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RAPCOL: a range-free power efficient cooperative localization with heterogeneous devices for industrial internet-of-things

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Abstract
Industrial applications and automation controls are closely connected with heterogeneous Wireless Sensor Network (WSN); thus, Industrial Internet-of Thing (IIoT) enhances the productivity, scalability, and flexibility of the operations. However, in many cases such as tracking a device or service localization becomes very crucial to state back the operations at times. Existing literature show a various localization solutions, but they face the drawbacks of high energy consumption, and non-coherence in heterogeneity. Besides, in a WSN-based IIoT, non-cooperativeness exists among nodes due to various system and environmental parameters, which make the system resource-exhaustive. In this paper, we introduce a novel localization algorithm that addresses the above-mentioned problems. We call our proposed algorithm *RAnge-free Power efficient COoperative Localization (RAPCOL)*. Specifically, the use of co-operative beacon nodes to broadcast the information to Base Station and low energy consumption highlights the novelty of the work. RAPCOL uses weight metrics for selecting optimal cooperative beacon nodes to prolong the network lifetime. We also introduce an Improvised Particle Swarm Optimization (IPSO) that credits in the contribution in RAPCOL. We run a overall nine sets of experiments to analyze the localization accuracy, effect of beacon nodes, sensor nodes, network connectivity, and sensing field, error frequency, residual energy, time, and network lifetime. A comparative study with the existing localization models shows that RAPCOL is 30% better than the existing models in terms of accuracy and resource consumption. We observe stable performance of RAPCOL with a differentiated effect of beacon nodes and sensor nodes. We also observe that our proposed IPSO 20% better in fast convergence to the optimal solution. Though RAPCOL localization time is 12% higher than other existing protocols, RAPCOL's accuracy and energy saving mechanism make it efficient for IIoTs.

Keywords Localization · Error · Network lifetime · Cooperative communication · Particle Swarm Optimization

1 Introduction

Industry automation and controls are in a revolution where heterogeneous Wireless Sensor Network (WSN) integrates with them to provide a full-fledged development of Internet-Of-Thing (IoT) systems. The use of a control system with machines, actuators, sensors devices, and processors to accomplish the automation within the process is called industrial automation. The WSNs-based platform gives the resources for gathering, handling, and controlling of data from cyber-physical environments in a configurable and interoperable way. The platform has been implemented in various organizations, which gives positive evaluation by reducing reduce waste, unscheduled downtimes, and enhancing the overall quality of products. From the industrial aspects, the ISA SP100 workgroup has introduced six different classes (Class 5–Class 0) of industrial wireless communication applications, where WSNs also contribute as a major part [1, 2]. Currently, these WSNs are utilized in various fields such as military, environmental monitoring, disaster application, quality control in industry, mines, power plants, and agronomy [3–7].

Heterogeneous WSNs are the collection of sensor nodes that have different operating features such as operating power, computational, and communication capability. WSNs being the constituent of every industrial automation-based framework, a concern of sensor localization arises for functional bug fixing or state measurements. Previously, a Global Positioning System (GPS) with all sensor nodes of WSNs was integrated to ease the task. However,

Extended author information available on the last page of the article the cost and limited resources exclude the use of 100% GPS-embedded sensors in WSNs. Thus, for finding the location of all sensor nodes, localization algorithms use only a few beacon nodes (with GPS); the remaining nodes' (unknown nodes) locations are estimated by these beacon nodes. This process significantly reduces the cost and resource exploitation. Nevertheless, it is expected that the number of beacon nodes must be minimized to reduce the maintenance cost [8, 9]. We can classify the beacon-based localization approach into two major classes: range-free and range-based approaches [10, 11]. The range-based approach requires range measurement parameters for the location estimation process; such a process is not always possible for industry infrastructure, but the range-free approach uses nodes connectivity and hop information [12] to estimate such location coordinates. Some of the important algorithms like Distance Vector-Hop (DV-hop), centroid method, Multi-Dimensional Scaling-MAP (MDS-MAP), and amorphous method come under the range-free approaches. The range-free approaches in WSNs provide a less precise location, but this category gains more attention due to its low cost, higher lifetime, and design simplicity. However, sensor networks for high-risk environments, irrespective of the localization approaches, are resources constrained in terms of power, size, memory, bandwidth, and cost of sensor nodes [13–15]. Hence, less energy consumption and more network lifetime are the most desirable aspects of WSNs. Therefore, improvement in the energy efficiency, accuracy, and network lifetime of the localization algorithm is the most challenging concern for WSNs, which are suitable for the industrial automation paradigm.

1.1 Current state of the research

In this section, we emphasize the part of localization in industry automation and review some important contributions in the direction of range-free approaches and cooperative communication in WSNs-based industries. The authors in [16] show a range-free localization using a genetic algorithm with multi-step-localization (MSL) for improving localization accuracy. Amendatory Simulation Curve Fitting (ASCF) with beacon nodes are also in use for the localization [17]. A series of DV-hop localization algorithms have been developed claiming the improvements in many ways using different optimization techniques to improve the accuracy [18–22]. Distance Compensation Algorithm (DCA) is another variant of DV-hop algorithm [23]. An advanced DV-Hop localization algorithm with approximation coverage, reducing bounding box, and introducing PSO is available in [24]. Hybrid chaotic strategy-based localization has been proposed in WSNs. Initially, a Glowworm Swarm Optimization based on chaotic mutation and inertial weight updating has been introduced to control the movement of each firefly [25]. A distributed range-free localization is able to reduce localization error in three-dimensional WSNs and the concept of coplanarity is introduced to reduce error due to the collinearity of beacon nodes [26]. Further, the complexity of the algorithm is reduced by using Fuzzy Logic System (FLS) [27]. A novel range-free localization algorithm uses swarm intelligence [28]. To improve the centroid localization algorithm, Linear Weighting and Neighbor Weighting have also been introduced recently. In the former, the distance among the nodes are linearly weighted and in the latter number of intersections between nodes are estimated [29]. An iterative centroid algorithm has been shown for WSNs. The centroid location is evaluated on the basis of Received Signal Strength Indication (RSSI) and connected beacon nodes between unknown nodes and the centroid. In order to diminish the localization error, the beacon nodes with small RSSI is replaced by virtual beacon nodes [30].

A localization algorithm with one or more mobile beacon nodes uses Particle Swarm Optimization (PSO) for WSNs [31]. The beacon nodes broadcast their information periodically to unknown nodes for computing the location themselves. The effectiveness of localization in the presence of mobile beacon/anchor nodes is more interesting and is also considered. Localization also uses a single mobile anchor that broadcasts its location information periodically by traveling the deployment area in a trajectory [32]. A Mobile-Assisted Monte Carlo Localization (MA-MCL) has been proposed as an alternative to a single mobile beacon-assisted approach. Generally, Monte Carlo method is used for the movement of a single mobile-assisted seed (converging initialization value) by evading the diverging route [33]. Another mobile beacon-based approach uses analytical geometry in which unknown nodes select the two nearest beacon nodes and compute their own locations based on the radius and half-length of the chord [34]. Mobile anchor/beacon-assisted localization with static path planning algorithm mitigates the problem of co-linearity of the localization process in WSNs [35]. Recently, MAC protocols are also in use for energy-efficient localization algorithms. Cooperative communication improves the throughput and network lifetime. An optimization process for such an algorithm has been formulated with single-hop and multi-hop networks [36]. A multi-path routing scheme for wireless body area network shows the use multi-path routing scheme based on priority to classify the routing paths [37]. However, the classification is unbalanced and leads to under-utilization of a dedicated path.

Cooperative MAC (CMAC) protocol is also suggested for underwater WSNs. CMAC improves latency, throughput, and single-hop packet delivery ratio [38]. Sensor node cooperation with the power optimization algorithm can also prolong the network lifetime. This way cooperative nodes are identified based on channel gain and higher residual energy to broadcast the information to the BS [39]. A cross-layer-based protocol uses cooperative MAC to prolong the network lifetime. A constant data rate is utilized in a cross-layer power allocation scheme for desired outage probability [40, 41]. This cross-layer cooperative MAC protocol also has been introduced for multi-hop WSNs, which improves end-to-end delay, and throughput, and reduces energy consumption [42–45]. In a recent study, we see the use of cooperative communication and network coding strategy to minimize channel impairment and body fading effect in a wireless body area network [46]. Hence, the work claims for reducing the ensued faults, bit error rate, and energy consumption.

The advancements in WSN technology, embedded devices, and the demand of various applications require WSNs to move from static to dynamic network scenarios. Estimating the location of sensor nodes with energy efficiency and high accuracy in mobile network scenarios is more critical. Thus, our proposed range-free localization scheme is a solution to address the issues of mobility, energy consumption, and network QoS. An existing problem is identified after analysis of the previous research works and these problems have been addressed by the proposed solution shown in Table 1.

1.2 Motivation and contribution

The industrial revolution shows a new paradigm of the manufacturing process in Industry 4.0 by including smartness and security. Autonomous vehicles take the next step in the above-mentioned direction [51]. Such industries require cooperative localization indeed [52]. The requirement of a low-cost positioning system with high accuracy leads to our motivation for the work. At present, MAC protocols provide the strongest impact for cooperative localization algorithms in WSNs. However, the use of MAC in localization with reduced energy consumption is missed by the existing works. The overall performance of the network in terms of a lifetime can be significantly upgraded through proper utilization of energy by sending packets at the MAC layer with cooperative communications for localization. Thus, our proposed localization scheme, RAnge-free Power efficient COoperative Localization (RAPCOL), is contributory and novel. To this end, RAPCOL has the following contributions and key features that are discussed point-wise:

- **Cooperative communication at MAC:** In WSNs, randomness deployment of sensor nodes is done because nodes may be situated far away from each other. Hence, direct communication among nodes consumes more power for their operations. To make the system more energy efficient, a range-free Power Efficient Cooperative localization algorithm at MAC for heterogeneous devices in WSNs for Industrial Applications is proposed. The cooperative nodes are selected based on weight metric, residual energy, and distance among nodes.
- **Optimal cooperative node selection:** Optimal cooperative nodes are selected based on the highest weight metric, but firstly it is verified whether it is able to diminish overall energy consumption than direct communication. The nodes with the smallest energy factor are nominated as optimal cooperative nodes.
- **Improvised PSO algorithm:** A mathematical model for heuristic improvised PSO is incorporated to improve localization accuracy. All the tasks of localization and optimization are performed by Base Station (BS) instead of beacon nodes. The proposed algorithm

Table 1 Addressing existing problem with proposed algorithm

Existing algorithm	Existing problems	Solution in proposed algorithm
IDV-Hop [14]	Redundancy of sensor nodes make the process complex and also heavy load distribution to some particular nodes	Nodes are selected based on weight metric, residual energy, and distance among nodes
NDV-Hop [19]	Validation for mobile environment is not considered	In the proposed solution, all sensor nodes (beacon nodes as well as unknown nodes) are mobile in nature, therefore proposed solution supports full mobility of the network
Modified DV-Hop [21]	As beacon nodes are selected on the basis of the maximum degree of connectivity, partial exhaustion of the network exists	Only those beacon nodes are selected for localization whose residual energy is high
Improved DV-Hop [22]	As target nodes act as beacon nodes after localization, therefore consume more energy for localization	By selecting optimal cooperative nodes, the overall energy maintained balanced

ensures energy efficiency by utilizing cooperative communication and prolongs the overall network lifetime.

