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Optimized Routing Method With Distributed SDN-AI for Energy-Efficient Large-Scale IoT Networks

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Abstract-Increased distributed compute-dependent Software Define Network (SDN) with high-level Intelligent - Internet of Things (I-IoT) has been the focus of effective study. There are certain resource limitations associated with wireless sensor networks. However, only a select few, like energy, are frequently configured. constraint and the coordinated needs that are essential to the performance of IoT application routing. One important method for addressing the growing scalability of networks is the use of Mobile Sink (MS). primarily in large-scale IoT networks, the creation of the best possible path for data transmission, the identification of the ideal collection of data-gathering points (ODG and MS) scheduled with dynamic networks for energy-efficient procedures, and the network's lifetime in significant challenges. The study project suggests the following research goal:

i) Create a large-scale IoT network routing method that uses less energy. inside an SDN system that is cloud-based.

ii) Use Artificial Bee Colony (ABC), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) to optimize load balancing, network scalability, and lower-level routing.

The main goal of SDN in the cloud the following using AI: a load-balanced Cluster Table (CT), an optimal ODG point, an MS optimal path, and a lower level routing in the perception layer. The proposed routing's primary contribution is i) Energy Minimization

(EM), which reduces the amount of energy that the Cluster Head (CH) disperses in crucial circumstances (EM-CH).

ii) Energy Balance (EEB) Enhanced: TThe EC-based SDN provides improved energy balance during network routing (EEB-SDN) by taking into account both Mobile Sink (MS) and Optimal Data-Gathering (ODG) developments. The suggested model stability is validated by research findings.

that, when compared with different models, increases the network lifetime by up to 63%, lowers energy consumption in the network by up to 78%, increases the volume of data loaded into the MS by up to 95%, and reduces the OMSpath delay by 69%.

Key Word- Artificial intelligence, cloud-computing, intelligent-Internet of Things, mobile sink, software defined network

Introduction-The Internet of Things is thought of as a collection of dispersed, decentralized devices that can sense, process, and build networks. a significant item that transmits data in the Internet of Things. The frequency of radio waves

Advances in sensor sorting and radio frequency identification (RFID) are used to address a new challenge in which information and correspondence structure are subtly incorporated into the surrounding environment [1]. As a result, enormous volumes of data are produced, which must be efficiently stored and processed within a standardized framework. IoT devices with feature-rich performance that communicate at regular intervals. These services are provided with a virtual foundation by cloud computing, which comprises device identification and reservations, testing, customer transportation, and perception phases [2]. Organizations and clients can support applications on cloud platforms with end-to-end administration provisioning thanks to the system model value that the cloud process gives. request from any location.

Internet of Things (IoT) is the exchange of several physical objects with artificial intelligence over the internet. IoT "physical items to observe, listen, think, perform tasks, share data, and standardize" are made possible by these things. [3]. Wireless Sensor Networks (WSN) are generally intended to be tools for achieving the Internet of Things.
The radio communication limits, storage and administration capacity, and a weak battery are the main constraints on the WSN sensor.
Because physical gadgets are typically arbitrary and unique, changing a device's battery is an almost ridiculous task. It is imperative to suggest an artificial intelligence-based, energy-efficient routing method that precisely balances the device's load and works at any network scale, thus extending the life span of the whole Io Tenterprise
.

Tiny, modest low-density sensors, actuators, and handling equipment are needed to transform associated objects into Internet of Things devices. These components are part of the robot's complicated practices, which include social communications, automated route planning, and item evaluation, among other things.

The AI technique makes sense for the Internet of Things and turns common robots into highly powerful machines whose status and perfection on Earth lead to behaviors that forbid constant human supervision. [4] A major transition from a network of late sensors to one of intelligence sensors permitted with operated instruments can be facilitated by an Internet of Things standard model. In networks of the future
the "Internet of Intelligent Things" is made up of [6]. This model builds the intelligence of a universal, intelligent, alive internet at the next stage of system administration development. It was born out of the need to provide common items the ability to comprehend their surroundings and make decisions on their own [7]. From now on, choices shouldn't be made by central dynamic nodes. Instead, intelligence should be sent to sensors, allowing them to make judgments based on the intelligence sensors' motivations. The Internet of Things should be designed to adapt to time-sensitive situations so that decisions are made in a dispersed manner. IoIT extracts knowledge and insight from the relationship between objects and individual things. Rather than focusing on linking and managing intelligent objects, it takes note of and enhances the intelligence of the IoIT framework by dissecting the interactions between people and intelligent objects (e.g., carrying cell phones, driving by smart cars, and passing by road cameras). To put it another way, the focus is on how the IoIT recognizes high-level information about objects (e.g., Different IoT devices), communication range (e.g., inter-cluster and intra-cluster ordering), and maintaining devices (e.g., SDN, Cloud) by examining the performance metrics (e.g., signal strength, data size, transmission route) collected by the devices while cooperating withIoT devices cannot provide high-level intelligence directly; instead, information must be gathered and sophisticated data mining and AI techniques must be used. It addresses the information obtained using the "Embedded Intelligence (EI)" human-IoT connection [9], [10] that demonstrate the understanding of social interaction, delimited aspects, and human life.
EI-improved IoT refers to a sizable group of innovative applications, such as knowledge search, point-to-point and intelligence communication, network detection, etc. in certain zones [11].

A rising body of research is currently focusing on the Internet of Things (IoT) and its applications; nevertheless, there is still a clear gap in the integration of cutting-edge energy-efficient routing technologies that can manage a sizable and intricate IoT network. A lot of the methods used today still rely on centralized frameworks, which are prone to flaws and inefficiencies. Furthermore, the significance of

Current studies do not fully address how to integrate AI efficiently in order to integrate with the IoIT era. Tests still need to be conducted on load balancing, secure advancements, and efficient data acquisition. A field that is still in its infancy is making use of cloud and edge computing opportunities and comprehending how they interact with IoT. Thus, the goal of this research is to close these gaps by creating Internet of Things (IoT) systems that are dependable, scalable, efficient, and open to everyone. As a result, this study suggests a load-balancing network scheduling method that uses cloud resources and an effective intelligence algorithm at any size. Internet of Things

network. The method is based on the GA methodology, which maximizes the physical layer clustering of heterogeneous IoT nodes so that MS may gather data over a vast data collection field. The main goal of this project is to maximize the energy consumption in the system that balances the load of MS scheduling, IoT device load, and network sleep/wake cycles as needed. Consequently, the effort decreases the amount of energy dispersed in devices and extends the lifespan of the system.

