Chapter 2

Prior Related Works

This chapter provides a detailed review of recent and relevant MS-based data routing approaches for IoT-enabled WSNs. In IoT-enabled WSNs, static sink-based data routing approaches suffer from energy-hole problems. It adversely affects the network's lifetime and performance. MS-based data routing schemes reduce the data transmission energy loss of sensor nodes as well as improve the overall performance of the network. However, MS-based data collection mechanisms suffer from several challenges. In MS-based data collection, inefficient RP selection leads to imbalanced energy consumption among sensor nodes. It leads to premature death of the network. Furthermore, a heterogeneous WSN contains sensor nodes of different capacities. Therefore, MS-based data-gathering approaches that are developed for homogeneous WSNs can not be directly applied to heterogeneous WSNs due to the different nature of sensor nodes. On the other hand, large-size real-life network areas contain several obstacles. These obstacles prevent MS movement and hamper the data collection process. Therefore, an MS-based obstacle-avoiding data collection scheme is needed. In IoT-enabled WSNs, sensor nodes are prone to various faults due to chemical explosions, natural disasters, and harsh environments. Faulty sensor nodes disconnect the network into multiple isolated segments. Therefore, a network cut detection and recovery scheme is needed for

IoT-enabled WSNs. Recently, IoT-enabled WSNs are used in emergency evacuation for the safe evacuation of evacuees. In these systems, considering only the current fire situation while designing the path causes long detours and panic in evacuees. Therefore, it is necessary to consider both current and future fire shapes while designing the evacuation path for safe and quick evacuation of individuals. Based on the key points discussed, this chapter provides a thorough literature review of energy-efficient data routing, obstacle-aware data gathering, network cut detection methods and IoT-based emergency evacuation systems.

2.1 Literature review

In recent years, researchers have proposed various data-gathering mechanisms for IoT-enabled WSNs. Fig. 2.1 shows a taxonomy of literature review. The literature review is divided into the following sections.

- Data collection in homogeneous networks
- Data collection in heterogeneous networks
- Obstacle-aware data gathering
- Network cut detection and recovery
- Emergency evacuation system

2.1.1 Data collection in homogeneous networks

In this section, we review the current MS-based data-gathering studies, which are designed for homogeneous WSNs. Cheng et al. [44] proposed an MS-based data-gathering scheme for WSNs. In this approach, some common data acquisition locations are selected within the network depending on the coinciding regions of nodes. Furthermore, a Travelling Salesman Problem (TSP) is applied to build a path for MS movement. This

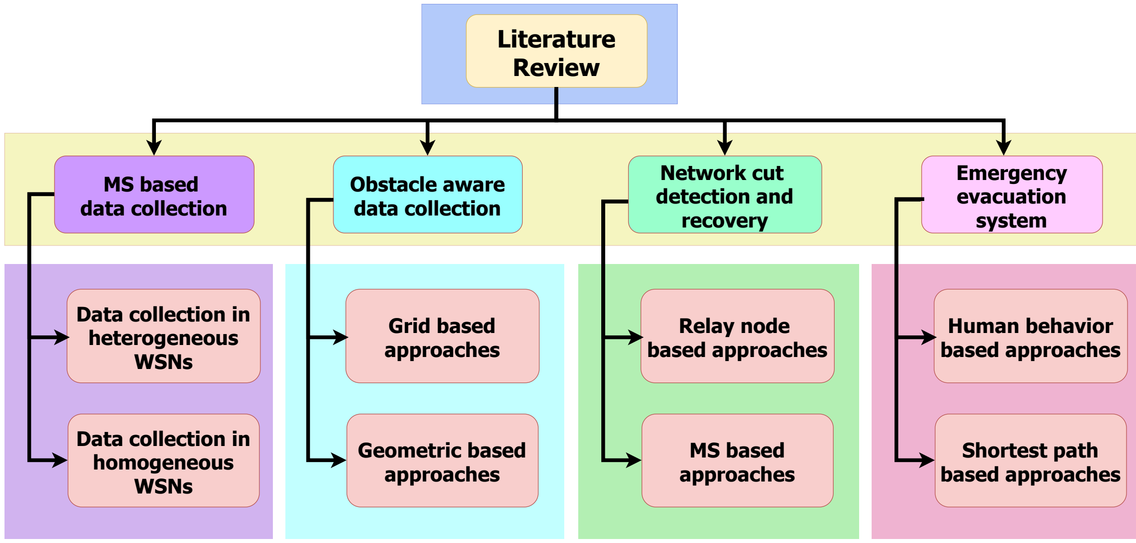

Figure 2.1: Taxonomy of literature review.