1.3 Paper organization

We organize the remaining parts of the paper as follows. Section 2 describes the network model and related method for the localization process. We also discuss the node deployment, deployment environment, and definitions for better clarity of the network model. We show the proposed algorithm and discuss the simulated results in Sect. 3. We show the simulation parameters and the evaluation process along with the metrics in this section. Finally, we conclude our work in Sect. 4.

2 Proposed method

In this section, we describe the network model. Based on this model and the WSN scenario, we show the cooperative communication at the MAC layer, handshake procedure, and cooperative node selection process. We also show the conditions for transmission power usage and the condition for residual energy and channel gain usage of the cooperative nodes and derive the formulation used for different calculation processes.

2.1 Network model

We can model WSNs as an undirected graph $G(V, E)$, where V have total N sensor nodes and E describes the edge set of G. In the proposed algorithm, we consider m beacon nodes $(m = i_1, i_2, i_3 ... i_m)$ and u unknown nodes $(u = j_1, j_2, j_3, ..., j_u)$ for localization in 2-dimensional (2-D) plane. All sensor nodes have been deployed randomly with random way-point mobility in the sensing area S of dimension $L * L$ where L represents the length of the side. As the network scenario is heterogeneous, all the sensor nodes deployed are with different features. Each sensor node has a different transmission range. The transmission range represents a circle, where a corresponding node itself represents the center of the circle. In a network, each sensor node has a unique MAC address and different initial energy values. Multiple mobile sensor nodes share the wireless channel. Deployment of both sensor nodes with random way-point mobility is shown in Fig. 1 and represents scenario at the different instant of time. Black nodes represent unknown nodes and red nodes are beacon nodes.

By introducing the concept of cooperative communication, one-hop transmission between beacon nodes to BS is replaced by the two-hop transmission for broadcasting the information. The neighbour unknown nodes are selected within one hop for localization. Furthermore, we consider some assumptions throughout the paper: (i) some special nodes are distributed with prior known (x_i, y_i) through GPS called beacon nodes and these nodes help to find the location of unknown nodes. All sensor nodes are distributed with random mobility. Beacon nodes have been deployed with more resources and communication capability than unknown nodes, (ii) Base Station (BS) is considered in the network that can control all the beacon nodes as well as unknown nodes and it is static. All the computing task of localization for nodes is performed by BS. Therefore, BS is most powerful in terms of resources and computational capability, and (iii) some of the beacon nodes act as helper nodes or cooperative nodes at any instant to broadcast the information from one point to another point. Helper nodes just receive the information from the source beacon nodes and forward that information to BS. We use the following two definitions for better clarity of the network model.

Definition 1 The sensing field $S(B_i, R_i)$ represents the coverage area covered by beacon nodes in the network, where $(i = 1, 2, 3, ..., m)$. The coverage area for each beacon node has been computed by Eq. 1. Every unknown node placed in this area represents one-hop neighbors of the beacon node.

$$S(i_n, R) = \pi R^2. \tag{1}$$

Definition 2 We consider ξ the average number of sensor nodes placed within the transmission range of the beacon node called average connectivity. Therefore, ξ of beacon nodes can be different at a different time interval and given by Eq. 2.

$$\xi = \lambda \pi R^2. \tag{2}$$

$$\lambda = \frac{|U|}{(m)}, \tag{3}$$

where $|U|$ and m represent the total number of unknown nodes and beacon nodes, respectively. We use the distances among nodes for computing the mobility of sensor nodes. We compute the estimated distances using Friis free space propagation model [42]. We use the following equation for computing received power P_r.

$$P_r = P_t \times G_t \times G_r \times \frac{(wave\ length)^2}{(4 \times \pi \times Distance)^2}, \tag{4}$$

where P_t represents the transmitted power, G_t and G_r represents the gain of the transmitting and receiving antenna.

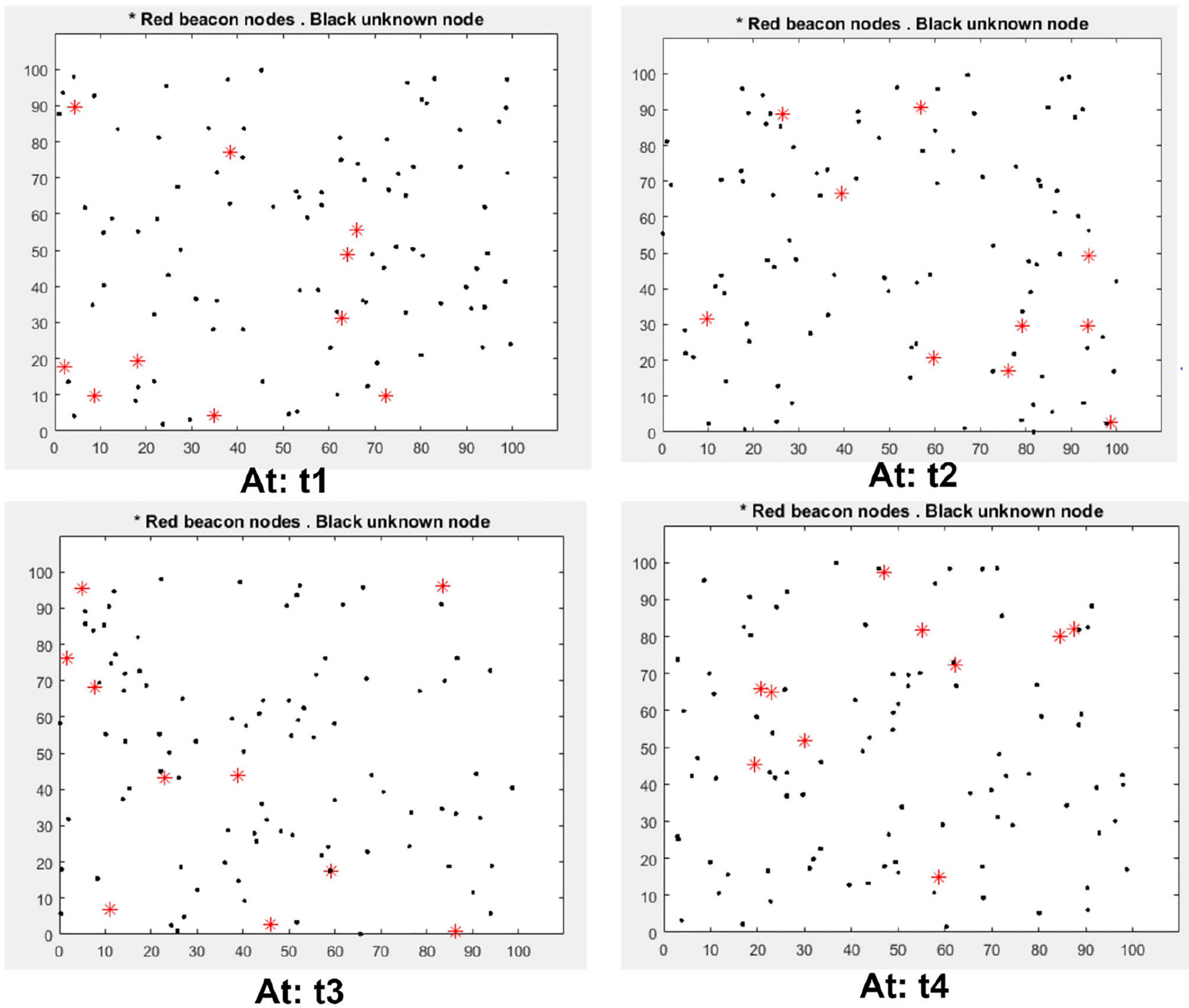


Fig. 1 Random deployment of nodes at different time using random mobility

$$wave\,length = \frac{c}{f}, \tag{5}$$

where c and f describe the speed of light and operating frequency of the signals, respectively.

Estimated distances between beacon nodes and unknown nodes have been computed as follows.

$$Distance^{t}_{(b,u)} = \frac{k}{\sqrt{P_r}}. \tag{6}$$

With the help of the aforementioned equation, we get the exact locations of unknown nodes, which represent the approximation of distances between nodes. Relative mobility between nodes can be computed as follows.

$$M^{t}_{(b,u)} = Distance^{t}_{(b,u)} - Distance^{(t-1)}_{(b,u)}, \tag{7}$$

where $Distance^{t}_{(b,u)}$ and $Distance^{(t-1)}_{(b,u)}$ represent the distance between beacon node b and unknown node u at time t and $t-1$, respectively. The relative mobility of nodes describes whether the nodes move closer or away from each other in the network. All the sensor nodes move with speed v and stay at each location for a pause time t_{pause}. Let d be the distance between two waypoints and the average speed of nodes is computed as follows.

$$v_{avg} = \frac{(v \times d)}{(d + (v \times t_{pause}))}. \tag{8}$$

The proposed algorithm is initialized by broadcasting the position of BS with its coordinates to beacon nodes across the network. The distance between BS and beacon nodes has been estimated based on coordinate information received by each beacon node. The format of a broadcast message by BS is as follows.

BS $\rightarrow$ Beacon nodes: $\{BS\_address, (X, Y)\}$,

where (*X*, *Y*) represents the coordinates of BS. After that, the beacon nodes broadcast Nearest Neighbor Request (*NNReq*) to one hop neighbor unknown nodes. The format of broadcasted packets as follows:

NNReq: $\{Id_i, (x_i, y_i), Hop\_count = 0\}$,

where Id_i represents the serial number of i_{th} beacon node and (x_i, y_i) describes coordinates of i_{th} beacon node with count initialized by zero. The transmission of *NNReq* has been limited to 1-hop nodes. When unknown nodes receive the request by beacon nodes, unknown nodes reply with Nearest Neighbor Reply (*NNRep*) with Id_u and hop count value 1. The format of NNRep packets is as follows.

$NNRep : \{Id_i, (x_i, y_i), Hop\_count = 1, u\_Id\}$.

Id_u represents the identification of the unknown node. It may happen the same message has been received by two-hop unknown nodes. In such cases, if Hop_{count} value is more than 1, the receiving unknown nodes simply discard the message and stop Hop_{count} counter. After receiving the reply from unknown nodes, each beacon node enlists its neighbor nodes lying within one-hop Neighbor Node List (*NNL*) for the localization process. Now, the Neighbor Nodes List (*NNL*) is transmitted to BS either directly or with the two-hop transmission.

Beacon node $\rightarrow$ BS: NNL= $\{Id_i, (x_i, y_i)|u\_1, u\_2, ...\}$.

In random network scenarios, beacon nodes may be situated far away from the BS; therefore, direct communication between beacon nodes and BS consumes more power during transmission. This problem is solvable by cooperative communication by developing a new paradigm beyond the traditional point-to-point and point-to-multipoint communication models. We show an example of cooperative communication in Fig. 2. Beacon node *S*1 is situated two-hops away from BS and a large amount of energy would be consumed for direct communication between *S*1 to *BS*. The energy consumption can be reduced if the information is broadcast through *S*6 or *S*2 to BS. This communication is called cooperative communication and *S*6 or *S*2 can act as helper nodes.

