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Kalpna Guleria, Anil Kumar Verma, Nitin Goyal, Ajay Kumar Sharma, Abderrahim Benslimane, et al.. An enhanced energy proficient clustering (EEPC) algorithm for relay selection in heterogeneous WSNs. *Ad Hoc Networks*, 2021, 116, pp.102473. 10.1016/j.adhoc.2021.102473 . hal-03634363

**HAL Id: hal-03634363**

**<https://hal.science/hal-03634363v1>**

Submitted on 15 Mar 2023

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# An Enhanced Energy Proficient Clustering (EEPC) Algorithm for Relay Selection in Heterogeneous WSNs

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## ARTICLE INFO

### Keywords:

Clustering,  
Cluster Head,  
Enhanced Energy Proficient  
Clustering (EEPC),  
Power consumption,  
Sensor data fusion

## ABSTRACT

The recent advancements in Wireless Sensor Networks (WSNs) have brought attention to the field of sensor tracking events. Habitat monitoring is considered as one of the most important applications of WSNs, which ensures wildlife conservation. Researchers have proposed various solutions to select the optimal path in the field of sensor tracking. However, energy dissipation of sensor nodes and fault tolerance during data transformation is still one of the major challenges of the WSN environment in dynamic scenarios. In this paper, an Enhanced Energy Proficient Clustering (EEPC) is proposed to reduce the energy consumption of the entire sensor nodes in the field of tracking events. The network is created with both fixed and mobile nodes. Initially, fixed nodes broadcast information, and mobile nodes select the cluster head from fixed nodes. The mobile nodes select their cluster head (CH) based on their associated placement and energy level. Mobile sensor nodes (SNs) transmit data to the CH. It introduces the concept of finding relay nodes, which are fixed nodes. The EEPC algorithm selects the relay nodes based on their velocity and location by calculating particle fitness value. The selected intermediate relay nodes transmit the collected information to the Base Station (BS) using the sensor data fusion technique. The link fault of nodes could be predicted based on the deviation value. The simulation results show that the proposed approach points out progress with reference to various performance metrics. The proposed work minimizes the energy depletion and enhances the network lifetime compared to other existing protocols.

## 1. Introduction

The advance combination of micro-electro-mechanical systems (MEMS) and radio frequency integrated circuits (RFIC) have brought a revolution in the wireless sensors networks (WSNs) for monitoring and control applications [1]. The typical applications of WSNs are military surveillance, structural health monitoring, traffic monitoring in smart cities, industrial monitoring and control [2]. One of the most interesting applications of WSNs is wildlife monitoring, which requires careful handling of mobility aspects and energy-efficient optimal path selection in an energy constraint environment. Event monitoring applications track the target based on time and location. The target monitoring is used to protect endangered animals. Insufficient energy of sensor nodes makes the target tracking system to be despondent.

In the recent past, industry-wide research is going on in the domain of wireless sensor networks to achieve energy-efficient communication to enhance the network lifetime and achieve better resource allocation[3][4][5]. It is revealed from the literature that the utilization of SNs in WSNs, in an energy-efficient manner is still an open area that needs to be researched [3][4][5][6][7].

In WSNs, clustering is an efficient technique to lower down the energy consumption of SNs [8][9][10][11]. Clustering conserves the communication bandwidth, which limits the exchange of redundant messages among the SNs [8]. The concept of data aggregation at CHs conserves the energy of SNs. Clustering is a hierarchical approach that leads to the higher scalability of WSNs [11]. In clustering, generally, SNs direct data to CH, and thereafter CH sends data to BS. In contrast, CHs near the BS may suffer from high-energy consumption and drain out quickly, it can create hot spots or energy holes in the network [9][10]. Unequal clustering is one of the promising methods to avoid hot spot problem [10][12]

which decreases the size of clusters nearer to the BS and the size of clusters keep on increasing as the distance between BS and CHs increases. This approach maintains energy balance between the clusters which is achieved with less intra-cluster energy consumption in the clusters closest to the BS. Eventually, high intra-cluster traffic is in the faraway clusters. Fig.1 illustrates the common unequal clustering process.

Further, it is worth mentioning that energy-efficient communication is a very challenging aspect in heterogeneous wireless sensor networks, where dynamicity of operation is involved. The mobility of sensor nodes poses another challenge to deal with link failures [11].

Therefore, the proposed research is an effort to find an optimal path selection for energy-efficient communication in wireless sensor networks during dynamic scenarios.

## Our Contribution:

A lot of research has been carried by researchers to ensure energy-efficient communication in WSNs static scenarios where SNs are fixed in nature; however, to the best of our knowledge, we would like to highlight that dealing with the dynamicity of SNs in an energy constrained environment is an open issue which needs to be researched [11]. Energy-efficient communication becomes a challenging aspect in WSNs, especially in dynamic scenarios when SNs are mobile because topology management and connectivity issues arise.

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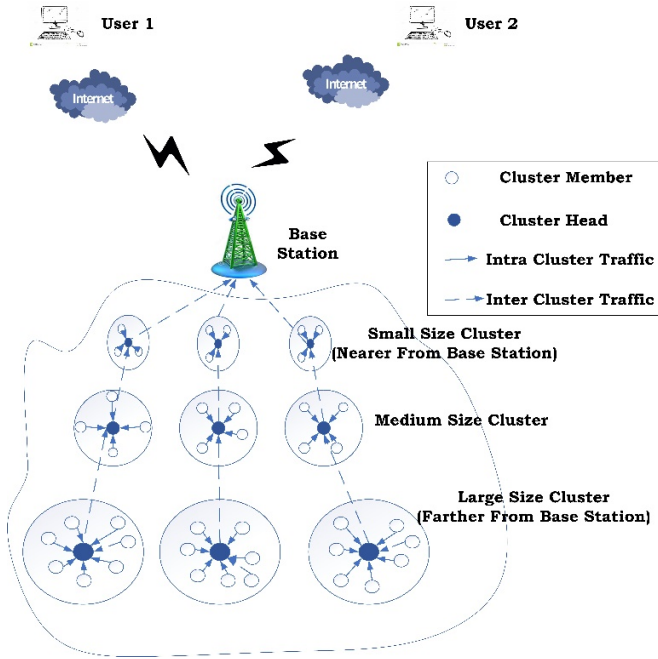


Fig. 1 Unequal Clustering

Handling mobility of SNs is a challenging aspect that requires dealing with link failures. Hence, we would like to mention that ensuring energy-efficient communication in WSNs, especially in dynamic scenarios, is an area that needs to be explored. Our proposed work is focused on energy-efficient communication in heterogeneous WSNs in dynamic scenarios.

The proposed work is focused on sending sensed data to the BS in a dynamic and intermittently connected network with limited bandwidth, power, and storage resources. The main challenge is accomplishing simultaneous data delivery, which needs to limit the sensing information. The proposed work concentrates on reducing energy consumption by determining feasible relay nodes using enhanced energy proficient clustering (EEPC) technique. A decentralized sensor data fusion technique has been implemented to prevent the sensor node from transmitting redundant data, which results in providing high quality sensing information. The research highlights of our proposed work are mentioned as:

- An energy-efficient relay selection technique is proposed to reduce the long-distance communication between cluster head and BS. The selection of optimal relay nodes avoids the direct communication of CH to BS, which leads to energy conservation. The proposed efficient relay selection and optimal path construction technique utilize enhanced particle swarm optimization.
- The sensor data fusion technique is applied with the determined relay nodes to reduce the number of messages in data transmission. Decentralized sensor data fusion avoids the redundant data transmission of messages, which leads to energy conservation. The proposed work implements a track-by-track fusion method in order to track the sensing nodes and concerns only with sensing data communication. Therefore, the additional burden and complexity of data fusion is reduced.

- The proposed work performs novel cluster head selection and utilizes unequal clustering, which maintains a fair balance between inter and intra-cluster communication load in order to reduce energy consumption.
- Cluster reformation is performed during link fault conditions, which ensures link connectivity. The process of dealing with link failures reduces the target missing rate effectively.

The remaining part of the paper is organized as follows: Section 2 highlights related works for energy-aware communication and clustering techniques in the same domain. Section 3 presents the network model. Section 4 elaborates the proposed method regarding CH selection and unequal clustering, optimal path selection, relay node identification, sensor data fusion technique, and dealing with link failures. Section 5 illustrates the performance comparison of the proposed EEPC with existing algorithms. Section 6 concludes the research work along with future directions.

## 2. Related Work

This section elaborates the existing algorithms that have been used for energy minimization and reliable routing mechanism of WSN. Sahoo et al. [7] have proposed an energy efficient PSO based clustering approach with mobile sink. The CH selection is based on various factors which include remaining energy, average energy, energy consumption rate, distance and node degree. The proposed approach achieves better stability and enhanced network lifetime. However, the future enhancements are required to reduce the end to end delay by adopting a hybrid approach. Guleria and Verma[12] proposed an energy efficient unequal clustering approach which utilizes meta-heuristic ant colony optimization (MH-ACO). Optimal CH selection is based on node degree, residual energy, proximity and distance to BS. The MH-ACO performs load balancing, enhances the CH's lifetime which in turn leads to enhancement of network lifetime. However, further enhancements are required to explore the mobility of SNs and BS.