approach reduces the length of the data gathering path by considering common data collection points. The main drawback of this approach is high data transmission delay and poor network performance. Wang et al. [45] presented a cluster-based data-gathering approach. In this approach, a Particle Swarm Optimization (PSO) mechanism is used for cluster formation. Furthermore, residual energy and position of the sensor node are used to select Cluster Heads (CHs) within the network. MS travels in the network and collects data from the CHs. The limitation of this approach is that it is not suitable for large areas because overall energy consumption and delay increase when the number of clusters is increased. Krishnan et al. proposed a multiple MSs based data acquisition scheme for WSNs [46]. In this approach, a modified LEACH algorithm is applied for clusters formation. Furthermore, an Ant Colony Optimization (ACO) is used to calculate the optimal path for MS. Each MS is assigned a unique set of clusters. MS starts data collection from the initial node of the cluster and visits all cluster member nodes. However, the major drawback of this approach is that it suffers from huge message overhead and poor network performance. Huang et al. [47] presented a compressive sensing technique to reduce the data size. In this approach, clusters are formed based on the cluster radius. Nodes send their data in raw form to the CHs. CH compresses these data before sending it to MS. The limitation of this technique is that it cannot be used for sensitive applications where data is required in the original form. Ghosh et al. [48] proposed a grid-based data collection mechanism for WSNs. In this approach, the whole network is divided into different grids. The MS moves through each grid and collects data from the grid nodes by single-hop communication. If any node has emergency data, then either the node transfers that data towards the MS or waits for the MS. Virtual Grid Based Route Adjustment (VGDRA) technique proposed by Khan et al. [49] where the whole network is divided into the same size cells and cell heads are selected in each cell. The cell heads collect data from all other nodes of cell. MS moves along the boundary of a rectangle-shaped network, and cell heads that are closer to the boundary collect data from other cell heads and send it to MS. The limitation of this approach is that it increases the routing overhead by applying multi-hop data transmission at cell heads.

Krishnan et al. [50] proposed a dynamic clustering scheme for data collection in the WSNs. In this approach, CHs are selected based on node degree, residual energy, and the distance between sensor nodes and CHs. Furthermore, they have used ACO to design an optimal path for the MS. The limitation of this approach is that it has a high message overhead. Naghibi et al. [51] proposed a data collection method for WSNs that uses two MSs to collect data from WSNs. In this approach, the whole network is divided into different cells. MSs move in concentric diamond shape paths to collect data that significantly increases data gathering delay. Salarian et al. [52] proposed a Weighted Rendezvous Planning (WRP) approach to enhance the network lifetime. In this approach, RPs are selected based on hop count and the number of data packets forwarded by a sensor node. Sensor nodes send their data to RP, and MS visits each RP to collect data. However, This approach suffers from unbalanced energy consumption because the number of nodes sending data to RP varies largely with each RP. Tabibi et al. [53] proposed a PSO based approach for the selection of RP. This approach selects RP based on a weight value. The drawback of this approach is poor network lifetime. Lu et al. [54] proposed an Artificial Bee Colony (ABC) algorithm-based data gathering strategy for MS. This approach minimizes the hop counts between sensor nodes and RPs, and then ABC is applied to design an optimal path for MS. In this approach, the authors have only considered hop counts for RP selection that increases the average distance per hop. Therefore, this approach also suffers from poor network lifetime. Kaswan et al. [55] proposed an MS based data routing scheme for WSNs where two algorithms namely Reduced K-means (RKM) and Delay Bound Reduced K-Means (DBRKM) are used for RP selection and path planning. In RKM, initially, k-means clustering is used for potential RP selection. Furthermore, this approach calculates the optimal number of RPs based on predefined parameters. In DBRKM, an initial set of potential RP is selected based on the k-means algorithm. Furthermore, the author minimizes the set of RPs in such a manner so that MS can collect data from the network within an allowable time limit. The limitation of this approach is that the authors have assumed an equal load on each node during the path planning. As a result, this approach does not prevent the premature death of the network. Alsaafin et al. [56] presented an MS based distributed data gathering scheme for WSNs. In this approach, a projectile path is composed for MS. To diminish the energy expenditure and delay, this approach used three different algorithms. The Reduced Energy Path (REP) algorithm is designed for energy-efficient data gathering. Reduce Delay Path (RDP) and Delay Bound Path (DBP) algorithms are used for faster and emergency data gathering. Kaswan et al. [57] proposed a rendezvous point based data collection scheme for WSNs. In this approach, multiple rendezvous points are selected by applying the multi-objective particle swarm optimization technique. This approach connects all RPs and a data-gathering path is designed by using the traveling salesperson problem. The limitation of this approach is that it causes non-uniform energy consumption in network. An Energy-Aware Path Construction (EAPC) algorithm proposed by Wen