2.2 Cooperative communication at MAC layer

The NNL of beacon nodes is broadcast to BS either in direct communication or with cooperative communication. In Direct communication, the sender-beacon nodes $(Sender_{BN})$ directly send the information to BS otherwise the information is broadcast using cooperative communication. For cooperative communication, all beacon nodes calculate weight metrics based on residual energy and distance from BS. Cooperative or helper nodes $(Cooperative_{BN})$ are selected based on weight metric for efficient cooperative communication.

$$\begin{cases} W_i = w_1 \times E_r^b + w_2 \times \left[log\left(\dfrac{1}{Distance_{BS}^b} \right) \right] \\ w_1 + w_2 = 1,\ 0 < w_1 \ and \ w_2 < 1 \end{cases} \tag{9}$$

where E_r^b represents the residual energy of beacon node, $Distance_{BS}^b$ represents the distance between beacon node and BS, and $(w_1 + w_2)$ represents random factor for bias. We select a beacon node with the highest weight metric as a $Cooperative_{BN}$ by the nearest beacon nodes. Each beacon node maintains a cooperative table that has information about the helper nodes as shown in Table 2. The nodes update the cooperative table periodically and record the latest information about the helper nodes.

2.3 Handshake procedure in proposed RAPCOL

IEEE 802.11 MAC recommends three control frames: Request-to-Send (RTS), Clear-to-Send (CTS), and Acknowledgment (ACK) for data broadcasting. We use these three control frames along with two additional frames: Helper-to-send (HTS) and Cooperative-CTS (CCTS). We introduce these two novel control frames as a contributory to the novelties of our proposed RAPCOL.

Before transmitting information from the sender beacon to the destination beacon, the $Sender_{BN}$ first senses the channel to check if it is idle. If the channel is idle for Distributed Interframe Space (DIFS), the RTS frame is transmitted through the channel after the completion of the required backoff procedure. The RTS frame reserves the channel for Network Allocation Vector (NAV) during which channel is busy and we computed it by Eq. 10, where ζ represents the ratio of the length of the data packet to the rate of transmission.

$$NAV(RTS) = 5 \times SIFS + T_{HTS} + T_{CCTS} + T_{ACK} + \zeta. \tag{10}$$

$$\zeta = \frac{Length}{Datarate}. \tag{11}$$

When neighboring nodes of $Sender_{BN}$ receive the RTS frame, the cooperative node is elected for communication based on weight metric and reserves the channel for *NAV*(*HTS*) duration as computed by Eq. 12.

$$NAV(HTS) = 4 \times SIFS + T_{CCTS} + T_{ACK} + \zeta. \tag{12}$$

After receiving RTS and HTS frames, $Destination_{BS}$ forwards a CCTS frame which means the cooperative transmission is ready and reserves the channel for *NAV*(*CCTS*) calculated by Eq. 14. If the destination receives the RTS frame, but HTS is not received within HTS_time_{out} duration, $Destination_{BS}$ forwards CTS frame. This shows that

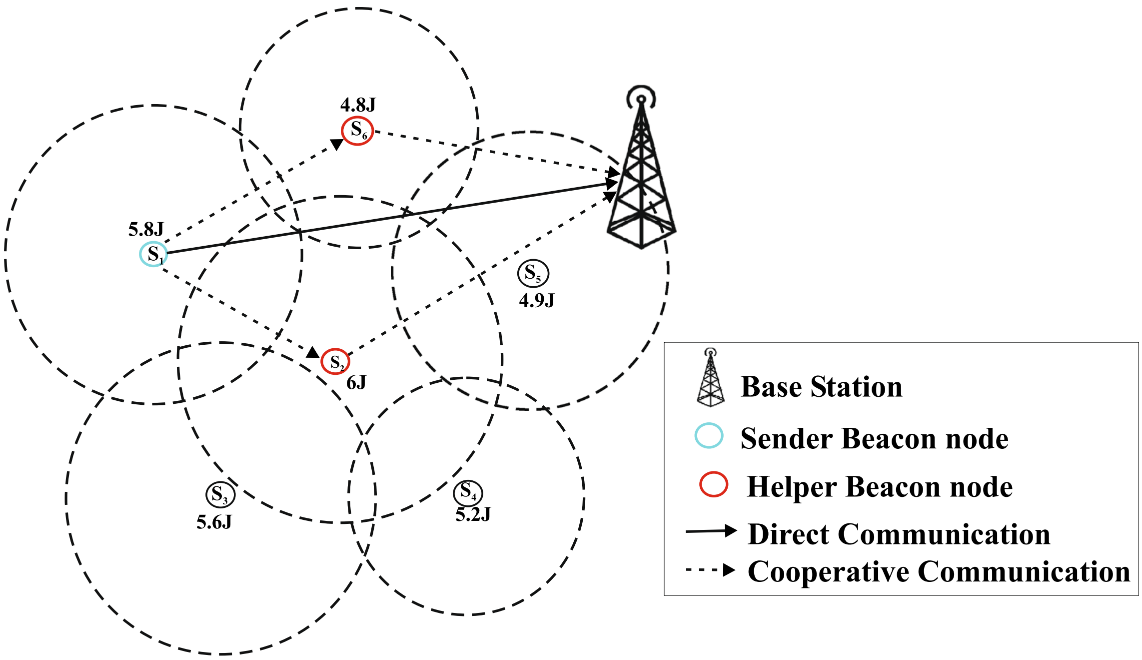


Fig. 2 Network Example with Direct and cooperative communication

direct communication is ready. We calculate HTS_time_{out} duration by the following equation.

$$HTS\_time_{out} = (SIFS + T_{HTS}). \tag{13}$$

$$.NAV(CCTS) = 3 \times SIFS + T_{ACK} + \zeta \tag{14}$$

CCTS and CTS frames hold low power during transmission from $Sender_{BN}$ to $Destination_{BS}$. After receiving CCTS frame, the optimal helper nodes compute their minimum power to transmit information to the $Destination_{BS}$. Only the first arrived HTS frame has been received by $Sender_{BN}$ and it transmits information with optimal cooperative node if it receives HTS and CCTS frame within $CCTS\_time_{out}$. The location information is directly transmitted from $Sender_{BN}$ to $Destination_{BS}$, if S_{BN} receives a CTS frame and the transmission takes place with minimum transmission power for $NAV(CTS)$ duration computed by Eq. 16.

$$CCTS\_time_{out} = (2 \times SIFS + T_{maxBackoff} + T_{HTS} + T_{CCTS}). \tag{15}$$

$$NAV(CTS) = 2 \times SIFS + T_{ACK} + \zeta. \tag{16}$$

After successful reception of information, $Destination_{BS}$ forwards an ACK frame directly to $Sender_{BN}$. The information transmission is successful if $Sender_{BN}$ gets ACK; $Sender_{BN}$ goes idle till the next transmission. If the ACK frame is not received by $Sender_{BN}$ in ACK_time_{out}, which indicates that transmission of information fails and $Sender_{BN}$ contends the channel again for data transmission. We compute ACK_time_{out} by Eq. 17.

$$\begin{cases} ACK\_time_{out} = (2 \times SIFS + \zeta + T_{ACK}) \;\; i.e.\ ACK\ in\ Cooperative\ transmission \\ \quad ACK\_time_{out} = (SIFS + \zeta + T_{ACK}) \;\; i.e.\ ACK\ in\ Direct\ transmission. \end{cases} \tag{17}$$

Fig. 3 represents the procedure for cooperative communication and direct communication between $Sender_{BN}$ and D_{BS} during information transmission respectively. Figure 4 shows the flowcharts of frame exchanges at $Sender_{BN}$, $Cooperative_{BN}$ and $Destination_{BS}$, respectively.

2.4 Selection of optimal cooperative nodes

When $Sender_{BN}$ wants to transmit the list of neighbours to $Destination_{BS}$, it ensures the possible number of neighbor helper nodes for cooperation. After receiving RTS and CCTS frames, the helper node is selected based on the highest weight metric and verifies whether it is able to diminish overall energy consumption in direct communication by cooperative transmission. Energy consumption in

Table 2 Cooperative table format

MAC address of helper node	Weight metric	Distance from source node to helper	Distance from helper to BS	Residual Energy
h_1	w_1	$Distance_{SN}^{h_1}$	$Distance_{BS}^{h_1}$	E_r^1
h_2	w_2	$Distance_{SN}^{h_2}$	$Distance_{BS}^{h_2}$	E_r^2
.	.	.	.	.
h_n	w_n	$Distance_{SN}^{h_n}$	$Distance_{BS}^{h_n}$	E_r^n

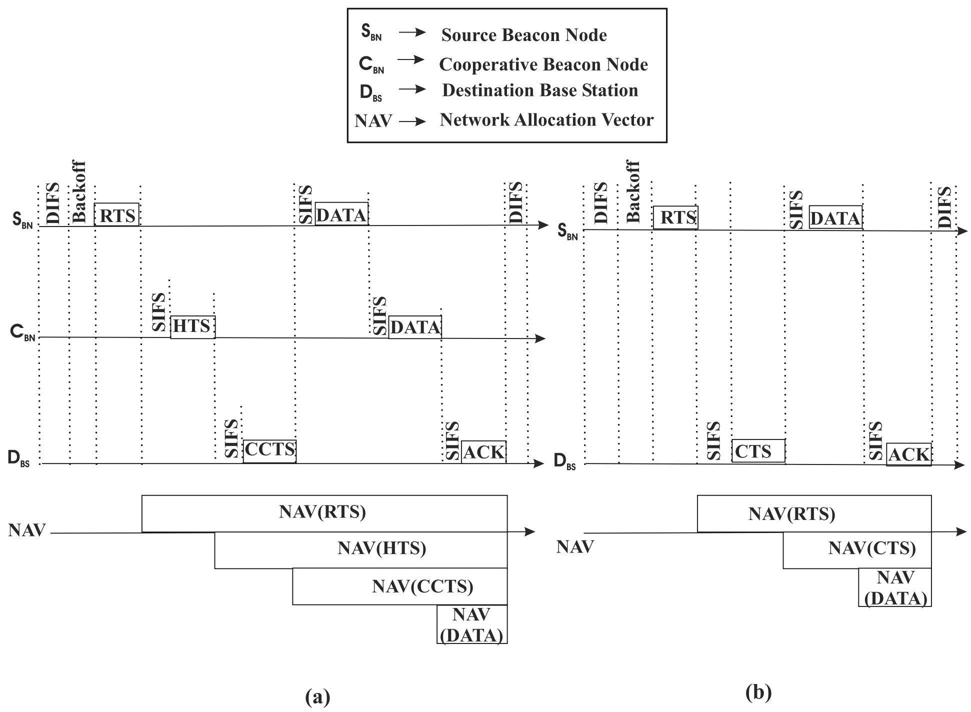


Fig. 3 **a** Procedure for cooperative communication and **b** procedure for direct communication

direct communication and cooperative communication is computed by Eqs. 18 and 19, respectively.

