Data Aggregation Methods for IoT Routing Protocols: A Review Focusing on Energy Optimization in Precision Agriculture

Parijata Majumdar[1], **Diptendu Bhattacharya**[1], and **Sanjoy Mitra**[2†], Non-members

ABSTRACT

Agriculture productivity can be enhanced by IoT-enabled real-time monitoring of weather and soil parameters. Increased volume of sensor data demands a significant amount of memory and power. It also overloads the network, making real-time parameter monitoring very difficult. A large volume of sensor data reduces the lifetime and latency of the network, decreasing the overall throughput. Hence, a reduction in data overload becomes necessary for energy optimization of these energy-constrained sensors. Data aggregation is an effective way of optimizing energy consumption by reducing the volume of redundantly sensed data. Data aggregation helps in designing energy-efficient routing algorithms to transmit information by consuming minimum energy to increase the operational period of the network. This paper surveys different routing algorithms for data aggregation with a focus on energy optimization in precision agriculture. The survey includes IPv6 routing protocol for low-power and lossy networks (RPL) to reduce network overload during data transmission, nature-inspired algorithms for energy-optimized intra-cluster communication, and energy-efficient compressive sensing (CS) to minimize redundant data by aggregation. It also examines duty-cycling algorithms for reducing average energy consumption by periodically placing sensors into the sleep mode during inactive state to save energy. Different performance benchmarks are evaluated to determine the suitability of the routing algorithms in agriculture.

Keywords: Duty Cycling, Data Aggregation, Nature-Inspired Algorithms, RPL, Compressive Sensing

1. INTRODUCTION

Agriculture is the main source of livelihood for farmers and maximizing profit in commercial markets. Hence, there is a need for automation in acquiring weather parameters by monitoring on a continuous basis using IoT-enabled sensors. The Agriculture Internet of Things (IoT) comprises a large number of sensors for the accurate real-time monitoring of soil fertility, soil pH, soil moisture, temperature, humidity, wind speed, and wind direction, such as weather parameters to maintain the productivity of agricultural land and ensure crop growth. IoT-enabled devices like cameras, drones, etc., are used to track the fields continuously linked to the base station. Wireless sensors connected to the base station have different power consumption modes, ranging from low to high according to the type of application required. Since sensors are mostly battery-powered, they have energy limitations [1]. The transmission of a large volume of sensor data across the network not only requires a huge amount of memory to be saved and processed but also consumes high bandwidth, exhibits latency, and lessens the operational period of the network, ultimately reducing the throughput of the desired application. Non-uniform traffic sensor distribution causes the sensors nearer the sink to act as a relay point for interchanging more data in comparison to other far away sensors, resulting in energy deficiency [2]. Therefore, data aggregation from heterogeneous sensors is needed before routing these data to the gateway to prevent redundant data transmission while balancing the data load over the network.

In this paper, different cluster-oriented routing optimization techniques are used for energy efficiency and to increase the lifetime of a distributed network. This paper surveys different nature-inspired routing algorithms for cluster formation. Cluster formation involves identifying the number of clusters, cluster heads, cluster membership, and relay node energy loss minimization during data forwarding to base stations. Communication between clusters requires less energy for sensors located far away from the cluster head. The data are then aggregated and transmitted to the base station via relay node. Duty-cycling algorithms to achieve synchronization among sensors are also used to balance the energy consumption rate by placing the sensors in sleep mode when not in use for data collection [3].

The IPv6 routing protocol for low-power and lossy networks (RPL) is also studied, where a topology is created resembling a directed acyclic graph in which each network node has an associated rank which rises when the nodes within the network move away from the

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[1]The authors are with the Department of Computer Science and Engineering, National Institute of Technology, Agartala, 799046 India.

[2]The author is with the Department of Computer Science and Engineering, Tripura Institute of Technology, Agartala 799009 India.

[†]Corresponding author: mail.smitra@gmail.com

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Table 1: *Contribution of this survey work.*

Other Survey Works	This Survey Work
Although other reviews on data aggregation using routing protocols can be found, none focus on energy minimization, particularly in the context of precision agriculture [4, 5].	Different data aggregation methods applying nature-inspired algorithms, intracluster routing, compressive sensing, duty cycling, and routing protocols for low-power and lossy networks, are analyzed and reviewed in this paper. They are extensively reviewed bearing in mind their potential application in precision agricultural monitoring and focusing on energy minimization.
No standard survey on data aggregation methods using routing protocols can be found in the existing literature, where such a large number of performance optimization metrics are similarly addressed and analyzed in the precision agriculture monitoring context. These include average energy consumption, data recovery ratio, data reduction, average execution time, network lifetime, throughput, packet loss ratio, average path length, etc.	Performance evaluation metrics such as average energy consumption, data recovery ratio, data reduction, average execution time, network lifetime, throughput, packet loss ratio, and average path length of each algorithm are studied to draw a comparison and evaluate their efficiency to help develop a robust precision agricultural monitoring application in future.

root node. The nodes send back the packets selecting routes with the lowest range. It is specifically designed for low power consumption since wireless sensors are energy constrained [6]. All these routing schemes are used to optimize the energy requirement of sensors, extending the network lifetime while also helping to overcome redundant data transmission with multiple sensors using data aggregation. Table 1 describes the main contributions of this survey work.

2. DATA AGGREGATION IN IOT BASED PRECISION AGRICULTURE

Data aggregation in the wireless sensor network is gaining increasing attention to achieve multifarious objectives, such as reducing redundant data transmission, increasing the network operational period, minimizing bandwidth consumption, and most importantly, designing low power consumption techniques for data collection and transmission.

Numerous sensors are employed in the agricultural field to ensure crop growth and soil fertility. Sensors constantly gather real-time weather and soil data to enable the farms to schedule suitable irrigation patterns for optimum crop growth. The large volume of time-series data transmitted periodically by each sensor can cause network overload, bandwidth consumption, and transmission delay. The key objective of data aggregation is to properly accumulate all data with low energy consumption.

Sensors and base stations are energy constrained since they operate under battery limitations, hence, the role of energy-saving routing mechanisms has become increasingly significant. Typical energy-saving approaches include nature-inspired routing algorithms, routing protocol for low-power and lossy networks, compressive sensing and duty-cycling algorithms designed to minimize sensor energy consumption, and a base station to increase network life and save processing time by applying data aggregation. Here, data aggregation is employed to reduce redundant data sensed by multiple sensors.

In precision agriculture, aggregated data is only required on a portion of farmland where network aggregation like the routing protocol for low-power and lossy networks will reduce the data transmission rate to avoid network overload and decrease energy consumption [7]. Based on the observations cited above, the routing techniques for data aggregation have been surveyed, bearing in mind their potential application in optimizing energy in precision agriculture.

In flat networks, all sensors have the same power supply and behave identically. As with floods, data aggregation necessitates data-centric routing, whereby the sink transmits data packets to sensor nodes. Flooding sensors store data that matches data packets and returns response data packets to the sink. The high rates of energy consumption in flat networks are frequently attributable to the fact that any type of communication and processing places a strain on the sink. The data is aggregated in hierarchical networks using a specific node, reducing the number of data packets transmitted to the sink [4, 8]. As a result, a structure such as this enhances the overall energy efficiency of hierarchical networks including centralized, in-network, tree-based, and cluster-based.

In the centralized approach, all sensors use the quickest feasible path to deliver data packets to a central node. The aggregator is responsible for combining data from several nodes and sending it as a single packet. The in-network method is responsible for collecting and processing data at the intermediate nodes as well as routing data through multi-hop networks. Its major goal is to minimize the quantity of energy used during the process [4, 8].

In size-reducing aggregation, the number of packets to be transmitted is minimized to the sink node, while data packets from sensor nodes via their neighbor nodes are merged and compressed. In aggregation without size reduction, when combining the packets of multiple neighbor nodes into one, the data value is not processed.

In the tree-based approach, all data transfers involve the building of minimum spanning trees, called data aggregation trees (DAT). All nodes in the network have a parent-child connection whereby data is routed in a

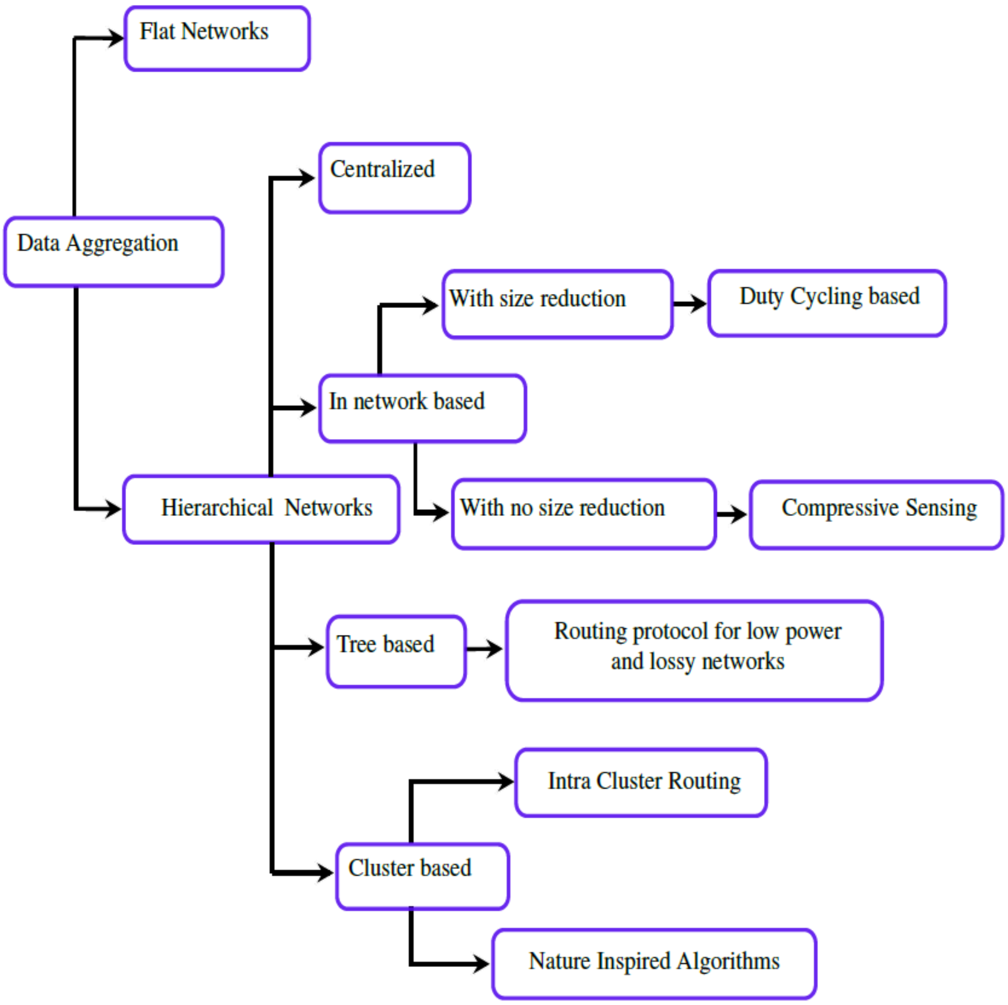

Fig. 1: *Classification of data aggregation approaches.*

bottom-up manner [4, 8]. The data travels from the leaf nodes to the sink node, with the data being aggregated by the parent nodes within the networks.