RELATED WORKS

IoT combines D2D, a device to distributed storage, a device to nature or living things and vice versa, and a variety of communication techniques. Intra-domain communication in homogeneous systems or up heterogeneous
systems (cross-domain). Furthermore, D2D communication can frequently occur in a single or multiple hop procedure without humanintervention. When linked devices attempt to communicate via a network framework—which could be a base station or a transition point—this is known as single-hop communication.

Devices exchange data in multi-hop to enable end-to-end communication between any two devices. A recent study trend claims that significant improvements in QoS routing can be achieved in IoT networks by implementing artificial intelligence approaches with bioinspired inspiration.

Janabi et al. provide a centralized routing infrastructure for the Internet of Things using SDN. [12] in order to lower the energy consumption of IoT devices and increase network lifespan. In the Internet of Things network, AI-driven PSO and GA are utilized to generate energy-efficient routing. The results indicate that the suggested work lowers latency in IoT and lengthens the lifetime of the network.

Other QoS elements like throughput, jitter, etc., are not taken into account in this approach. A secure trust-based RPL routing technique with unique authentication is suggested by authors Bandarupalli Rakesh et al. [13] for an Internet of Things (IoT) network that is backed by mobile sinks. The goal of the suggested approach is to resolve the shortcomings and limitations of the RPL protocol, which include high power consumption, ineffective authorization, and significant packet losses. The suggested SecRPL-MS technique consists of an authentication procedure for data transfer, a mobile sink deployment to lessen the frequency of IoT node deaths, an enrollment procedure, as well as safe routing using the sailfish optimization algorithm. The effectiveness of the suggested technique is assessed using the Network Simulator 3 (NS3) in terms of packet delivery ratio, delay, energy usage, key generation time, and accuracy in identifying malicious nodes. The suggested SecRPL-MS technique outperforms existing solutions in terms of malicious node identification accuracy and provides exceptional protection against attacks such as man-in-the-middle, Sybil, blackhole, and rank attacks. These limitations tackle issues with data transfer packet loss, available node opposition, and IoT network energy loss. The author [14] suggests a Deep Learning approach utilizing Pointer Networks as well as a methodology for characterizing device vulnerabilities.

The suggested methodology scales better than the current AI methodology and generates a wide range of excellent results. The suggested approach is contrasted with existing AI algorithms, and the usage of the Normal Constrained Method (NCC) to frame the final solution set is also mentioned in the study. The suggested work is more efficient in terms of time and solution quality, according to experimental data. In closing, the author discusses upcoming projects and the necessity of testing the suggested strategy under actual circumstances.

In order to reduce the amount of time that data gathering delays, the study [15] suggests using multi-hop transmission in mobile data acquisition. To enhance the process further, it incorporates a constrained relay combining-reduction ability. In addition, the authors give a modified mixed frog jump algorithm employing chaotic techniques and an adaptive step-modifying algorithm with delay limitations. Additionally, a method for acquiring data based on Bayesian Compression Detection (BCD) is developed. Additionally, a cloud-architected large-scale Internet of Things routing technique based on PSO and GA is suggested.The research [16] explores DAOSVM (Data Acquisition through Mobile Sink for WSNs with Obstacles using Support Vector Machine), a suggested method for mobile sink-based data gathering in wireless sensor networks (WSNs) with restrictions. Path building and visiting point selection are the two stages of the DAOSVM algorithm's execution. Utilizing a support vector machine

The visiting point selection process makes use of both the path selection and a spanning tree technique. The proposed method seeks to address the problem of giving WSNs an obstacle-aware path so that the mobile sink can gather information. To reduce unnecessary packet communications between sensor nodes (SNs) and rendezvous points (RPs), the virtual rendezvous point (VRP) selection process is not included in the work.

The study also demonstrates that the mobile sink's journey distance may be dynamically built and improved, similar to previous methods. A lightweight data fusion and AI-driven network load optimization technique designed for Internet of Things use is presented in the study [17]. This technique uses MiniMax layered sampling to reduce data redundancy and correlation.

Moreover, it incorporates Discrete Particle Swarm Optimization and a real-valued Genetic Algorithm to guarantee network traffic balance. It's also advised to use a dynamic service migration approach to distribute the load evenly among edge servers.

The approach is not without flaws, though: the migration strategy ignores potential overload circumstances while basing itself on current resource utilization; the load optimization ignores variations in resource processing speeds; and the data fusion relies on predetermined criteria that are inappropriate for every situation. A deep learning Artificial Intelligent System (AIS) that functions as the foundation of the Intelligent-IoT (I-IoT) architecture for healthcare applications is presented in the study [18].

as an overseer. With the goal of intelligently choosing cluster heads and their members to maximize packet flow, this AIS is built on the EG-CRNN structure, which is a combination of DL-RNN and EleAttG. To speed up weight updates and training, a related training algorithm is also provided. While the EG-CRNN outperforms traditional CNN-based structures in terms of training speed and error reduction, the research does not address any potential drawbacks, leaving open questions about scalability, adaptability in the real world, and resilience to fluctuating IoT traffic.

PROBLEM DESCRIPTION AND OBJECTIVES

The main goal of the suggested system is to provide an IoT network routing method that uses less energy. Because of battery-related physical layer limitations, processing systems, communication range, and storage. It is not easy to balance the physical objects aspect. One way to address heterogeneity in clustering is by offering an optimization strategy. In the process of aggregating data, a clustering methodology is utilized to manage the energy in the network. The first step in creating a cluster is deciding where the CHs will be located, after which CMs data will be gathered and sent to the sink. Consequently, CHs use up their energy even faster than CMs because of the following: the unstable cluster system that causes some CHs to

use more energy than others when it comes to controlling data aggregation points and sending data to the mobile sink. Furthermore, it is technically challenging to control the whole network from a static sink in a large-scale IoT network. Additionally, using a sink in a large-scale network system causes the CHs to consume a lot of power and creates a hot spot problem on the network that is scheduled to use the sink.

