one. If the consumed energy increases more than the remaining energy, then the better value will be lesser than one resulting in the inconsistency of the network. Therefore, this is considered to select SPs to balance OPT_{energy} that should not get reduced than 1.

The deviations of node energy and unit value are the conditions for achieving the reduction criterion which is given by

$$nE(r) = \sum_{p=1\& p\in r}^{L} 1 - E(R_p) \times E(CH_c);\ 1 < r < CH_c^n \tag{6}$$

where $E(CH_c)$ is the energy of the anchor node, which is the SP for MCV, $E(R_p)$ is the energy of the pth RSN, and $E(R_r)$ is the energy of the rth RSN, respectively.

$$OPT_{m\text{-}energy} = \sum_{r=1}^{CH_c} nE(r) \tag{7}$$

$$OPT_{n\text{-}energy} = CH_c^n \times Max_{p=1}^{CH_c^n}\left[E(R_p)\right] \times Max_{r=1}^{CH_c^n}\left[E(R_r)\right] \tag{8}$$

In this case, the better SPS procedure results in a lower value of $OPT_{m\text{-}energy}$ in Eq. (7). Since the minimum value is considered in SP selection, MCV will charge the nearby nodes faster than faraway ones. Thus, the SP is selected to be the minimum energy level node to gain energy more quickly during recharging [8].

4.2.2. Distance (OPT_{dis})

$$OPT_{dis} = \frac{OPT_{dis(m)}}{OPT_{dis(n)}} \tag{9}$$

$$OPT_{dis(m)} = \sum_{p=1}^{N} \sum_{r=1}^{CH_c} \left\| R_p - CH_c^r \right\| + \left\| CH_c^r - BS \right\| \tag{10}$$

$$OPT_{dis(n)} = \sum_{p=1}^{N} \sum_{r=1}^{N} \left\| R_p - R_r \right\| \tag{11}$$

The fitness function for the distance factor is computed in Eq. (9) [25]. Here $OPT_{dis(m)}$ calculates the distance between all the nodes as in Eq. (11), and $OPT_{dis(n)}$ calculates the distance from the sensor node to its SP and then to BS as in Eq. (10). N is the total number of clusters of the WRSN.

4.2.3. Delay (OPT_{delay})

As the chosen SP is the anchor node of the cluster, the increased number of nodes in a cluster will increase the delay resulting in congestion during intra-cluster communication and in sending the charging request to MCV since on-demand charging requests collected by the anchor node should arrive at the MCV quickly to schedule the charging rapidly. The fitness value calculation considers the delay factor and is evaluated

$$OPT_{delay} = \frac{Max_{r=1}^{CH_c}\left(CH_c^r\right)}{L} \tag{12}$$

where L is the total number of clusters and Max in Eq. (12) is the maximum count of nodes at the SP to notice the density of the cluster.

4.2.4. Trust (OPT_{trust})

The reliability of an SP is calculated based on the packet service ratio and distance factor. The lower the collision at SP, the higher the SP's reliability. The trust factor mainly depends on the packet service ratio P_{SR} and is calculated by

$$P_{SR} = \frac{P_{ser}}{R_{scd}} \tag{13}$$

where R_{ser} is the packet service rate and is computed from the packet service time T_{ser}. R_{scd} is the packet schedule rate

$$\begin{cases} R_{scd} = R_{ser},\ if\ P_{SR} < \mu \\ R_{scd} = \beta \times R_{ser},\ if\ P_{SR} = 1 \end{cases} \tag{14}$$

where $0 < \mu < 1$, $0 < \beta < 1$ are constants.

The fitness function of the trust factor is computed based on direct and indirect trust. The direct trust D_{trust} is calculated between any sensor node N_i and its corresponding anchor node CH_i. In contrast, the indirect trust ID_{trust} is calculated between the remaining nodes RN_i of the cluster and its anchor node CH_i and is measured through the sum of all nodes. The direct trust D_{trust} and indirect trust ID_{trust} are given by

$$D_{trust} = (CH_i, N_i) = \frac{E(N_i) \times P_{SR}}{Dis(CH_i \leftrightarrow N_i)} \tag{15}$$

$$ID_{trust} = D_{trust}(CH_i, RN_i) \times D_{trust}(RN_i, N_i) \tag{16}$$

where $E(N_i)$ is the energy of any sensor node N_i, $Dis(CH_i \leftrightarrow N_i)$ gives the distance between an anchor node and a sensor node. The final trust factor, OPT_{trust}, which combines direct and indirect trust is computed by

$$OPT_{trust} = \zeta \times D_{trust} + (1-\zeta) \times ID_{trust} \tag{17}$$

Thus, the better value of these four parameters is calculated for all RSNs to compute the objective function of the proposed hybrid system.

4.3. Proposed hybridization approach for SPS

The proposed HMA-SPS algorithm enhances the performance of DA by integrating GWO and FA with its exploration (Phase I) and exploitation (Phase II) steps, and is depicted in Fig. 3. During the exploration phase of DA, each agent moves independently and explores the region for searching a food source with the aid of FA. Whereas in the exploitation phase, the agents move in groups, and their movements are controlled by DA. Towards the target positioning for identifying the food source, GWO is adopted by DA to make faster target acquisition.