Table 2.1: Summary of MS-based data collection approaches in WSNs

Contributions	***Structure***	***Multiple MS***	***Communication***	***Energy Consumption*** *($\mathcal{EC}$)*	***Data Collection Delay*** *($\mathcal{DCD}$)*
Based on coinciding regions of nodes some common data acquisition locations are selected within the network. TSP is applied to build MS path [44].	-	No	Single-hop	Medium	High
PSO algorithm is used for cluster formation. Sensor node location and residual energy is used for CH selection [45].	Cluster	No	Multi-hop	High	High
A modified LEACH algorithm is applied for clustering. ACO is applied for MS path design [46].	Cluster	Yes	Multi-hop	High	Medium
The network is divided into grids. MS visits each grid and collects data directly from nodes. Emergency data is transmitted via multi-hop communication [48].	Grid	No	Multi-hop	Medium	High
The network is presented as a graph, and the MS path is designed by determining the tree's diameter. Nodes are divided into unequal-sized clusters. Nodes transmit data to CH, and CH forwards data to MS [59].	Cluster	No	Multi-hop	High	High
WSN is divided into different regions and sensor nodes grouped into cells. Nodes send their data to MS via multi-hop tree structure of cells GN [60].	Cluster	No	Multi-hop	High	Medium
Sensor nodes are divided into two groups. Nodes closer to the MS path are called GNs, and other nodes are called FNs. FNs send their data to MS through GNs [61].	Graph	No	Multi-hop	High	Medium
Some sensor nodes as data collection points. The sensor node creates a tree structure with data collection points as the root node. Nodes send their data to the root node and MS follows a designed path and collects data from collection points [58].	Tree	No	Multi-hop	High	Medium
WSN is presented in the form of a graph. MS path is designed by determining the tree's diameter. Some equal and some unequal size clusters are created. Nodes transmit data to CH and CH forwards data to MS [59].	Cluster	No	Multi-hop	High	High
WSN is divided into different regions. SNs are grouped into cells. Data is sent to MS via a spanning tree of cells [60].	Cells	No	Multi-hop	High	High
MS path is predefined. Nodes closer to the MS path are called Gateway Nodes (GNs), and other nodes are called Far-away Nodes (FNs). FNs send data to GNs, and GNs forward data to the MS [61].	-	No	Multi-hop	High	Medium
The proposed approach uses the MOGWO algorithm for optimal RP selection and clustering. It minimizes the transmission distance, intermediate hops counts and distance among nodes of the same cluster.	Cluster	No	Multi-hop	Low	Low

et al. [58]. This algorithm first selects a few sensor nodes as data collection points in the network and then designs a path connecting those points. Sensor nodes create a tree structure with a data collection point, where the collection point is the root node. Senor nodes send their data to the root node and MS follows a designed path and collects data from collection points. The limitation of this approach is that it suffers from high data loss. Tang et al. [59] proposed an MS-based data collection scheme for strip-shaped WSNs. In this approach, the network is presented as a graph, and the MS path is designed by determining the tree's diameter. A backbone network is created using nodes in the MS path. The backbone network is divided into equal size clusters. The rest of the nodes are divided into unequal-sized clusters. Nodes transmit data to CH, and CH forwards data to MS. The limitation of this approach is that multi-hop communication between CHs and sensor nodes causes high energy consumption at sensor nodes. Wedaj et al. [60] proposed a territory-bound data collection approach using MS. This approach divides the WSN into different regions and groups sensor nodes into cells. The region containing MS is called active, and the rest of the regions are called passive. Passive regions send their data to the active region through a spanning tree of cells. However, the limitation of this approach is that sensor nodes within cells of the active region transmit more data compared to other sensor nodes. It causes high energy consumption at sensor nodes and low network lifetime. Kumar et al. [61] proposed a heuristic approach for data collection using path-constrained MS. In this approach, sensor nodes are divided into two groups. Nodes closer to the MS path are called Gateway Nodes (GNs), and other nodes are called Far-away Nodes (FNs). A set of sub-paths is calculated along the MS route. GNs send data to MS when it traverses their sub-path. The major drawback of this approach is that it suffers from the energy hole problem due to high energy consumption at GNs.

2.1.2 Data collection in heterogeneous networks

This section reviews the state-of-the-art MS-based data collection approaches in WSNs. Verma and Jain [62] presented an Energy and Delay Efficient Data Acquisition (EDEDA) approach for WSNs. This approach creates a virtual grid over the network and selects a grid cell head in each grid. In this approach, some grid cells are selected as visiting points. The MS visits the visiting points and collects data from adjacent cell heads. This approach applies the Hamiltonian cycle to design the MS movement path. However, this approach suffers from uneven energy consumption at cell head nodes, which leads to poor network lifetime. This approach also divides the network into different isolated segments due to the early death of the cell head nodes. Yang et al. [63] applied a Deep Reinforcement Learning (DRL) algorithm to develop a data collection mechanism for MS. In this approach, MS visits each sensor node to collect data. However, this approach suffers from a high data collection delay due to the selection of a longer data-gathering path. Another major limitation of this approach is that it loses data due to buffer overflow in large-size networks. Sulakshana and Kamatam [64] selected the RPs in WSNs using the Expectation-Maximization clustering mechanism. In this approach, the authors use linear programming to design an order in which MS visits RPs and collects data from the sensor nodes. The main drawback of this algorithm is that it exchanges huge control packets among sensor nodes to manage cluster and RP selection. It drastically reduces the network lifetime and overall performance of the network.

Jiao et al. [37] proposed an Improved Reed-Deer Algorithm (IRDA) based CHs selection mechanism for data routing in WSNs. This approach uses the K-Nearest Neighbour (KNN) to predict the location of MS within the network. In this approach, sensor nodes send their data to CH. CH forwards this data to a CH nearest to MS via multi-hop communication. The limitation of this approach is that the multi-hop communication causes high energy consumption at CHs. Additionally, continuous MS