In order to create an AI-powered energy-efficient routing strategy that would extend network lifetime for IntelligentIoT, the following goals are taken into account:

1) To increase the network lifespan.
2) To reduce network energy usage.
3) To increase the volume of data sent.
4) To reduce the average delay.

PROPOSED SYSTEM

utilizing a clustering procedure for dynamically structured heterogeneous nodes utilizing GA that reduces the amount of energy wasted in the nodes is one proactive way to reduce the amount of energy wasted in the nodes.

creates a framework for organizing various heterogeneity network and cluster elements, such as residual energy, network location, active time utilization, anticipated energy consumption, and the search for the best path to reach CHs and dynamic networks for heterogeneous IoT. Subsequent MS use intern lowers the CH load. Significant challenges with IoT network performance include: MS optimal path identification and ODG, coordination between the CHs and MS, and technical

.

NETWORK ARCHITECTURE

The technology is designed to use the least amount of energy on average across the network. The most recent technologies, such as edge computing and cloud-based SDN, are combined with optimal algorithms to create the suggested method.

The suggested system design is created from Fig.1. separated into three main layers: the application layer, the operation layer, and the perception layer. The data gathering and sensing layers are two of the sub-layers that make up the perception layer, which runs parallel to the data-link layer from SDN. The sensor data is first gathered by the sink or gateway, which then either creates a cloud to store the data or forwards and processes the data to the SDN to enable insightful route-based decisions. The SDN controller operates over the cloud and comprises the following functionalities: network-based OMSpath determination from ABC methodology, GA-based heterogeneous clustering, ODG identification by PSO algorithm, and cluster construction by AI using cloud methods.

arranging. The suggested solution lessens the complexity of the network. Additionally, the network gains significant advantages from the data processing, storing, and SDN spotting done over the cloud. For instance, the SDN controller makes use of the data center as a major computing resource in the network while implementing the system's optimized algorithms. The developed proposed system minimizes the redundant pathways offered at the sink node, prevents congestion at the sink, and provides a useful framework and efficient mapping in the selection of CHs and sink nodes.

CLUSTER FORMATION

The suggested method builds an ideal routing strategy for IIoT systems by utilizing distributed SDN on the cloud. This section provides information on a few specific goals, like the energy level of the CM and CH currently, their distance from each other, and the CH degree for

effective cluster building. Once the CH has been chosen, the remaining nodes join the network by forming an affiliation with an active CH, and the CH grants them authorization based on the SDN use. Fig. 1 depicts the suggested design for the SDN-based routing system. The cluster-based routing technique maps the sensor device to the cluster heads with the cluster member nodes or directly for data-efficient routing.
The suggested approach finds the shortest route by using an SDN-based GA algorithm 1 and keeps going in the direction of effective data packet routing. The suggested system determines the best path from the source CM to the CH it is connected to. The path from source CM → CH for the GA chromosomes is noted.
The routing path's total CMs number length is the ideal

route. Fitness Function (FF) is used to calculate the initial genetic population once it has been placed through the random generation set. The top performers are chosen based on the final fitness values, and they collaborate. The optimal path is determined by the fitness function. Every chromosome in this case reflects a specific route from CM → CH. Alg. 1 suggests the improved Chromosome length and the CH selection process from GA are dependent on TNCM.

Fit_Func(pos) = AVG(CM,CH) + TNCM N + NOofpart + NCN (1)

The ith chromosomal value is provided by Fit_Func(pos), the total number of cluster members is given by TNCM, the average distance from the cluster member to CH is given by AVG(CM,CH), and NCN is the entire cluster member in the route. By connecting the MS moving cost that gathers cluster construction processed data, the system provides an AI-based intelligent energy-efficient routing strategy, reducing the amount of energy needed when data is transported over the network. Cloud-based SDN regulates the construction of the cluster, processes it with edge computing, and creates the CT by using a load-balanced PSO technique. The device coordinates are the only information used by the SDN to create the CT table in the first round. The SDN process using the data gathered for subsequent rounds is dependent on the amount of energy left and the distance toAdditionally, an achieved CT procedure is carried out in each round, and if a new device tries to connect to the network, a CH uses up its energy or

An energy harvesting technique is used by a new device to increase its energy output. The devices in the proposed work are heterogeneous, containing a range of energy levels, and no device inside the system would get additional energy during the execution process. As seen in Fig. 1, the data above was arranged around the clusters, the CMs set, and the CHs connected to the surrounding CH. Additionally, the CT is communicated to all devices by the MS. A cluster of stochastic particles (GSP) is created from Fig. 1 to process PSO. Each particle (p) in the cluster is a D distance vector that is measured by the Fit_Func.

From now on, the PSO solution can only be found after a positive number of iterative rotations. As a result, each p in the swarm guarantees both its personal (Pbest) and global (Gbest) values. Here, SDN counts the number of CHs (NCH) in a matrix by taking into account the device's residual energy that remains alive after every cycle and retaining its data, where the higher energy value is bigger than the average value of CH. Furthermore, PSO optimizes the cost of the subsequent function:

cost = α Pk j=1 Eng(CH(i,j)) PN i=1 Eng(ni) + β X k j=1 NAr PNCp,i i=1 distCH(p,i),ni + τ (LBavg) 2 δ + Pk j=1 (NC(p,j) − LBavg) 2 + γ SDG OMSpath (2) LBavg = (NAr − k) k (3)

The values α, β, τ and γ are coefficients that weights adjusted and balance the impact of all sub-objects and it's