Vimalarani et al. [13] utilized the particle swarm optimization (PSO) technique and clustering for energy optimization in the WSNs. The algorithm was implemented in a centralized manner along with the BS, but the CHs were elected by PSO in a distributed fashion. The sensed tracking data was aggregated in CH and transmitted to BS. However, the continuous involvement of CH near the BS, in data transmission activity may lead to reduced lifetime of CH's. Su and Zhao [14] developed a cluster construction method for WSNs based on fuzzy C-means. Unequal distribution of SNs and unpredictable behavior of radio channel are the main reasons, which have led to the fuzzy-based partitioning during cluster construction. In addition, the node density is considered as the main parameter for the optimal CHs calculation. The objective function is based on the weight of membership value and distance measure of SNs to CH. Fuzzy C mean algorithm ensures better distribution of CHs and

balances energy consumption. However, further improvements are required for real-time WSN applications.

Arioua et al. [15] provided a clustering-based method that utilizes hybrid characteristics of LEACH and Minimum Transmission Energy (MTR). The main advantage of this work is an enhancement of LEACH, which extends the WSNs' lifetime. However, higher CH energy consumption is still an unresolved issue. Sabet and Naji [16] developed a Multilevel Route aware Cluster-based routing (MLRC) algorithm for distributed WSN, which minimizes the energy consumption. A routing tree is maintained, which is based on the information of available routing paths among SNs. Moreover, MLRC functions in a decentralized style where each node communicates with their adjacent nodes. Control packet overhead is avoided by performing the process of building clusters and tree construction simultaneously. MLRC elects CHs based on density, node degree, hop count, proximity, remaining energy, and distance to BS. It avoids the early death of CHs, which are near to BS due to energy exhaustion, and balances the energy consumption as well. However, further enhancements are required to explore the mobility aspects and scalability of the proposed approach for large WSNs scenarios. Chamam and Pierre [17] proposed a CH selection procedure that utilizes a three-way communication method among individual sensors and neighboring nodes. Residual energy and node degree are the parameters considered for a node to participate in the CH selection procedure. However, multilevel clustering and protocol functioning in multiple transmission ranges is still an area to be explored.

Li et al. [18] have addressed the issues related to unequal clustering, which are how to decide or quantify the size of CHs to ensure better scalability. An iterative method for optimal cluster construction is provided, which conserves the energy and makes it scalable. Further, the CH rotation frequency, its optimal value and data aggregation model for large scale WSNs is still a challenging aspect which needs to be researched.

Oracevic et al. [19] have developed a secure and reliable object tracking algorithm for WSNs environment. The authors provided an enhancement to reliability by proposing a reputation-based trust model for every SNs. This model easily finds out violator nodes and avoids their participation in network activities, which leads to energy conservation whereas the scalability aspects of the protocol need to be explored further for large WSNs scenarios. Wang et al. [20] have developed a clustering algorithm that utilizes fisher information about Kalman filter for target tracking applications. SNs use this fisher information matrix and residual energy as a basis for the selection of CH nodes. Cluster members perform target estimation and pass this information to CHs. This method achieves improved tracking accuracy along with reduced overall energy consumption. However, further enhancements are required to optimize the energy consumption of CHs near the BS.

Nematollahi et al. [21] have provided a distributed clustering method that performs task scheduling for WSNs environment. The reduced energy consumption was achieved by a new innovative approach called Dynamic Hyper Round Policy (DHRP), which fragments various clustering tasks. A round-based policy is utilized for cluster construction and cluster

reconstruction in the next round. The rotation-based CHs selection policy is used based on remaining energy criteria, which balances the energy consumption of SNs. It leads to load balancing as well. However, cluster reconstruction overhead in each round is still a challenge. Naeem et al. [22] have proposed a dynamic clustering approach for cooperative behavior and energy constraint environment of WSNs. This methodology balances the energy consumption among CHs through dynamic clustering and chooses an optimal number of SNs for event detection. A distributive architecture based dynamic clustering with optimal neighbor selection method is formulated for event and time-based applications. The Universal Dynamic Clustering scheme (UDCS) performs the CH selection, neighbor, and supporting cooperative node selection in a distributed manner instead of centralized. The decentralized behavior of UDCS decreases the broadcast data. Further, to explore the behavior of protocol for dynamic network scenarios is an open issue for future research. Fu et al. [23] have presented LEACH-TLCH (Two Levels of CHs) to strengthen the routing operation of the LEACH protocol. If a CH's remaining energy is less than the average energy metric or distance measure between CH and BS is larger than the average distance, then a secondary CH which has higher remaining energy is chosen in the same cluster. The secondary CH receives data, performs data fusion, and forwards it to the next level of CHs, which further sends it to the BS. LEACH-TLCH protocol increases the network lifetime and achieves reduced energy consumption than LEACH whereas, the scheme suffers from early death of CH near the BS due to higher network load in the same area.

Baradaran and Navi [24] have presented a new clustering methodology with reference to the Steiner tree and C-means algorithm and named it as CAST-WSN. Node density and distance are two important parameters taken into account during cluster formation. A quality function is applied on the C-means algorithm when it obtains an optimal number of clusters. CHs selection is done if the clusters are of good quality. Otherwise, the cluster construction process is repeated again. The CAST-WSN achieves an enhancement over network lifetime and an improvement for energy consumption than C-Means clustering. However, the protocol performance for dynamic network scenarios need to be explored. Darabkh et al. [25] have introduced an improvement over adaptive head clustering algorithms named as Improved Adaptive Head (IAH) and Improved Prediction Based Adaptive Head (IPAH). IAH algorithm attains energy-efficient operation through dynamic clustering and optimal CH selection. A prediction-based component is introduced to IPAH to enhance the performance of IAH. IPAH shows better network lifetime and scalability than IAH whereas the optimal clustering considers only residual energy and distance measure. Gherbi et al. [26] have developed a Hierarchical Energy Balancing Multipath (HEBM) protocol for the WSN environment. The focus of HEBM was the energy-efficient operation and balanced energy consumption. A load-balanced operation is ensured by introducing an optimal CH selection mechanism and balanced distribution of CHs in the deployed network area. A fixed sleep schedule for SNs is ensured by turning off their radios, which adds to energy optimization. However, the mobility

aspect of protocol needs to be explored along with a reliability mechanism for CHs and BS.

Oladimeji et al. [27] have developed a heuristic algorithm for clustering hierarchy (HACH). During cluster construction,

HACH utilizes sleep scheduling for SNs in each round. A random probability distribution based algorithm is used for the selection of inactive nodes during sleep scheduling.

Table 1. Summary of State of art Cluster based routing approaches for Energy Efficient WSNs

Authors & Reference No.	Name of Protocol	Methodology			Advantages	Research Gaps
		Technique/ Algorithm	Data Aggregation	Parameters of CH selection		
Sahoo et al. [7]	PSO based energy efficient clustering and sink mobility (PSO-ECSM)	Particle Swarm Optimization and mobile sink approach	Yes	Remaining energy, average energy, energy consumption rate, distance and node degree	Better Stability and Enhanced network lifetime	To reduce end to end delay through a hybrid routing method.
Guleria and Verma [12]	MH-ACO (Meta-Heuristic Ant Colony Optimization) based Clustering	Unequal clustering and ACO for optimal path construction	Yes	Node degree, residual energy, proximity, and distance to BS	Enhanced network lifetime, balanced Inter and Intra cluster load, Maximization of CHs lifetime	Enhancements are required to explore the mobility aspects.
Vimalarani et al. [13]	Enhanced PSO based Clustering Energy Optimization (EPSO –CEO)	Particle Swarm Optimization	Yes	Distance from member node to BS, residual energy	Energy conservation of SNs using PSO	Reduced lifetime of CHs, which are nearest to the BS.
Su and Zhao [14]	Optimized Clustering Method Fuzzy C-Mean (OCM-FCM)	Fuzzy C-Means Clustering	Yes	Node's Density, Fuzzy C-means	Ensures better distribution of CHs and balances energy consumption.	Further improvements are required for real time WSN applications where mobility is concerned.
Arioua et al. [15]	Multi-hop cluster based routing	Hybrid technique using LEACH and Minimum Transmission Energy (MTR)	Yes	Priori optimal probability	Enhanced network lifetime in comparison to LEACH.	Optimization of energy consumption of CHs considering the remaining residual energy is required.
Sabet and Naji [16]	Multi-Level Route aware Cluster based routing (MLRC)	Least transmission cost based optimal routing tree	Yes	Node density, hop count, proximity, remaining energy and distance to BS	Less control packet overhead, avoids early death of CH's near the BS.	Implemented for Static WSNs scenario, further enhancements are required to explore the mobility aspects. Scalability aspects for large WSN scenarios has not been revealed.
Chamam and Pierre [17]	Energy Efficient Cluster Formation (EECF)	Distributed Clustering	Yes	Residual Energy, Degree	Enhancement of network lifetime and better ratio between number of CHs and number of SNs	Multilevel clustering and protocol functioning in multiple transmission ranges is still an area to be explored. Mobility aspects need to be researched.
Li et al. [18]	COCA (Constructing Optimal Clustering Architecture)	Distributed protocol for energy aware and unequal clustering	Yes	Residual Energy	Energy hole problem is avoided. Better energy conservation. Good Scalability	CH rotation frequency, its optimal value and data aggregation model for large scale WSNs is a challenging aspect.
Oracevic et al. [19]	Secure and Reliable Prediction based Target Tracking Protocol (SRPTT)	Adaptive quantized variation filtering (QVF) algorithm	Yes	Higher reputation value, higher residual energy	Enhancement to reliability by proposing a reputation based trust model for every SN.	Scalability aspects of the protocol need to be researched for large WSN scenarios.
Wang et al. [20]	Dynamic Clustering in WSN	Filtering algorithm and Fisher Information criteria	No	Residual Energy, Fisher information matrix	Improved tracking accuracy	Optimization of energy consumption of CHs near the BS.
Nematollahi et al. [21]	Distributed clustering task scheduling	Dynamic Hyper Round Policy (DHRP)	Yes	Rotation based hyper round policy	Load balancing	Cluster reconstruction overhead in each round is an issue
Naem et al. [22]	Universal and Dynamic Clustering Scheme (UDCS)	Dynamic Clustering and neighborhood formation framework	Yes	Distance from the centre of cluster, residual energy	Reliable data transmission Energy efficient and scalable	To explore the behavior of proposed scheme in mobile WSN environment
Fu et al. [23]	Energy Balanced Algorithm for LEACH	Two Levels of CHs (TLCH-LEACH)	Yes	Threshold value,	Better energy conservation than	Early death of CH near the BS due to higher