$$E_{direct} = (P_t + P_r) \times \varphi + \left(P_t^{Sender_{BN}} + P_r\right) \times \zeta. \tag{18}$$

$$\varphi = T_{RTS} + T_{CTS} + T_{ACK}, \tag{19}$$

where, E_{direct} represents the energy consumed in direct communication, P_t represents the total power required for transmission of RTS, CTS, and ACK frames, ϑ represents the total time duration for transmission of RTS, CTS, and ACK frames, $P_t^{Sender_{BN}}$ represents the transmission power for data packet transmission from $Sender_{BN}$ to $Destination_{BS}$ indirect transmission and P_r describes the power for reception that can be calculated using free space propagation model [29].

$$E_{Cooperative} = (P_t + P_r) \times \alpha + \left(P_t^{Sender_{BN'}}\right) + P_t^{Coopertaive_{BN}} + 2P_r) \times \zeta. \tag{20}$$

$$\alpha = (T_{RTS} + T_{CTS} + T_{HTS} + T_{ACK}) \tag{21}$$

where, $E_{Cooperative}$ represents the energy consumption during cooperative communication and α is the total time duration of RTS, CTS, HTS, and ACK frames. The information has broadcast to $Destination_{BS}$ through cooperative transmission only when cooperative transmission reduces energy consumption, otherwise, information transmission takes place directly.

$$\Delta_E = E_{direct} - E_{Cooperative}. \tag{22}$$

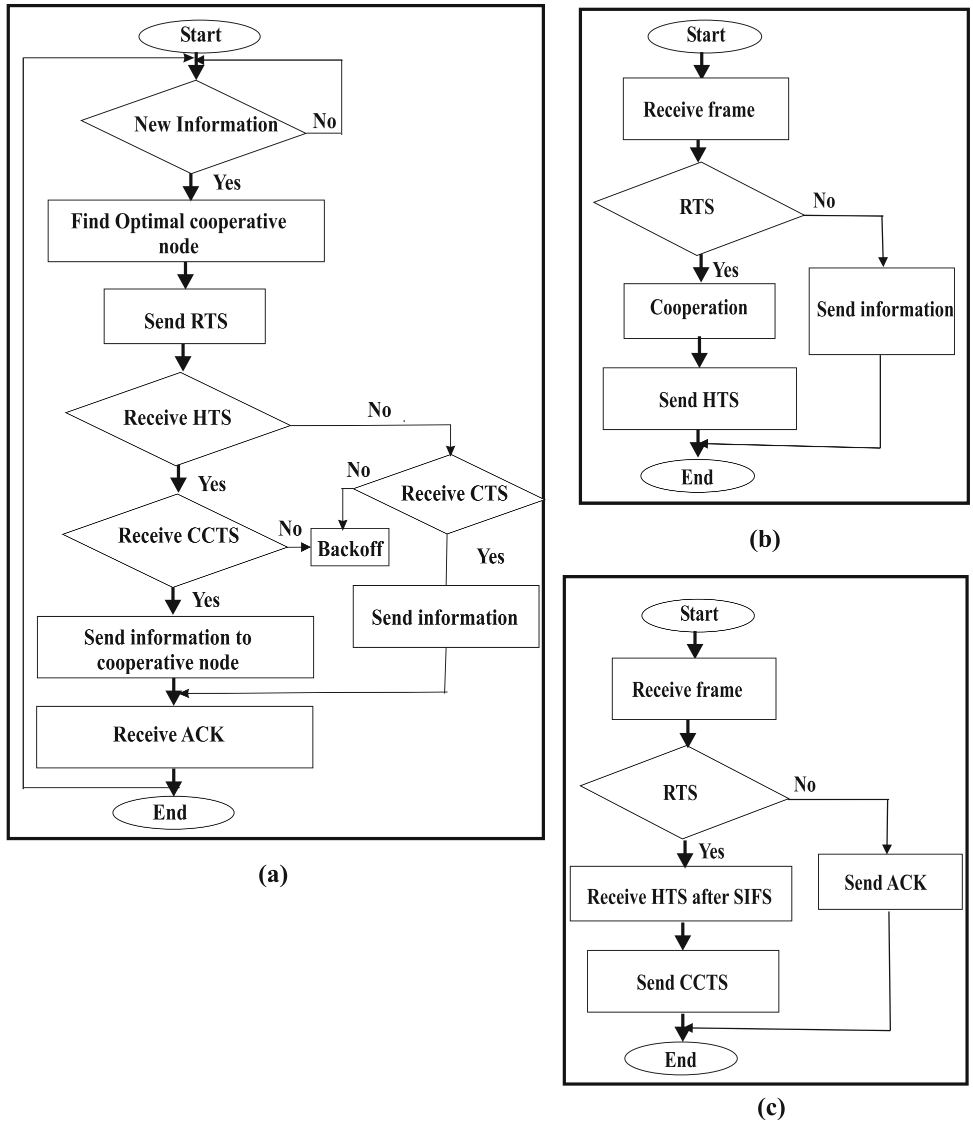


Fig. 4 Flowcharts for **a** frame exchanges at $Sender_{BN}$. **b** Frame exchanges at $Cooperative_{BN}$ and **c** Frame exchanges at $Destination_{BS}$

$$\Delta_E = (P_T \times T_{HTS}) + \Big(P_t^{Sender_{BN}} - P_t^{Sender_{BN}'} - P_t^{Cooperative_{BN}} - P_r\Big) \times \zeta. \tag{23}$$

For cooperative transmission, $Coopertaive_{BN}$ satisfies the following condition.

$$\Delta_E > 0. \tag{24}$$

The beacon node satisfying the above condition is selected for cooperative communication. Δ_E equal to zero means any transmission can be used for information broadcast. To select an optimal $Cooperative_{BN}$ within the neighborhood, the energy factor denoted by ξ is introduced and computed as follows.

$$\xi = \frac{E_c^b}{E_r^b}, \tag{25}$$

where E_c^b and E_r^b represent the total consumed energy and residual energy of the cooperative node, respectively. In this paper, the energy consumption required for data transmission is considered for simplicity, and other energy consumption during sensing and data processing is ignored. The nodes with the smallest ξ are selected as cooperative nodes. By introducing an energy factor, the proposed algorithm can efficiently evade the situation in which random nodes are selected for cooperation resulting in a degraded network lifetime.

2.5 Condition for transmission power

To improve the performance of our proposed RAPCOL, the transmission power for $P_t^{Sender_{BN}}$ and $P_t^{Cooperative_{BN}}$ should satisfy two conditions for data transmission efficiency. According to the Shannon theorem, the transmission power of $Sender_{BN}$ should satisfy the following condition given in Eq. 26.

$$B_u \leq \frac{1}{2} log_2 \left[1 + \left(\frac{P_t^{Sender_{BN}}}{N_0} \right) \right], \tag{26}$$

where B_u represents the bandwidth utilization during data transmission and N_0 white Gaussian noise. In cooperative communication, the information is transmitted from $Sender_{BN}$ to $Destination_{BS}$ by two-hop transmission shown as follows.

$$\begin{cases} Sender_{BN} \rightarrow Cooperative_{BN} \\ Cooperative_{BN} \rightarrow Destination_{BS} \end{cases}$$

Therefore, $\frac{1}{2}$ factor is introduced in Eq. 26 due to the requirement of half of the channel resources for one-hop transmission and it can be deduced as follows.

$$\left(\frac{P_t^{Sender_{BN}}}{N_0} \right) \geq 2^{2R} - 1. \tag{27}$$

The condition shown in Eq. 27 should be satisfied by $Cooperative_{BN}$ in data transmission. The sensor nodes should adjust their maximum transmission power expressed in Eqs. 28 and 29.

$$0 < P_t^{Sender_{BN}} \leq P_{max}. \tag{28}$$

$$0 < P_t^{Cooperative_{BN}} \leq P_{max}. \tag{29}$$

$P_t^{(Sender_{BN})}$ remains positive because it is essential power to transmit information from $Sender_{BN}$. $P_t^{(Cooperative_{BN})}$ can be zero because in case of zero power information can be transmitted directly to $Destination_{BS}$ without any cooperation. In our proposed RAPCOL, We utilize the Shannon theorem to constrain the transmission power within the range of maximum transmission power. Shannon's theorem provides the boundary to the transmission power of the beacon nodes.

2.6 Condition for residual energy and channel gain of cooperative nodes

To improve the network lifetime, minimum residual energy among $Sender_{BN}$ and $Cooperative_{BN}$ during information transmission should be maximized and can be expressed by Eqs. 30 and 31, respectively. In Eq. 30, $E_r^{(Sender_{BN})}$ represents the residual energy of $Sender_{BN}$ after current packet transmission, T represents the duration of packet transmission, $E^{(Sender_{BN})}$ represents the residual energy of $Sender_{BN}$ before data packet transmission and φ represents total energy consumption required for data transmission. In Eq. 32, $E_r^{(Cooperative_{BN})}$ represents the residual energy after information packet transmission, $E^{(Cooperative_{BN})}$ represents the residual energy before information packet transmission, and χ describes the total energy consumed for data packet transmission at cooperative nodes.

$$E_r^{Sender_{BN}} = min\{E^{Sender_{BN}} - \vartheta\}. \tag{30}$$

$$\vartheta = (P_t + P_r \times \varphi \times T). \tag{31}$$

$$E_r^{Cooperative_{BN}} = min\{E^{Cooperative_{BN}} - \chi\}. \tag{32}$$

$$\chi = (P_t + P_r \times \alpha \times T). \tag{33}$$

In order to prolong the network lifetime, the factor ϑ and χ should be optimized to maximize the residual energy for both $Sender_{BN}$ and $Cooperative_{BN}$ in cooperative communication as expressed in Eq. 34.

$$[max.\{E_r^{Sender_{BN}}, E_r^{Cooperative_{BN}}\}]. \tag{34}$$

The Beacon node is selected as $Cooperative_{BN}$ only when its residual energy and channel gain between itself and $Sender_{BN}$/ $Destination_{BS}$ satisfy certain conditions. The residual energy of $Cooperative_{BN}$ before cooperative communication should be larger than $Sender_{BN}$ residual energy after transmitting information directly to $Destination_{BS}$.

$$E^{Sender_{BN}} - P_D T < E^{Cooperative_{BN}}, \tag{35}$$

where P_D represents the required transmission power for direct transmission and direct power from $Sender_{BN}$ to $Destination_{BS}$ is calculated by Shannon theorem as follows.

$$B_u \leq log_2 \left[1 + \left(\frac{P_D}{N_0} \right) \right]. \tag{36}$$

After rearranging Eq. 36, we obtain:

$$2^n - 1 \leq \left(\frac{P_D}{N_0} \right) \bigg]. \tag{37}$$

$$P_D \geq (N_0(2^{B_u} - 1)). \tag{38}$$

All the beacon nodes transmit the list of neighbors' unknown nodes to BS through an optimal cooperative node or direct transmission. We summarize the process of optimal cooperative node selection in Algorithm 1.