Cluster-based networks are divided into numerous clusters comprising many sensor nodes, one of which is chosen as the cluster head. The cluster head is responsible for data aggregation and sending it to the sink. Due to fewer packets requiring delivery, the bandwidth is kept to a bare minimum. It lowers any directly transmitted packets to the base station and less energy is required due to the shorter transmission distance [4, 8].

Fig. 1 shows the data aggregation classifications reviewed in this paper, falling under the broader category of hierarchical networks.

3. RELATED WORKS

In this paper, five different types of data aggregation algorithms are reviewed for routing sensor data, namely, nature-inspired routing algorithms, intracluster routing, compressive sensing, duty cycling, and the routing protocol for low-power and lossy networks.

3.1 Nature-Inspired Algorithms

Swarm intelligence is an area of artificial intelligence where the main inspiration is the cooperative behaviors of social insects. Multi-agent intelligent systems are formed in a decentralized manner that duplicates swarm behaviors. Some of the optimization techniques inspired by swarm intelligence behavior include ant-colony optimization, particle swarm optimization (PSO), intelligent water drops optimization, genetic algorithm, cuckoo search, etc.

The use of nature-inspired algorithms in swarm intelligence is an effective method of data aggregation, forming groups of similar data known as clusters. In most cases, evolution begins with a population of randomly created individuals and proceeds in generations. Each individual represents a single solution while fitness represents an individual who takes a candidate solution to the problem as input and produces it as output, depending on how good a fit the individual is. In each generation, the fitness of an individual in the population is assessed, and multiple individuals from the current population selected based on fitness and then updated to create a new population. The algorithm ends when the

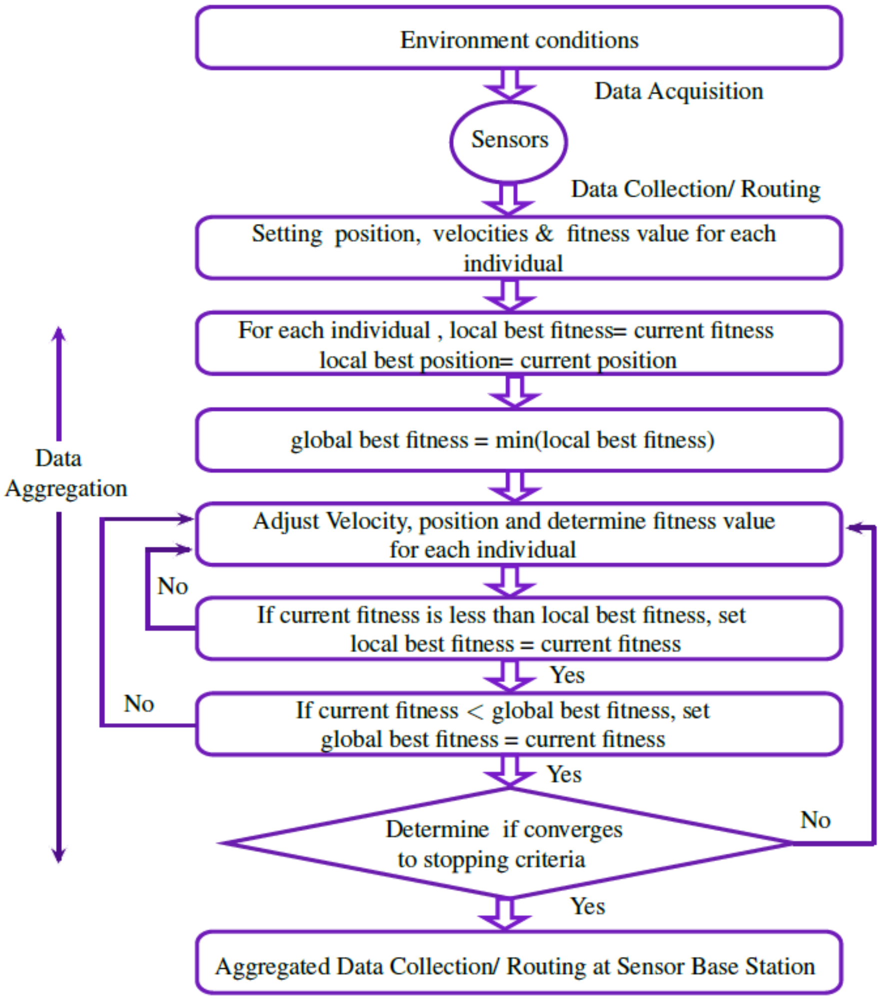

***Fig. 2**: Generalized framework of nature-inspired algorithms.*

population has reached a satisfactory fitness level or the maximum number of generations has been achieved.

Fig. 2 shows a generalized framework of nature-inspired algorithms for data aggregation which can be applied during real-time monitoring of the agriculture field. Some of the research works in the field of data aggregation using nature-inspired algorithms are described in the following section.

Devika *et al.* [1] proposed ant-cuckoo optimized relay-based data aggregation that uses ant-colony optimization to decide on the number of clusters to be employed for grouping sensors, number of cluster heads, sensors to be classified under clusters, and relay node used to preserve the energy of a cluster head by transmitting aggregated data to the base station (BS). The cuckoo search is used for cluster formation and communication within clusters to preserve the energy of sensors located far away from the cluster head, data aggregation, and transmission. The designed algorithm requires no prior information to form clusters but instead decides on the number of clusters forming a dynamic network. The relay node identified during the cluster formation phase is mainly responsible for the energy conservation of the cluster head to circumvent long-distance communication [1]. Thus, the energy conservation of battery-operated sensors can be utilized in the precision agriculture scenario for prolonging the lifespan and reducing the power requirement for sensors during the long-term monitoring of field data.

The optimization of intelligent water drops imitates nature where their populations are used to construct the best possible path among all available routes. The nature associated constraints represent the optimization problem to be solved while a stream of water drops represents the best possible route for the given problem. An aggregation tree is formed with the excitation of attracting other water drops in the successive round of tree construction where two branches meet in the tree. Sometimes, when no aggregation point is found during the earlier rounds, in order to enhance the probability of finding the aggregation point, Hoang *et al.* [9] proposed the formation of new intelligent water drops in all sensors visited by an intelligent water drop along the base station. With fewer iterations, the likelihood of bringing aggregation nodes closer to the sources increases, while energy conservation and

***Table 2**: Significant approaches to data aggregation based on nature-inspired algorithms.*

Method	Key Features	Shortcomings	Improved Parameters	Future Work
Devika *et al.* [1]	ACO, Cuckoo search for data aggregation	Converging time for ACO is not fixed. Cuckoo search converges with local optimal and convergence rate is also slow.	Network lifetime, average energy consumption, and throughput.	More nature-inspired algorithms for multi-hop, multi-layer communication to increase the energy efficiency and reliability of the base station needs to be explored.
Hoang *et al.* [9]	IWD optimization for data aggregation	Increased computation time and lack of optimal solution as random probability is used to visit next unvisited node.	Network lifetime, average energy consumption	Optimization of algorithm to reduce the chances of visiting an already visited node when the aggregation node increases.
Lu *et al.* [10]	ACO and GA for probabilistic data aggregation	Converging time and probability distribution for ACO are not fixed. GA takes more computation time.	Network lifetime, average energy consumption, aggregation delay, communication interference.	Optimization of computation time and convergence of ACO to the global optimum solution within a fixed time duration.
Sahoo *et al.* [2]	ACO based data aggregation	Converging time for ACO is not fixed	Network lifetime, end-to-end delay, and throughput.	Comparison of performance metrics with other clustering algorithms for data aggregation.
Sun *et al.* [11]	PSO, distributed clustering through fog computation	Convergence to local optimum in high dimensional space and rate of convergence is also low.	Network lifetime, node survival rate remaining energy.	Partial optimism leading to unregulated speed and direction needs to be addressed at the time of convergence.
Wang *et al.* [12]	Resampling PSO, ACO	Partial optimism leading to regulated speed and direction. Converging time and probability distribution for ACO is not fixed.	Network lifetime, data transmission, energy consumption.	Network connectivity, accuracy, and computation speed of resampling PSO need to be addressed.
Yin *et al.* [13]	Hierarchical data aggregation with PSO, differential evolution for velocity updating	Partial optimism leading to unregulated speed and direction. Differential evolution is dependent on control parameters.	Network lifetime, energy consumption.	Adaptivity for heterogeneous formation of network to meet diverse IoT applications.
Sung *et al.* [14]	ACO for center data aggregation	Converging time and probability distribution is not fixed and changes with each iteration.	Network lifetime, energy consumption	Real-time simulation in large-scale farming and small-scale plantation like an indoor greenhouse.

power reduction in the battery-operated sensors can be achieved through agriculture monitoring to ensure long-term availability of field data.

Lu *et al.* [10] proposed ant-colony-based routing to find the best possible route for data aggregation. In order to avoid a slower convergence rate, a genetic algorithm is applied on the root node. New packets arriving on in-between nodes other than the root can be forecasted using a sliding window. These new packets are employed to adjust the interval of the arrival rate. This adaptive timing policy is responsible for faster transmission and improving the probability of data aggregation. This adaptive timing policy is responsible for faster data transmission and improving the probability of data aggregation being utilized for timely prediction of droughts or floods using weather sensors that can quickly sense and transmit the weather variables for scheduling irrigation.

Sahoo *et al.* [2] designed an efficient cluster-based data collection method where optimal energy-efficient cluster heads are selected based on optimal transmission weight. The ideal path for a mobile sink is determined by ant-colony optimization to collect data along with the cluster centroid. Since it is expected to incur minimum energy to transfer data from cluster head to centroid, the energy consumption of battery-operated sensors will be reduced in agricultural monitoring to ensure the long-term power-efficient monitoring of field data.