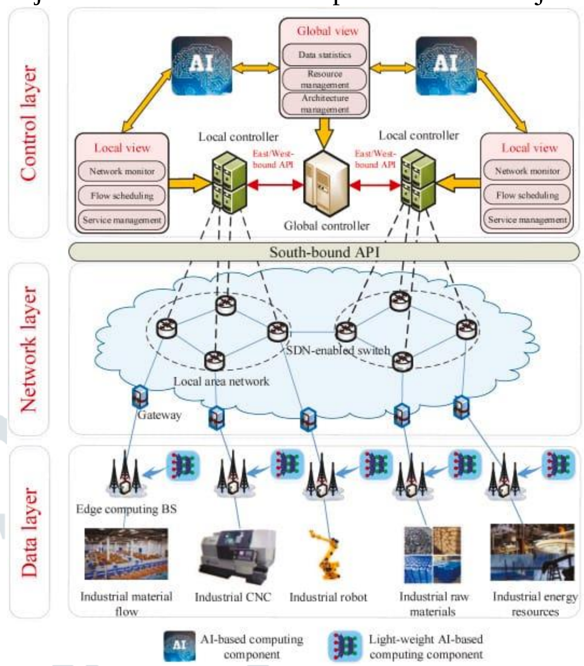

FIGURE 1. A system framework based SDN-AI

For example, Table 1 lists the constants for energy, communication range, load balance, and OMSpath. The system evaluates the collected CHs using a CHs high of Equation 2. energy rate, selects the cluster sets with the highest load-balance rate, and finds the cluster with the lowest communication costs between the CMs and CHs (dist). In Eq. 2, δ is a constant variable that applies a strategy to remove the PSO process from local maxima, while N, K, and NC stand for the number of IoT devices, CMs, and CHs, respectively. In order to implement a load-balancing strategy, the SDN chooses a cluster's set fromuse Equation 2. The total number of IoT devices is represented by NAr, and the value LBavg from Eq. 3 represents the CM's mean value of each cluster.

gadgets active during the round r. The MS optimal path is referred to by ODG and OMSpath. As seen in Fig. 2, the cluster formulates the suggested approach with optimum MS operation upon selecting the routing methodology.

DATA AGGREGATION POINTS

FIGURE 2. The system flow diagram.

Algorithm 1 Network Route Deployment With GA
Input: Argument that deploys the IoT sensor nodes
Output: Sensed data are sent to the CH in the optimal path using GA from SDN Initialize IoTN nodes parameters
1: for (each IoT nodes) do
2: Compute X & Y co-ordinates
3: Operate all nodes location
4: Collects the neighboring nodes information
5: end for
6: Visualize the IoT node formation
7: GA algorithm procedure
8: start()
9: Generate initial population of IoT network
10: Calculate the fitness value of IoT nodes and store in the elite library
11: if (iter < INTR) then
12: Selection, crossover and mutation operation by roulette and save in the elite library
13: Generate a new population and split the operation to improve the GA
14: Collect solutions from each group and store them in an elite library
15: Remove N chromosomes from the elite library
16: Perform NVS search method on the optimal solution to obtain new optimal solution S'
17: if (f(S) < f(S')) then
18: iter += 1
19: else
20: Replace S' with S and update iter+1
21: Go to step 11
22: end if
23: else
24: Optimize the population path
25: if (iter == max iteration) then
26: Output the optimized route
27: Transmit sensed data to CH
28: else
29: Go to step 16
30: end if
31: end if

and DG is the amount of ODG selected in the range of 0 to 1. Moreover, the optimal ODG from PSO method by increasing the FF cost value

cost = 8f1 + ψf2 + μf3 (4)
f1 = X i=1 ODG Pki j=1 CHsi,j ODG(5)
f2 = X i=1 ODG k Pki j=1 dist(CH(p,i),ODG) (6)
f3 = ODG optimaldistance (7)

Algorithm 2 Algorithm for Optimized PSO-Based Clustering and Data Aggregation Point in I-IoT Network
Input: Cluster heads & its surrounded cluster members
Output: Cluster construction & SDG by SDN controller
Initially: (i) SDN controller collects the coordinates of the devices and builds the CT
(ii) Later from collected values the SDN controller relates the remaining energy & distance, and forms best groups of CHs, thus the construction of CT is obtained.
1: Initialize → PSO parameters:
2: MaxIT = 1000, nPoP = 100, W =1, Wband = 0.99, c1 = 1.5, c2 = 2.0.
3: Initialize empty particle position, cost, velocity, best position, best cost and global best cost based on CT
4: (A) Group of cluster head construction:
5: Define number of clusters head and compute: number of decision variables, size of decision variable matrix, lower bound and upper bound
6: for (iteration) do
7: Use Eq. 2 and collect the values.
8: Joining CH-neighbours and establishing connectivity among them
9: Mark → SDN controller
10: Connect CHs with the SDN controller
11: end for
12: if (New nodes appended) then
13: Employee energy harvesting technology
14: end if
15: SDN controller sends the CT to the MS and forms scheduling information about the clusters.
16: (B) Data Aggregation points formation:
17: The number of SDG is equal to (DGxK), here DG is the selection SDG percentage range (0, 1)
18: Optimal SDG is form by maximizing the cost of the following fitness function
19: for (i ← 1:nPoP) do
20: 1) evaluate the cost associated with the ith particle using cost f () from Eq. 4
21: 2) Eq. 5 tells the maximum number of CHs in cluster
22: 3) Eq. 6 form shortest distances between the CHs and their data aggregation point
23: 4) Eq. 7 forms the data aggregation point with the MS shortest path.
24: 5) Update → particles Personal best, global best position 25: 6) Evaluate the best cost matrix from the values
26: end for
27: Each CH is associated to the closest SDG point
28: Continue → the process till the MAX Iteration

Table 2 provides the constant value of 8, ψ and μ. From Eq. 5 f1 is to select the ODG that holds the maximum number of CHs. Later, the Eq. 6 f2 determine the ODG consist of the shortest distance from the CHs and its data aggregating points, the ODG with the MS shortest path is chosen by Eq. 7 f3. Furthermore, the shortest path from the last MSOpath iteration that was discovered in the last

cycle that made use of ODG and OMSpath fractions. The ABC determines the best course of action and benefits from lowering network latency, which lowers the energy used by the CHs to wait for the MS. Since the suggested technique has been built and each CH and its nearest ODG are connected, the maximum average distance between a CH and its closest ODGi—referred to as CHavd—is not greater than the threshold (Th) value. In the routing approach, an additional aggregation point is combined if the distance exceeds Th in order to satisfy a CH's high level