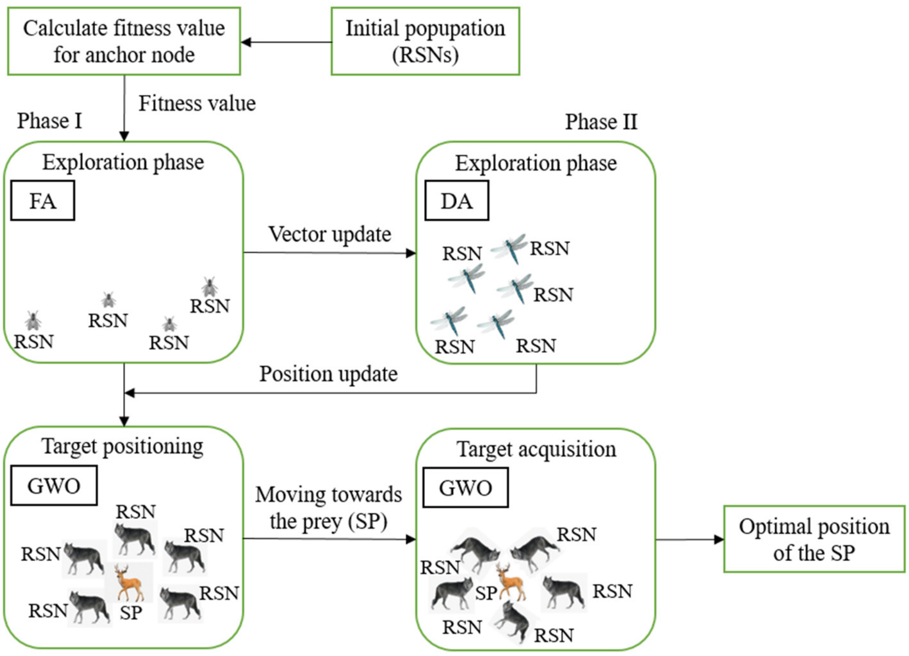


Fig. 3 Depiction of the proposed algorithm

The proposed SPS approach initializes the dragonfly population, and then the fitness value using the objective function O_{fn} of each agent is calculated.

$$X\left(i+1\right)=\frac{X_{\alpha}+X_{\beta}+X_{\gamma}}{3} \tag{18}$$

After evaluating the fitness value of all search agents or members of the population in the current iteration i, the top three solutions are obtained by GWO termed as α, β, and γ to find a better position as in Eq. (18) for the next iteration. Consequently, the remaining search agents update their positions by the best search agents' locations.

Then the adversary and food source are updated using DA that enables the sensor nodes to move towards the nearby anchor node to form a cluster. The two vectors, step V_S and position V_P of DA are evaluated for updating the location of dragonflies in an exploration space and completing their movements. More specifically, the step vector reveals the dragonfly's movement, and the position vector reveals the location of the dragonfly, and these vectors are determined by

$$V_S\left(t+1\right)=\left(aSE_i+bAL_i+cCO_i+dAT_i+eDT_i\right)+wV_S\left(t\right) \tag{19}$$

$$V_P\left(t+1\right)=V_P\left(t\right)+V_S\left(t+1\right) \tag{20}$$

These vectors are used to update the position P of dragonflies in an exploration space and to wrap up their movements, where a is the separation weight, b is the alignment weight, and c denotes cohesion weight. The food factor is represented by d, the adversary factor is represented by e, w symbolizes the inertia weight, and the iteration counter is denoted by t. With these constants, initial parameters in DA such as separation SE_i, alignment AL_i, cohesion CO_i, attraction AT_i and distraction DT_i are calculated for the further movement updation.

The separation parameter SE_i is evaluated by

$$SE_i=-\sum_{j=1}^{N}Y-Y_j \tag{21}$$

where Y_j means the jth position of the neighboring member, Y denotes the current individual's position, and N is the number of neighboring individuals.

Alignment AL_i is calculated using the corresponding equation

$$AL_i=\frac{\sum_{j=1}^{N_e}Q_j}{N_e} \tag{22}$$

where Q_j is the velocity of the jth neighboring person. Furthermore, the formula for cohesiveness CO_i is presented in

$$CO_i=\frac{\sum_{j=1}^{N_e}Y_j}{N_e}-Y \tag{23}$$

where Y_j represents the location of the jth adjacent individual, N_e means the neighbor count, and Y represents the current individual's position.

Attraction AT_i towards a food resource is calculated by

$$AT_i\leftarrow Y^{+}-Y \tag{24}$$

where Y^{+} represents the location of the food source and Y represents the current person's location.

Distraction DT_i from an adversary is stated in

$$DT_i \leftarrow Y^- + Y \tag{25}$$

where Y^- denotes the adversary's current location and Y is the current location of individuals.