				secondary CH	LEACH	network traffic
Baradaran and Navi [24]	CAST-WSN: (Clustering Algorithm based on Steiner Tree and C-Means)	Steiner Tree and C-Means Algorithm	Yes	CH's based on grid centers, gravity centers of SNs and energy centers of SNs	Better energy Conservation than C-Means clustering	Mobility aspects of SNs in dynamic scenarios need to be explored.
Darabkh et al. [25]	Improved Clustering	Improved Adaptive Head (IAH) and Improved Prediction Based Adaptive Head (IPAH) Clustering	Yes	Residual Energy, distance between the SNs and sink, distance from target to SNs	Scalable algorithm, IPAH shows better energy conservation than IAH	CH selection only considers energy and distance measure
Gherbi et al. [26]	Adaptive Clustering Approach	Hierarchical Energy-Balancing Multipath routing (HEBM) Algorithm	Yes	Residual energy, node weight, condition distance with BS, condition distance between SNs	Fixed sleep schedule of SNs ensures energy conservation. Better load balancing	Mobility aspects need to be explored. Fault tolerance/ reliability mechanism for CHs, BS.
Oladimeji et al. [27]	Heuristic Algorithm for Clustering Hierarchy (HACH)	Sleep scheduling by stochastic selection, Heuristic-crossover Enhanced Evolutionary algorithm for Cluster Head Selection (HEECHS)	Yes	Residual energy and distance from neighboring CH	Distributes CHs evenly throughout the network to avoid coverage and connectivity problems.	CH rotation frequency and its optimal value is a challenging aspect for large WSN scenarios.
Kuila and Jana [28]	Particle Swarm Optimization	Particle encoding approach, multi-objective fitness function	Yes	Fitness function based on CH's lifetime, average distance of SNs from CH	Energy conservation and enhanced network lifetime	Consideration of more than one hop among SNs may lead to hot spot problems. Residual energy and distance are the only parameters considered for CH selection.
Gupta and Jana [29]	Energy Efficient Clustering based on GA	Linear programming and genetic algorithm for clustering and routing	Yes	Residual energy, distance from SNs	Network longevity, energy conservation	Clustering in a dynamic WSN environment is subjected to link failure problems, and is still an area to be explored further.
Rao et al. [30]	Energy efficient CH based on PSO (PSO-ECHS)	Particle Swarm optimization	Yes	Remaining energy, distance from sink and intra-cluster distance	Reduced energy consumption, enhancement of network lifetime	The inclusion of other important parameters can result in better network performance.
Chandirasekaran and Jayabarathi [31]	Cat Swarm Optimization for optimized CH selection	Cat Swarm Optimization	Yes	RSSI, remaining energy, intra-cluster distance	Enhanced network lifetime as compared to LEACH and PSO.	To deal with the re-clustering issues is a challenging aspect which needs to be explored.
John and Rodrigues [32]	Multi-Objective Taylor Crow Optimization (MOTCO)	Taylor series and the Crow Search Algorithm (CSA)	Yes	Cluster's traffic density, energy of SNs, distance between SNs in cluster, data transmission delay	Energy conservation and higher throughput	Computationally complex algorithm.
Alghamdi [33]	Energy Efficient protocol for optimized CH selection	Dragonfly and firefly algorithm	Yes	Delay, security, distance, energy	Better statistics for alive nodes, network convergence and energy conservation	To achieve a trade-off between performance and computational cost is a challenging task, which needs to be explored in future.

The cluster construction process selects higher energy nodes as cluster heads in a distributed fashion, which results in network longevity. HEECHS protocol is utilized to distribute CHs evenly throughout the network to avoid coverage and

connectivity problems. The CH rotation frequency and its optimal value is a challenging aspect for large WSN scenarios. Kuila and Jana [28] have proposed a PSO-based method that utilizes a multi-objective fitness function and particle encoding scheme for enhanced network life and lowers energy consumption. Further, the proposed approach may suffer from hot spot problems due to the consideration of more than one hop among SNs.

Gupta and Jana [29] had proposed an energy-efficient clustering method that utilizes a genetic approach. The primary parameters considered for clustering are the remaining energy of CHs and the distance of SNs from designated CHs. The trade-off between the frequency of data forwards and the remaining energy of CHs forms the basis of the optimal path selection. The protocol exhibits better performance for energy conservation. However, clustering in a dynamic environment subjected to link failure problems is still an area to be explored further.

Rao et al. [30] proposed energy efficient CH selection based on PSO (PSO-ECHS) to enhance the network lifetime of WSNs. The fitness function parameters include remaining energy, sink distance and intra-cluster distance. The inclusion of other important parameters in the CH selection may enhance the optimality and network performance of the proposed approach.

Chandirasekaran and Jayabarathi [31] presented the concept of cat swarm optimization to enhance the network lifetime. Authors considered RSSI, intra-cluster distance, remaining battery for CH selection and achieved better network lifetime as compared to LEACH and PSO. However, to deal with the re-clustering issues is a challenging aspect which needs to be explored further.

John and Rodrigues [32] utilized the concept of taylor crow optimization for CH selection based on multi-objective function (MOTCO). The multi-objective function considers various parameters for optimal CH selection which include cluster's traffic density, energy of SNs, distance between SNs in cluster, data transmission delay. MOTCO shows better statistics for energy conservation and throughput whereas the algorithm is computationally complex. Alghamdi [33] presented an energy efficient protocol for optimized CH selection which utilizes dragonfly and firefly algorithms. The approach utilizes delay, energy, security and distance for optimal CH selection and exhibits better performance statistics for alive nodes, network convergence and energy conservation. However, to achieve a trade-off between performance and computational cost is a challenging task, which needs to be explored in future.

The proposed work in this paper focuses on alleviating the issues related to higher energy consumption due to direct communication between CH and BS, unbalanced network load, handling the mobility of SNs by dealing with link failures problems, traffic overhead, and tracking accuracy in dynamic WSNs scenarios. A novel relay node discovery algorithm is proposed. The optimal selection of relay nodes using EEPC reduces the energy depletion of CH nodes. A decentralized data fusion method and link maintenance procedure to deal with link failures is another enhancement to

the proposed work. Decentralized data fusion reduces the complexity of data transmission and contributes for enhanced network lifetime.

### 3. NETWORK Model

The network model defines the basic assumption made for the proposed work:

- There is N number of SNs, some of which are fixed and some are mobile. The fixed SNs are the nodes whose location is not varying, it's permanent. Some of these fixed nodes will be selected as relay nodes. In contrast, mobile nodes can move within the deployed network and may act as cluster members only.
- Sensor nodes are heterogeneous in nature, battery-operated, and having an unchangeable battery.
- BS is positioned at the center of the area to be inspected, and there is no energy constraint about it.
- Partial SNs, which are static, participate in CH election procedure.
- All SNs are location-aware, and every SN has a unique identity.

It is assumed that every SN can communicate with other SNs within its transmission range. Each sensor node gives a binary output value as per the sensed information. The sensor node covers the area as a circle having a radius  $R_s$ . It is assumed that the ideal sensor node value will be one if the mobile node comes within the radius  $R_s$ ; otherwise, it indicates 0. The identification of target nodes depends upon the distance of the mobile node to the fixed sensor node. This can be defined as

$$d = \begin{cases} 1, & d \leq R_s \\ 0, & d > R_s \end{cases} \quad (1)$$

Where  $d$  - distance of the target to the SN;  $R_s$  - sensing radius of the SN. The statically positioned sensor nodes are conscious of their whereabouts using GPS based location estimation. Neighboring nodes' location information is calculated and accumulated at each SN at the start of the tracking time to boost the routing performance.

Fig. 2 shows the network model, which depicts the network model's layered architecture, BS, relay nodes, sensor nodes, inter and intra-cluster traffic with the formation of unequal clustering.