Algorithm 1 Power-Efficient Cooperative Communication at MAC

Initialize all parameters
Input: Deployment of Base Station (BS), a set B and U of beacon nodes (BN) and unknown nodes (UN)
Output: Direct or cooperative communication
$BS \rightarrow BN$: $(BS_{address}, X, Y)$
$BN(i) \rightarrow BN(j)$: $NNRep(Id_i, (x_i, y_i), Hop\_count = 0)$
$BN(j) \rightarrow BN(i)$: $NNReq((Id_j, (x_j, y_j), Hop\_count = 1))$
$BN(i)$: Compute NNL
for each beacon node **do**
$BN(i) \rightarrow BS$: NNL
if $Distance_{BS}^{(Sender_{BN})} < Distance_{(Sender_{BN})}^{(Cooperative_{BN})}$ **do**
NNL:BS with direct communication $(Direct_{communication})$
else
Cooperative communication $(Cooperative_{communication})$
if $(W_k < W_j)$ **do**
$BN(j)$ selected as cooperative node
else
$BN(k)$ selected as cooperative node
if $\Delta E > 0$ **do**
$Cooperative_{communication}$
else
$Direct_{communication}$
end if
end if
end if
end for

2.7 RAPCOL in heterogeneous WSNs

After receiving the NNL from each beacon node, the process of location estimation is performed by BS. In two-dimensional WSNs, we consider total m beacon nodes and u unknown nodes are randomly distributed with mobility. The vector $\rho = [v_1, v_2, v_3, ...v_{(m+u)}]$ has the initial coordinates of the nodes and $v_i = [x_i, y_i]^T$. The coordinates of m beacon nodes are represented by $[(x_1, y_1), (x_2, y_2), ..., (x_m, y_m)]$. Therefore, the localization problem can be mathematically represented by the following.

$$(\hat{x}, \hat{y}) = F_{i=1,2,...m}(x_i, y_i, d_i), \tag{39}$$

where $(\hat{x}, \hat{y})$ represents the coordinates of unknown nodes, (x_i, y_i) represents the coordinates of i^{th} beacon nodes, and (d_i) describes the distance among nodes. The main concentration of estimating the coordinates of unknown node in such a way that it contains the least localization error.

2.7.1 Localization of unknown nodes

After receiving the information, we apply $2D$ hyperbolic method instead of trilateration or triangulation at BS to compute the position of unknown nodes. The hyperbolic positioning algorithm transforms the nonlinear problem into a linear problem that can be solved with a least squares estimator, which minimizes the overall localization error. So to reduce overall localization error, we used hyperbolic trilateration. The distances among unknown nodes and all beacon nodes are computed using the following equation.

$$Distance_i^{est} = \sqrt{(x_i - \hat{x})^2 - (y_i - \hat{y})^2}, \tag{40}$$

where $Distance_i^{est}$ represents the estimated distance between an unknown node and the beacon node. By rearranging the above equation, we have the following expression.

$$x_i^2 + y_i^2 - 2x_i\hat{x} - 2y_i\hat{y} + (\hat{x})^2 + (\hat{y})^2 = (Distance_i^{est})^2. \tag{41}$$

$$A_i = x_i^2 + y_i^2. \tag{42}$$

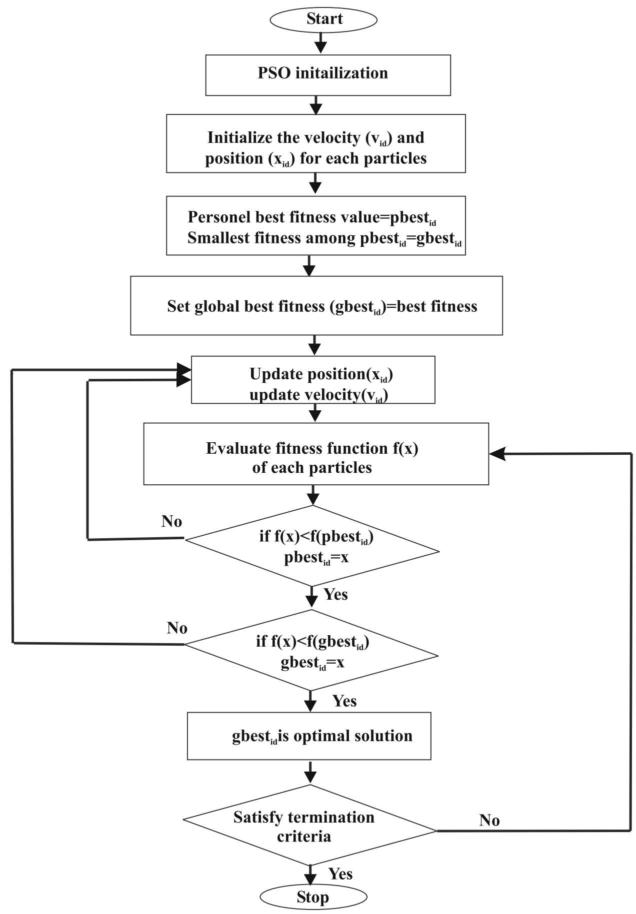


Fig. 5 Flowchart for PSO optimization algorithm

$$
\begin{aligned}
&B = (\hat{x})^2 + (\hat{y})^2.\\
&(Distance_i^{est})^2 - A_i = -2x_i\hat{x} - 2y_i\hat{y} + B\\
&P_c = [\hat{x}, \hat{y}, B]^T\\
&K_c = \begin{pmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ . & . & . \\ . & . & . \\ -2x_i & -2y_i & 1 \end{pmatrix}\\
&H_c = \begin{pmatrix} (Distance_1^{est})^2 - A_1 \\ Distance_{est}^2 - A_2 \\ . \\ . \\ (Distance_i^{est})^2 - A_i \end{pmatrix}
\end{aligned} \tag{43}
$$

For a system of two unknown variables, i.e., X coordinate and Y coordinate of an unknown node can be modeled as shown in Eq. 44.

$$K_cP_c = H_c. \tag{44}$$

With the help of the least square method, the coordinates of unknown nodes are estimated using the following equation.

$$P_c = (K_c^TK_c)^{-1}K_c^TH_c. \tag{45}$$

Now, the coordinates of an unknown node are represented as follows:

$$\begin{cases} \hat{x} = P_c(1) \\ \hat{y} = P_c(2) \end{cases}$$

To get more accuracy in location estimation, the difference between actual distances and $Distance_i^{est}$ must be minimized. In localization, the $Distance_i^{est}$ between nodes is affected due to Gaussian noise in WSNs. Therefore, we adjust $Distance_i^{est}$ as follows.

$$\hat{D_i} = Distance_i^{est} + n_i. \tag{46}$$

In the aforementioned equation, n_i represents the noise that affects the estimated distances in the range of $\{Distance_i^{est} \pm Distance_i^{est}\frac{P_n}{100}\}$, where P_n represents the percentage of noise.

2.7.2 Improvised PSO algorithm

We introduce the improvised PSO algorithm in our proposed RAPCOL that improves the estimated distances between nodes. PSO is a popular heuristic algorithm used to explore the search space of a given problem to discover the parameters required to maximize specific objective [43]. The velocity and position of the particle are signified by v_{id} and x_{id}, respectively. The personal best of i^{th} particle is represented by $pbest_{id}$ and the smallest F among $pbest_{id}$ is denoted by $gbest_{id}$, which indicates the global best solution. At each iteration k, the velocity v_{id} and position x_{id} of each particle are updated by using Eqs. 47 and 48.

$$v_{id}(K+1) = \omega \times v_{id}(K) + c_1 \times r_1 \times (pbest_{id} - x_{id}) + c_2 \times r_2 \times (gbest_{id} - x_{id}). \tag{47}$$

$$x_{id}(K+1) = x_{id}(K) + v_{id}(K+1), \tag{48}$$

where ω represents the inertia weight of the particle, c_1 and c_2 represents the acceleration constants, and r_1 and r_2 are random variable lies between [0, 1]. We show a flowchart for the proposed improvised PSO algorithm in Fig. 5. Let $(\hat{x}, \hat{y})$ be the coordinates of unknown nodes U, (x_i, y_i) represents the coordinates of beacon nodes $B_i(i = 1, 2, ..., m)$. Therefore, to minimize the localization error objective function can be formulated as:

$$f(\hat{x},\hat{y}) = \frac{1}{m}\sum_{i=1}^{m}\left(\sqrt{(\hat{x}-x_i)^2+(\hat{x}-y_i)^2}-\hat{D_i}^2\right), \tag{49}$$

where m represents the total number of beacon nodes. The localization problem can be solved by minimizing the value of the objective function given in the aforementioned equation. A minimum value of F has closer to the optimal global solution than other particles with larger F. The value of the objective function must be minimized to get an accurate location estimation of unknown nodes.

3 Results and Discussion

We perform the experimental simulations in MATLAB 2017 to evaluate the outcomes of our proposed RAPCOL algorithm. We list the simulation parameters considered for experimentation in Table 3.

3.1 Simulation parameters and performance metric

In the simulation, we evaluate the results based on various performance metrics including localization error, error variance, and network lifetime. Therefore, the influence of node density, beacon nodes, communication radius, and sensing field has been analyzed on localization error.

3.1.1 Localization error ($Error_u$)

$Error_u$ represents the difference between estimated coordinates to true coordinates of an unknown node u. We measure $Error_u$ as follows.

$$Error_u = \sqrt{\left(x_u^{est}-x_u^{act}\right)^2+\left(y_u^{est}-y_u^{act}\right)^2}, \tag{50}$$

where(x_u^{est}, y_u^{est}) and (x_u^{act}, y_u^{act}) represent the estimated and actual position of unknown node u, respectively.

3.1.1.1 Average localization error (ALE) It represents the sum of localization error to the total number of unknown nodes and is evaluated as follows.

$$\gamma = \frac{\sum_{u=m+1}^{N}\sqrt{(x_u^{est}-x_u^{act})^2+(y_u^{est}-y_u^{act})^2}}{(N-m)\times R}. \tag{51}$$

$$LEV = \sqrt{\frac{\sum_{u=m+1}^{N}\left(\sqrt{(x_u^{est}-x_u^{act})^2+(y_u^{est}-y_u^{act})^2}-\gamma\times R\right)^2}{(N-m)\times R^2}}, \tag{52}$$

where LEV represents the localization error variance and R represents the communication radius. The accuracy of the localization algorithm is computed as follows.

$$Accuracy = (1-ALE)\times 100. \tag{53}$$

Proportion of Localized Sensor Node (PLSN):

PLSN can be defined as the ratio of a total number of successfully localized nodes to the number of unknown nodes. PLSN gives the measurement of positioning coverage and it is formulated as follows.

$$PLSN = \frac{S_{LN}}{N-m}. \tag{54}$$

Proportion of Unlocalized Sensor Node (PUSN): It represents the ratio of number of unlocalized nodes to the total number of localized and it shows the stability of our RAPCOL algorithm. The unlocalized sensor nodes remain unlocalized after the localization process and can be evaluated as follows:

$$PLSN = \frac{U_{LN}}{S_{LN}}. \tag{55}$$

The unlocalized nodes are those nodes that have localization errors more than $\frac{R}{2}$.