During the position update, if the dragonfly has no neighbors Ne, the traditional levy update is used to update its position, but in the proposed HMA-SPS algorithm, the FA algorithm is utilized to do the position update ST_i. Can be expressed by

$$ST_i(t+1) = ST_i(t) + ATT(i,j)\left[ST_j(t) - ST_i(t)\right] + r\varepsilon_i \tag{26}$$

$$ATT = ATT_0 e^{-yc^2} \tag{27}$$

where ε_i is the random number. In Eq. (26), the three parameters, such as the present location of ith firefly (RSN), attraction (ATT), and a random walk involving a variable r, is used to update the anchor node position as SP with the help of firefly movement. ATT portrays the attraction factor of fireflies, and ATT_0 represents the level of attraction at $c = 0$. When $ATT_0 = 0$, the movement is solely determined by random walks. The variable y has a significant impact on convergence speed. c is the distance between two fireflies f_{ik} and f_{jk}, and is given by

$$C_{ij} = v\sqrt{\sum_{k=1}^{k=n}\left(f_{ik} - f_{jk}\right)^2} \tag{28}$$

The letter n denotes the dimensionality difficulties. Another more beautiful firefly j attracts the ith firefly's movement. To summarize all these steps, for all the flies or agents (RSNs), the fitness value is determined using the objective function (Eq. (1)). At each round, the agents move towards the best result based on the four factors in the proposed objective function to obtain the SP. Before starting a trip, the proposed algorithm selects this better point as an SP, and the node at the point is chosen as an anchor node for that round, which will then collect cluster data. Once MCV comes to the SP of the cluster, the anchor node passes information about the cluster for a future update. The detailed algorithm is given in Algorithm 1.

Algorithm 1: Hybrid metaheuristic algorithm for stop point selection (HMA-SPS)

Input (for RSN): Initial Population I_P, packet service ratio P_{SR}, inertia weight w, separation weight s, alignment weight a, cohesion weight c, food factor f, enemy factor e, position p, neighbor radius R_{ne}, food source S_f, and adversary A_d.

Output (SP): Separation H, alignment B, cohesion G, attraction F, distraction E, and fitness for SP O_{fn},

Initialize I_P
While (end condition)
    While ($I_P \leq$ n)
        $O_{fn} \leftarrow \tau f_m + (1-\tau) f_n$
    End while
    For all I_{Pi} **do**
        Get α, β, γ with GWO then
        $X(i+1) \leftarrow \frac{X_\alpha + X_\beta + X_\gamma}{3}$
        Update S_f & A_d
        Update P_{SR}, w, a, b, c, d, and e
    End for
    For $I_P \leftarrow 1$ to n **do**
        $SE_i \leftarrow -\sum_{j=1}^{N} Y - Y_j$
        $AT_i \leftarrow Y^{\pm Y}$
        $CO_i \leftarrow \frac{\sum_{j=1}^{N_e} Y_j}{N_e} - Y$
        $AT_i \leftarrow Y^+ - Y$
        $DT_i \leftarrow Y^- + Y$
        Update R_{ne}

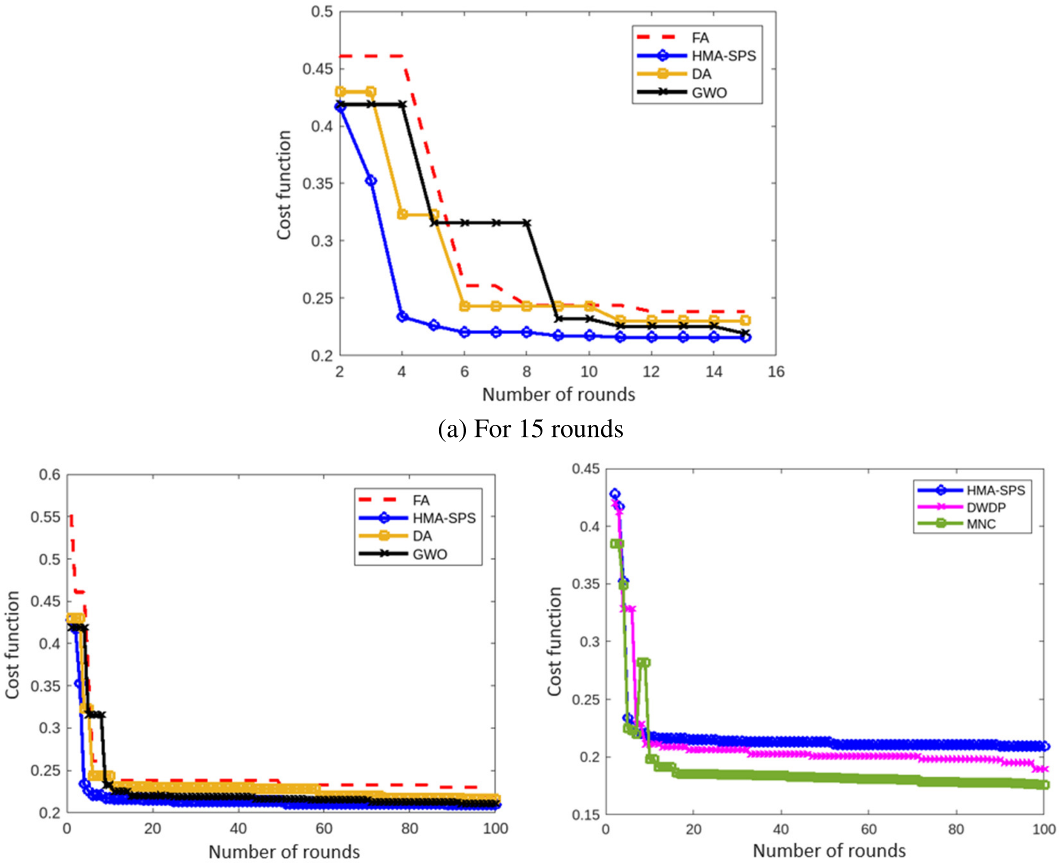
If (DF_{i+1} == 1) **then**
    $V_s(t+1) \leftarrow (aSE_i + bAL_i + cCO_i + dAT_i + eDT_i) + wV_s(t)$
    $V_p(t+1) \leftarrow V_p(t) + V_s(t+1)$
Else
    $ST_i(t+1) \leftarrow ST_i(t) + ATT(i,j)\left[ST_j(t) - ST_i(t)\right] + r\varepsilon_i$
End if
End for
End while