OPTIMAL MOBILE SINK PATH DETERMINATION

The goal of this subchapter is to locate the MS optimum routing path inside the search space. After identifying the ODG using PSO, the SDN uses the bio-inspired ABC approach to ascertain the OMSpath, which travels through each ODG data aggregation point, collects data from CHs, and transmits it in a single hop to the MS. The cognitive and related natural behavior, especially exhibited by honey bees, is crucial for locating food sources and potential mates. The strategy used by a bee hive to obtain food naturally is frequently linked to and planned from the collective pattern of CHs in IoT networks that are effective at communicating with each other despite limitations like energy levels, packet error rate (PER), and transfer delay. energy levels, transmission delay, and packet error rate (PER). These designs frequently attain great heights in cooperative networking and communication frameworks such as IoT and require energy-saving communication at every stage. The study carried out an optimization of the ABC approach to facilitate cluster-based routing and related situations in the Internet of Things, thereby continuing its mathematical design. The complete swarm bee is divided into three separate divisions: employee honey bee, observer bee, and scouts. The bee swarm is an intelligent organism that is imitated throughout computing. The IoT network mimics the swarm bee's developing intelligence, and energy exhibits a critical role as a food supply. The forging behavior of the swarm in

In actuality, there are two different ways that this is accomplished: (1) the need for a nectar or food supply, and (2) getting rid of a food source that is useless. The comprehensive ABC-based optimized routing modeling execution flow is depicted in Alg. 3. When the I-IoT communication framework is being implemented, the active IoT nodes are initially sent with random food source distribution patterns. The mathematical computing process produces randomness in the production of closeness, energy, and centrality variables. Every round, during the communication phase, a new food source is Selectively available, connected to the preceding one, and mistreats worker honey bees/CH IoT nodes (XIoT), bystander honey bees/part IoT nodes (nIoT), and overall IoT nodes (IoT). The novel food supply uses proximity for an IoT related search and nectar amount for energy level. A common method for calculating CH is to create the following numerical statement.

1(ij) = XIoTij + γij(IoTij − nIoTjk) (8)

Here, XIoTij indicates the employed bees/CH IoT nodes, nIoTjk refers to onlooker bees/IoT members, and IoTij is the total number of bees. 1(ij) defines the amount of nectar from the food source.

quantity of IoT nodes. The fitness probability factor and the amount of nectar from the food source are directly connected. The assessment of the fitness of every solution by an observer bee, or in this case, the unemployed bee/IoT members, is based on the calculation of the probabilistic factor P(i). Fitness(i) represents the global best fitness value, fitIoTn denotes the fitness solution of a specific I-IoT node, and the associated data regarding the food sources is provided by the employed bees. The following mathematical equation, Eq. 9, can be used to assess the solution's fitness.

P(i) = fitness(i) PnumIoTn n=1 fitIoTn (9)

NETWORK SCHEDULING

Using the pipeline or waiting in line for a chance to send data when the network runs out of energy is how this technique saves energy. Within the suggested framework, this
approach is presented as a network scheduling message (NSM) and is managed by the SDN. Here, data is used to program the CH's sleep/wake schedule according to the MS reach time. Additionally, the SDN with Time Division Multiple Access (TDMA) schedule organizes the period of the data transfer. In order to conserve network energy, each CMs uses the TDMA to transmit its ID, remaining energy, and data to its associated CH during its designated time slot and power-off signal above all others.

When MS has not yet arrived, each CM and CH can turn off its signal to save energy; after it is finished, the devices can turn on their radio signal from NSM. The entire delay of the system
is equivalent to the amount of time the MS needs to complete one round.

where Gi is the MS time used at ODG to gather data from Ki CHs number, that apply to i aggregating point. Additionally, Gi is determined as ensure:

Gi = X Ki j=0 X Nj M=0 Tslot(j,M) + AllocatedTimei (10)

Nj is the CM number connected to CHj and is recognized by the SDN as the process of the TDMA. Tslot(j;M) produce to device M time slot to data send to CHj . the price Di,i+1,

Algorithm 3 ABC Based Optimized Path Determination

Input: Data aggregation point in a network, Probability, Distance, Priority & Energy of the cluster Output: Optimal Mobile Sink Path Determination to traverse the MS for all SDG points in the network

1: Collect Probability, Priority, Distance and Residual energy of the clusters from from SDN controller
2: Deploy Aggregation points with random orientation Initially → ABC parameters Initiate ABC() routing based on shortest path passing
3: for (each(iteration)) do
4: for each employee bee do
5: Compute→[food, range & lower bound]
6: Compute → fitness(soln) and food collected distance from nectar
7: Apply the greedy selection technique
8: Forward the values to an onlooker
9: end for 10: for each onlooker bee do
11: Sort fitness(soln) in descending order
12: Choose the global best depends on the local best value
13: Produce new best fitness(soln)
14: Select the optimized ODG point based on the fitness values
15: Forward MS to all the fitness values and collect data
16: Apply the greedy selection technique
17: end for
18: Obtain the best optimized routing of ODG and compute the energy
19: Memorize the best fitness solution achieved so far
20: end for
21: Repeat iterations until the optimization criteria are met.

in Eq. 11 the MS delay is moving from ODGi to ODGi+1 and is decided as ensure:
Di,i+1 = Dedi,i , i + 1 VMS (11)

Dedi,i , i + 1 is from euclidean distance between ODGi+1 and ODGi, and VMS is MS movement.

As from Fig. 3 the long-term scheduling procedures are often partitioned into two prime reactions:
1) It is performed by the MS, which was recently received from SDN
. 2) Executed by the network node. Original MS performance initiates the SDN that computes the CT, TDMA, NSM and OMSpath from CHs nodes location and sends the data to the MS and communicates them to the system nodes to be used for data scheduling. The system nodes will have the choice to admit it as CMs and CHs in the later round. Later, as indicated by the OMSpath, CT and the MS speed, the system gets the MS data next arrival time.

PERFORMANCE EVALUATION RESULTS

N dynamic IoT devices are randomly arranged in a 500 m × 500 m sq. meter network space to make up the suggested system model. Additionally, the system is created by many degrees of

in terms of device diversity, As an illustration, consider 1–50% of dynamic devices and the remaining regular devices. It is expected that the advanced nodes with 1J and the MS and the standard devices with 0.5 J of initial energy are acceptable in terms of resources. As K is to represent 1–15% of all surviving devices (NAr) in each round, the ODG is initially set at 50% of K. Furthermore, the ODG value continues to rise until it satisfies the work's average limits. Table 2 introduces each compatible network simulation parameter.
1) Alive node: The total number of devices that remain alive after a round of execution repeats from the start until the last device dies is known as the network lifespan. Furthermore, the

The lifespan of a network can be divided into two phases: the stable stage, which occurs when communication occurs prior to the first device in the network dying, and the unstable stage, which occurs when the first device dies before the last.