Sun *et al.* [11] projected the fog nodes for collecting data with fog computation used in distributed clustering based on the type of data aggregation routing performed. The PSO algorithm is used to select a group of optimal sensors as the cluster heads to balance energy consumption and the network lifetime. Since increasing the lifetime of the network is directly proportional to the reduction in the energy requirement of sensors, application of this technique in precision agriculture appears promising.

Table 2 presents the significant contributions of authors in the field of data aggregation using nature-inspired algorithms.

Wang *et al.* [12] proposed a data aggregation method

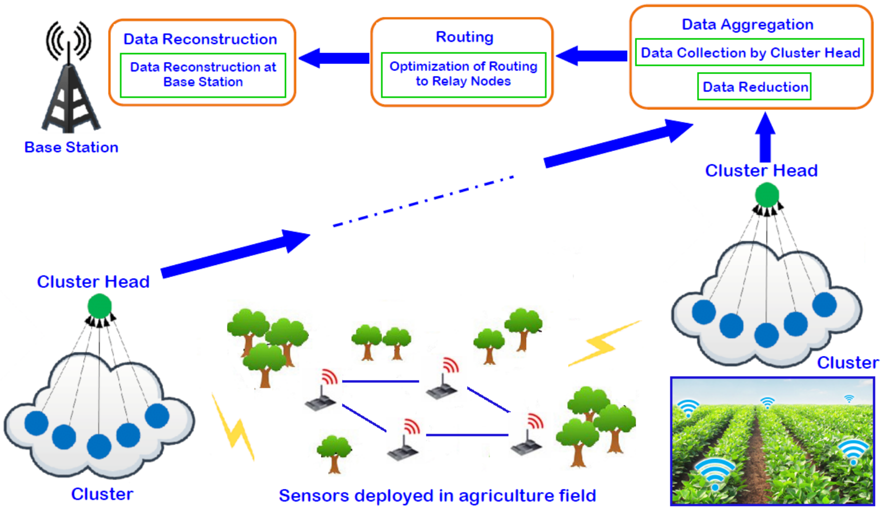

***Fig. 3**: Clustering and data aggregation in smart agriculture.*

where the cluster head is selected while data transmission takes place at the base station using resampling particle swarm optimization and multi-hop transmission. The selection of relay nodes between cluster heads and the base station is performed using ant-colony optimization. The sensors are then selected within the radius of the threshold, based on the energy consumption communicated to the base station directly. Since long-term monitoring of agriculture is needed for the accurate prediction of irrigation schedules, controlling the energy consumption of sensors using this technique in agriculture requires further investigation.

Yin *et al.* [13] proposed hierarchical data aggregation where fitness function accords with the design of different relational matrices. The optimal solution with the initial position of particles is then enclosed and the population initialized according to node distribution characteristics. Velocity is updated using differential evolution. Since increasing the network lifetime is directly proportional to reducing the energy requirement of sensors, the application of this technique in precision agriculture appears promising.

Sung *et al.* [14] proposed a ZigBee protocol-based weather stations with energy-efficient center data aggregation based on an ant-colony algorithm to increase the lifetime of battery-operated sensor nodes, while also developing a remote web-based human machine interface (HMI). A similar path is shared by an ant colony, minimizing the energy requirement and increasing network lifetime in agricultural monitoring.

3.2 Energy-Efficient Clustering

Non-overlapping subsets of sensor nodes are assembled to form individual clusters and the clustering process is an energy-efficient data aggregation method. Clustering techniques are mainly responsible for the efficient utilization of resources, providing network stability and aggregating similar data, resulting in energy-saving. Fig. 3 describes the basic organization of clustering and data aggregation in smart/precision agriculture.

3.2.1 Intracluster routing

Intraclustering algorithms perform single-hop data aggregation, providing the optimal transmission route from sensors to the base station using stand-alone sensor energy balancing, performed when source and destination are within the same cluster. Direct routing is performed to route the data received by the cluster head from the relay and forward the data to be stored in the base station.

On the other hand, inter-clustering is a multi-hop form of data aggregation specifically designed to minimize energy consumption and extend the network lifetime. Typical intracluster algorithms considered to be very energy efficient for precision agriculture applications include: low energy adaptive clustering (LEACH), power-efficient fathering in a sensor information system (PEGASIS), threshold sensitive energy-efficient sensor network (TEEN), hybrid energy-efficient distributed (HEED) algorithms, etc. Fig. 4 depicts a typical framework of intracluster routing algorithms for agricultural monitoring.

Table 3 details the significant contributions of authors in the field of data aggregation based on intracluster routing techniques. Relevant research works are described in the following paragraphs.

Manjeshwar *et al.* [15] proposed a threshold sensitive energy-efficient sensor network to facilitate intracluster-based data aggregation. Energy efficiency will help energy-constrained sensor nodes to avoid energy consumption during the long-term monitoring of agriculture.

Lindsey *et al.* [16] designed intracluster-based data aggregation where each sensor communicates with the closest cluster head and data transmitted over a path consuming minimum energy between the cluster head

***Table 3**: Significant approaches to data aggregation based on intracluster routing algorithms.*

Method	Key Features	Shortcomings	Improved Parameters	Future Work
Manjeshwar *et al.* [15]	ACO, threshold based intracluster data aggregation	Accuracy and energy consumption are user controlled.	Response time, average energy consumption.	Sensors within the cluster should not have any collisions.
Lindsey *et al.* [16]	Intracluster data aggregation	When a root node is selected, its energy level is not evaluated and since there exists an individual root node, it may cause delay in transmission.	Network lifetime, average energy consumption.	Extension of network simulator ns-2 to simulate PEGASIS, LEACH, and direct transmission protocols required to verify network longevity and quality of network links.
Heinzelman *et al.* [17]	Intracluster distributed adhoc protocol for data aggregation	Data aggregated at the cluster nodes will never reach its destination if the cluster head dies and the clusters are not evenly distributed.	Network lifetime, average energy consumption.	Micro sensor networks can be built based on energy efficient, easily configurable protocol.
Li *et al.* [18]	Adhoc energy efficient on-demand distance vector-based intracluster routing.	If routes are not checked at periodic intervals, data transmission after route discovery is time-consuming.	Network lifetime, energy efficiency and throughput.	Real-time application of the proposed protocol.
Younis *et al.* [19]	Distributed adhoc intracluster routing	Sensors that are not selected as final cluster heads might have some unvisited sensor nodes that can be within the range of other cluster heads.	Network lifetime, energy efficiency, and fault tolerance.	Multi-level hierarchy protocol can be designed by optimizing resources based on minimum selection probability and a network operation interval is needed.

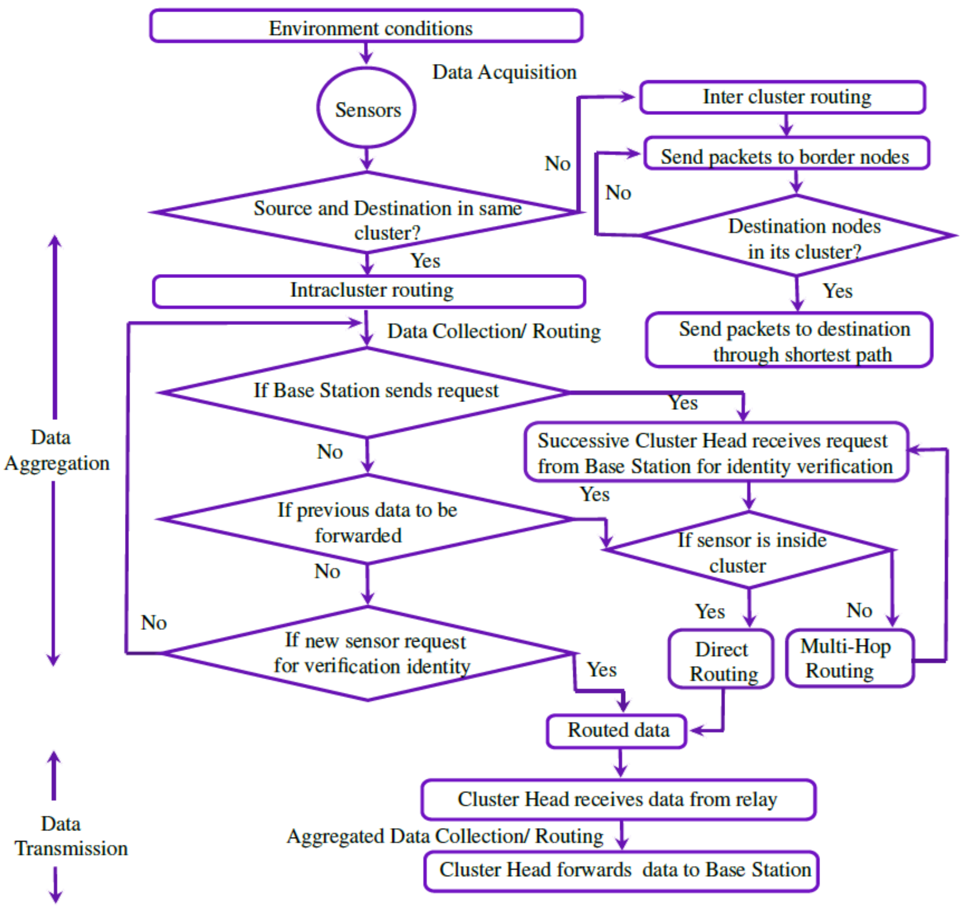

***Fig. 4**: Basic framework of intracluster routing algorithms for agricultural monitoring.*

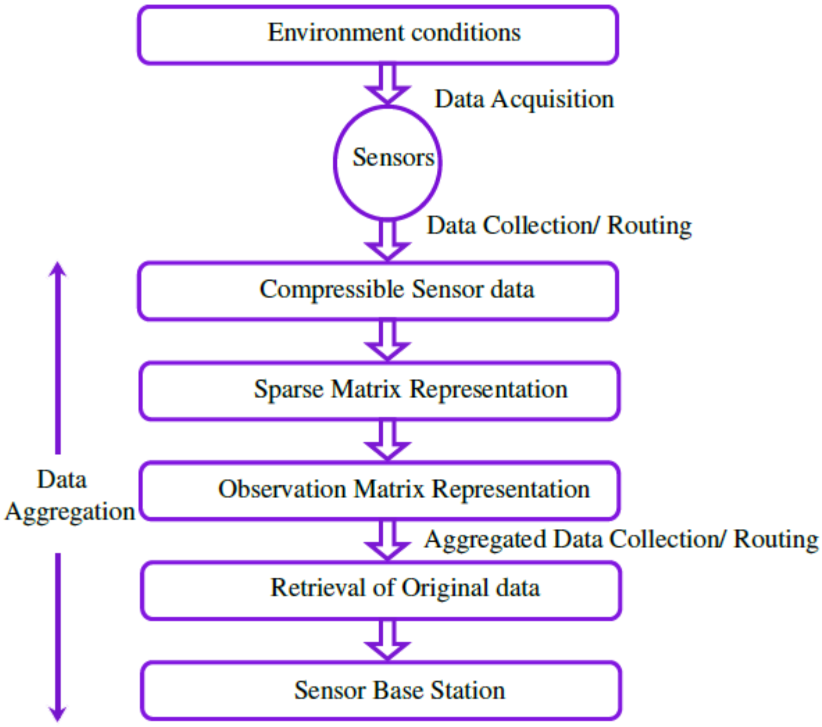

Fig. 5: *Basic framework of compressive sensing for wireless sensors used in agricultural monitoring.*

and base station. As an increase in network lifetime is directly proportional to the reduced energy requirement of sensors, the application of this technique in precision agriculture can be considered very significant.