5. Simulation Results and Analysis

The conventional FA, DA, and GWO algorithms are simulated to predict the SPs in WRSN to evaluate the performance of the proposed HMA-SPS algorithm. The proposed HMA-SPS algorithm is also compared with some of the benchmark algorithms namely DWDP [19] and MNC [6]. For all these algorithms, network energy, delay, active nodes, and trust factor are measured and compared with the proposed algorithm. The benchmark algorithms are also implemented in MATLAB by adjusting their parameters up to the proposed algorithm.

These algorithms are simulated using MATLAB R2016b on an Intel(R) Core(TM) i7-6700 CPU 3.40 GHz RAM 16 GB. Simulation is carried out with 100 sensor nodes deployed over a 100 m × 100 m square area with a centralized BS. The initial energy of each node is set up to 2J. The energy of the power amplifier is set at 0.0013 nJ/bits/m^2. The energy of the transmitter and receiver is set at 0.05 µJ/bit. Also, the energy of data aggregation is assumed as 0.5 µJ/bit. After certain trial and error, the α, β, and γ values of GWO are taken as [0.25,0.2,1]. By taking into account the previous works and numerical trials, the value of ζ in calculating the trust factor and the value of t in calculating the objective function are taken as 0.25 respectively.

5.1. Convergence analysis



(a) For 15 rounds

(b) For 100 rounds(traditional)