Table 2.2: Summary of MS-based data collection approaches in heterogeneous WSNs

Contributions	***Structure***	***Multiple MS***	***Heterogeneity***	***Energy Consumption ($\mathcal{EC}$)***	***Data Collection Delay ($\mathcal{DCD}$)***	***Data Packet Dropped***	***Network Partitioning***
Expectation maximization algorithm is used for clustering and linear programming for MS path design [64].	Cluster	No	No	High	High	High	Yes
Bald eagle search is used for CH selection and hybrid neural network with GTA for MS path design [36].	Cluster	No	No	High	Medium	High	Yes
A set of visiting points are selected in the network. Hamiltonian cycle is applied to design MS path [62].	Grid	No	No	High	Medium	High	Yes
DRL is applied for MS based data collection [63].	-	Yes	Yes	Medium	Medium	High	No
IRDA is applied for CH selection and KNN for MS location prediction [37].	Cluster	No	No	High	Medium	High	Yes
Network area is divided into equal sized rectangles. GA is applied for RP selection [38].	Cluster	No	No	High	Medium	High	No
TEO-MCRP algorithm is used to jointly determined CHs and MS path [65].	Cluster	No	Yes	High	Medium	High	Yes
Residual energy of sensor nodes is used to design MS movement [66].	Cluster	No	Yes	Medium	High	High	Yes
ACO is used for clustering and MARL for MS path planning [67].	Cluster	No	No	Medium	Medium	High	No
A set of VS nodes are selected in WSN. MS moves in ring path, collecting data from VS nodes [68].	Ring	No	No	High	Medium	High	Yes
The network is divided into regions. Separate MS is assigned to each region [69].	Cluster	Yes	No	High	Medium	High	Yes
Proposed approach uses EERPS algorithm for optimal RP selection and DPDP for MS path design.	Cluster	No	Yes	Low	Low	Low	No

location prediction and update also create high message overhead and high energy consumption at sensor nodes. Singh et al. [38] proposed a Genetic Algorithm based Sink Mobility Technique (GA-SMT) for WSNs. This approach divides the network into several rectangular-shaped clusters and selects a dedicated RP for each cluster on the boundary of the rectangle. The MS path is designed in such a way that it touches at least one boundary of each cluster. However, the length of the data-gathering path is very high in this approach. It increases the data-gathering delay and creates complexity in the network management process. Yalçın and Erdem [65] proposed a Thermal Exchange Optimization Clustering Routing Protocol (TEO-MCRP) for WSNs. It is influenced by Newton's cooling law. In this approach, the CHs and the MS path are jointly determined by the temperature equation from Thermal Exchange Optimization (TEO). However, the main drawback of this approach is that it does not consider sensor node buffer capacity during the CH selection. This leads to high data loss at sensor nodes.

Rahnemay et al. [70] proposed a cost-effective data collection scheme using MS for heterogeneous WSNs. This approach considers two types of nodes in the network, i.e. super nodes and normal nodes. Super nodes have a higher communication range and higher initial energy than normal nodes. This approach applies PSO with time-varying acceleration coefficients to select CHs in the network. ACO is applied to design MS path. However, this approach does not consider the buffer capacities of sensor nodes while selecting CHs. It causes buffer overflow at nodes and results in loss of data. Ghorbani and Barati [69] proposed an MS-based data routing approach for WSNs. It divides the monitoring region into different parts. A dedicated MS is appointed for data collection from each part. It selects CHs based on the sensor node score. MS collects data from CHs within its allotted region. After data collection, MS transmits data to the BS. The main drawback of this approach is that it suffers from a huge message overhead due to the complex cluster management strategy.

Gowda and Jayasree [36] proposed a Group Teaching Algorithm (GTA) based data routing mechanism for WSNs. This approach selects CHs using the bald eagle search mechanism. Furthermore, the RP selection is done using the hop distance and communication traffic conditions. An optimal path for MS-based data collection is designed using the hybrid neural network with GTA. This approach suffers from huge message overhead and communication delays due to the use of a complex bald eagle search mechanism for CH selection. Madhavi and Madheswaran [66] proposed a Region Energy Conscious Sink Movement (RESM) mechanism for heterogeneous WSNs. In this approach, the network is divided into equal-sized regions. In each region, sensor nodes are grouped into clusters. The total energy of a discrete region is calculated, and MS moves to the centre of the region with the minimum total energy. The main drawback of this approach is that it suffers from huge data collection delays and hot spot problems due to imbalanced energy consumption among sensor nodes. Furthermore, some regions within the networks are not visited by MS for a long time due to the inefficient MS movement mechanism. It leads to data loss due to the sensor node buffer overflow. Ghabel et al. [67] presented a Multi-Agent Reinforcement Learning (MARL) based MS path planning approach. This approach uses the ACO algorithm to create clusters within the network. Furthermore, it applies the Genetic Algorithm (GA) to update clusters in each round. The limitation of this approach is that it does not consider the buffer capacity of sensor node while selecting CH nodes. It leads to buffer overflow and data loss. Jain et al. [68] proposed an MS-based data routing approach where multiple concentric rings are created to perform MS-based data collection within the network. A set of Virtual Structure (VS) nodes are selected on rings. VS nodes collect data from sensor nodes and forward it to MS along the ring path. However, the limitation of this approach is that it consumes high energy due to VS nodes. Therefore, this approach suffers from poor network lifetime.