Table 3 Simulation parameters

Parameters	Value of parameters	Parameters	Value of parameters
RTS	160bits	Population size	30
HTS	192bits	$k_{max.}$	30
CCTS	120bits	c_1, c_2	2.0
CTS	128bits	Sensor nodes	$100-400$
Sensing field	$100\times 100m^2$ to $400\times 400m^2$	Initial energy	$4-6J$
ACK	112bits	$\omega_{max.}$	0.9
SIFS	$10\mu s$	Beacon nodes	$10-40\%$
DIFS	$50\mu s$	Communication radius	$15-60m$
$P_{max.}$	$50mw$	Network topology	Random way point mobility
B_u	$10khz$	Maximum iteration	500

$$\begin{cases} E_{Tx}(k, Distance) = k \times E_{Elec} + k \times E_{FS} \times Distance^2 & Distance < d_0 \\ E_{Tx}(k, Distance) = k \times E_{Elec} + k \times E_{MP} \times Distance^4 & Distance \geq d_0 \\ d_0 = \sqrt{\frac{E_{FS}}{E_{MP}}}. \end{cases} \quad (56)$$

$$E_{Rx}(k) = k \times E_{Elec}, \quad (57)$$

where $E_{Tx}(k, Distance)$ represents the required energy for transmission of k bits data from one node to another node at a particular distance, $E_{Rx}(k)$ represents the energy required for receiving k bits data, E_{Elec} represents the energy consumed by an electronic circuit, E_{FS} represents the energy required for free space model amplifier, and E_{MP} describes the required energy for the multi-path fading model amplifier. The average residual energy E_r^{avg} of beacon nodes is an important parameter to evaluate the performance of RAPCOL.

$$E_r^{avg} = \frac{1}{m} \sum_{(j=1)}^{m} E_r^b. \quad (58)$$

The variance of the residual energy of all nodes is computed as follows.

$$E_r^{var} = \sqrt{\frac{1}{m} \sum_{(j=1)}^{m} (E_r^b - E_r^{avg})^2}. \quad (59)$$

Proportion of Unlocalized Sensor Node (PUSN)

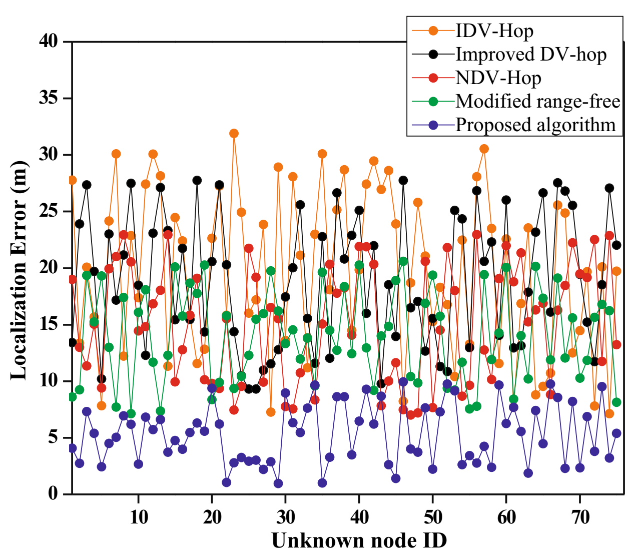


Fig. 6 Localization error for each unknown node

3.2 Simulation results

We compare the outcomes of our proposed RAPCOL with four existing models: (i) IDV-HOP [14], (ii) NDV-Hop [19], (iii) Modified DV-Hop [21], and (iv) Improved DV-Hop [22]. We evaluate the performance of our proposed RAPCOL by varying the parameters of beacon node ratio, sensor node density, transmission range, sensing field, and residual energy. Therefore, to analyze the behavior of the proposed RAPCOL, we execute a set of experiments.

- **Experiment 1: Evaluating Average Localization Error (ALE)**
- **Experiment 2: Effect of ratio of beacon nodes**
- **Experiment 3: Effect of total number of sensor nodes**
- **Experiment 4: Effect of sensing field**
- **Experiment 5: Frequency of error occurrence**
- **Experiment 6: Residual energy**
- **Experiment 7: Localization time**
- **Experiment 8: Effect of Network Connectivity on localization**
- **Experiment 9: Effect of ratio of beacon nodes and total sensor nodes on LEV**

Experiment 1: Average Localization Error (ALE)

For experiment 1, we distribute 100 nodes with random mobility in $100 \times 100m^2$ area having 25% beacon nodes. Due to the heterogeneity of the network, the range of communication and initial energy is assumed as $25 - 40\,m$ and $4 - 6J$, respectively. Localization error computed for each node has been displayed in Fig. 6. The figure shows that the proposed RAPCOL is better as compared to other algorithms. We summarize the maximum, minimum, and average localization errors in Table 4.

Experiment 2: Effect of ratio of beacon nodes

The number of beacon nodes in the network solely affects the localization performance. In experiment 2, ALE can be determined with the variation in the ratio of beacon nodes. 100 number of sensor nodes are distributed in $100 \times 100m^2$ sensing field have considered with $15 - 60m$ transmission range for simulation. The ALE of different algorithms with variable ratios of beacon nodes is depicted in Fig. 7. The outcomes show that as the ratio of beacon nodes increases, the ALE of all algorithms decreases because large information can be accumulated by more beacon nodes. From the figure, we infer that our proposed RAPCOL has the least localization error as compared to the other algorithms. The localization accuracy of an algorithm has also affected by the transmission range shown in Fig. 7 and the ALE of the algorithms decreases as the transmission range increases. It happens because the network becomes more connected when the transmission range increases.

Table 4 Comparison of localization error for different algorithms

Algorithm	Maximum localization error	Minimum localization error	Average localization error
IDV-Hop [14]	7.1274	31.099	20.226
Improved DV-Hop [22]	9.3037	27.7576	18.9072
NDV-Hop [19]	6.2963	22.9624	15.2289
Modified DV-Hop [21]	6.0042	20.2041	14.0147
Proposed Algorithm	9.9561	0.9601	5.34

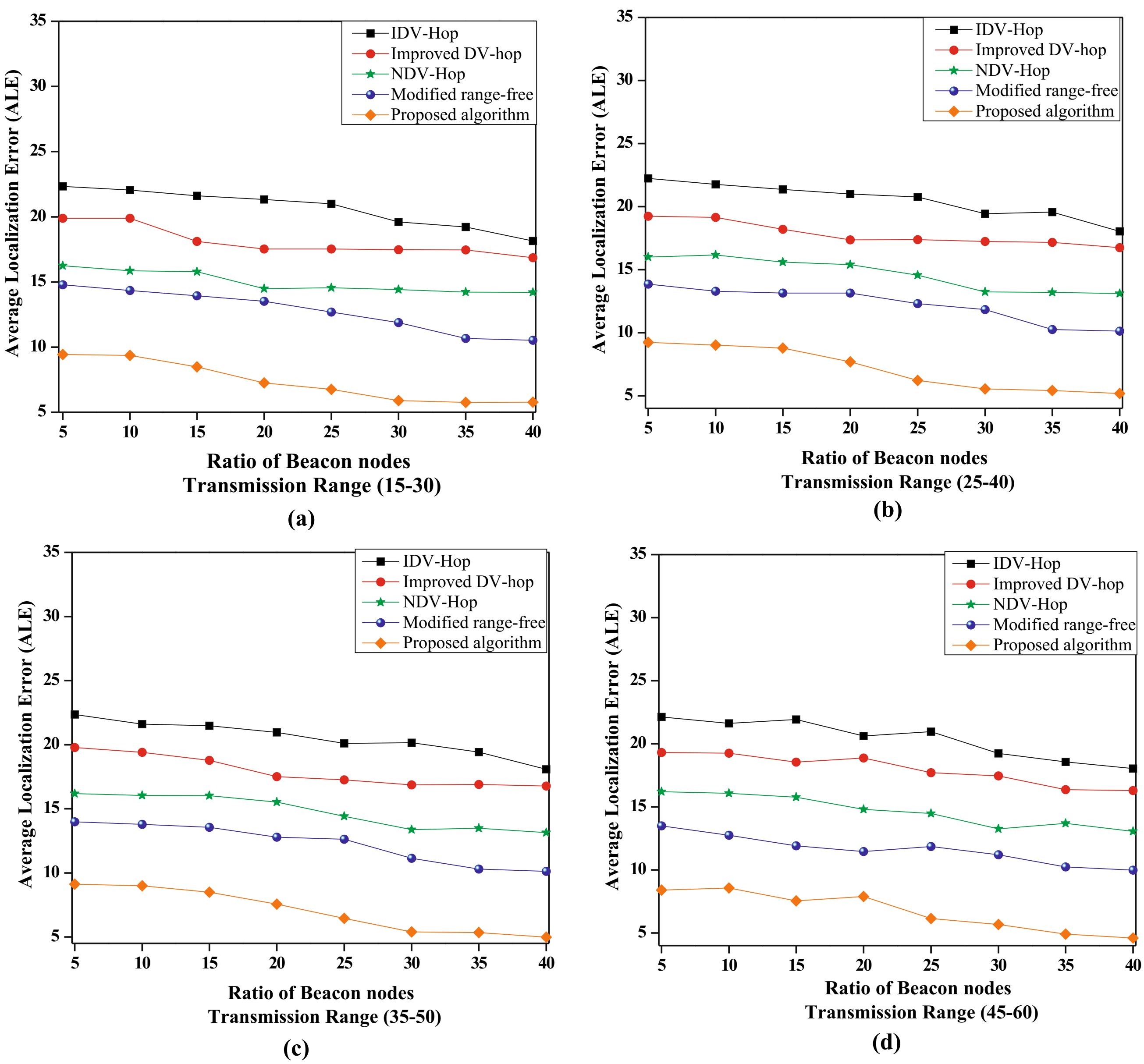


Fig. 7 : Effect of ratio of beacon nodes and transmission range on ALE

Experiment 3: Effect of nodes density on ALE

Node density solely influences the location estimation process in terms of localization accuracy. The performance has been evaluated in terms of error by varying node density in experiment 3. To evaluate the performance, we deploy 100 to 400 nodes in $100 \times 100m^2$ with 20% beacon nodes having transmission range within $15m$ to $60m$. From the simulated outcomes, we observe that the expansion of node density reduces the ALE for all algorithms. As the node density increases, the connectivity of the network also increases; it results in the accumulation of large location information. After reaching a certain limit of sensor nodes, network connectivity do not contribute more variation and also minor variation takes place in ALE. Figure 8 demonstrates the influence of node density on ALE. It has been examined from the simulated outcomes that our RAPCOL performs effectively as compared to the other algorithms.