Heinzelman *et al.* [17] designed an intracluster-based data aggregation method where the cluster head is selected at random with data transmission taking place to the cluster head in a cyclical way. The cluster head overcomes similar data transmission using the proximity principle to reduce data transmission at the base station. Since LEACH distributes energy dissipation evenly among sensors, the system network lifetime is doubled while decreasing energy consumption considerably, making it suitable for agricultural applications.

Li *et al.* [18] proposed adhoc EAODV-based intra-cluster routing where sensors select a routing path dynamically, requiring minimum power and using a marker bit to establish a transmission path to update the route whenever sensors are energy-intensive. Interruption is updated passively using the residual energy of a node and the remaining energy of its neighboring nodes to move toward a more energy-efficient path, reducing energy consumption and prolonging network lifetime, making it suitable for agricultural use.

Younis *et al.* [19] proposed distributed ad hoc intracluster routing where the cluster head is selected periodically according to the remaining energy, nearness to other sensors, or total number of neighbors for each sensor. Network lifetime is crucial for reliable data transmission of real-time weather conditions without energy loss of the sensor nodes used in agriculture.

3.3 Compressive Sensing and Other Miscellaneous Approaches

The need for new mechanisms to minimize parameters such as power consumption, expense, delay, and traffic is also growing as WSNs continue to expand. The compressed sensing theory offers promising changes to these parameters. According to CS theory, from a small number of random linear measurements, sparse signals and information in WSNs can be reconstructed precisely. The sensor data is initially represented as a sparse matrix at the root node, where a random integer is multiplied with sensor data for the appropriate time duration, and then turned into an observation matrix at the root of a tree topology termed a destination-oriented directed acyclic graph. In this graph, the aggregated data from different paths are collected and may be obtained from a combinatorial problem [20]. Fig. 5 shows the basic framework of CS for wireless sensors used in agricultural monitoring.

Table 4 identifies the significant contributions in the field of data aggregation using CS. Related research works are also described in the following paragraphs.

Tirani *et al.* [21] utilizes CS to retrieve the scattered signal at a lower level than the Nyquist rate utilized by sensors for data collection. Sensors are organized into several clusters, with the weighted routing tree used to optimize energy consumption and minimize network overload. Multiple root nodes are used to traverse the entire network to collect aggregated data from cluster heads using single-hop transmission. Network overload is decreased to maximize network lifetime while

Table 4: *Significant approaches for data aggregation based on compressive sensing and other miscellaneous methods.*

Method	Key Features	Shortcomings	Improved Parameters	Future Work
Tirani *et al.* [21]	Compressive sensing, Weighted data aggregation trees, cluster-based routing	Time complexity increases with increasing number of sensors.	Energy efficiency, reduced energy requirement variance, network delay.	Need to define a valid starting point as the global minimum but might not be obtainable due to the rate of change in function derivative.
Wang *et al.* [22]	Compressive sensing, initial-point selection method, Constraint-convexification method for data aggregation	Global minimum might not be obtained every time due to rate of change of function derivative. It cannot find the global optimal solution if there are a large number of sensors in the network.	Energy efficiency, data recovery ratio.	Data recovery ratio even if a large number of sensors added to the network have to be optimized.
Uddin *et al.* [23]	Data aggregation based on two-hop wireless network architecture, power allocation as mixed-integer non-linear programming.	Ultra-dense heterogeneous networks needed, such that a high number of small base stations coexist with traditional macro base stations.	Reduced power, energy consumption.	Co-existence of small BSs that perform aggregation and concatenation and send aggregated traffic to macro base station.
Rolim *et al.* [24]	Set covering problem to determine good quality links, K-Means clustering	Noise sources remain unaddressed. Difficult to predict initial K-value, partitions forming different final clusters.	Reduced RAM memory, execution time.	Real time application of the proposed protocol.
Iftikhar *et al.* [25]	Time granularity-based data aggregation using MySQL database, RelaXML for bidirectional data exchange	Data Processing time has to be reduced. Performance optimization is needed.	Network life time, data reduction.	Rule-based data aggregation and exchange is needed.

decreasing energy consumption considerably, rendering this method suitable for agricultural applications.

Wang *et al.* [22] uses CS for data aggregation to construct a measurement matrix based on the network structure to assign a unique column vector for each node that becomes enlarged as soon as new sensors join the network where the weight vectors of existing sensors remain unchanged but optimized measurement vectors are updated for new sensors, hence consuming less energy. This energy-efficient sensor data acquisition makes it suitable for long-term agricultural monitoring.

Data aggregation is performed based on two-hop wireless network architecture to minimize energy consumption by selecting the optimal data aggregator for merging data and transmitting power allocation like mixed-integer non-linear programming [23]. This energy-efficient sensor data acquisition approach is preferable for long-term agricultural monitoring.

Rolim *et al.* [24] determines the minimum number of data aggregation points, where communication takes place through good quality wireless links. The quality of links is determined using the set covering problem. The MOSKOU algorithm is used to divide the graph into sub-instances using K-Means clustering. Unlike a grid that divides the original graph into equal-sized cells causing an unbalanced sub-graph, MOSKOU organizes nearby sensors in clusters without considering any specific geometric region. These groupings are more balanced and involve fewer sub-graphs, require less execution time, as well as being the least interrelated. This approach is suitable for the timely prediction of droughts or floods since the execution time is less based on weather parameters for setting irrigation schedules in agricultural monitoring.

Iftikhar *et al.* [25] proposed time granularity-based data aggregation using the MySQL database, RelaXML, for bidirectional data exchange. It is responsible for the reduction of data volume by allowing thorough gradual granular aggregation as the data gets older. Reducing data volume by the removal of redundant data is crucial for agricultural monitoring since some weather sensors sense similar types of data which overloads the network and significantly increases the processing time.

3.4 Duty-Cycling-Based Data Aggregation

Duty cycling is mainly concerned with time-period division in which a sensor can be either in an active (enabling data transmission) or sleep state (no data transmission). To increase the operational period of the network, the value of the duty cycle should be kept as low as possible. During duty-cycling, the base station (BS) to which sensors are connected calculates energy consumption at any random time instance to control data transmission and non-data transmission periods independently to save energy and increase network lifetime. In duty cycling, the consumed energy must be less than the saved energy. Fig. 6 provides a simple illustration showing the potential application of duty cycling in smart agriculture. Fig. 7 shows the basic

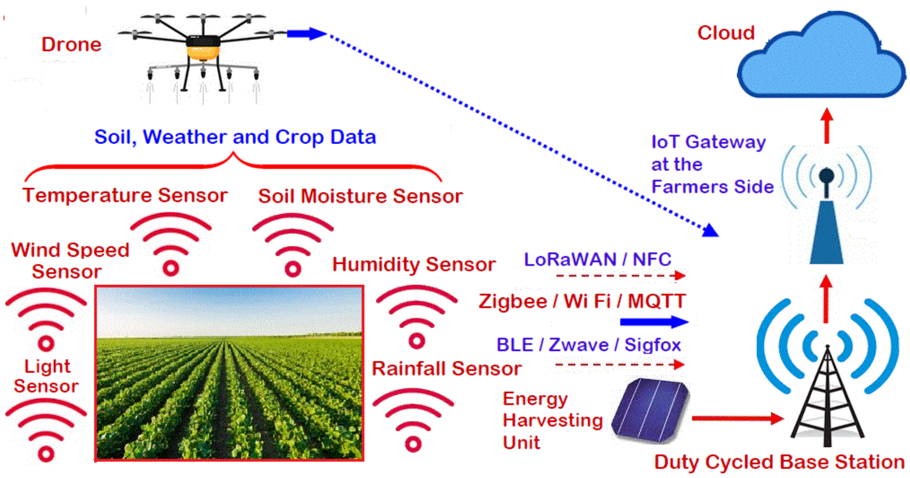

***Fig. 6**: Duty cycling in smart agriculture.*

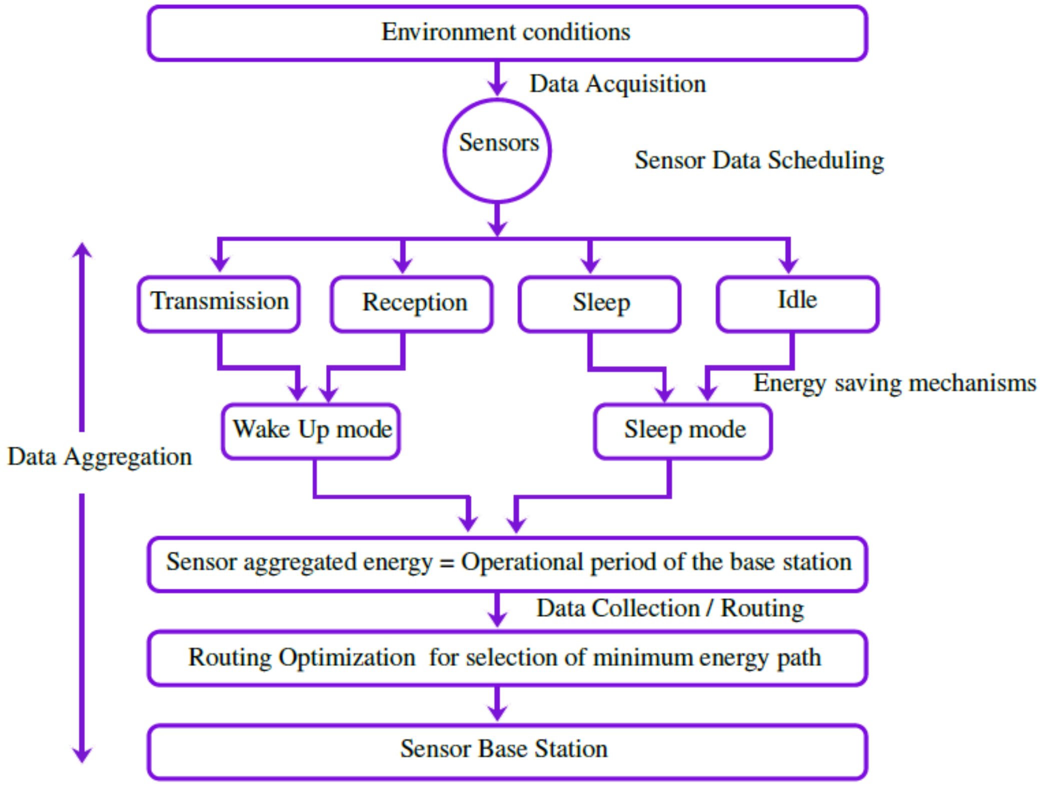

***Fig. 7**: Framework of duty-cycling based data aggregation for agricultural monitoring.*

framework of duty-cycling-based data aggregation for agricultural monitoring.