(c) For 100 rounds

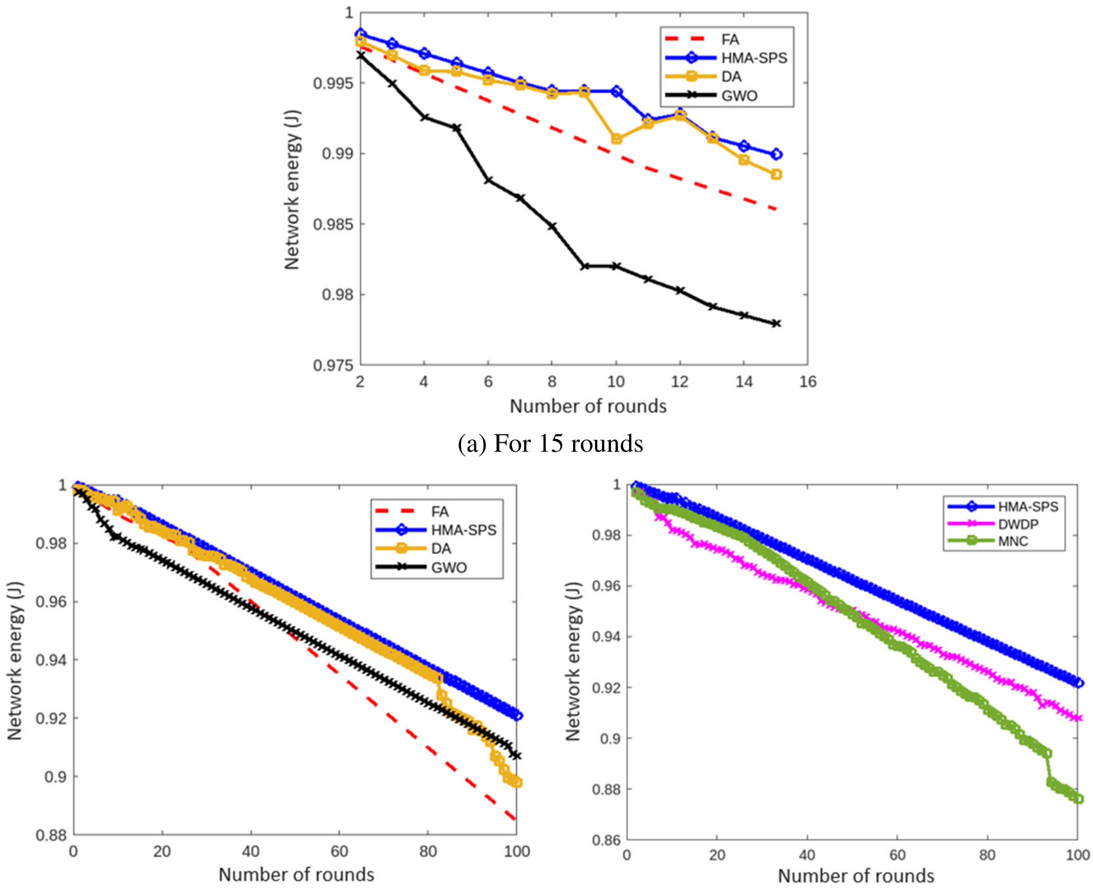
Fig. 4 Convergence analysis

Figs. 4(a) and 4(b) depict a comparison of the cost function of the proposed HMA-SPS algorithm and other algorithms (FA, DA, and GWO). According to the experimental results, the proposed model outperforms the other compared strategies in terms of outcomes. Fig. 4(a) shows the analysis for the first 15 rounds, and Figs. 4(b) and 4(c) show 100 rounds. Compared to GWO, the HMA-SPS model exhibits high-cost results from iterations 1 to 3 can be attributed to updating the agents' positions. Then it is gradually decreased and becomes constant after some rounds resulting in faster convergence than the existing algorithms. The proposed HMA-SPS algorithm produces superior results than the existing DWDP and MNC algorithms and is depicted in Fig. 4(c). Compared to DWDP and MNC algorithms, HMA-SPS has fewer SPS, which lowers the cost function and improves system performance.

5.2. Residual energy analysis

The residual energy of the entire network at the end of each round is measured for the algorithms FA, DA, and GWO and plotted in Fig. 5(a) and 5(b) for the first 15 rounds and 100 rounds, respectively. The energy dissipation in the proposed HMA-SPS algorithm is reduced by searching for a better SP for MCV, which increases the residual energy of the network. Compared to the current DWDP and MNC algorithms, the proposed algorithm has increased the network's residual energy by featuring a reduced charging delay and more charging nodes for each cluster. The existing MNC algorithm increases unnecessary charging cycles by periodically charging all of the nodes in its partitioned cells or cluster cells. As a result, the network uses more energy, and RSNs with higher energy levels are charged more frequently than necessary.

When using the DWDP algorithm, fewer on-demand RSNs are charged for each cell at each MCV trip, which results in longer wait times for nodes to recharge and lower overall network energy. Fig. 5 shows the residual energy of the network is more for the proposed algorithm than other existing algorithms. This results in a longer network lifetime. This is primarily due to the SPs using the hybridization approach quickly reaching their ideal positions and reducing energy loss.



(a) For 15 rounds

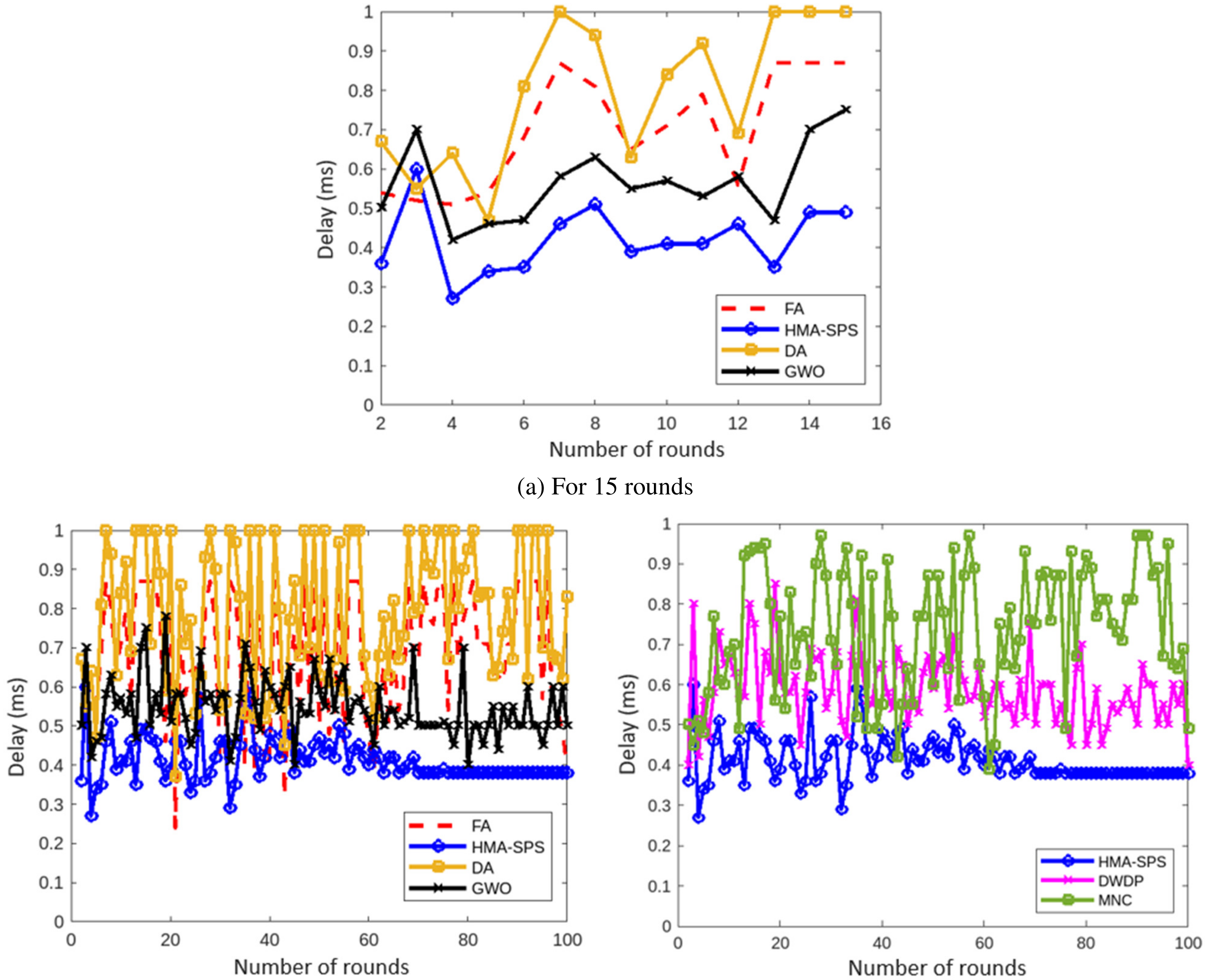
(b) For 100 rounds(traditional)