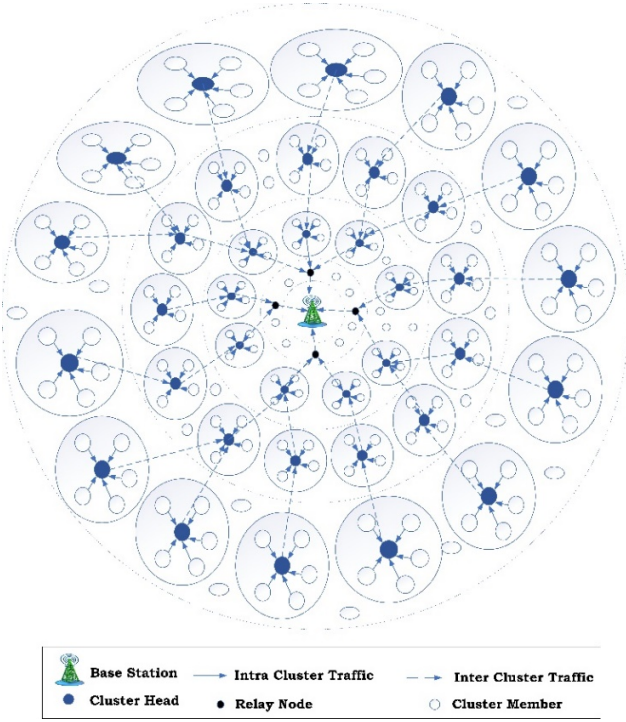


Fig. 2 Network Model

#### 4. Proposed Method

In this section, a comprehensive explanation of the proposed methodology has been presented. The primary objective of this work is to decrease the energy consumption by selecting fixed nodes as relay nodes to route the data from the current node to reach the BS. The network is constructed with fixed and mobile SNs. Initially, fixed SNs broadcast information, and mobile nodes select the cluster head from fixed nodes. The mobile nodes select their cluster head (CH) based on their associated placement and energy level. The mobile SNs transmit data to CH; further, it transmits sensed information to BS. However, the CHs near the base station suffers from energy depletion issues due to the heavy traffic load intensity. This is a major drawback of the existing WSNs environment. The proposed approach introduces the concept of finding relay nodes, which are fixed nodes. The proposed EEPC algorithm selects the relay nodes based on their velocity and location by calculating particle fitness value. The selected intermediate relay nodes transmit the collected information to the BS using the sensor data fusion technique. The link fault of static nodes could be predicted based on the deviation value. The proposed method finds an alternate path based on selected fixed nodes, which acts as relay nodes. In the absence of relay nodes, mobile SNs, which have a high energy level, may serve as relay nodes. The proposed work operates in three stages: unequal clustering process, relay node discovery, and data fusion.

In Fig. 3, the first stage illustrates the process of cluster head selection and unequal clustering. An attribute-based CH selection method, based on the parameters: neighborhood proximity value, the remaining energy of SNs, and communication link quality factor (LQF), has been used. The

detailed explanation of CH selection and unequal clustering has been given in section 4.2.

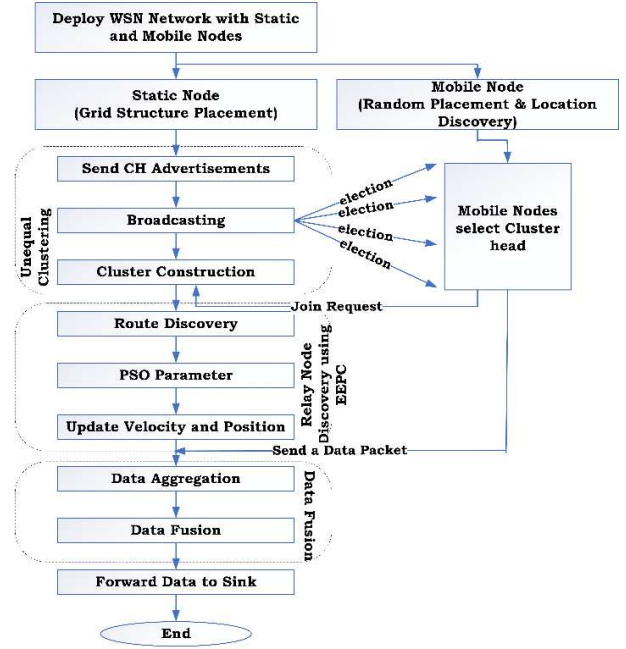


Fig. 3 Proposed work flow

The second stage determines the optimal relay nodes. There will be many fixed nodes near the CH. The proposed Enhanced Energy Proficient Clustering (EEPC) is applied to find the optimal relay nodes. In the next stage, the sensing information is transmitted through relay nodes based on the sensor data fusion technique. Fixed and mobile nodes always transmit a bulk amount of time-dependent sensing information to the cluster head. The EEPC algorithm for relay node discovery and optimal route construction has been explained in section 4.3. Despite CH collecting data and transmits it to BS, frequent data transmission degrades the network's performance due to higher energy consumption. The proposed work utilizes the data fusion technique, which collects the data in a fixed time interval and transmits it to BS. Therefore, the energy ingestion of CH and fixed nodes is minimized. The sensor data fusion has been explained in section 4.4. Prior to CH selection and clustering, it is important to discover the neighboring links; therefore, the neighbor node discovery process is performed.

##### 4.1 Neighbor discovery

The main objective of neighbor discovery is to get knowledge about neighboring nodes to build a good neighborhood connection during the communication process. In this stage, each SN transfers a HELLO packet with its network ID. Sensor node accepts these packets and updates its neighbor information table, which comprises node Id, distance from BS, and Received Signal Strength Indicator (RSSI). Each fixed node and the mobile node share their location and energy level with neighboring nodes. The node ID, the node's distance from the base station, and RSSI information are fetched in this phase. This phase ensures that each node has current updated



values of the abovementioned parameters about its neighborhood nodes.

#### 4.2 CH Selection & Unequal clustering

Generally, there are three methods to select the CH within the cluster. These can be listed as a probabilistic method, attribute-based and preset method. The proposed work focuses on the attribute-based CH Selection method [12].

The proximity of the neighbor node is mentioned as follows:

$$N_p = \frac{1}{N_{tot}} \sum_{i=1}^{N_{tot}-1} dist(n, i) \quad (2)$$

Where,

$N_{tot}$  - Total number of neighbor SNs in the wireless sensor network

$dist(n, i)$  - Distance measure between SN  $n$  and its neighbor SN  $i$ .

The LQF between the source node and the destination node is mentioned as follows,

$$LQF(S, D) = \sum_{i=0}^n (Qs_i + Rt_i + BW_i - IR_i) \quad (3)$$

Where,  $Qs_i$ - Queue size,  $Rt_i$ - Response time,  $IR_i$  - interference ratio,  $BW_i$  Bandwidth of the link.

$Qs_i$  is mathematically defined as,

$$Qs_i = \frac{\text{Total Queue Size} - \text{Occupied Queue size}}{\text{Frame length}} \quad (4)$$

The response time estimation is described as follows:

$$Rt_i = (T_{DERX} - T_{DDTX}) + (T_{ACKETX} - T_{ACKDRX}) \quad (5)$$

Where,

$T_{DERX}$  -Amount of time data packet is en-queued at Rx\_Port

$T_{DDTX}$  -Amount of time of data packet is de-queued at Tx\_Port

$T_{ACKETX}$  -Amount of time acknowledgment packet is en-queued at Tx\_Port

$T_{ACKDRX}$  -Amount of time acknowledgment packet is de-queued at Rx\_Port.

The value of RSSI depends on the distance between the source and destination of SN [34]. Mobility metric defines the direction of mobile SNs with the speed of an SN towards its direction. The distance among the SNs is obtained utilizing a constant 'k' and required power for transmission/reception ( $P_t, P_r$ ). It is mentioned as below:

$$d = \sqrt[4]{k \cdot P_t / P_r} \quad (6)$$

Relative velocity is defined as:

$$\vec{v} = \frac{\Delta d}{\Delta t} \quad (7)$$

The equation 6 and 7 depict the distance and the velocity of the nodes. It is considered to select the mobile node, which is nearly located and contains more energy in the absence of a relay node (or relay node is drained out). It may act as a relay node when the energy loss occurs. RSSI is used to estimate the

distance also the future prediction of moving sensor nodes. To improve the relay selection procedure, the distance and relative velocity among the nodes is determined. Relative velocity is an important measure, which is used to obtain the directional information about a node. If velocity is greater than zero, then SN moves in the direction of the BS. Otherwise, it moves away from BS. RSSI and LQF both factors measure the goodness of a link, whereas the other metrics such as response time and bandwidth are temporal in nature.

In the proposed work, there is no cluster construction done in the first layer near the BS. However, nodes in the first layer communicate with the BS and perform the task of relaying packets from outer layers to BS. CHs broadcasts CH advertisements, which contain CH<sub>ID</sub> (Cluster Head ID) and advertisement header. CH broadcasts its advertisement within its advertisement radius. The advertisement radius is defined as:

$$R_{adv} = \left[ \left( 1 - w \frac{Nd_{max} - dist(CH_i, SN)}{Nd_{max} - Nd_{min}} \right) \times \left( \frac{E_{current}(CH_i)}{E_{initial}(CH_i)} \right) \right] R_{adv_{max}} \quad (8)$$

Where,  $Nd_{max}$  - Maximum value of distance measure from SN and BS.