Research works relating to data aggregation techniques based on duty-cycling algorithms are described in the following paragraphs.

Agrawal *et al.* [3] proposed a duty cycling algorithm where the sensor aggregated energy equivalent to the operational period of the base station is computed for data aggregation. The energy needed at the base station is obtained by the expected number of active periods according to the varying power requirement multiplied by the energy required during the operating period. To schedule energy saving between the sleep and active modes of sensors, residual energy parameters are used. Since the energy requirement at the base station is calculated randomly, it will help in devising an energy-saving mechanism suitable for IoT-enabled precision agriculture.

Dhall *et al.* [26] proposed a duty-cycling algorithm for data aggregation where sensors are connected at the base station and the shortest possible path is chosen for data transmission to the gateway after selecting the minimum energy node. Since an increase in network lifetime is directly proportional to the reduced energy requirement

Table 5*: Significant approaches for data aggregation based on duty-cycling algorithms.*

Method	Key Features	Shortcomings	Improved Parameters	Future Work
Agrawal *et al.* [3]	Duty-cycling-based data aggregation	End-to-end message delay. Waiting time increases for sensors to become active. Packet collision rate increases due to shorter interval transmission. Overhead control is required to achieve packet synchronization.	Average energy consumption, residual energy processing, time, and throughput.	Energy harvesting should be increased to balance energy consumption and utilization in real-time applications.
Dhall *et al.* [26]	Duty-cycling-based data aggregation	End-to-end message delay. Waiting time increases for sensors to become active. Packet collision rate increases due to shorter interval transmission. Overhead control is required to achieve packet synchronization.	Average throughput, processing time, energy consumption.	Incorporation of clustering techniques to prolong network lifetime.
Zheng *et al.* [27]	Duty-cycling-based data aggregation.	Numerical relationship between data aggregation and network parameters is not implemented practically. Data transmission duration is also high.	Energy efficiency.	PCF protocol variants such as BD-POLL and polling-based protocols need to be analyzed to evaluate energy efficiency.
Xu *et al.* [28]	Duty-cycled-based intercluster and intracluster data aggregation using multi-hop balanced energy efficiency	Lack of balance between power consumption and user experience.	Energy consumption, network lifetime.	Sensors with differing abilities for network access need to be considered. The cost-effectiveness of different communication technology needs to be considered.

of sensors, application of this duty-cycling algorithm in IoT-enabled agriculture is expected to be very efficient as it balances the energy requirement of sensors during monitoring even in adverse weather conditions.

Zheng *et al.* [27] proposed duty-cycling-based data aggregation where a parallel gated poll access mechanism is applied using the point coordinated function where during a contention-free period, idle sensors switch to sleep state while others transmit data using polling. Thus, it enables energy saving by sensor scheduling during weather data acquisition, making duty cycling suitable for smart agricultural applications.

Xu *et al.* [28] proposed a data aggregation method where the cluster head is selected using fewer iterations, and sensors in a low-density area are kept alive for a longer period of time. The selection of communication interfaces and cluster heads in intraclustering is performed according to the current context with the highest quality of user experience in the 5G network.

Table 5 identifies the significant data aggregation techniques based on duty-cycling algorithms. Multi-hop communication allows for power balance and long-range communication between individual sensors, increasing the energy efficiency of sensors during data acquisition and long-term monitoring in agriculture.

3.5 IPv6 Routing Protocol for Low-Power and Lossy Networks (RPL)

The IPv6 routing protocol is specifically designed for low-power and lossy networks to address network jamming, radio noise, and bandwidth consumption during times of high data transmission over the network which demands a significant amount of energy. In this protocol, DODAG is built rooted to the root node.

Here, every sensor maintains one or more routing tables to signify the entire network topology which is continuously updated with the latest routing information for every sensor. A user-specified objective function is used to find the shortest possible energy-efficient route to the root node from all sensors by comparing the candidate parent node with the smallest distance from the root.

Minimum rank with the hysteresis objective function (MRHOF) is another routing metric for finding routes with the minimum path cost. It selects a new route if the cost is less than the current route according to the threshold. MRHOF utilizes the expected transmission count for calculating the link quality.

In RPL, the route is selected based on the smallest hop count and link quality where sensors closer to the root suffer from packet loss while exhibiting unequal load and energy distribution due to the high transmission rate in a crowded network. The chosen parent node in RPL

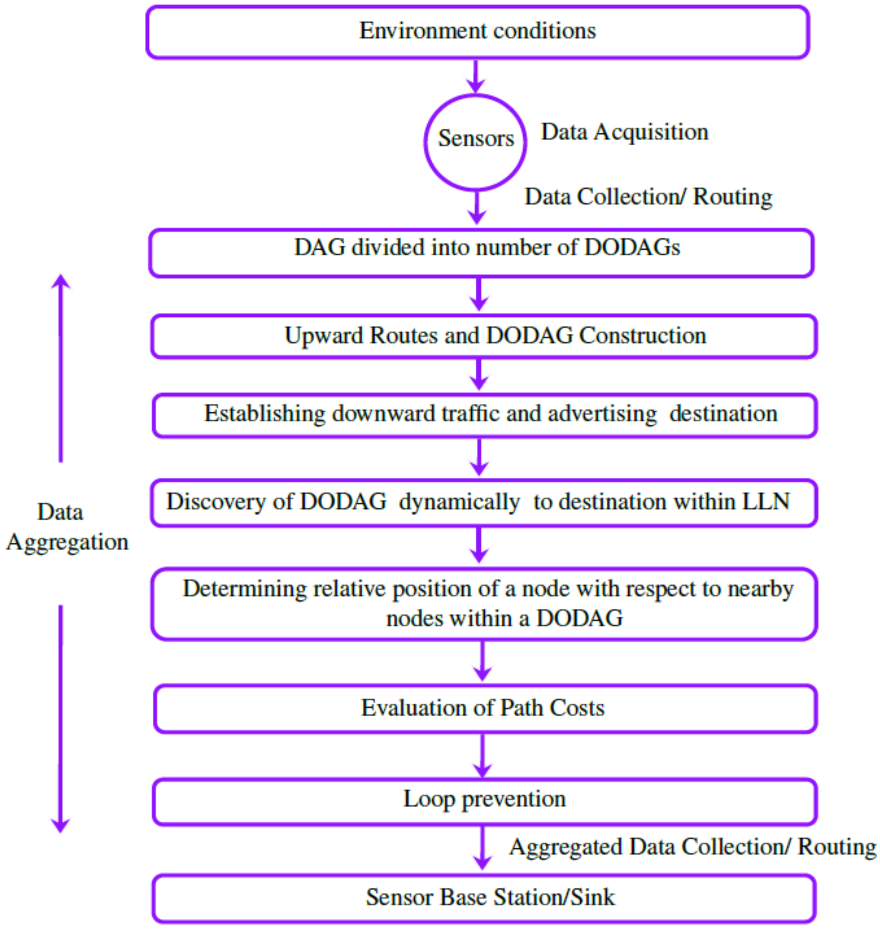

Fig. 8: *Framework of the IPv6 routing protocol for low-power and lossy networks for agricultural monitoring.*

has multiple child sensors which may fail since it loses energy much faster than other sensors. Fig. 8 shows the basic framework of the IPv6 RPL used in agricultural monitoring.

The DODAGs are divided here, with the advertisement for DODAG then displayed. To establish downward traffic, RPL employs an object message. RPL enables on-demand DODAG to a specific destination within low-power lossy networks. To determine the path costs, all the paths from DODAG must be examined. To detect loops during topological changes, a rank-based data-path validation method is applied. The data is then aggregated and sent to the base station for storage [29].

Table 6 shows the significant contributions of authors in the field of data aggregation using RPL. Some of the related research works are described in the following paragraphs.

Sankar *et al.* [7] proposed an energy-aware grid-based data aggregation scheme under the routing protocol where grids of the same size are created for ease of communication with the neighboring grid. The grid head is selected on the basis of probability and its parent on the expected transmission count to select a suitable parent grid head node for data communication. Network lifetime is crucial for the reliable data transmission of real-time weather conditions without energy loss in the agricultural sensor nodes. Since an increase in the network lifetime is directly proportional to a reduction in the energy requirement of sensors, this approach can be considered to have good potential for precision agriculture applications.

Kim *et al.* [6] proposed RPL routing-based data aggregation where the data transmitted to the root node is reduced to mitigate the network burden as each sensor node transmits a large volume of data using periodic inter-sensor multi-hop communication. The network overload and bandwidth consumption are limited as data volume is reduced by using aggregation to maximize network lifetime which is directly proportional to the reduction in energy consumption, hence making it suitable for agricultural monitoring.

Fathallah *et al.* [30] proposed partition aware RPL (PA-RPL) routing based on in-network data aggregation where a tree-like structure of sensors gathered under its respective parcel head is created under a given parcel. Network burden is reduced along with data exchange using in-network aggregation to maximize network lifetime which is directly proportional to the reduction in energy consumption, rendering it suitable for agricultural monitoring.