Alive node: The total number of devices that remain alive after a round of execution repeats from the start until the last device dies is known as the network lifespan. Furthermore, the

Two phases make up a network's lifetime: the stable stage, which occurs when communication occurs prior to the first device in the network dying, and the unstable period, which occurs from the first to the last device dying.

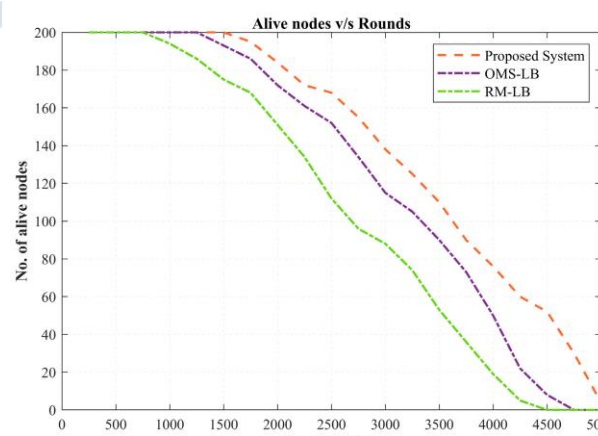

FIGURE 4. Life time of the network.

Figure 4 shows the lifetime of the network. The outcomes clearly show that, when compared to the original plan, the suggested strategy automatically increased the system network's overall lifetime.

additional routing protocols. The development of the general system network lifetime and the long steady stage were validated during the cluster development process by taking load balancing, ODG, sleep/wake network scheduling, and the OMSpath via PSO method into consideration. Furthermore, as illustrated in Fig. 4, the data indicate that the first IoT device dies around at the 1580th round. the outcomes of using the ABC method to calculate the MS optimum route and the adaptive load-balancing technique.

where DG is the amount of ODG chosen between 0 and 1. Moreover, by raising the FF cost value, the ideal ODG using the PSO approach is:

the outcomes of using the ABC method to calculate the MS optimum route and the adaptive load-balancing technique. It is evident that the The suggested method uses less energy and functions more effectively for large-scale networks than various protocols. Furthermore, the overall execution was found to be 17%, 25%, and 37% percent higher than OMS-LB, RM-LB, and the suggested way of the system lifespan within the primary instance.

2) Remaining energy: System performance, distance traveled, and the average amount of energy left in the network are displayed in Figures 5 and 6. The first system network is comprised of an same initial energy degree. Compared to the compared methodology, the proposed method has greater residual energy. First off, the system as a whole survives for a longer amount of time because to the suggested method's effective distribution of energy consumption, which places all of the devices in each cycle into distinct comparison.

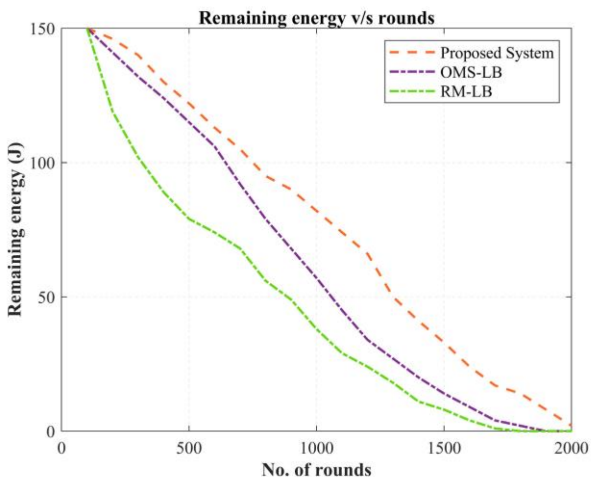

FIGURE 5. Remaining energy of the network.

Due to the sensible loadbalancing method from SDN over the cluster building process from Equations 1 and 3, there has been such effective propagation. Furthermore, the support and categorization

of the OMSpath using AI techniques advances data collection over a shorter distance relative to the system size and ensures that every node saves energy for subsequent transmission and systemcommand. Additionally, the overall execution showed that, for the system's remaining energy within the main case, it performed better than OMS-LB, RM-LB, and the suggested system.

by 31%, 38%, and 54% percent, and by 35%, 40%, and 51% in the distance.

3) Data volume sent: Compared to the various protocols in Fig. 7, the suggested method finally transmits a larger number of packets to the target point because of energy diffusion through the system.

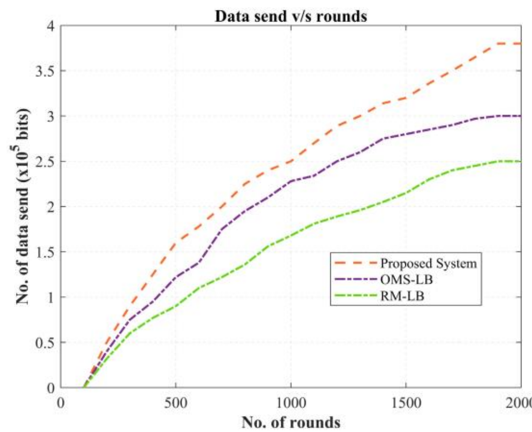

FIGURE 7. Amount of **data** send.

When comparing the total data supplied from the network to OMS-LB and RM-LB with a large-scale system, the improvements are roughly 62%, 33%, and 28%, respectively.

network. The suggested routing technique reduces the number of intermediary nodes in two phases. i) from the detected nodes to their CH, and ii) using the PSO approach, from CHs to ODG locations. It reduces the number of hops and controls the amount of system energy wasted in intermediary nodes. Additionally, the system uses ABC to schedule the entire system, allowing most IoT nodes to save energy by disguising their radio signals. As a result, as the system's lifetime extended, so did the amount of data transmitted. 4) End-to-end delay: With reference to the delay constraints, Figs. 8 and 9 examine the suggested system as well as OMS-LB and RM-LB. In turn, the network length shortens the system

delay caused by not having to retransmit a packet. The results demonstrate that the system's MS delay has been reduced to the OMS-LB, RM-LB approach. This reduction is the result of the efficient application of AI, i.e., PSO to distinguish between the best set of ODG and the ABC path identification process. With a short MS path and minimal latency, RM-LB selects the coordinates of the CHs as an aggregate point from OMS-LB and forwards priority to data collection.