$Nd_{min}$  - Minimum value of distance measure from SN to BS.

$E_{current}(CH_i)$ - Current Energy of CH<sub>i</sub>.

$E_{initial}(CH_i)$ - Initial Energy of CH<sub>i</sub>.

$R_{adv_{max}}$  - is the value of maximum  $R_{adv}$ .

$w$  - is the difference of cluster size.

The value of  $R_{adv}$  is kept small for clusters near the BS and large for farther clusters. SNs opt for CH, which has the highest RSSI of CH<sub>Adv</sub> (CH advertisement) because a higher RSSI of CH<sub>Adv</sub> means it is the nearest cluster. SNs sends cluster membership request (C\_Mem\_Req). C\_Mem\_Req has SN's ID, CH\_ID. CH's selects their chosen members and form a TDMA schedule for inter-cluster communication. In order to maintain a fair balance of energy among cluster members and CH's, the role of CH is distributed among cluster members. Therefore, after a time period, neighbor discovery, CH selection, and clustering are performed again.

#### 4.3 Optimal Route Discovery and Relay selection

Optimal route construction for inter-cluster communication is an important task. Determination of relay nodes is a major part of our proposed work. Relay nodes are introduced to reduce the long distant communication between cluster head and BS. Selection of optimal relay nodes avoids the direct communication of CH to BS which leads to energy conservation. The proposed efficient relay selection and optimal path construction technique utilizes enhanced particle swarm optimization. Fig. 3 illustrates the relay selection process in the proposed workflow. The mobile and fixed nodes present in WSN select the cluster head depending upon the node's energy standard, LQF, and node proximity. In the proposed method, a node's link stability can be pre-determined depending on movement deviation among the clusters. The proposed EEPCC assumes that WSN sensor nodes exhibit a self-organized behavior. It examines the movement of sensor nodes in a similar way as of swarm bases. The determined optimal solution particles cover the problem space to search for the optimal solution. These particles can be initialized in an unspecified manner. The fitness function calculates the fitness value of every particle. The fitness value is utilized for

optimization in every generation. The particle has its  $p_{best}$  and overall  $g_{best}$  of all the agents. The swarm particle maintains both velocity and placement positional values, which listens to the flying of particles. In every single reiteration, a new generation is calculated as per new values of velocity and position. The agent update equations for velocity and related position are mentioned as per equations (9) and (10), respectively.

$$V_{id} = V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^n - X_{id}) \quad (9)$$

$$X_{id} = X_{id} + V_{id} \quad (10)$$

The parameters used in Equations (9) and (10) are defined in Table.2.

Table. 2 Description of Variables

Variable	Description
$P_{id}$	It represents the personal best position of a particle
$P_{id}^n$	It shows the global best position of all particles
$\eta_1$ and $\eta_2$	constants, and it is used to determine the influence of $P_{id}$ and $P_{id}^n$
$r_1$ and $r_2$	Random number
$N$	Total number of nodes
$D$	The dimension of the problem in search space

The position and velocity are representative features of particles. The formulae (9) and (10) calculate the velocity and position, which are utilized in the EEPC algorithm. This algorithm searches the problem space and finds the optimal relay nodes based on fitness value.

### Algorithm: EEPC

*Input: N number of sensor nodes*

*Output: Optimized path*

*\\ Calculate the fitness value of the global best particle*

*\\  $P_{id}^n$ : Position of a particle with different fitness value in the nodes*

*Initailazing all particles in the node*

*For each particle 'i'*

*do*

*Initialize the position ( $X_{id}$ ) randomly*

*Initialize the velocity ( $V_{id}$ ) randomly*

*$X_{id} = V_{id}$*

*Evaluate the particle's fitness value  $F(i)$ :*

*If ( $f_{best} < F(i)$ )*

*{*

*$f_{best} = F(i)$*

*$P_{id}^n = X_{id}$*

*}*

*End of for loop:*

*Iteration\_count = 0;*

*While (iteration\_count < max\_iteration)*

*\\ max\_iteration = maximum number of iteration*

*for each particle 'i'*

*do*

*Calculate the velocity  $V_{id}$*

*$V_{id} = V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^n - X_{id})$*

*Where,  $i = 1, 2, \dots, N$ , and  $d = 1, 2, \dots, D$*

*Update the position  $X_{id}$*

*$X_{id} = X_{id} + V_{id}$*

*If the static node is overhead or dead, then the mobile node acts as a relay node to forward the packets*

*Evaluate the particle fitness value  $F(i)$*

*Update position  $P_{id}$*

*if ( $f_{best} = F(i)$ )*

*{*

*$f_{best} = F(i)$*

*$P_{id}^n = X_{id}$*

*}*

*end of if*

*Iteration\_count ++*

*end of while*

---

These optimal relay nodes are used to transmit the sensing information to the BS. The best global optimal solution is

analyzed based on the distance  $d$ . This reduces the iteration process of PSO to find the optimal solution. The enhancement is done to the basic PSO by introducing additional parameters to improve the relay selection procedure. In the proposed method, the idea of adding static node's received signal strength indicator (RSSI) for the distance estimation has been introduced.

It also uses the deviation of the mobile nodes for future prediction of moving sensors. Based on the deviation value, the signal's attenuation varies, which affects the value of the RSSI indicator. It can be utilized to estimate the distance between CH and the mobile nodes using the following equation [35]

$$RSSI = P + G - PL(d) \quad (11)$$

Where  $P$  - transmit power,  $G$  - antenna gain,  $d$  - the distance between the current node and the source node,  $PL(d)$  - path loss at the receiving node.

Where  $PL(d)$  can be obtained from the equation (11). From equation (11), we can derive the  $d$  as follows.

$$10k \cdot \log\left(\frac{d}{d_0}\right) + X_G = PL(d) - PL(d_0) - X_G \quad (12)$$

Where,  $d_0$  - ideal distance (1m),  $X_G$  - Gaussian distribution variance (default value =2)

The appropriate relay node is selected on the basis of maximum value of the fitness function if multiple nodes satisfy the condition. The complexity of our proposed approach is  $O(n)$ .

#### 4.4 Sensor Data Fusion Technique

Sensor data fusion collects and merges the data derived from various sensor nodes, which is more efficient and potentially more accurate than achieved using a single source. The sensed information is in the form of videos and images, which consumes more memory space and takes a longer time to reach the BS. In order to tackle the issue of low battery power of sensor nodes, the sensed data is integrated and transferred to the BS through relay nodes. In WSNs, every node has the potential to transmit and receive sensing data. The data fusion utilizes the decentralized data fusion mechanism. Self-monitored information and the adjacent node's conveyed information have to be collected by every individual node for the sensor data fusion method. This method is deployed in a distributed manner. There is no need for centralized node for fusion or universal decision to be applied. The sensor data fusion method is performed only in relay nodes, which transmit the sensing information to the BS. The proposed work implements a track-by-track fusion method in order to track the sensing nodes. Centralized sensor data fusion algorithms focus on their importance based on states and probabilities. However, the proposed decentralized algorithm concerns only with sensing data communication. Therefore, the additional burden and complexity of data fusion is reduced. In order to achieve dynamic node tracking, the relevant events should not be missed in the temporal coverage. The sampling rate, duty cycle, and communication delay of

nodes decide the various levels of event missing rate. Cooperative, redundant and complementary are the various types of sensor fusion techniques. Complementary sensor data fusion deals with the sensors that are not directly dependent on each other but can be combined to provide an accurate image of the sensed information.

From Fig. 4, it could be observed that both Sensor 1 (S1) and Sensor 2 (S2) are independent sensors. The event detection achieved by both the sensors is data (a) and data (b), respectively. These two data sets could be integrated to get a perfectly matched complete set of data  $(a + b)$ . The resultant data is the combination of two sensors S1 and S2. Thus, the incompleteness of data can be resolved. The two distinct sensor nodes can observe the same mobile node. Complementary data fusion appends the vision of two independent sensors. If two or more independent sources deliver the same data, then this data is fused to increase the associated confidence.

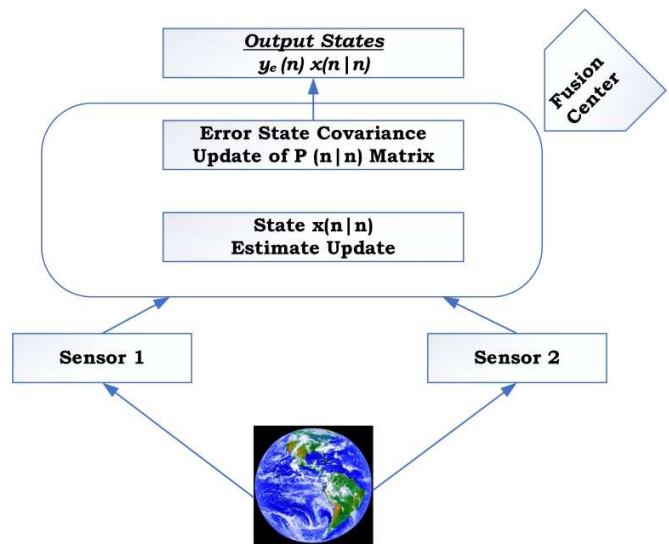


Fig. 4 Complementary data fusion

The proposed work uses the Kalman filter [36] for the implementation of complementary data fusion. It uses both a low pass filter and a high pass filter to estimate the angle resultant from the accelerometer to assess the tilting angle. This technique can be used for both static and dynamic environments. The initial state and output of the filter will be 0. It works based on predict and update operations. During predict operation, the filter performs an estimation of the current state and error covariance matrix at time  $T$ . whereas, during the update process, the filter calculates the difference of measured value and its previous value. Two types of the update are considered for data fusion, which are observation update and time update. The objective is to find the appropriate value of innovation KF gain  $M(n)$  for the optimal filtering.