2.1.3 Obstacle-aware data gathering

This section reviews the existing state-of-the-art research on obstacle-aware data collection approaches in WSNs, with their merits and demerits. Habib et al. [71] proposed a starfish routing algorithm to select an optimal set of rendezvous nodes within the obstructed network. Furthermore, they used Mixed Integer Linear Programming (MILP) to design the MS movement path. However, this approach suffers from high energy consumption at intermediate sensor nodes. It leads to poor network lifetime. This approach also did not remove sharp edges and turns from the designed path for MS movement. Therefore, it is unable to collect data from all deployed sensor nodes. Ghabel et al. [67] applied the ACO algorithm for initial clustering and a GA for updating clusters. This approach jointly used GA and MARL for MS path design. The authors further extended this approach in [72]. The extended approach uses the Floyd–Warshall algorithm to calculate the cost between two non-adjacent RPs. However, this approach did not consider the load on the forwarding sensor nodes that causes high energy consumption at sensor nodes. Also, this approach is unable to construct a smooth path for MS movement. It significantly increases data collection delay due to multiple collisions between MS and obstacles/sensor nodes.

Pasha et al. [73] proposed a heuristic algorithm to find the visiting order of RPs and then applied a BUG2 algorithm to design an obstacle-avoiding path for MS. However, this approach did not keep a safe distance between the path and obstacles which increases the risk of collision between MS and obstacles. This approach also did not consider smooth path construction. Therefore, it significantly increases data gathering time. Anwit et al. [21] proposed a greedy heuristic approach for the set cover problem to select RPs. Furthermore, the BUG2 algorithm and Bezier curve are applied to design an obstacle-avoiding path for MS. This approach only considers a single-hop communication between sensor nodes and RPs, which increases the path length and data collection delay. Furthermore, in this approach, the designed path is very close to

Table 2.3: Summary of existing obstacle-aware data routing approaches

Contributions	***Structure***	***Obstacles***	***Communication***	***Energy Consumption ($\mathcal{EC}$)***	***Data Collection Delay ($\mathcal{DCD}$)***	***Collision Probabilty***	***Smooth Path***
A starfish routing algorithm is applied to select an optimal set of rendezvous nodes. MILP is used to design MS path [71].	Ring-canal	Yes	Multi-hop	High	Medium	High	No
ACO algorithm for initial clustering and a GA for updating clusters. GA and MARL are jointly applied to design MS path [67].	Cluster	Yes	Multi-hop	High	Medium	High	No
K-medoids and hierarchical agglomerative clustering are used for cluster construction. ACO is used to design path connecting RPs. GA is used for updating clusters. Floyd-Warshall algorithm is applied to compute cost of traversing between two RPs [72].	Cluster	Yes	Multi-hop	High	High	High	No
A heuristic algorithm is applied to find visiting order of RPs. BUG2 algorithm is applied to design obstacle avoiding MS path [73].	Cluster	Yes	Multi-hop	High	High	High	No
Proposed a greedy heuristic approach for the set cover problem to select RPs. BUG2 algorithm and Bezier curve are applied to design an obstacle-avoiding path for MS [21].	Cluster	Yes	Single-hop	Medium	High	High	Yes
Node energy, distance to RP, and packet density are used to select RPs. Proposed a hybrid meta-heuristic algorithm to design a path for MS [74].	RP Node	No	Multi-hop	High	Medium	High	No
K-means algorithm is used for creating clustering. Christofides method is applied to create an obstacle-avoiding path for MS [75].	Cluster	Yes	Single-hop	Medium	High	High	Yes
Spectral clustering algorithm is applied for RP selection. RRT is applied to design an obstacle avoiding path for MS [39].	Cluster	Yes	Single-hop	Medium	High	High	No
Proposed approach uses MRFO algorithm for optimal RP selection and EBS-A* for MS path design.	Cluster	Yes	Multi-hop	Low	Low	Low	Yes

the obstacles, which can cause MS to collide with obstacles.

Rajagopal et al. [74] presented a farm irrigation management system based on MS-based data gathering. In this approach, a hybrid meta-heuristic algorithm is proposed to design a path for MS. In this approach, the construction of a smooth path for MS is ignored. Nannapanenia et al. [75] applied the K-means algorithm for creating clusters in the networks. Next, they used the Christofides method to create an obstacle-avoiding path for MS. This approach did not design a smooth path for MS. It also did not keep a gap between obstacles and the designed path. It increases the risk of MS collision with obstacles. Keshari et al. [76] applied the Voronoi diagram to divide the network area into Voronoi cells. The vertices of cells are selected as potential RPs. A cost function is designed to optimize the RPs. The limitation of this approach is that it is unable to design a smooth path for MS. Furthermore, it also suffers from poor QoS and huge data transmission delay. Boyineni et al. [39] used a spectral clustering algorithm to select RPs in the network. In this approach, rapidly-exploring random tree algorithm is applied to design an obstacle avoiding path for MS. The limitation of this approach is that it did not design a smooth path for MS movement. It significantly increases data collection delay and reduces overall network performance.