Experiment 4: Effect of sensing field

In experiment 4, the impact of the sensing field on ALE is examined. We can compute ALE by varying sensing area from $100 \times 100m^2$ to $400 \times 400m^2$ with 20% beacon

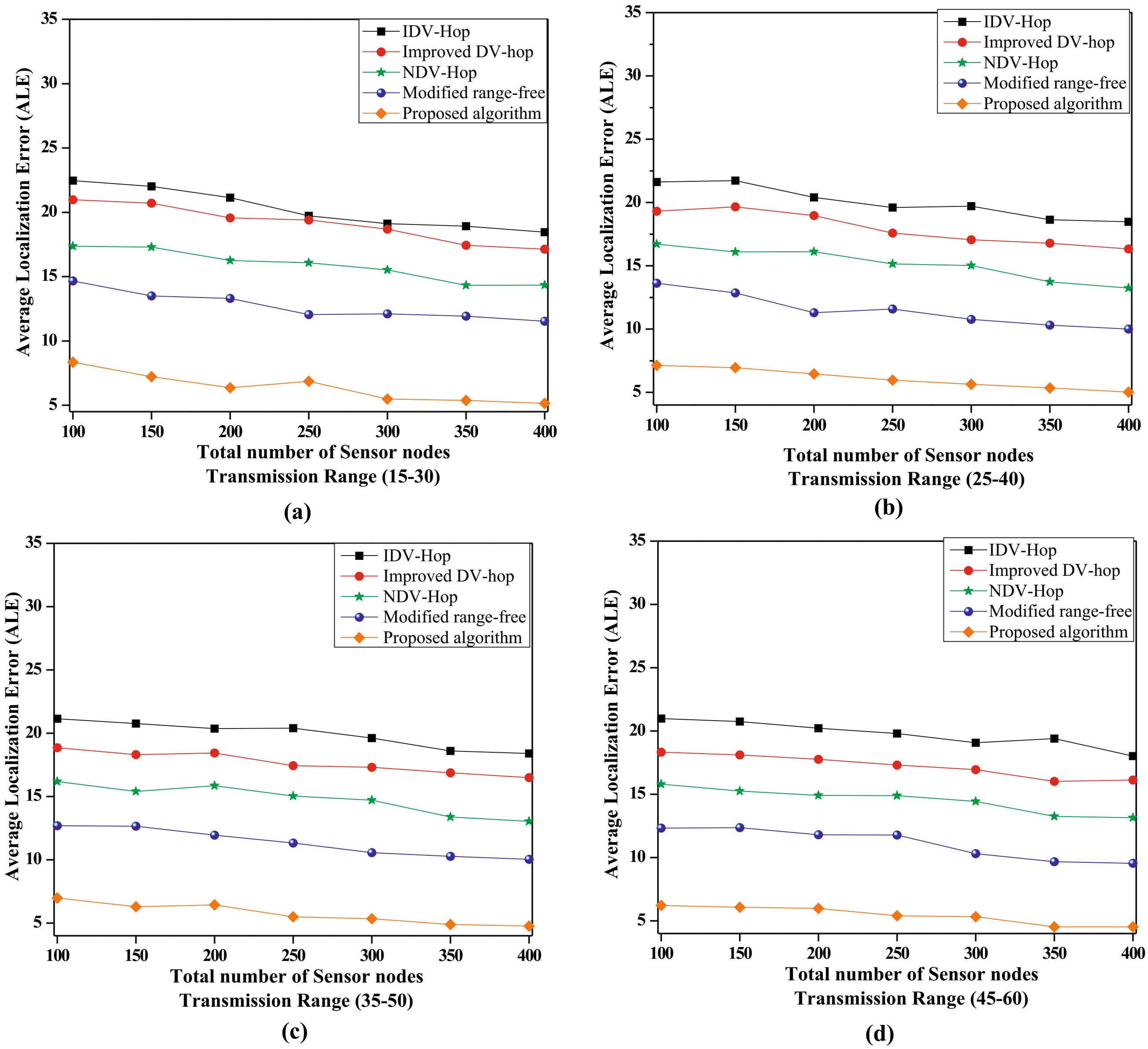


Fig. 8 Effect of nodes density and transmission range on ALE

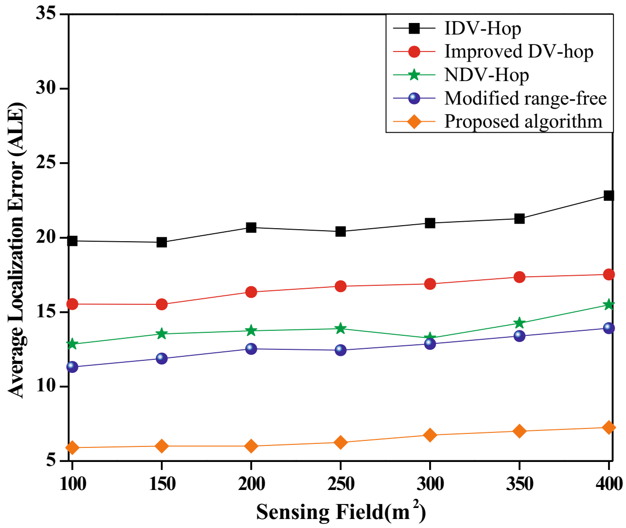


Fig. 9 Effect of variation in sensing field on ALE

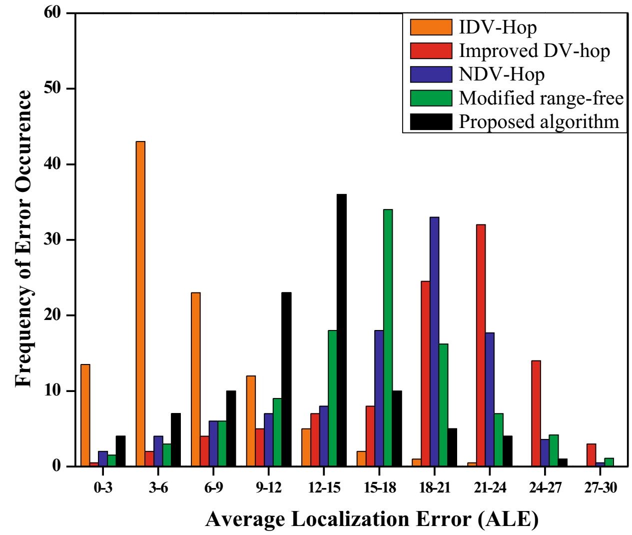


Fig. 10 Frequency of error occurrence for different algorithms

nodes and total 100 nodes distributed with $25-40m$ transmission range. We see that ALE increases as the sensing field increases. The connectivity of the network decreases as the sensing area increases, which influences the performance of the algorithm. From Fig. 9, it has been realized that our proposed algorithm outperforms with respect to other existing algorithms.

Experiment 5: Frequency of error occurrence

We examine the frequency of localization errors in Experiment 5. We use 100 nodes in $100 \times 100m^2$ area having 20% beacon nodes. To compute the ALE for all algorithms, we simulate the experiment for 100 times and observe the average accuracy. Figure 10 reveals that most localization error lies in intervals of $3-6$ and $6-9$ for our proposed RAPCOL. The proposed algorithm has the lowest localization error compared to the other algorithms. We show the summarized results in Fig. 10.

Experiment 6: Impact of the ratio of beacon node and total sensor nodes on the percentage of Residual energy

We execute experiment 6 to examine the percentage of residual energy for all algorithms and to evaluate the performance. We distribute 100 to 400 nodes with 10 to 40% of beacon nodes using $25-40m$ transmission range and $4-6J$ initial energy. Further, the information of all unknown nodes collected by beacon nodes is transmitted through cooperative beacon nodes to BS. We compute the location of all unknown nodes at BS by performing optimization and localization tasks; therefore, the minimum message exchanges take place between beacon nodes and unknown nodes. Figure 11 represents the influence of variation in beacon node ratio and the total number of sensor nodes on the residual energy percentage of the network. We understand from the simulated results that our RAPCOL has more residual energy with respect to other algorithms.

Experiment 7: Effect of ratio of beacon nodes and total sensor nodes on LEV

We observe the effect of beacon nodes ratio and total sensor nodes on LEV in experiment 7. We use 100 to 400 sensor nodes with 10% to 40% beacon nodes in the transmission range $25-40m$. We observe the influence of both factors on LEV from Fig. 12.

Experiment 8: Influence of network connectivity on localization

The proportion of localized nodes and unlocalized nodes are the critical metrics for measuring the performance of the localization algorithm in WSNs. To examine the effect of network connectivity on the coverage of the algorithm, we compute PLSN and PUSN by altering connectivity from 2 to 16. Figure 13 depicts PLSN and PUSN by varying network connectivity for different algorithms. From Fig. 13, we see that after approaching network connectivity 9, all the unknown nodes are localized successfully by our proposed RAPCOL. The simulated results reveal that RAPCOL has better coverage.

Experiment 9: Computational Efficiency and computational complexity

The computational cost of an algorithm represents the evaluation of complexity and can be computed by estimating the consumed time to perform a specific task by an algorithm. It is the computational time required for computing the location of unknown nodes. We show the localization time of all the algorithms in Fig. 14. We see from Fig. 14 that IDV-HOP [14] has the lowest localization time and the modified range-free approach [21] requires more time because of TLBO optimization. Our RAPCOL requires more time than NDV-Hop [19] because

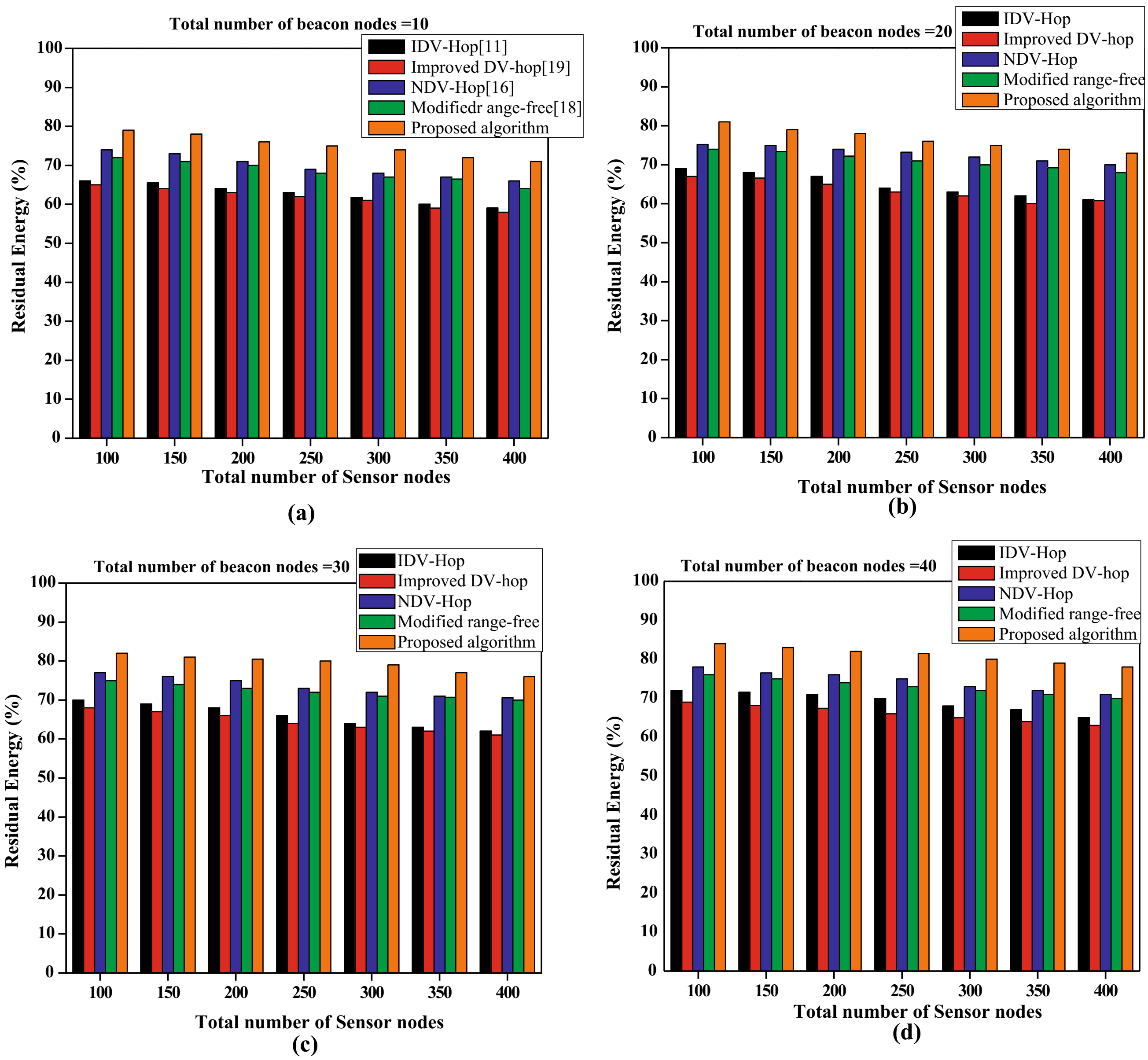
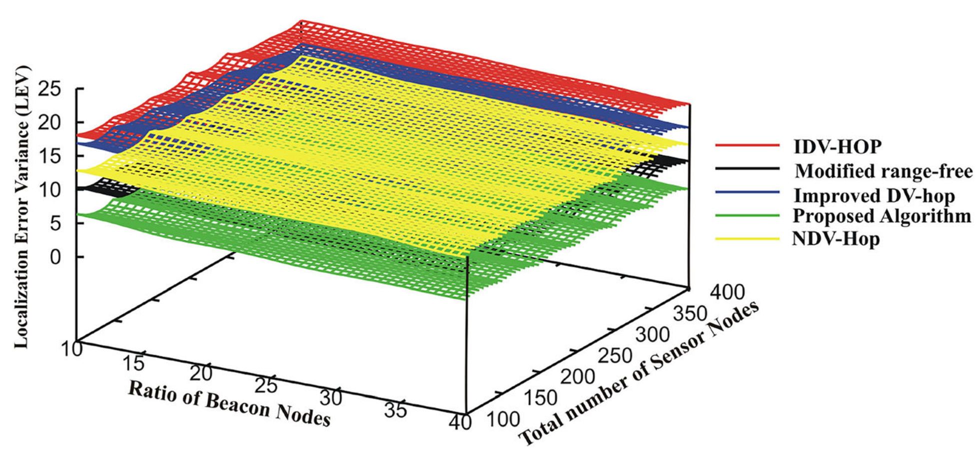