(c) For 100 rounds(related)

Fig. 5 Network energy

5.3. Delay analysis

Fig. 6 demonstrates the superiority of the presented HMA-SPS model in terms of delay in the SP selection process. The obtained results show that the proposed model has a significantly lower delay compared to the FA, DA, GWO, DWDP, and MNC models. This reduction in delay decreases the energy dissipation of the system, thereby increasing the network's lifetime. The proposed model's delay is less and approaches a constant value after fewer rounds. In each round of charging tour, more RSNs are recharged in each cluster, thus reducing the number of MCV trips and charging delay. However, fewer RSNs are recharged in each cell in MNC and DWDP than in HMA-SPS, increasing the number of MCV trips and charging delay.



(a) For 15 rounds

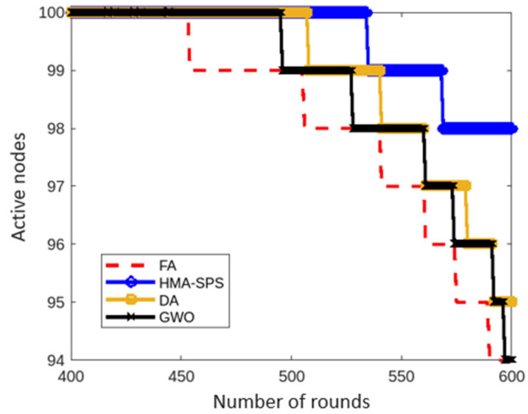
(b) For 100 rounds(traditional)

(c) For 100 rounds(related)

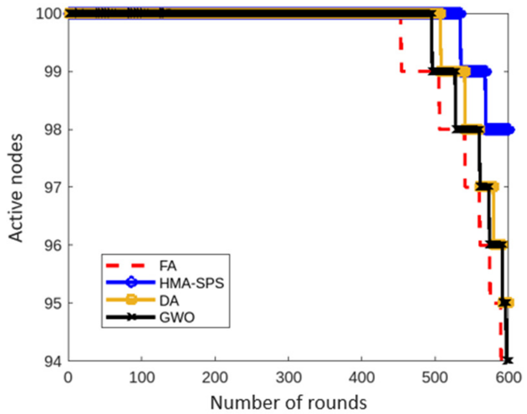
Fig. 6 Delay

5.4. Number of active nodes

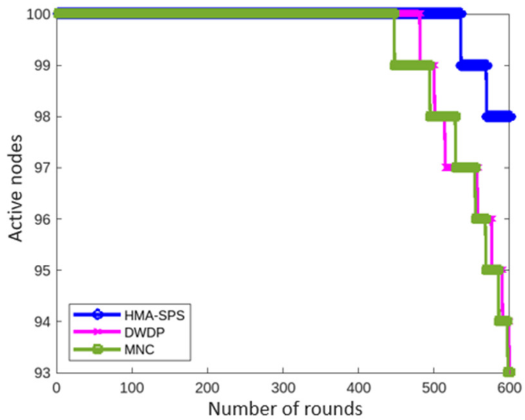
The number of active nodes is high in the proposed HMA-SPS than FA, DA, and GWO as depicted in Figs. 7(a) and 7(b). Due to the better position update and SPS, the energy dissipation and delay of the clusters will be lower. More RSNs are grouped in each cluster by the proposed HMA-SPS algorithm, increasing the number of nodes charged in each MCV round. However, there are fewer nodes in each cell in MNC and DWDP, which lowers the number of charging nodes during each charging round. This resulted in a higher number of alive nodes for the HMA-SPS algorithm than the existing algorithms (DWDP and MNC) and is shown in Fig. 7(c). The hybridization in HMA-SPS shows faster convergence in selecting better SPs than the existing algorithms. The distance factor enhances the packet relay, thus increasing the number of alive nodes, thereby increasing the network's lifetime.



(a) For 200 rounds



(b) For 600 rounds(traditional)

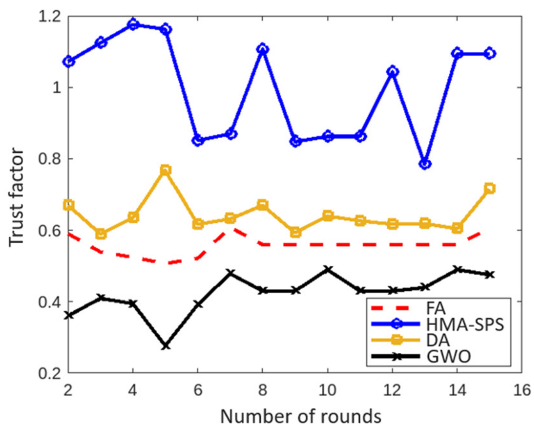


(c) For 600 rounds(related)