Innovation KF Gain:

$$M(n) = P \begin{pmatrix} n \\ n-1 \end{pmatrix} C^T / \left( C P \begin{pmatrix} n \\ n-1 \end{pmatrix} C^T + R(n) \right) \quad (13)$$

Complementary resultant data is derived from the following equations.

Every KF works by computing residual formula

$$r(n) = Y_v(n) - C_x \left( \frac{n}{n-1} \right) \quad (14)$$

Estimation of state vector is calculated using

$$X \left( \frac{n}{n} \right) = X \left( \frac{n}{n-1} \right) + M(n) r(n) \quad (15)$$

Error Covariance Update

$$P \left( \frac{n}{n} \right) = [I - M(n)C]P \left( \frac{n}{n-1} \right) \quad (16)$$

Estimated Filter Output

$$Y_s = C_x \left( \frac{n}{n} \right) \quad (17)$$

Error Covariance

$$\text{Error cov} = C P \left( \frac{n}{n} \right) C^T \quad (18)$$

Time update

$$\text{State Time Update } X X \left( \frac{n+1}{n} \right) = A X \left( \frac{n}{n} \right) + B u(n) \quad (19)$$

Error Covariance Time Update

$$P \left( \frac{n+1}{n} \right) = A P \left( \frac{n}{n} \right) A^T + B Q(n) B^T \quad (20)$$

Where,  $M(n)$ = Gain,  $n$  - discrete time,  $C$  - observation vector,  $A$  - state transition matrix,  $B$  - input coupling vector,  $x$  - state vector,  $Y_v(n)$  - plant observation,  $v(n)$ - sensor or observation noise,  $w(n)$  - process noise,  $Q$  - process noise covariance matrix,  $R$  - observation noise covariance matrix.

The fused data is applied in the subsequent information, which is subjected to inaccuracies and imperfection of entire contributing sources. The angle of vision and the distance of the mobile node may change for two sensor nodes. However, both sensors are involved in capturing the same mobile node. Each node selects the nearest CH for sending data to BS. The optimal path is selected to transmit the message from the relay to CH and CH to BS. The amount of message transmissions is reduced through optimal path selection using the proposed EEPC and sensor data fusion.

#### 4.5 Link fault

Fig. 5 demonstrates the cluster reformation in link fault detection. The mobile node-tracking scenario suffers from a high level of frequent link failures. The link fault is observed when the mobile nodes move out of radio range, and the mobile nodes cannot be located. Topological issues and tag orientation can cause this failure. The 75% of connection reliability is acceptable. The mobile sensor nodes continuously transmit the data to CH, and CH continuously forwards data to relay fixed nodes. An alternate routing path is identified in the case of link failure. New CH is selected when the existing CH node fails, or link connection failure occurs. In link fault analysis, nodes, velocity, and location are taken into consideration.

Let  $(X_x, Y_y)$  represents the actual location of SN  $j$ ; it is obtained by localization technique. Node  $j$  calculates the deviation PL(d) as mentioned in equation (21).

$$PL(d) = \sqrt{(X_x^j - X_q^j)^2 + (Y_y^j - Y_q^j)^2} \quad (21)$$

Table. 3 Variables Description

Variables	Definition
$X_x^j, Y_y^j$	The coordinate of SN $j$ at time $T_i$
$V_x^j, V_y^j$	The velocity of SN $j$ towards the $x$ and $y$ -axis at time $T_i$
$T_i$	Time of final beacon broadcast
$T_q$	The present time
$X_q^j, Y_q^j$	The projected position of SN $j$ at the present time

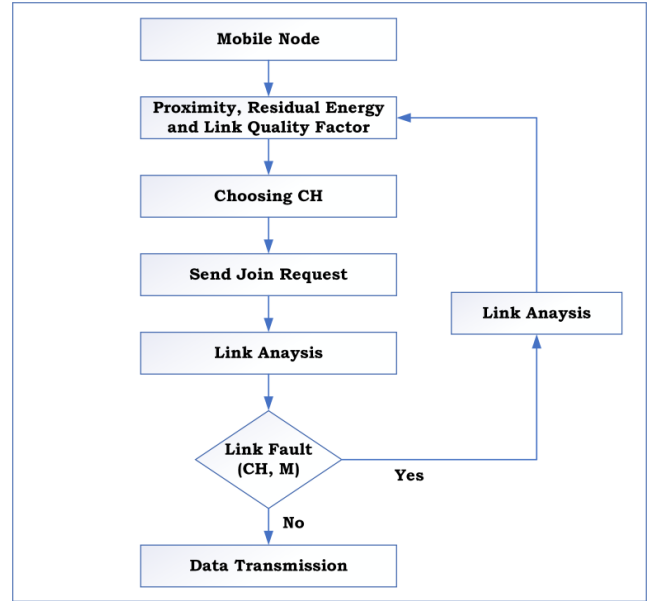


Fig. 5 Cluster reformation in link fault condition

The deviation of a sensor node can be calculated using formula (21) at time interval  $T_i$ . Table 3 describes the variable description of the same and description of time parameters. The link failure is predicted based on the node's location and the velocity with which it moves out of radio range. If the deviation of a mobile SN becomes more than the threshold limit, then it means that the link is going to fail. In this case, the mobile node goes out of range, and there is no coverage of other sensor node that means the node cannot be located and the link is identified as a fault. Generally, the wireless radio communication range will be 250 m. If the calculated deviation range reaches near 200m, then the node automatically starts to find its cluster head to reform its link, as shown in Fig. 5. The proposed approach reduces the energy consumption in every phase, such as CH selection, optimal path selection, relay node selection, and data fusion. Thus, the network lifetime is extended, and it increases the number of alive nodes. Therefore, this process of dealing with link fault/failures reduces the target missing rate in an effective manner.

## 5 Performance Evaluation

The performance of the proposed EEPC protocol has been evaluated through extensive simulations using NS-2 [37]. The Performance of EEPC is evaluated by considering mobile sensing tracking as an event and is compared with PSO based

Enhanced Clustering and Cluster head selection (PECC) [13], Optimized Clustering Method Fuzzy C-Mean (OCM-FCM) [14], Enhanced Cluster head Selection-PSO (ECS-PSO) [8][14] having two-dimensional coverage area 1000m x 1000m. The performance of the proposed EEPC is evaluated with reference to various performance metrics.

### 5.1 Simulation Setting

The simulation network setup is constructed with hundred nodes, which comprises both fixed and mobile nodes. It is comprised of 36 fixed nodes and 64 mobile nodes. The fixed nodes are located in non-moving constructions, and dynamic sensors are placed in the mobile entities called mobile nodes. In order to form the link, the IEEE 802.11P MAC protocol is used. The mobile nodes collect information about the tracked event and environment. This collected information is further forwarded to fixed nodes. The simulation coverage area is 1000m x1000m. The simulation period is 100 seconds. The initial energy of nodes is 10J, queue length set as 50, and data rate is 256-512 kbps. The maximum sensing radius is considered 20m, the transmission range of SNs 250m (<200m), sensing power is assumed as 0.10W, receiving power is 0.25W and idle power is 0.04W. The simulations are carried out in NS-2. Table 4 shows simulation parameters.

Table 4 Simulation parameters

Simulation Parameters	
Simulator	NS -2 simulator
Protocol	EEPC with PSO
Coverage Area	1000m x 1000m
Number of SNs	100 (36 Static SNs, 64 Mobile SNs )
Simulation Period	100 Seconds
Initial energy	10J
Queue Length	50
Data Rate	256-512 kbps
Max Sensing Radius	20m
Transmission Range	250m(<200m)
Interface Type	Wireless Physical Interface
Power for Sensing	0.10 W
Power for receiving	0.25W
Transmission Power	0.75W
Idle Power	0.04W
Antenna Type	Omni Directional Antenna
Energy Model	True

### 5.2 Number of packets received

Fig. 6 shows the number of packets received at BS by the proposed EEPC and existing PECC, ECS-PSO, and OCM-FCM. The X-Axis stands for the simulation rounds, and the Y-axis points to the quantity of received packets. The resultant graph indicates that the proposed algorithm yields a higher number of aggregated packets than other existing techniques. The proposed EEPC achieves 1684 packets at the end of 200 simulation rounds. However, OCM-FCM receives 1554 packets at the end of 200 rounds. Proposed EEPC achieves 7.71% more number of packets than OCM-FCM because of

data fusion. The ECS-PSO and PECC receive 1521 and 1252 packets, respectively, at the end of 200 simulation rounds. The proposed EEPC achieves 9.67% and 25.65% more packets at BS with respect to ECS-PSO and PECC, respectively.