2.1.4 Network cut detection and recovery

This section reviews the recent and relevant works on network cut detection and recovery in WSNs. Yin et al. [23] proposed a mobile relay and static relay-based data transmission approach for disconnected WSNs. Mobile relays are deployed between two disconnected segments for data transmission to the BS. Furthermore, multiple static relays are deployed to reconnect isolated segments for data transmission with minimum delay. The limitation of this approach is that it is unable to detect network cuts that occur during the data transmission. On the other hand, it exchanges huge control packets to manage mobile and static relay nodes within the network. It leads to poor network lifetime. Pei et al. [22] proposed a connectivity reestablishment mechanism for segmented WSNs using an Unmanned Aerial Vehicle (UAV) swarm. This approach connects isolated network segments by deploying UAVs in hover and flying mode. However, the drawback of this approach is that it did not identify the network cut which occurs during the network lifetime. Therefore, it creates disconnected network segments after some initial rounds. It leads to poor network performance. Zear et al. [77] proposed a multi UAV based connectivity re-establishment scheme for partitioned WSNs. This approach positions UAVs in place of failed Articulation Point Nodes (APNs) in the WSNs. UAVs act as relay nodes to maintain the connectivity of the network. The major drawback of this approach is that it only identifies network cuts due to APN failure. It fails to identify network cuts that occur due to other sensor nodes' failure. Therefore, other sensor node failure divide the network into multiple isolated segments and reduces network performance drastically. Zear et al. [78] proposed network partition detection and recovery mechanism using multiple UAVs. In this approach, UAVs visit failed nodes to detect network cuts. UAVs are used to deploy multiple relay nodes between disconnected network segments. The major limitation of this approach is that it suffers from a huge message overhead and data transmission delay. Furthermore, this approach also did not optimize the network cut detection. It causes a high delay in the network recovery.

Rajeswari et al. [79] proposed MDC based data collection approach for disconnected WSNs. In this approach, some aggregator nodes and one sojourn location are selected in each segment. Furthermore, the Donkey And Smuggler Optimization (DASO) algorithm is applied to design the path for MDC. The limitation of this approach is that it suffers from a huge message overhead. It reduces the network lifetime and overall performance of the network. Min et al. [80] defined the problem of data gathering in a disconnected WSN as a Generalised Travelling Salesperson Problem (GTSP). They proposed meta-heuristic algorithm-based techniques for determining RPs and computing the MDC path for data gathering from the predefined network segments. Furthermore, this approach also reduces the MDC's path length based on the sensor nodes' communication range. The limitation of this approach is that it did not consider the distance between RPs and sensor nodes while selecting RPs. Hence, sensor nodes lose a huge amount of energy for transmitting data to the RP. It causes a low network lifetime. Rajeshwari et al. [81] proposed an obstacle-aware data-gathering technique for partitioned WSNs. This approach first detects partitioned segments in the network. In each partitioned segment, one representative node is selected. Sojourn locations are selected near representative nodes in the network. MDC visits the sojourn location through an obstacle-avoiding path and collects data from the representative nodes. The limitation of this approach is that it suffers from a huge message overhead. It increases the overall energy consumption of the network and leads to poor network lifetime.

Liu et al. proposed two convex hull-based path design mechanisms for data gathering in partitioned WSNs. The first approach divides the network into grids [15]. One RP is selected in each segment from the grid that is closest to the network centre. A convex hull is designed using RPs for MDC-based data collection. The limitation of this approach is that it selects a random node as an RP in the boundary region of a segment. Random RP selection causes high energy consumption at sensor nodes and leads to the premature death of the network. In the second approach [82], each segment is divided into several sub-regions. The RP is chosen from the subregion that is closest to other segments and the network centre. A Convex hull-based scheme is used to design a path for MDC movement. The limitation of this approach is that it fails to detect the formation of isolated segments which are created due to node failure. It reduces the overall network performance. Sun et al. [83] divided the network segments into layers based on their distance from the network centre. Initially, RPs are selected at the boundaries of segments. Next, a convex hull is created using outer segment RPs. The RPs of inner segments are adjusted to bring them closer to the path. In this approach,

Table 2.4: Summary of network cut detection and recovery approaches

Contributions	***Predefined Network Segments***	***Energy Consumption ($\mathcal{EC}$)***	***Data Collection Delay ($\mathcal{DCD}$)***	***Network Cut Detection***		***Network Operation Cost***
				APN Failure	***Non APN Failure***	
A set of mobile relays and static relays are deployed in the network. Mobile relays connect two disconnected segments, and multiple static relays are used to connect two segments with minimum delay [23].	Yes	High	Medium	No	No	High
Proposed connectivity re-establishment using multiple UAVs. UAVs are placed in place of failed APNs in the WSNs. UAVs act as relay nodes to maintain the connectivity of the network [77].	No	High	Medium	Yes	No	High
Proposed network cut detection and recovery using multiple UAVs. UAVs visit failed nodes to detect network cuts. UAVs are used to deploy multiple relay nodes between disconnected network segments [78].	No	High	Medium	Yes	Yes	High
Some aggregator nodes and one sojourn location are selected in each segment. DASO algorithm is applied to design the path for MDC [79].	No	High	High	No	No	Medium
Defined the problem of data gathering as a GTSP. Proposed meta-heuristic algorithm-based techniques for determining RPs and computing the MDC path [80].	Yes	High	High	No	No	Medium
Network is divided into grid. A node in the grid closest to the network center is selected as RP. Convex hull is used to design MDC path [15].	Yes	High	High	No	No	Medium
Network segments are divided into layers. A convex hull path is created using outer layer segment RPs. Inner layer segment RPs are adjusted to bring them closer to the path [83].	Yes	High	High	No	No	Medium
A convex hull is designed to find the number of RPs. Jaya meta-heuristic to optimize the number of RPs and MDCs in the network [84].	Yes	High	High	No	No	Medium
Proposed approach uses RLBSO algorithm for optimal RP selection and MDC path design. Novel MDC based network cut detection algorithm and network recovery algorithms are proposed for detecting cuts in the network.	No	Low	Low	Yes	Yes	Low

the positions of RPs are not optimal, which leads to high energy consumption in the network. Anwit et al. [84] first created a convex hull to find the number of RPs in the network. Furthermore, they applied the Jaya metaheuristic to optimize the number of RPs and MDCs in the network. However, the number of RPs is very high in this approach. It increases MDC tour length and leads to high data collection delays.