Fig. 7 Number of active nodes

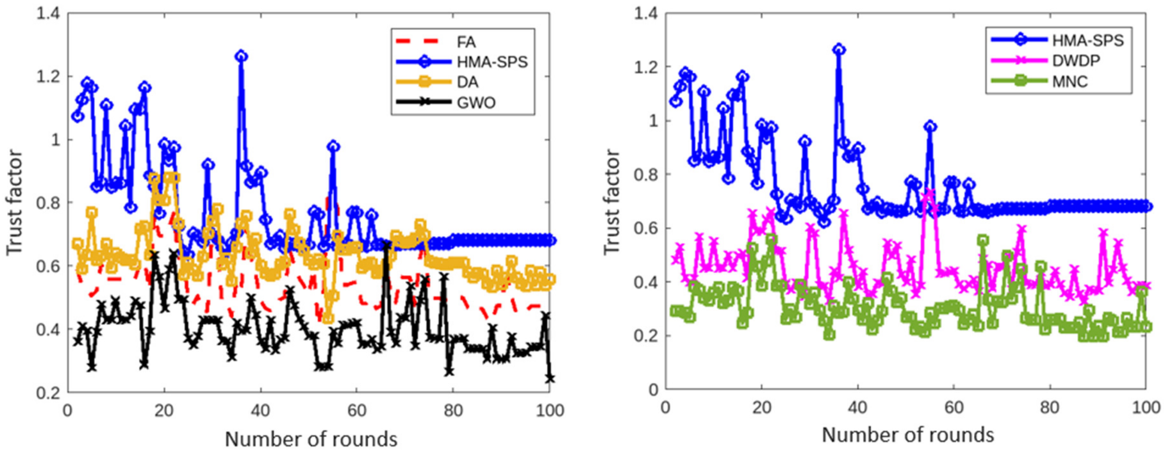
5.5. *Trust factor*

The trust factor is calculated by considering the amount of energy and the level of congestion. Trust enhances the direct and indirect reliability of the cluster. In Figs. 8(a) and 8(b), the trust factor value is increased by the proposed algorithm, whereas it is reduced in other existing algorithms (FA, DA, and GWO). The limited SP in DWDP causes the MCV to receive numerous on-demand requests, which worsens the congestion and brings down reliability. Frequent MCV trips and periodic charging reduce the service rate in MNC by creating a demand for charging among RSNs. The diminishing of this factor also increases the delay of the network. It means that nodes in the HMA-SPS algorithm are more reliable than nodes in the existing algorithms, which increases the robustness and throughput of the proposed network. The increased service rate of the proposed HMA-SPS makes it possible to achieve a higher trust factor than DWDP and MNC, as shown in Fig. 8(c).



(a) For 15 rounds

Fig. 8 Trust factor



(b) For 100 rounds(traditional) (c) For 100 rounds(related)

Fig. 8 Trust factor (continued)

6. Conclusion

This study presents an HMA-SPS to enhance charging efficiency in WRSN. The algorithm combines FF, GWO, and DA to predict improved SPs within each cluster based on the energy, distance, delay, and trust factor of RSNs. By selecting these SPs, a greater number of RSNs can be recharged in fewer MCV trips.

The proposed algorithm is extensively simulated and evaluated using various metrics, including network energy, delay, the number of active nodes, and trust factor. The key findings are as follows:

(1) Comparative analysis with existing approaches demonstrates that the proposed algorithm outperforms others in terms of extending network lifetime.

(2) The proposed algorithm effectively maintains high network energy levels, thereby increasing the number of active network nodes.

(3) The proposed system significantly reduces delay, resulting in enhanced charging efficiency.

(4) The higher trust factor achieved by the proposed HMA-SPS ensures reduced MCV trips and improved on-demand charging.

It is worth noting that the proposed work focuses on static nodes and does not consider the dynamic nature of RSNs. Future efforts will aim to address this limitation by incorporating dynamic parameters for SP selection, CH selection, and MCV scheduling, specifically tailored for dynamic RSNs.

Conflicts of Interest

The authors have no conflicts of interest to declare.

References

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, “Wireless Sensor Networks: A Survey,” Computer Networks, vol. 38, no. 4, pp. 393-422, March 2002.

[2] D. Kandris, C. Nakas, D. Vomvas, and G. Koulouras, “Applications of Wireless Sensor Networks: An Up-to-Date Survey,” Applied System Innovation, vol. 3, no. 1, article no. 14, March 2020.

[3] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljacic, “Wireless Power Transfer via Strongly Coupled Magnetic Resonances,” Science, vol. 317, no. 5834, pp. 83-86, July 2007.

[4] J. Chen, S. He, and Y. Sun, Rechargeable Sensor Networks: Technology, Theory, and Application-Introducing Energy Harvesting to Sensor Networks, Singapore: World Scientific Publishing Company, 2014.