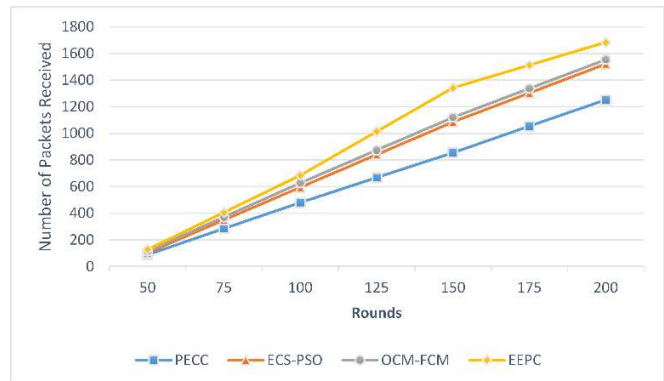


Fig. 6 Number of received packets

### 5.3 End- to-End delay

It is the time used by packets to reach at receiving end from a particular source. In target tracking event, sensed information reaches cluster head, and thereafter it is aggregated by sensor data fusion technique. The fused data is sent to the relay nodes, which further transmit this data to the BS.

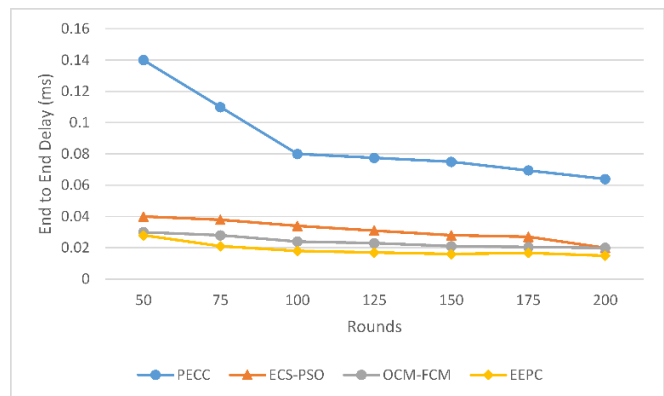


Fig. 7 End-to-End delay

The source is mobile SNs, and the destination is the base station. Fig. 7 shows the end to end delay for existing and proposed techniques. The performance of EEPC is evaluated through extensive simulations, which range up to 200 rounds. The packets in the proposed EEPC exhibit very less end to end delay while reaching the destination through the data fusion technique. It has also been observed that in the proposed EEPC, end-to-end delay remains steady with an increased number of rounds. At the end of 200 rounds, the proposed EEPC shows 0.015ms of end-to-end delay. However, OCM-FCM and ECS-PSO show 0.02ms. Proposed EEPC shows a 25% reduction in end-to-end delay in comparison to existing OCM-FCM and ECS-PSO.

### 5.4 Packet Dropping Ratio

It is defined as the percentage of packets lost with respect to packets sent. It occurs due to the compromised bad node

behavior as it drops all or some of the packets that need to be forwarded. Packet loss and packet dropping is a common problem in WSN, which minimizes the packet delivery ratio. It could be caused by signal deterioration in the medium due to multipath dropping.

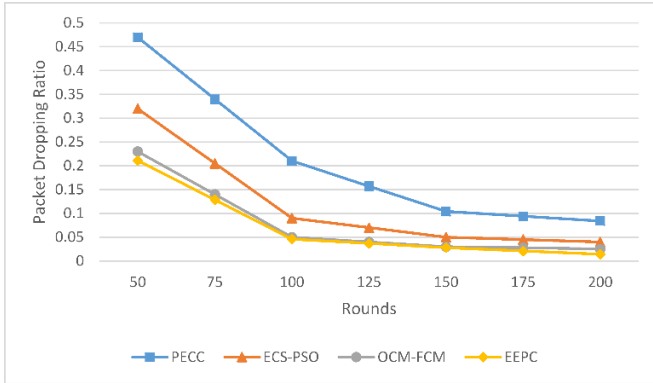


Fig. 8 Packet dropping ratio

Fig. 8 shows the packet-dropping ratio of proposed and existing techniques. In the proposed EEPC, the packet dropping ratio is calculated as 0.0142 at the end of 200 rounds. However, other existing algorithms OCM-FCM, ECS-PSO, and PECC, exhibit 0.025, 0.04, and 0.084 packet dropping ratios. Proposed EEPC performs well from the first round to the end of the 200<sup>th</sup> simulation round. This is because of balanced load distribution by unequal clustering and involvement of relay nodes.

### 5.5 Packet Delivery Ratio

It is defined as the ratio of sums of packets effectively received to the entire amount of packets transmitted, which is called as packet delivery ratio. It is represented in terms of % age.

$$PDR = \frac{\text{Number of Packets Received}}{\text{Number of Packets Transmitted}} * 100$$

Tracking event deals with temporal data. The packet delivery should be fast enough in the event of target tracking. If the packet delivery ratio is too low, then it means that we cannot achieve accurate and complete data. The sensor data fusion technique overcomes the incompleteness of data. In order to achieve high performance, the tracking mechanism should have a high packet delivery ratio as well. Fig. 9 shows the PDR of the proposed EEPC and existing techniques. The experimental results show that the PDR of the proposed EEPC is increased in comparison to other existing techniques. Proposed EEPC exhibits 98.86% PDR at the end of 200 simulation rounds. However, OCM-FCM, ECS-PSO, PECC exhibit 97.81%, 96.02%, 89.584% PDR for 200 simulation rounds, respectively.

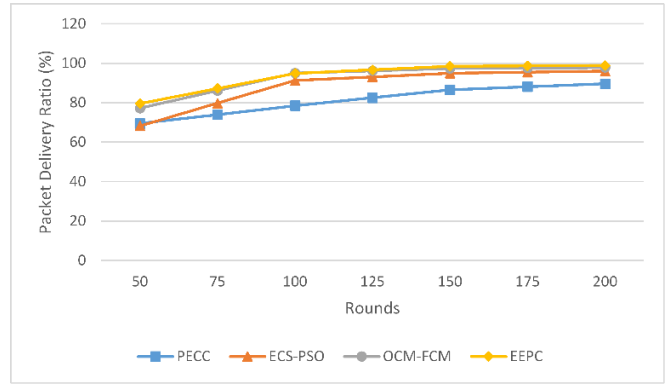


Fig. 9 Packet delivery ratio

### 5.6 Routing Packet Overhead

In the proposed simulation, setup the routing takes place between the CH and fixed relay nodes. There is no problem with relay nodes, which transmit data to the BS. However, sometimes the group of mobile nodes may increase in a particular radio range due to to which the data transmission increases within a particular range. The CH and static nodes are overwhelmed with a huge amount of data. The network should sustain such a situation in the dynamic sensing environment. The proposed system performs well from the beginning to the end.

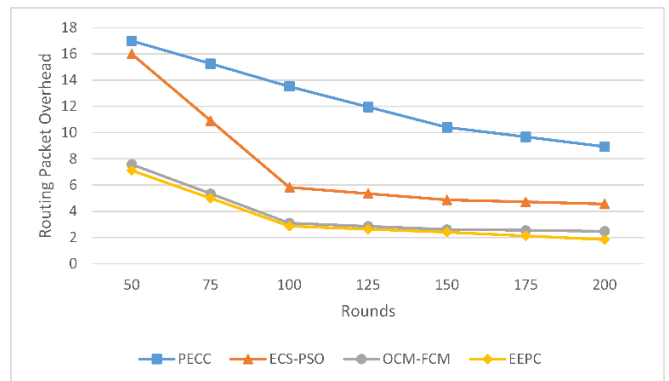


Fig. 10 Routing packet overhead

Fig. 10 shows the path determination overhead of proposed and existing techniques. The proposed EEPC suffered from only 1.84 routing packet overhead in the 200 simulation round. PECC and ECS-PSO suffered by 8.94 and 4.56 routing packet overhead respectively by the end of the 200 simulation round. OCM-FCM performed equally well as EEPC. However, it suffered from 2.48 routing packet overhead when it reached the last round of simulation. The routing packet overhead in the proposed EEPC is decreased by 25.8% compared to the existing OCM-FCM. The inclusion of data fusion in the proposed EEPC reduces the routing packet overhead.

### 5.7 Throughput

Throughput is measured as the volume of data packets effectively directed towards the endpoint terminus within the total simulation period. It is conveyed as

$$\text{Throughput} = \frac{\text{number of data packets sent (bits)}}{\text{Time period (seconds)}}$$

The mobile sensors might move out of the radio range and bond with other range. Some of the data is forwarded by one CH, and other partial data is forwarded to BS by another CH. Therefore, throughput metric plays a significant role. Fig.11 represents the throughput of proposed and existing techniques. The graph indicates the number of rounds on the X-axis and throughput on the Y-axis in bits per seconds. The existing PECC technique provides the minimum throughput of 32500 bits per second as compared to the other techniques by the end of the 200 simulation round. ECS-PSO, OCM-FCM, and proposed EEPC exhibit 39438, 40200, 45850 bits per second, respectively, in the last simulation round. The proposed EEPC offers a 12% higher throughput value as compared to OCM-FCM. Dynamic selection of CH and relay nodes reduces the energy depletion constraint and increases the overall throughput of the proposed EEPC.