2.1.5 Emergency evacuation system

This section reviews existing state-of-the-art emergency evacuation systems. Q. Zhang et al.[85] presented an analysis of intelligent elevator systems, indication systems, and intelligent emergency lighting. It apprehends their progress and eminence. This article also reviewed and analyzed the imperfections and defects of present systems. As per the [85], the existing technology does not apply to the entire evacuation procedure. Also, the existing techniques do not carry out dynamic adjustment and intellectual analysis. Zong et al. [86] presented an emergency evacuation process that evacuates people using a visual-guided artificial bee colony algorithm. In this approach, the leading bee of a visual field guides individuals towards the exit. Congestion and the distance among evacuees are used to select leading bees. However, this approach does not consider the future fire spread during the evacuation path design. F. Kamoun et al. [87] presented a real-time dynamic evacuation system. This approach considers the changing circumstances and dangers associated with every hallway segment in terms of congestion, heat, walking stretch, and fire gases. In this approach, smart panels positioned at central intersections of the hallways are triggered for navigating evacuees toward a safe exit. However, the main drawback of this approach is that it does not consider the future spreading of fire with time.

A. Jindal et al. [88] proposed an Emergency evacuation system for Clogging free and Shortest-Safe path Navigation (ECSSN). This approach calculates a clogging-free and safe path for every individual in an emergency. Smoke sensors are used to detect fire/smoke, and PIR sensors are used to guide every individual towards safe exits. However, this approach only considered the static fire scenario. Y. Niu et al. [43] proposed a real-time evacuation strategy-based algorithm for emergency evacuation of people called Three Strategies for minimizing the Objectives of the route Distance/length, congestion State, and Unreliability value (TODSU). The main drawback of this scheme is that it does not consider the dynamic spreading of fire with time. Furthermore, it also takes a huge amount of time to compute the evacuation path in an emergency situation. F. Wang et al. [42] proposed a Fire Evacuation model for large public buildings based on Building Information Modeling (FEBIM). In this approach, the authors identify the tolerance limit of each evacuee by using fire dynamics simulator software. Furthermore, a building map is used to guide the evacuees toward the safe exits. J. Sharma et al. [89] proposed a deep Q-learning-based fire evacuation technique. They created a q matrix that contained the shortest distance from every room to the exit. Furthermore, the Deep q network is used to reproduce the q matrix in an emergency situation. However, the computational complexity of this approach is very high.

A. Lee et al. [90] proposed a lightweight approach for emergency evacuation. The authors used D* algorithm to design the dynamic path for the evacuee. However, it does not consider the dynamic fire spread during the evacuation path computation. C. Wang et al. [91] proposed a real-time fire condition understanding system using the multi-floor Dynamic Escape Route Planning (DERP) method for emergency evacuation. They built a 3D fire information model by combining the evacuee's density in particular regions and real-time fire aspects like CO concentration, temperature, and smoke concentration. Furthermore, this 3D fire information model defined a 3D route safety function where multiple indoor restrictions are considered for computing emergency escape routes. T. Tabirca et al. [92] used a dynamic graph-based method to solve dynamic emergency evacuation problems. This approach considers safety and dynamic hazard metrics to calculate the safe waiting time at a node of each individual.

In this approach, evacuees use the dynamic shortest routes to reach the exit in the least possible time. In contrast, injured evacuees or firefighters use dynamic safety routes to keep a reasonable wait margin.

H. Jiang et al. [93] presented an artificial intelligence-based system to solve the dynamic evacuation problem. A grid environment is set according to an engineering map of a shopping mall. Then an enhanced ant colony optimization algorithm is applied to find the optimal evacuation route by examining three distinct stages of fire. Ultimately, the guiding path is displayed by intelligent evacuation indicators. A. Benssam et al. [94] addressed the emergency evacuation problem by considering the dynamic factor of the emergency evacuation process. They demonstrate the need for novel approaches that maximize the entire efficiency of the current system. They also underline the partial consideration of the problem from a solo perspective in particular domains. Furthermore, they presented a dynamic approach for evacuation in emergencies. In this approach, changes occurring in the data associated with the different actors' are used to calculate the evacuation path.

Huang et al. [95] proposed a Radar-assisted State–Action–Reward–State–Action (RSARSA) algorithm for emergency evacuation path design. In this approach, two types of radar, exit radar and fire radar, are integrated into the SARSA algorithm to enhance the wayfinding process. SARSA is a reinforcement learning model that simulates pedestrian decision-making during emergencies. This approach designs the evacuation route in accordance with real-time fire scenarios. Chen et al. [96] proposed an agent-based simulation framework for developing the optimal rescue plan. This approach is specially developed for older adults in residential buildings during emergency evacuation. This approach analyzes the behaviour of evacuees and rescuers during an emergency. Furthermore, it uses a wayfinding index to guide the rescuers' decision-making process for the evacuation of older adults. The limitation of this approach is that it did not consider the future spread of fire with time.