5) Average routing overhead: The average routing overhead is shown in Figures 10 and 11. The PSO

algorithm suggested building clusters in the network using CHs and discovered

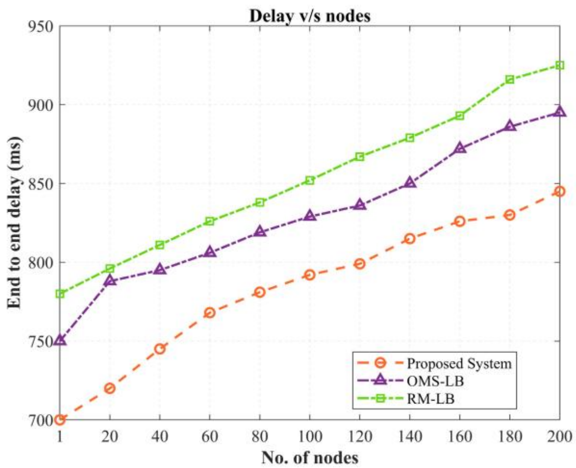

FIGURE 8. Delay with respect to nodes.

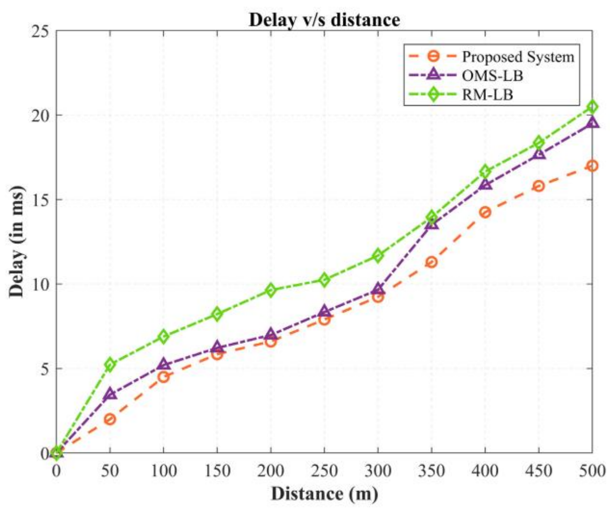

FIGURE 9. Delay with respect to distance.

Additionally, the entire execution shows that the average network routing overhead with the main case is lower when compared to OMS-LB, RM-LB, and the executed system.

by 21%, 26%, and 32% percent, and by 20%, 24.5%, and 31% in the distance.

6) Average throughput: The total throughput of all suggested I-IoT node methods is displayed in Figs. 12 and 13, together with network performance and distance traveled. The

High throughput boosts network performance because of sink utilization, which gathers a lot of data and sends it to the CHs in the network, extending their lifespan by lowering

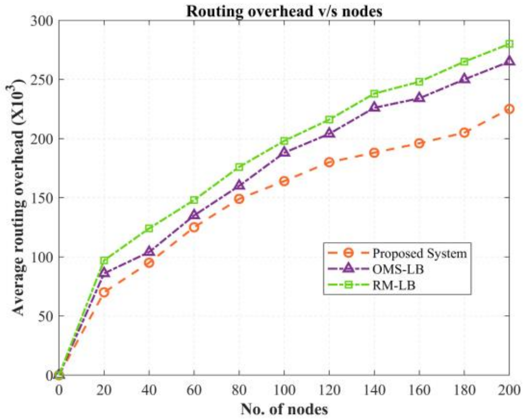

FIGURE 10. Routing overhead with respect to nodes.

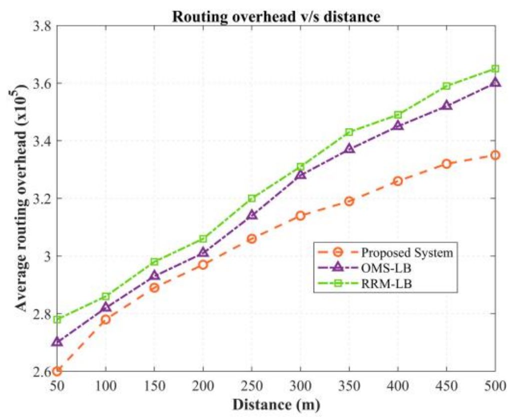

FIGURE 11. Routing overhead with respect to distance.

The maximum throughput is reached and compared with OMS-LB, RM-LB, and other protocols due to the CHs congestion and having an efficient MS movement in the network with ABC.

the system's suggested approach by 74%, 79%, and 86% in the primary scenario and by 70%, 75%, and 81% in the remote scenario.

8) Network complexity overhead: The network performance and network complexity overhead of each suggested technique for I-IoT nodes are displayed in Figs. 15 and 16.

distance traveled. An intern in network complexity represents the

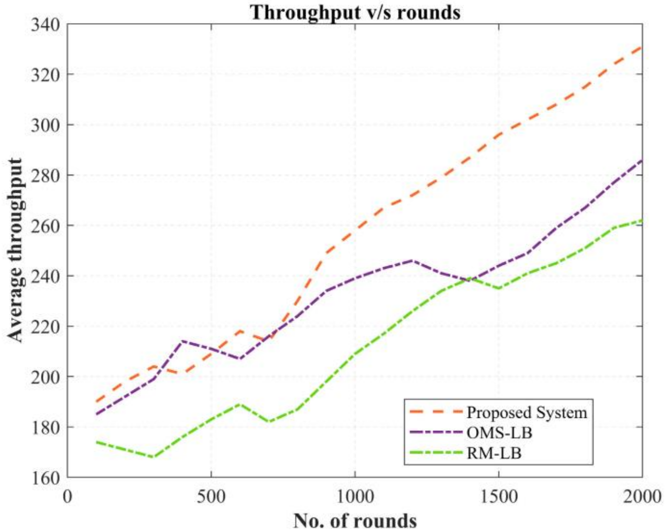

FIGURE 12. System average throughput.