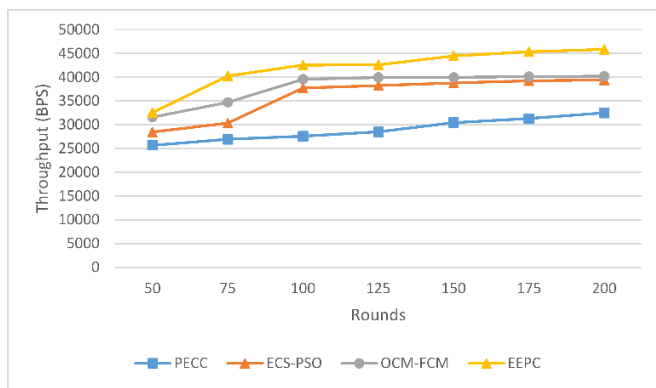


Fig.11 Throughput

### 5.8 Average Residual Energy

Energy level varies in every mobile and static sensor node at different locations within the tracking field. The sensor's lifetime is subject to the energy level in the deployed environment. If the static nodes are overwhelmed with the heavy network load, then it means that the energy level will be decreased, and there may be a need of using mobile nodes as relay nodes. During the simulation, the initial energy has been predefined to 10 Joules. Fig. 12 shows the average remaining energy of the proposed EEPC and existing algorithms. It is observed that at the end of 500 rounds, Two Level Cluster-based Routing protocol (TLCR) [14] lost its residual energy. However, ECS-PSO, OCM-FCM, EEPC survived with 2.89 Joules, 3.14 Joules, and 4.28 Joules, respectively. All the nodes in ECS-PSO and OCM-FCM are dead at the end of 600 and 650 simulation rounds, respectively. However, the proposed EEPC survived with 2.33 Joules at 650 rounds. Proposed EEPC lengthens the lifetime of SNs up to 650 simulation rounds.

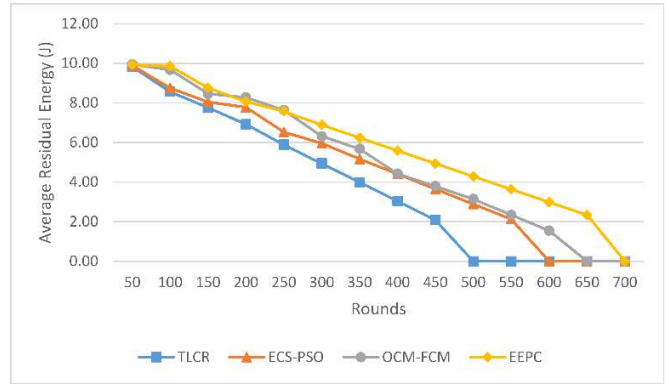


Fig. 12 Average residual energy

### 5.9 Alive nodes

Retransmission of data vitiates the performance of WSN in dynamic tracking. Transmission issues deplete the energy of nodes and increase the dead nodes. The alive nodes should be maximized in an efficient event-tracking algorithm. Fig. 13 shows the alive nodes count between the existing and proposed technique. All algorithms maintained the same number of alive nodes up to 300 rounds. After that, the existing TLCR technique affords a very less number of alive nodes as compared to all other techniques. It loses all nodes by the 500 round. The number of alive nodes becomes zero for ECS-PSO in the 600 rounds and OCM-FCM in 650 rounds. The proposed EEPC technique survives with 13% alive nodes in 650 simulation rounds. Proposed EEPC has achieved a 13% more number of alive nodes as compared to OCM-FCM. The amount of alive nodes decreases owing to energy weakening along with the simulation rounds. The percentage of alive SNs is directly proportional to the residual energy level. The proposed EEPC algorithm conserves the energy in every stage of processing.

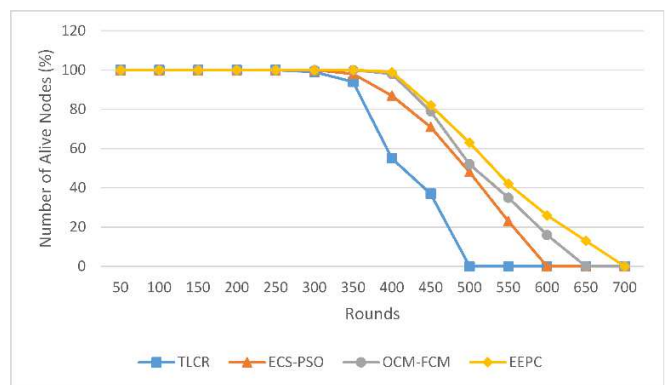


Fig. 13 Number of alive nodes

### 5.10 Total Energy Consumption

It is described as the amount of total energy consumed by all the SNs in the network to transmit the packets during the simulation period. Fig. 14 illustrates the energy consumption of the existing and proposed EEPC algorithm. It is assessed that the total energy consumption of the proposed EEPC is 68% at the end of 700 rounds. However, it has been observed that TLCR consumed 90%, ECS-PSO consumed 78%, and

OCM-FCM consumed 75% of total energy. The proposed EEPC algorithm consumed 22%, 10 %, and 7% less total energy compared to TLCR, ECS-PSO, and OCM-FCM, respectively. Limited battery capacity is the biggest challenge of the WSN environment, and the proposed EEPC consumes very less energy and increases the lifetime of sensors as well.

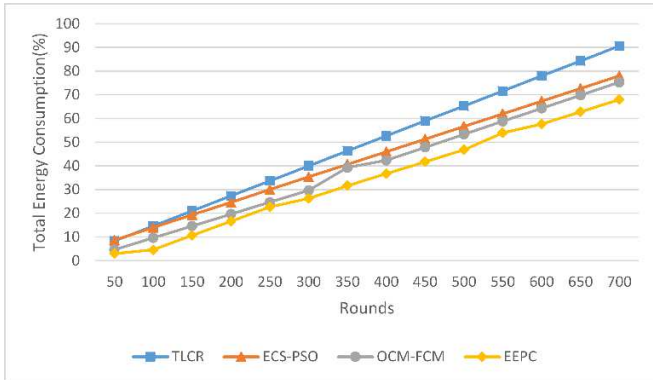


Fig. 14 Total energy consumption

### 5.11 Total Residual Energy

Total residual energy represents the lifetime of WSN networks. It should be maximized as much as possible, which results in a higher network lifetime. Fig. 15 indicates the total residual energy of the proposed EEPC and the existing algorithms. The algorithms are evaluated up to 700 simulation rounds to get the total residual energy level. It is measured that the total residual energy at the end of 500 simulation rounds is 17%, 28%, 44% for TLCR, ECS-PSO, and OCM-FCM, respectively. However, the proposed EEPC shows 48% of residual energy at the end of 500 rounds. It has achieved a 4% higher total residual energy than the OCM-FCM algorithm by the end of 500 simulations round, and it outperforms all other algorithms by a large margin. The proposed EEPC protocol lengthens the network lifetime by the end of the 650 simulations round.

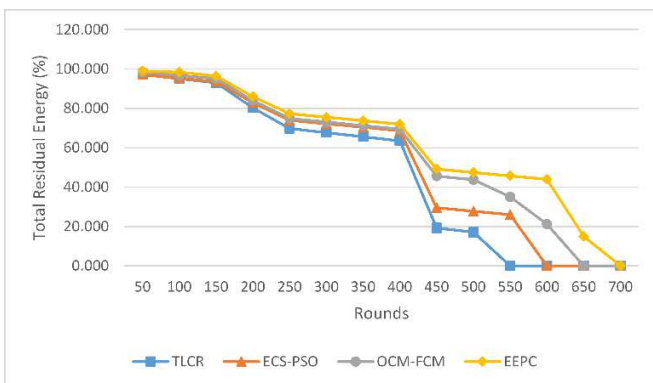


Fig. 15 Total residual energy

## 6 Conclusion and Future Scope

In this work, an Enhanced Energy Proficient Clustering (EEPC) protocol has been proposed to optimize the network path during data transmission, which considers the dynamicity of SNs. The main aim of this work is to enhance the sensor

network lifetime and improve the tracking and monitoring activity in the WSN environment. This work proposes an energy-efficient clustering algorithm for the WSNs to decrease the energy consumption and to prolong the network lifetime as well. The novelty of the proposed work lies in the concept of finding relay nodes using EEPC, which utilizes enhanced PSO and forwards the sensed information to the BS by applying a sensor data fusion technique to save energy. The proposed EEPC algorithm improves the lifetime of sensor nodes by proposing an enhanced swarm optimization technique. It also overcomes the common drawback where the CH itself transmits track-by-track event-driven data to the base station. Extensive simulations conclude that the proposed EEPC improves both energy efficiency and accuracy of mobile node tracking. The overall lifetime of the sensor nodes is maximized through the sensor data fusion technique. The simulation results show that the proposed approach points out progress with reference to various performance metrics. The proposed EEPC minimizes the energy depletion and enhances the network lifetime as compared to other existing protocols. In the future, the authors would like to implement the EEPC algorithm on real test-beds/ hardware.

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