***Table 6**: Significant approaches to data aggregation based on the IPv6 routing protocol for low-power and lossy networks (RPL).*

Method	Key Features	Shortcomings	Improved Parameters	Future Work
Sankar *et al.* [7]	Grid-based data aggregation for low-power and lossy network routing (RPL)	Slow convergence rate. Transmitted packet must carry the addresses of all sensors to destinations. Routing entries for each sensor cause memory overflow.	Average energy consumption, low packet loss ratio, end-to-end delay.	Real-time simulation.
Kim *et al.* [6]	IPv6 routing protocol for low-power and lossy network (RPL) based data aggregation	Data processing is time-consuming since it increases the number of sensors in the network.	Power consumption, packet delivery ratio, transmission delay, energy consumption.	Simulation is required on other OS for different Sky mote sensors using different scheduling algorithms.
Fathallah *et al.* [30]	Partition aware routing protocol for low-power and lossy networks (RPL).	Difficult optimization for destination-oriented DAG from the agricultural perspective.	Reduced network load and energy consumption.	Overhead of creating sensor partitions under each subtree needs to be reduced.
Homaei *et al.* [31]	Learning automata-based low power and lossy network routing (RPL) for data aggregation.	Computation complexity.	Energy efficiency, network lifetime, end-to-end delay.	Implementation needs to be evaluated for large-scale bidirectional networks.

***Table 7**: Average energy consumption of nature-inspired algorithms.*

Method	Average Energy Consumption (in Joules)
Bioinspired ant-cuckoo optimized relay-based energy-efficient data aggregation with low energy adaptive clustering hierarchy (BACREED-LEACH) [1]	Medium
Improved intelligent water drops optimization with updated soil parameters from every sensor neighbor (Improved IWD) [9]	Low
Ant-colony optimization (ACO) [2]	Medium
Energy-efficient cross-layer sensing cluster routing using particle swarm optimization (PSO) [11]	Low compared to distributed and morphological operation-based data collection algorithms, trust-based secure routing, and mobile data collectors [32–34]
Resampling particle swarm optimization-ant-colony algorithm (RPSO-ACO) [12]	Linearity increases along with the data and low compared to PSO, PSOC, and LEACH [35, 36]
Hierarchical data aggregation with particle swarm optimization (HDA-PSO) [13]	High
Ant-colony-based center data aggregation (ACO) [14]	Low compared to Fusion centers using ACO, greedy incremental tree [37, 38]

Homaei *et al.* [31] proposed learning automata using low-power and lossy network routing-based data aggregation where data routed in the same direction are aggregated in the network root while the data transmission rate is reduced by the presence of fewer children at the root node. As a result, there is less network overload due to reduced data transmission and consequently minimum energy consumption during agricultural monitoring using sensor data while also maximizing the network lifetime as network congestion decreases.

4. SURVEY RESULTS AND DISCUSSION

It can be observed that among all the nature-inspired algorithms, to maximize network lifetime, BACREED-LEACH [1], improved IWD [9], energy-efficient cross-layer sensing cluster routing using particle swarm optimization [11], and HDA-PSO [13] provide high efficiency. To reduce the average energy requirement, energy-efficient cross-layer sensing cluster routing using particle swarm optimization and HDA-PSO perform better in comparison to other algorithms. To maximize throughput, ACO [2] and HDA-PSO perform better than other algorithms. ACO-GA [10] and RPSO-ACO [12] demonstrate better performance in terms of increasing the transmission rate.

The average energy needed for nature-inspired algorithms is shown in Table 7, where the threshold values vary from low to high (Low = 0.0–0.05, Medium = 0.06–0.10, High = greater than 0.10).

In the case of duty cycling, the BEEM algorithm [28] for selecting the cluster head according to the current context provides a long network lifetime. Improved duty cycling (IDC) based on the remaining energy parameter

***Table 8**: Average energy consumption of duty-cycling algorithms.*

Method	Average Energy Consumption (in Joules)
Improved duty cycling (IDC) based on remaining energy parameter [3]	Low, medium for duty cycling [39], high without duty cycling
Improved duty cycling (IDC) based on energy thresholds for network and path selection for data transmission [26]	Low, medium for duty cycling [39], high without duty cycling
Point coordination function (PCF) based MAC protocol [27]	Low irrespective of increasing data rate when compared to PCF [40]
Smart balanced energy-efficient multi-hop clustering algorithm(BEEM) to select cluster head according to current context [28]	Low compared to LEACH [17], HEED [19]

***Table 9**: Average energy consumption of routing protocol for low-power lossy networks (RPL).*

Method	Average Energy Consumption (in Joules)
Energy-aware grid-based data aggregation for low-power and lossy networks (EGDAS-RPL) [7]	Low compared to E2HRC-RPL [41], RPL [42]
Low-power and lossy network routing (RPL) based multi-hop communication [6]	Low compared to ETX-RPL [43]
Partition aware for low-power and lossy network (PA-RPL) [30]	Low compared to RPL [40]
Learning automata for low-power and lossy network routing (LA-RPL) [31]	High

***Table 10**: Average energy consumption of intracluster routing algorithms.*

Method	Average Energy Consumption (in Joules)
Threshold sensitive energy-efficient sensor network (TEEN) [15]	Ranges from 0 to 2 J for 0–1200 s and increases linearly with time
Power-efficient chain-based protocol (PEGASIS) [16]	Low compared to LEACH
Low energy adaptive clustering hierarchy (LEACH) [17]	Low compared to direct transmission, minimum transmission-energy routing and high compared to PEGASIS
Energy-efficient and lifetime-aware routing protocol in ad hoc networks (EAODV) [18]	Low compared to ALMEL-AODV [44], AODV [45]
Hybrid energy-efficient distributed clustering (HEED) [19]	Ranges from 0.04 to 0.05 J for 300 to 700 sensors

[3] and point coordination function (PCF) based MAC protocol [27] exhibit low average energy consumption compared to IDC based on energy thresholds for network and path selection in data transmission [26] and BEEM for selecting the cluster head according to the current context. Both IDC based on the remaining energy and IDC based on energy thresholds for network and path selection in data transmission have high throughput and low processing time. The average energy needed for duty-cycling algorithms is shown in Table 8, where threshold values vary from low to high (Low = 0–13, Medium = 13.1–13.5, High = greater than 13.5).

Partition aware-routing protocols for low-power and lossy networks (PA-RPL) [30] require less energy compared to EGDAS-RPL [7] and LA-RPL [31] while the network lifetime is also prolonged. Throughput is high for RPL-based multi-hop communication [6]. The packet loss ratio and average end-to-end delay is low for EGDAS-RPL in comparison to RPL-based multi-hop communication. The average path length is longer in the case of LA-RPL compared to RPL-based multi-hop communication. Average power consumption is low for EGDAS-RPL and LA-RPL compared to RPL-based multi-hop communication.

Average energy requirement of routing protocol for RPL is shown in Table 9, where the threshold values vary from low to high (Low = 0.0–0.05, Medium = 0.06–0.08, High = greater than or equal to 0.09).

Among intraclustering algorithms, LEACH [17], EAODV [18] and HEED [19] perform better in the case of average energy requirement compared to TEEN [15]. To maximize network lifetime, LEACH, EAODV, and HEED perform better compared to PEGASIS [16]. The packet delivery ratio is high while average end-to-end delay is low for EAODV.

The average energy requirement for intracluster routing algorithms is shown in Table 10.

Compressive sensing using single-hop transmission [21] requires less average energy compared to two-hop wireless communication for smart grid applications [23]. The data recovery ratio for compressive sensing with initial-point selection [22] and constraint convexification

***Table 11**: Average energy consumption of compressive sensing and miscellaneous methods.*

Method	Average Energy Consumption (in Joules)
Compressive sensing using single-hop transmission [21]	Low and tends to remain low even with an increasing number of sensors
Two-hop wireless communication for smart grid applications [23]	Low and tends to remain constant with increasing power transmission

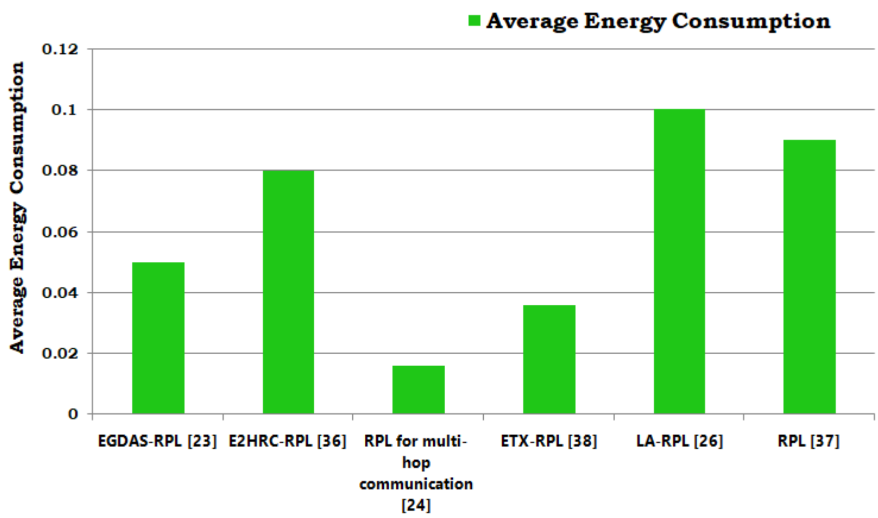

***Fig. 9**: Average energy consumption of RPL-based algorithms.*

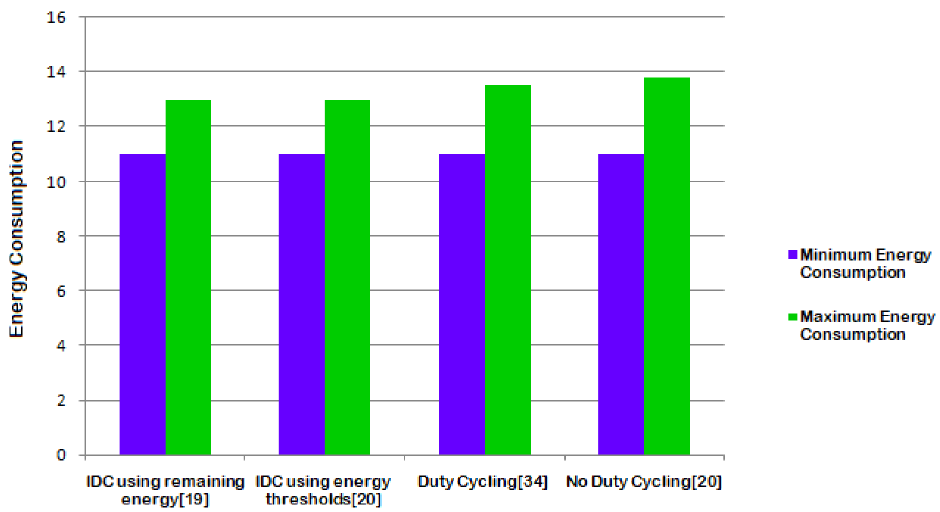

***Fig. 10**: Energy consumption of duty-cycling based algorithms.*

is high for a fewer number of sensors and low for an increasing number of sensors. Data reduction and average execution time are high for time-granularity-based data aggregation [25]. The average energy requirement for compressive sensing and other miscellaneous methods is shown in Table 11.