Fig. 11 Effect of ratio of beacon node and total sensor nodes on percentage of Residual energy

Fig. 12 Effect of variation in ratio of beacon nodes and total sensor nodes on LEV



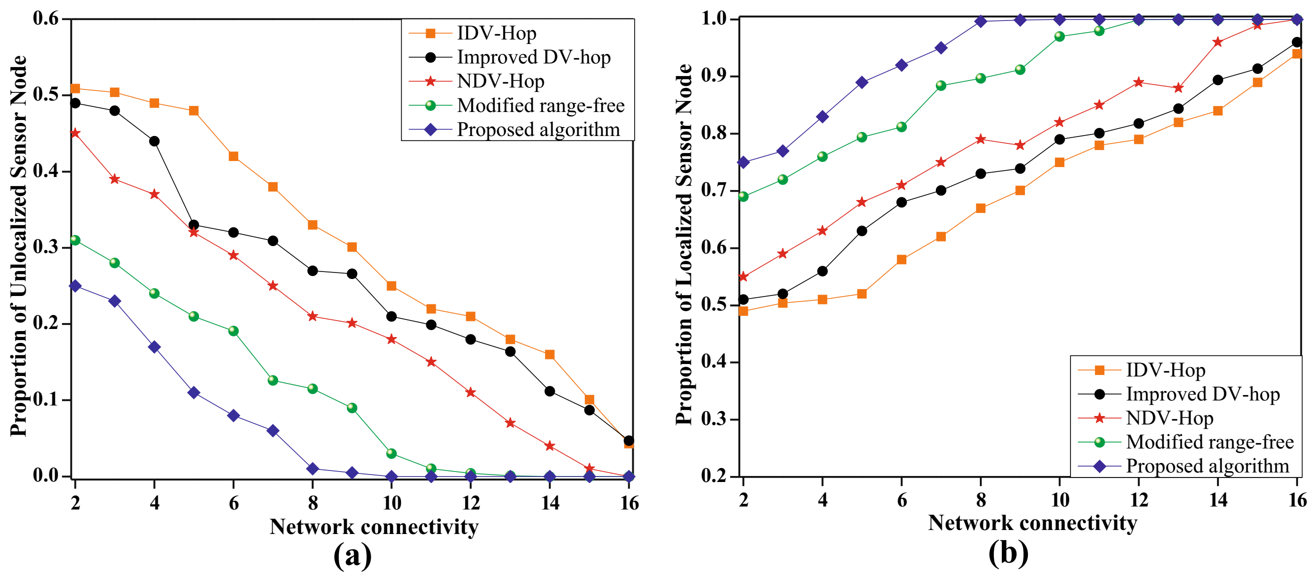


Fig. 13 Effect of variations in total sensor nodes on localization time

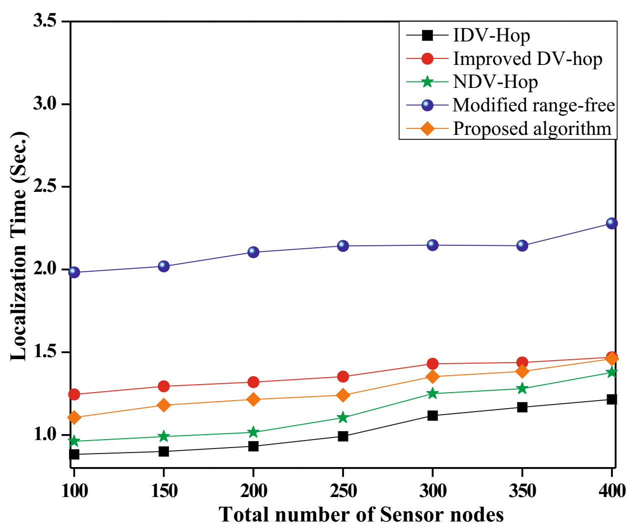


Fig. 14 Effect of total nodes on localization time

of improved PSO; however, the overall accuracy of RAP-COL is better than the NDV-Hop.

The overall computational cost of the proposed scheme is compared with existing algorithms shown in Table 5. It can be observed from 5 that the distribution of nodes took a bit more time for the proposed algorithm because of random mobility. The proposed algorithm proves its effectiveness in terms of weight metric computation, and node selection by consuming less time as compared to the existing algorithm. The order of Complexity of the proposed algorithm with respect to existing approaches is shown in Table 5.

Experiment 10: Impact of sensor nodes on packet loss

In this experiment, we analyzed the impact of total sensor nodes on packet loss and analysis is represented in Fig. 15, For this experiment, we have considered direct communication as well as cooperative communication. From the figure, it can be clearly observed that the packet loss in direct communication is more as compared to cooperative communication. It happens because of random mobility, at any instant of time if nodes are situated very far, so in direct communication chances of packet loss would be high because of distance. On the other hand, in cooperative communication, two-hop communication would be adopted.

Table 5 Computation cost comparison

	Nodes Distribution	Weight computation	Node selection	Transmission	Localization	Complexity of algorithm
IDV-Hop [14]	2.356	0.011	0.677	1.771	1.180	O(n∧4+m∧2 log(n)
NDV-Hop [19]	2.187	0.086	1.233	3.877	2.333	O(n∧4 m∧2 log(n+m logn)
Modified DV-Hop [21]	3.012	0.114	1.447	2.463	2.403	O[(n∧4+m∧2)+m log(n)]
Improved DV-Hop [22]	2.891	0. 239	0.969	4.517	4.117	O(nm∧2+n)∧4 m log(n)
Proposed scheme	2.917	0.026	0.79	1.43	0.91	O(mn∧2+nm log(nm)

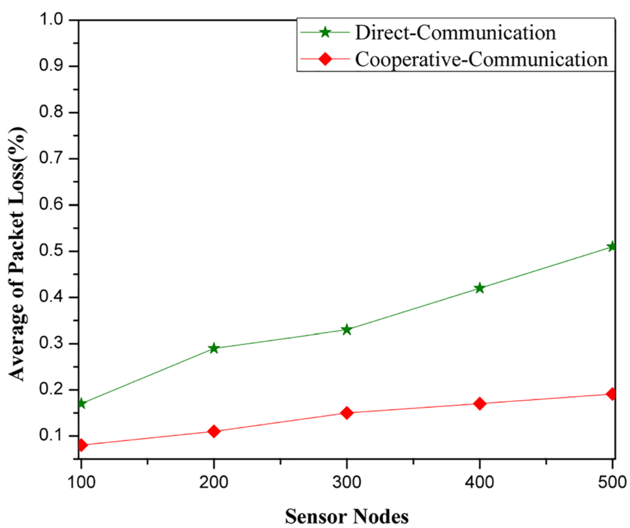


Fig. 15 Average of packet loss

4 Conclusion

In this paper, we show a novel range-free localization scheme, called RAPCOL, which uses cooperative MAC for power efficiency. We show that cooperative communication is advantageous as compared to traditional direct communication in terms of preserving residual energy and prolonging network lifetime. To maximize the network lifetime, information from beacon nodes to BS is communicated through cooperative beacon nodes. The cooperative beacon nodes are selected based on transmission power criteria to reduce energy consumption. Thus, RAPCOL is able to reduce the total energy consumption by 30% and prolong the network lifetime. Furthermore, RAPCOL minimizes the localization error of unknown nodes using an improvised PSO optimization algorithm. PSO ensures minimum message exchange between beacon nodes and unknown nodes as RAPCOL performs localization for one-hop neighbors. We compare the results of our proposed RAPCOL algorithm with the recent localization algorithms available in the literature. The comparative analysis shows that our proposed RAPCOL is superior in terms of accuracy and energy efficiency. We observe that RAPCOL provides 30% better accuracy in the mobility and heterogeneous network conditions. Thus, our proposed RAPCOL is efficient for WSNs.// Despite of significant contribution by the present study towards range-free localization with cooperative communication, it has a few limitations also. Firstly, the present study only focused on energy efficiency and accuracy, whereas, secondly, we have considered energy only for transmission. In future research direction, the researchers can consider load balancing and security of nodes for localization algorithm. Also, overall energy consumption in the network can be considered in the future.

Author contributions RG: Idea generation, algorithm development, manuscript writing. GK: Idea generation, algorithm development, Implementation. RS: Supervision of the work, algorithm feasibility study. MC: Supervision of the work, algorithm feasibility study. RT: Supervision and Proof Reading. TK: Supervision and result interpretation and analysis

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Data availabiltiy Enquires about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare no competing interests.

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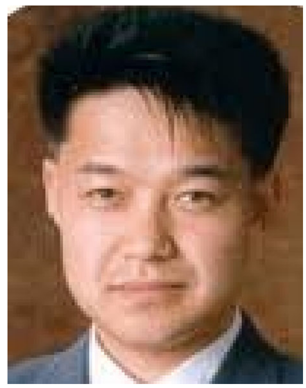

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