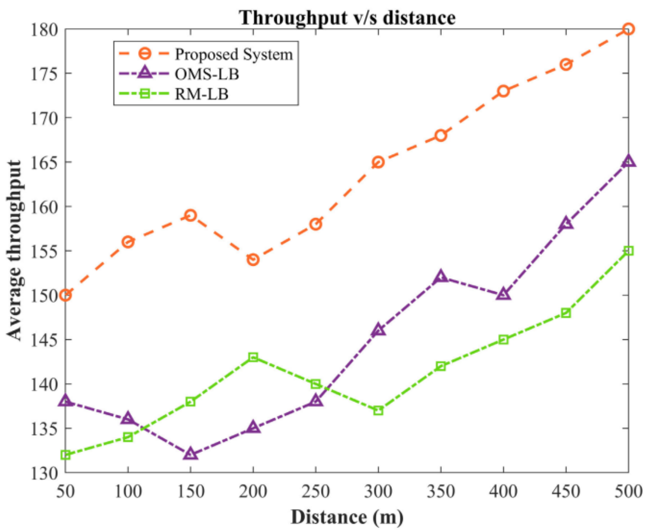

FIGURE 13. System average throughput with respect to distance.

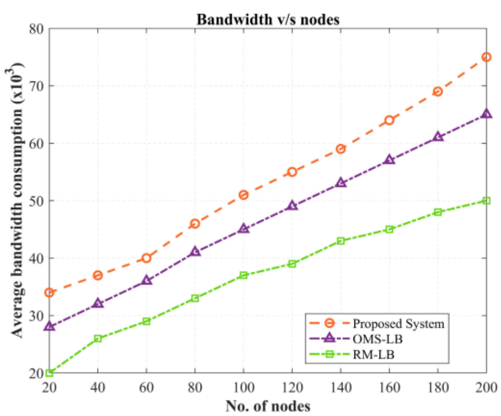

FIGURE 14. Bandwidth consumption in the network.

number of nodes and possible routes that make up a network. Network complexity is decreased by selecting an energy-efficient route and transferring data with less energy.

Using AI, several algorithms are applied at different network phases to pick the most efficient path. PSO provides CHs to CHs, while GA provides the most efficient path between the sensor nodes' CHs. It is compared with OMS-LB, RM-LB, and the proposed system within the main case by 65%, 61%, and 55% and in the distance by 68%, 62%, and 51%. Data transmission, optimal data gathering points, and MS with the assistance of ABC give an efficient path for MS in the network and load balance is achieved.

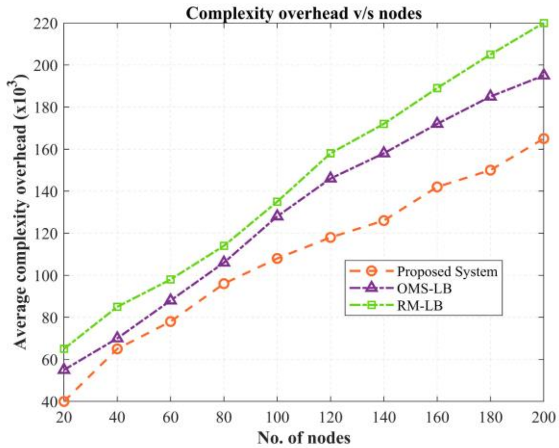

FIGURE 15. Complexity of the network

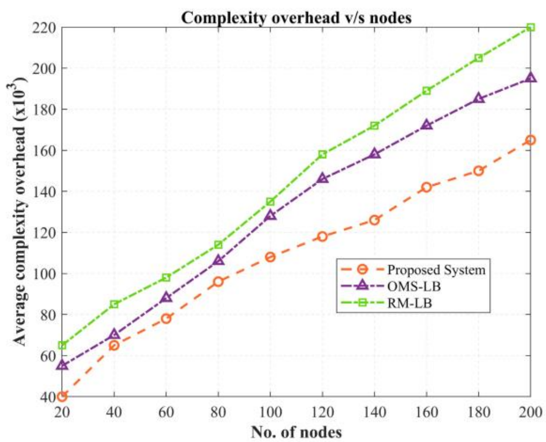

FIGURE 16. Complexity with respect to distance.

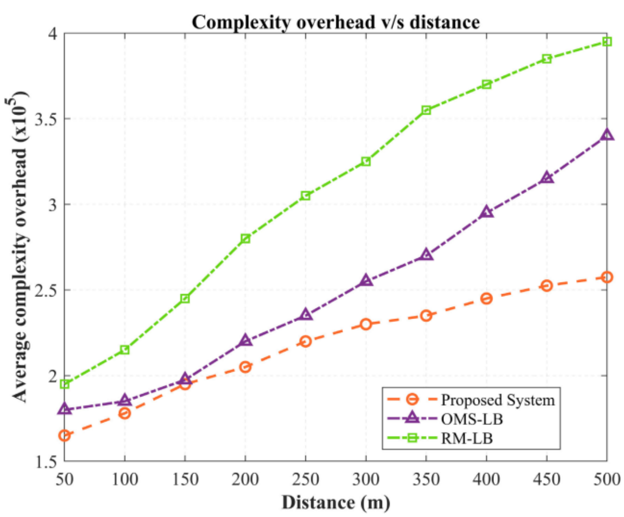

FIGURE 16. Complexity with respect to distance.

CONCLUSION

Large-scale IoT networks now have intelligent routing that is flexible and adaptive thanks to our effort. The suggested system plans a dispersed SDN deployment and manages the operates in the Internet of Things and using AI to indicate the optimal cluster formation and, consequently, the OMSpath for the network's data gathering. SDN makes use of a system that supports the impact of MS development on the cluster building procedure. The suggested system employs the ABC, PSO, and GA techniques. techniques to configure the OMSpath and ODG optimal point, which will reduce the amount of energy used by the CHs and lengthen the network lifetime. Furthermore, this arrangement guarantees that scope networks can be used with the suggested way, which is more adaptable. Moreover, SDN manages a load-balanced strategy that is economical and follows the PSO to sustain network clusters. Large-scale network development demonstrates the relationship between OMS-LB and RM-LB. The suggested method increases the amount of data sent to the MS by 82%, 86%, and 95%, respectively. It also lengthens the network's lifespan by up to 44%, 53%, and 63%, reduces energy consumption by up to 62%, 69%, and 78%, and furthermore, reduces network latency. More investigation is required to ascertain the proper balance between the methods used by the SDN controller and the network nodes. Additionally

It is also necessary to look into how SDN affects IoT networks, especially with regard to different controller types like Floodlight and NOX. In this case, more investigation is also required into the effectiveness and coordination of automated AI systems, particularly those built on deep learning.

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