Fig. 9 shows the minimum average energy consumption of RPL, and it can be observed that RPL based on multi-hop communication consumes minimum energy compared to other algorithms.

Fig. 10 shows the minimum and maximum average energy consumption of duty cycling and it can be observed that the IDC which uses energy thresholds and the remaining energy consumes minimum and maximum energy compared to algorithms without duty cycling.

Fig. 11 shows that the average energy consumption of nature-inspired algorithms with improved IWD is reduced to the minimum. This article was chosen by using relevant keywords in an automated search. The major search engine for finding relevant papers through

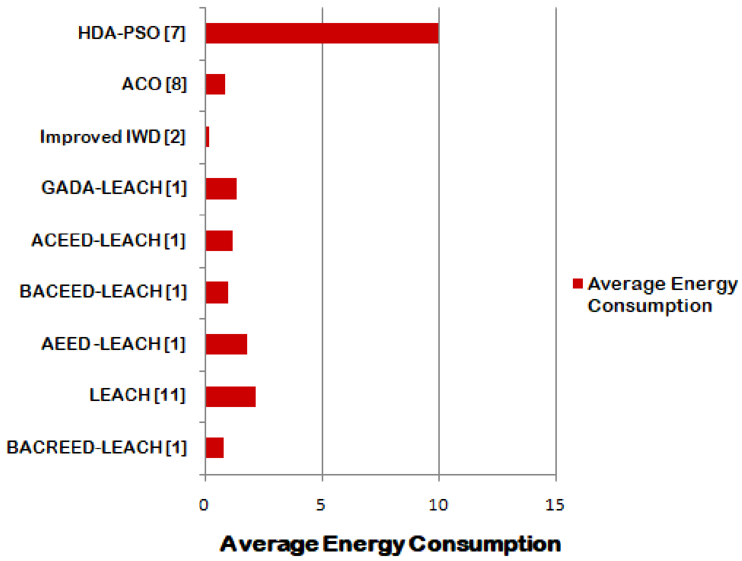

***Fig. 11**: Average energy consumption of nature-inspired algorithms.*

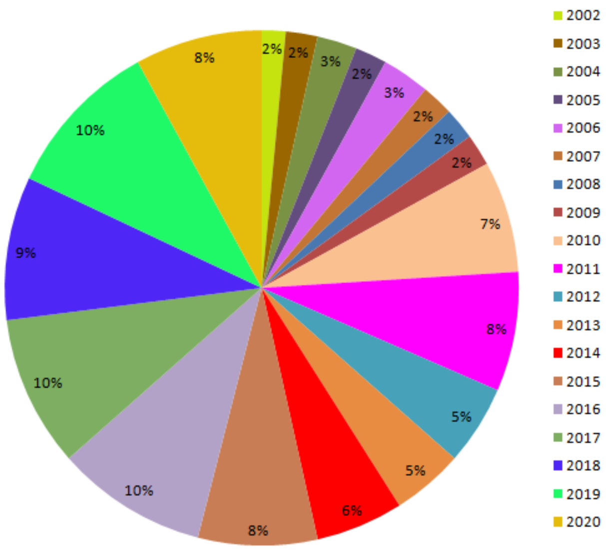

***Fig. 12**: Year-wise total number of published papers on IoT based sensor data aggregation.*

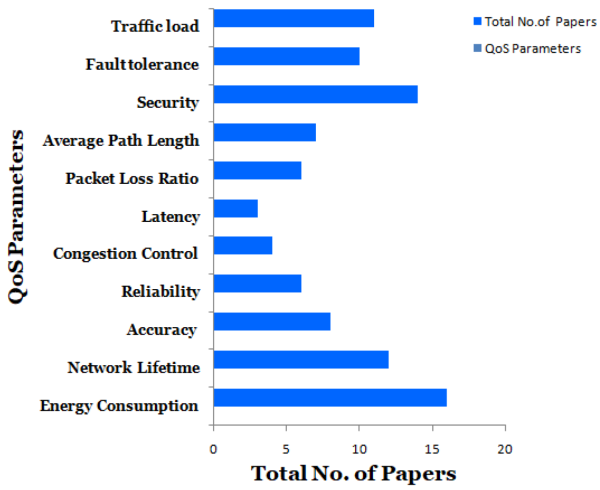

***Fig. 13**: QoS parameters applied in published papers.*

keywords is Google Scholar (wireless sensor network and aggregate IoT). As a result of the automated search, 42 items from journals, conference papers, and books were discovered. From 2002 to 2020, only relevant papers are displayed. The published articles had the highest ranking in 2019.

Fig. 12 shows the year-wise total of published papers. Secondly, paper selection is based on the publisher's title, abstract, and overall quality. This stage begins with the establishment of realistic screening criteria to ensure that only qualifying articles are considered for inclusion in the review. Ultimately, 31 articles were chosen for examination. The selected papers were obtained from reputed publishers like IEEE, Elsevier, Springer, Scientific, ACM, and IJISS based on their title and publisher. The selected articles were evaluated again to ensure they remain relevant. The essential concerns when deciding to include or omit an article are the topic, method, publication year, and journal rating. After applying the criteria, six well-known IoT publishers were chosen, resulting in the exclusion of 11 articles. Finally, 20 papers were collected and evaluated. Studies published in the IoT which clearly defined the suggested technique and improved some of the examination criteria were chosen for review.

Fig. 13 highlights the QoS parameters applied in published papers. The selected articles presented in Fig. 13, place a greater emphasis on certain factors such as energy consumption, network lifetime, fault tolerance, traffic load, and security. However, many data

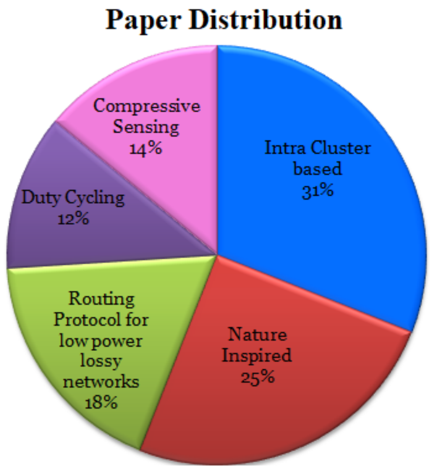

***Fig. 14**: Paper-wise distribution of algorithms from 2002 to 2020.*

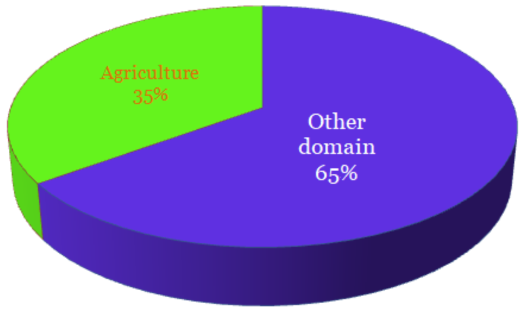

***Fig. 15**: Paper-wise distribution of data aggregation algorithms in precision agriculture.*

aggregation approaches ignore reliability, congestion control, packet loss ratio, and latency. These findings indicate that energy usage, traffic load, network lifetime, fault tolerance, and security need to be prioritized. As essential factors, reliability, congestion control, and packet loss ratio must be prioritized in the future. Latency and heterogeneity are two more critical study issues not considered in many data aggregation approaches.

Fig. 14 shows the paper-wise distribution of algorithms from 2002 to 2020. Seven articles out of 20 dealt with the intracluster approach. Five out of 20 articles dealt with the nature-inspired approach, and four out of 20 dealt with the RPL. Two out of 20 articles dealt with duty cycling and three out of 20 dealt with compressive sensing.

Fig. 15 shows the paper distribution of data aggregation specific to the context of precision agriculture.

5. CONCLUSION AND FUTURE WORK

From the precision agriculture perspective of the IoT where a huge amount of sensor data is generated, the routing of numerous data causes redundant data transmission, decreasing the operational period of the network and increasing bandwidth consumption. It is important to mention that significant energy loss occurs in battery-powered energy-constrained sensors and base stations. Data aggregation mechanisms for avoiding energy loss during routing are essential for prolonging network lifetime. Different data aggregation mechanisms for wireless sensors based on nature-inspired algorithms, RPL, compressive sensing, and duty-cycling algorithms are studied and compared in this paper. Performance evaluation metrics such as average energy consumption, data recovery ratio, data reduction, average execution time, network lifetime, throughput, packet loss ratio, and average path length are studied to ascertain the efficiency of each algorithm. Based on the comparative survey results, this paper attempts to combine the algorithms based on nature, duty cycling, and RPL to optimize each of the performance metrics simultaneously. Minimizing energy consumption is the main aim of data aggregation. Therefore, improving IWD, using the remaining energy for IDC and the network energy thresholds and data transmission path enables RPL based on multi-hop communication to be used in the design of a highly energy-efficient routing mechanism for data aggregation in the context of precision agriculture.

REFERENCES

[1] G. Devika, A. G. Karegowad, and D. Ramesh, “Bio-inspired ant-cuckoo energy efficient data aggregation algorithm:a solution for routing problem of wireless sensor networks [ACEED],” in *2017 2nd International Conference On Emerging Computation and Information Technologies (ICECIT)*, 2017.

[2] B. M. Sahoo, R. K. Rout, S. Umer, and H. M. Pandey, “ANT colony optimization based optimal path selection and data gathering in WSN,” in *2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, 2020, pp. 113–119.

[3] H. Agrawal, R. Dhall, K. S. S. Iyer, and V. Chetlapalli, “An improved energy efficient system for IoT enabled precision agriculture,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 6, pp. 2337–2348, Jun. 2020.

[4] S. Randhawa and S. Jain, “Data aggregation in wireless sensor networks: Previous research, current status and future directions,” *Wireless Personal Communications*, vol. 97, no. 3, pp. 3355–3425, Dec. 2017.