Table 2.5: Summary of existing emergency evacuation systems

Contributions	***Path Structure***	***Dynamic Fire***	***Appraoch Type***	***Evacuation Time***
A visual-guided ABC algorithm is proposed. One leader bee is selected among evacuees. The leader bee guides the evacuees towards exit [86].	Grid cell based	No	Shortest Path	High
Proposed an approach that designs the path based on congestion, heat, walking stretch, and fire gases. Smart panels positioned at central intersections of the hallways to guide evacuees towards exit [87].	Graph Based	No	Shortest Path	Medium
Proposed a clogging-free and safe path for every individual in an emergency. Smoke sensors are used to detect fire/smoke, and PIR sensors are used to guide every individual towards safe exits [88].	Grid cell based	No	Shortest Path	Medium
Proposed a Fire Evacuation model for large public buildings. A building map is used to guide the evacuees toward the safe exits [42].	Building map	No	Shortest Path	High
Proposed a deep Q-learning-based fire evacuation technique. A q matrix is created that contains the shortest distance from every room to the exit. Deep q networks is used to design evacuation path [89].	Graph Based	Yes	Shortest Path	Medium
Proposed a lightweight approach for emergency evacuation. It uses the D* algorithm to design the dynamic path for the evacuee [90].	Grid cell based	No	Shortest Path	High
Proposed a dynamic graph-based method for emergency evacuation. Safety and dynamic hazard metrics to calculate the safe waiting time at a node [92].	Graph Based	No	Shortest Path	Medium
A multi-floor dynamic escape route planning. A 3D fire information model is built. An emergency route is designed using this 3D model [91].	Grid cell based	No	Shortest Path	High
Proposed an agent-based simulation framework. Analyzes the behaviour of evacuees and rescuers during an emergency. It uses a wayfinding index to guide the rescuers during an emergency [96].	Grid cell based	No	Human behaviour	High
Proposed dynamic emergency evacuation approach. It designs a *firemap* and a *routemap* to design evacuation path while considring current and future fire shape.	Grid cell based	Yes	Shortest Path	Low

2.2 Research Gaps

Extensive research work has been addressing existing research problems of IoT-enabled WSNs. The researchers have proposed various effective approaches for solving different issues, such as MS-based data gathering in homogeneous networks, MS-based data collection in heterogeneous networks, obstacle-aware data gathering approaches, network cut detection and recovery, and emergency evacuation systems using IoT-enabled WSNs. However, in these existing works, there are several issues that still need to be addressed. The research gaps/limitations of existing literature are mentioned below.

2.2.1 Issues in data collection in homogeneous networks

1. An Optimal number of RP/CH selections is needed to establish a trade-off between the energy consumption of sensor nodes and data collection delay.

2. An Efficient clustering scheme is required to balance the transmission distance and hop counts between sensor nodes and RPs/CHs.

3. An Optimal path planning mechanism is needed for MS path design.

2.2.2 Issues in data collection in heterogeneous networks

1. Existing approaches do not consider sensor node buffer capacity during RP selection and MS path design. It causes huge data loss due to the buffer overflow at sensor nodes.

2. Existing state-of-the-art approaches are unable to prevent network segmentation due to early node death.

3. Varying energy capacities and varying communication ranges of sensor nodes need to be considered to effectively utilize network resources.

2.2.3 Issues in obstacle-aware data gathering

1. Existing MS-based data-gathering approaches did not consider a safe distance between the designed path and obstacles. It creates a possibility of collision between MS and obstacle during movement.

2. Smooth path construction needs to be considered for MS path design. A smooth path enables swift MS movement and reduces data collection delay.

3. Existing approaches did not optimize the sensor node load, which causes high energy expenditure at sensor nodes. It leads to poor network lifetime.

2.2.4 Issues in network cut detection and recovery

1. Existing approaches are unable to detect the network cuts that are generated due to node failures during the network lifetime. They only consider predefined network segments for MDC-based data collection path design.

2. Existing approaches do not identify the network cuts that are formed due to multiple non-APN failures. It creates disconnected segments in the WSN and leads to poor network performance.

3. Existing approaches did not consider the energy consumption of sensor nodes while selecting RPs. It causes high energy consumption at forwarding nodes, which leads to an energy imbalance in the network segment.

2.2.5 Issues in emergency evacuation system

1. Existing works only focus on finding the shortest-safe path for every individual by considering the current fire scene.

2. Existing approaches do not consider the future changes in the fire shape with the time that leads to significant detours and trapping of individuals in an emergency.

2.3 Summary

The literature review indicates that the current data-gathering methods for WSNs face several challenges, including energy holes, premature network death, network segmentation and unexpected network faults. These issues considerably diminish the overall performance of the networks. A high-performance WSN is essential for real-time data collection in any IoT-based system. Consequently, existing methods fall short of meeting the requirements for IoT-based systems. This Thesis proposes high-performance data-gathering schemes designed to address these challenges and fulfil the needs of IoT-based systems.

The next chapter discusses the MS-based data gathering in WSNs. A multi-objective grey wolf optimization is applied to select the optimal number of RPs in the network. RPs are selected in such a way that minimizes the energy consumption of sensor nodes and improves network lifetime. An optimal path is designed for MS.