[5] L. He, L. Kong, Y. Gu, J. Pan, and T. Zhu, "Evaluating the On-Demand Mobile Charging in Wireless Sensor Networks," IEEE Transactions on Mobile Computing, vol. 14, no. 9, pp. 1861-1875, September 2015.
[6] L. Xie, Y. Shi, Y. T. Hou, W. Lou, H. D. Sherali, and S. F. Midkiff, "Multi-Node Wireless Energy Charging in Sensor Networks," IEEE/ACM Transactions on Networking, vol. 23, no. 2, pp. 437-450, April 2015.
[7] O. Gouda, A. B. Nassif, M. AbuTalib, and Q. Nasir, "A Systematic Literature Review on Metaheuristic Optimization Techniques in WSNs," International Journal of Mathematics and Computers in Simulation, vol. 14, pp. 187-192, 2020.
[8] H. J. A. Nasir, K. R. Ku-Mahamud, and E. Kamioka, "Ant Colony Optimization Approaches in Wireless Sensor Network: Performance Evaluation," Journal of Computer Science, vol. 13, no. 6, pp. 153-164, 2017.
[9] P. Rawat and S. Chauhan, "Particle Swarm Optimization-Based Energy Efficient Clustering Protocol in Wireless Sensor Network," Neural Computing and Applications, vol. 33, no. 21, pp. 14147-14165, November 2021.
[10] H. Iscan and M. Gunduz, "A Survey on Fruit Fly Optimization Algorithm," 11th International Conference on Signal-Image Technology & Internet-Based Systems, pp. 520-527, November 2015.
[11] Y. Meraihi, A. Ramdane-Cherif, D. Acheli, and M. Mahseur, "Dragonfly Algorithm: A Comprehensive Review and Applications," Neural Computing and Applications, vol. 32, no. 21, pp. 16625-16646, November 2020.
[12] Dhirendra and P. K. Mishra "Clustering Using Firefly Algorithm for the Wireless Sensor Network," International Journal of Creative Research Thoughts, vol. 9, no. 3, pp. 2290-2296, March 2021.
[13] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," Advances in Engineering Software, vol. 69, pp. 46-61, March 2014.
[14] K. Sekaran, R. Rajakumar, K. Dinesh, Y. Rajkumar, T. P. Latchoumi, S. Kadry, et al., "An Energy-Efficient Cluster Head Selection in Wireless Sensor Network Using Grey Wolf Optimization Algorithm," TELKOMNIKA Telecommunication, Computing, Electronics and Control, vol. 18, no. 6, pp. 2822-2833, December 2020.
[15] T. O. Ting, X. S. Yang, S. Cheng, and K. Huang, "Hybrid Metaheuristic Algorithms: Past, Present, and Future," Recent Advances in Swarm Intelligence and Evolutionary Computation, vol. 585, pp. 71-83, 2015.
[16] L. Xie, Y. Shi, Y. T. Hou, W. Lou, H. D. Sherali, and S. F. Midkiff, "On Renewable Sensor Networks with Wireless Energy Transfer: The Multi-Node Case," 9th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), pp. 10-18, June 2012.
[17] G. Han, X. Yang, L. Liu, and W. Zhang, "A Joint Energy Replenishment and Data Collection Algorithm in Wireless Rechargeable Sensor Networks," IEEE Internet of Things Journal, vol. 5, no. 4, pp. 2596-2604, August 2018.
[18] L. Khelladi, D. Djenouri, M. Rossi, and N. Badache, "Efficient On-Demand Multi-Node Charging Techniques for Wireless Sensor Networks," Computer Communications, vol. 101, pp. 44-56, March 2017.
[19] C. Lin, Y. Sun, K. Wang, Z. Chen, B. Xu, and G. Wu, "Double Warning Thresholds for Preemptive Charging Scheduling in Wireless Rechargeable Sensor Networks," Computer Networks, vol. 148, pp. 72-87, January 2019.
[20] G. Han, J. Wu, H. Wang, M. Guizani, J. A. Ansere, and W. Zhang, "A Multicharger Cooperative Energy Provision Algorithm Based on Density Clustering in the Industrial Internet of Things," IEEE Internet of Things Journal, vol. 6, no. 5, pp. 9165-9174, October 2019.
[21] G. Han, H. Guan, J. Wu, S. Chan, L. Shu, and W. Zhang, "An Uneven Cluster-Based Mobile Charging Algorithm for Wireless Rechargeable Sensor Networks," IEEE Systems Journal, vol. 13, no. 4, pp. 3747-3758, December 2019.
[22] Q. Wang, F. Kong, M. Wang, and H. Wang, "Optimized Charging Scheduling with Single Mobile Charger for Wireless Rechargeable Sensor Networks," Symmetry, vol. 9, no. 11, article no. 285, November 2017.
[23] M. Srinivas, P. K. Donta, and T. Amgoth, "Mobile Charger Utility Maximization through Preemptive Scheduling for Rechargeable WSNs," 19th OITS International Conference on Information Technology (OCIT), pp. 126-131, December 2021.
[24] P. S. Prakash, M. Janardhan, K. Sreenivasulu, S. I. Saheb, S. Neeha, and M. Bhavsingh, "Mixed Linear Programming for Charging Vehicle Scheduling in Large-Scale Rechargeable WSNs," Journal of Sensors, vol. 2022, article no. 8373343, 2022.
[25] T. A. Alghamdi, "Energy Efficient Protocol in Wireless Sensor Network: Optimized Cluster Head Selection Model," Telecommunication Systems, vol. 74, no. 3, pp. 331-345, July 2020.
[26] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-Efficient Communication Protocol for Wireless Microsensor Networks," Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, pp. 1-10, January 2000.