[5] M. Kaur and A. Munjal, “Data aggregation algorithms for wireless sensor network: A review,” *Ad Hoc Networks*, vol. 100, Apr. 2020, Art. no. 102083.

[6] Y. Kim, P. Bae, J. Han, and Y.-B. Ko, “Data aggregation in precision agriculture for low-power and lossy networks,” in *2015 IEEE Pacific Rim Conference*

on Communications, Computers and Signal Processing (PACRIM), 2015, pp. 438–443.

[7] S. Sankar, P. Srinivasan, A. K. Luhach, R. Somula, and N. Chilamkurti, "Energy-aware grid-based data aggregation scheme in routing protocol for agricultural internet of things," *Sustainable Computing: Informatics and Systems*, vol. 28, Dec. 2020, Art. no. 100422.

[8] I. D. I. Saeedi and A. K. M. Al-Qurabat, "A systematic review of data aggregation techniques in wireless sensor networks," *Journal of Physics: Conference Series*, vol. 1818, 2021, Art. no. 012194.

[9] D. C. Hoang, R. Kumar, and S. K. Panda, "Optimal data aggregation tree in wireless sensor networks based on intelligent water drops algorithm," *IET Wireless Sensor Systems*, vol. 2, no. 3, pp. 282–292, Sep. 2012.

[10] Y. Lu, I.-S. Comsa, P. Kuonen, and B. Hirsbrunner, "Probabilistic data aggregation protocol based on ACO-GA hybrid approach in wireless sensor networks," in *2015 8th IFIP Wireless and Mobile Networking Conference (WMNC)*, 2015, pp. 235–238.

[11] Z. Sun *et al.*, "An energy-efficient cross-layer-sensing clustering method based on intelligent fog computing in WSNs," *IEEE Access*, vol. 7, pp. 144 165–144 177, 2019.

[12] X. Wang, H. Gu, Y. Liu, and H. Zhang, "A two-stage RPSO-ACS based protocol: A new method for sensor network clustering and routing in mobile computing," *IEEE Access*, vol. 7, pp. 113 141–113 150, 2019.

[13] X. Yin, S. Li, and Y. Lin, "A novel hierarchical data aggregation with particle swarm optimization for internet of things," *Mobile Networks and Applications*, vol. 24, no. 6, pp. 1994–2001, Dec. 2019.

[14] W.-T. Sung, H.-Y. Chung, and K.-Y. Chang, "Agricultural monitoring system based on ant colony algorithm with centre data aggregation," *IET Communications*, vol. 8, no. 7, pp. 1132–1140, May 2014.

[15] A. Manjeshwar and D. Agrawal, "TEEN: a routing protocol for enhanced efficiency in wireless sensor networks," in *Proceedings 15th International Parallel and Distributed Processing Symposium. IPDPS 2001*, 2001, pp. 2009–2015.

[16] S. Lindsey and C. Raghavendra, "PEGASIS: Power-efficient gathering in sensor information systems," in *Proceedings, IEEE Aerospace Conference*, vol. 3, 2002, pp. 1125–1130.

[17] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, 2000.

[18] W. Li, B. Jia, Q. Li, and J. Wang, "An energy efficient and lifetime aware routing protocol in ad hoc networks," in *Algorithms and Architectures for Parallel Processing*, J. Vaidya and J. Li, Eds. Cham, Switzerland: Springer, 2018, pp. 378–387.

[19] O. Younis and S. Fahmy, "HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Transactions on Mobile Computing*, vol. 3, no. 4, pp. 366–379, Oct. 2004.

[20] S. Sennan, S. Balasubramaniyam, A. K. Luhach, S. Ramasubbareddy, N. Chilamkurti, and Y. Nam, "Energy and delay aware data aggregation in routing protocol for internet of things," *Sensors*, vol. 19, no. 24, 2019, Art. no. 5486.

[21] S. P. Tirani, A. Avokh, and S. Azar, "WDAT-OMS: A two-level scheme for efficient data gathering in mobile-sink wireless sensor networks using compressive sensing theory," *IET Communications*, vol. 14, no. 11, pp. 1826–1837, Jul. 2020.

[22] X. Wang, Q. Zhou, Y. Gu, and J. Tong, "Compressive sensing-based data aggregation approaches for dynamic WSNs," *IEEE Communications Letters*, vol. 23, no. 6, pp. 1073–1076, Jun. 2019.

[23] F. Uddin, "Energy-aware optimal data aggregation in smart grid wireless communication networks," *IEEE Transactions on Green Communications and Networking*, vol. 1, no. 3, pp. 358–371, Sep. 2017.

[24] G. Rolim, D. Passos, C. Albuquerque, and I. Moraes, "MOSKOU: A heuristic for data aggregator positioning in smart grids," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 6206–6213, Nov. 2018.

[25] N. Iftikhar, "Integration, aggregation and exchange of farming device data: A high level perspective," in *2009 Second International Conference on the Applications of Digital Information and Web Technologies*, 2009, pp. 14–19.

[26] R. Dhall and H. Agrawal, "An improved energy efficient duty cycling algorithm for IoT based precision agriculture," *Procedia Computer Science*, vol. 141, pp. 135–142, 2018.

[27] G. Zheng, Y. Zhi-Jun, H. Min, and Q. Wen-Hua, "Energy-efficient analysis of an IEEE 802.11 PCF MAC protocol based on WLAN," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 5, pp. 1727–1737, May 2019.

[28] L. Xu, G. O'Hare, and R. Collier, "A smart and balanced energy-efficient multihop clustering algorithm (smart-BEEM) for MIMO IoT systems in future networks," *Sensors*, vol. 17, no. 7, 2017, Art. no. 1574.

[29] V. Gokilapriya and P. T. V. Bhuvaneswari, "Analysis of RPL routing protocol on topology control mechanism," in *2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN)*, 2017.

[30] K. Fathallah, M. A. Abid, and N. B. Hadj-Alouane, "PA-RPL: A partition aware IoT routing protocol for precision agriculture," in *2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC)*, 2018, pp. 672–677.

[31] M. H. Homaei, E. Salwana, and S. Shamshirband, "An enhanced distributed data aggregation method

in the internet of things," *Sensors*, vol. 19, no. 14, 2019, Art. no. 3173.
[32] Y. Lai, H. Lin, F. Yang, and T. Wang, "Efficient data request answering in vehicular ad-hoc networks based on fog nodes and filters," *Future Generation Computer Systems*, vol. 93, pp. 130–142, Apr. 2019.
[33] Z. Sun, G. Zhao, and X. Pan, "PM-LPDR: a prediction model for lost packets based on data reconstruction on lossy links in sensor networks," *International Journal of Computational Science and Engineering*, vol. 19, no. 2, pp. 177–188, 2019.
[34] Z. Zhou, J. Feng, B. Gu, B. Ai, S. Mumtaz, J. Rodriguez, and M. Guizani, "When mobile crowd sensing meets UAV: Energy-efficient task assignment and route planning," *IEEE Transactions on Communications*, vol. 66, no. 11, pp. 5526–5538, Nov. 2018.
[35] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, pp. 1942–1948.
[36] N. M. A. Latiff, C. C. Tsimenidis, and B. S. Sharif, "Energy-aware clustering for wireless sensor networks using particle swarm optimization," in *2007 IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, 2007.
[37] X.-M. Hu, J. Zhang, H. S.-H. Chung, Y. Li, and O. Liu, "SamACO: Variable sampling ant colony optimization algorithm for continuous optimization," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 40, no. 6, pp. 1555–1566, Dec. 2010.
[38] X. Y. Wang, R. K. Dokania, and A. Apsel, "PCO-based synchronization for cognitive duty-cycled impulse radio sensor networks," *IEEE Sensors Journal*, vol. 11, no. 3, pp. 555–564, Mar. 2011.
[39] D. Vasisht *et al.*, "FarmBeats: An IoT platform for data-driven agriculture," in *Proceedings of the 14th USENIX Symposium on Networked Systems Design and Implementation*, 2017, pp. 515–529.
[40] R. Palacios, F. Granelli, D. Gajic, C. Liß, and D. Kliazovich, "An energy-efficient point coordination function using bidirectional transmissions of fixed duration for infrastructure IEEE 802.11 WLANs," in *2013 IEEE International Conference on Communications (ICC)*, 2013, pp. 2443–2448.
[41] W. Zhang, L. Li, G. Han, and L. Zhang, "E2HRC: An energy-efficient heterogeneous ring clustering routing protocol for wireless sensor networks," *IEEE Access*, vol. 5, pp. 1702–1713, 2017.
[42] Y. Chen, J.-P. Chanet, and K. Hou, "RPL routing protocol a case study: Precision agriculture," in *First China-France Workshop on Future Computing Technology (CF-WoFUCT 2012)*, 2012.
[43] S. A. Hakeem, A. Hady, and H. Kim, "RPL routing protocol performance in smart grid applications based wireless sensors: Experimental and simulated analysis," *Electronics*, vol. 8, no. 2, 2019, Art. no. 186.
[44] J. Chen, J. Chen, and Z. Li, "Energy-efficient AODV for low mobility ad hoc networks," in *2007 International Conference on Wireless Communications, Networking and Mobile Computing*, 2007, pp. 1512–1515.
[45] Utkarsh, M. Mishra, and S. Chinara, "ESAR: An energy saving ad hoc routing algorithm for MANET," in *2012 Fourth International Conference on Advanced Computing (ICoAC)*, 2012.

Parijata Majumdar is serving as an Assistant Professor in Computer Science and Engineering Department at Techno College of Engineering, Agartala, since February, 2018. She joined Ph.D. programme as a part-time Research Scholar in National Institute of Technology Agartala in 2019. Her area of research interest includes Internet of Things, Green Communications, AI, 5G Technology and its real time applications, Swarm and Metaheuristic Algorithms.

Diptendu Bhattacharya is currently working as Associate Professor, Department of Computer Science and Engineering, National Institute of Technology, Agartala (Tripura). His area of interest includes Digital Image and Video Processing, Computer Vision, Intelligent Transportation System, Natural Language Processing, Artificial Intelligence and Soft computing, Time-series Prediction etc.

Sanjoy Mitra is presently serving as an Assistant Professor in the Department of Computer Science and Engineering at Tripura Institute of Technology, Agartala since 2008. His area of interest includes Internet of Things, AI, Image Processing, 5G Technology and Real Time Applications, Metaheuristic Algorithms, VLSI Systems.