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METHODS

Energy Efficient Optimized Routing Technique With Distributed SDN-AI to Large Scale I-IoT Networks

P. K. UDAYAPRASAD[1], J. SHREYAS[2], N. N. SRINIDHI[3], S. M. DILIP KUMAR[4], P. DAYANANDA[2], (Senior Member, IEEE), S. S. ASKAR[5], AND MOHAMED ABOUHAWWASH[6,7]

[1]Department of Artificial Intelligence and Machine Learning, Global Academy of Technology, Bengaluru 560098, India
[2]Department of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka 576104, India
[3]Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka 576104, India
[4]Department of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bengaluru 560001, India
[5]Department of Statistics and Operations Research, College of Science, King Saud University, Riyadh 11451, Saudi Arabia
[6]Department of Computational Mathematics, Science and Engineering (CMSE), College of Engineering, Michigan State University, East Lansing, MI 48824, USA
[7]Department of Mathematics, Faculty of Science, Mansoura University, Mansoura 35516, Egypt

Corresponding authors: J. Shreyas (shreyas.j@manipal.edu) and Mohamed Abouhawwash (abouhaww@msu.edu)

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ABSTRACT Effective research has been aimed at increasing the distributed compute dependent Software Define Network (SDN) with high-level Intelligent - Internet of Things (I-IoT). Wireless sensor networks come with a set of resource restrictions. Still, only a few functions are often configured such as energy restraint and the concerted demands that are vital for IoT application routing performance. A major technique for solving the expansion of network scalability by applying Mobile Sink (MS). The construction of data transmission optimal path, the detection of an optimal set data-gathering points O_{DG} and MS scheduled with dynamic networks for energy-efficient techniques, that the network's lifetime in enormous complications, principally in large-scale IoT networks. The research work proposes an Research Objective: i) Develop an energy-efficient routing technique for large-scale I-IoT networks within a cloud-based SDN system. ii) Optimize network scalability, lower-level routing, and load balancing using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). The prime aim of cloud-based SDN with AI is to determine: a lower level routing in the perception layer, a load-balanced Cluster Table (CT), an optimal O_{DG} points, and MS optimal paths O_{MSpath}. The main contribution of proposed routing is i) **Energy Minimization (EM):** The proposed routing minimizes energy dissemination by the Cluster Head (CH) in critical conditions (EM-CH). ii) **Enhanced Energy Balance (EEB):** The EC-based SDN, considering both Optimal Data-Gathering (O_{DG}) and Mobile Sink (MS) advancements, achieves enhanced energy balance during network routing (EEB-SDN). Research results validate the proposed model stability that improves the network lifetime up to 63%, the energy usage in the network is reduced up to 78%, the high volume data loaded to the MS up to 95%, and the delay of the O_{MSpath} by 69% when compared with various model.

INDEX TERMS Artificial intelligence, cloud-computing, intelligent-Internet of Things, mobile sink, software defined network.

I. INTRODUCTION

Internet of things seen as a loosely connected, decentralized device's network functionalities with sensing, processing, and network formation. In IoT, a momentous object that

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transfers the data in one form or another. Radio Frequency Identification (RFID) and sensor sorting advances are adopted to deal with a new difficulty, where information and correspondence structure are imperceptibly embedded in the surrounding area [1]. The outcomes lead to the generation of vast amounts of data that need to be stored and interpreted effectively within a consistent framework. IoT systems with performance that are features and transmit during conventional numbers. Cloud computing gives a virtual framework to such services that includes identifying and reserving devices, examination, customer conveyance, and perception stages [2]. The system model value that the cloud process offers allows end-to-end administration provisioning for organizations and clients to support applications on request from anywhere.

IoT is the communication of numerous physical devices to the internet with physical things with a layer of artificial intelligence. These things enable IoT "physical items to observe, listen, think, and perform tasks and share data and standardize" [3]. In general, Wireless Sensor Networks (WSN) are designed as resources that allow IoT achievement. The WSN sensor is limited by a deficient battery, radio communication limits, storage, and administration capacity. The physical devices are generally arbitrary and differing, which makes the substitution of any device's battery a nearly absurd exercise. It is essential to propose an energy-effective routing technique based on artificial intelligence that accurately balances the device's load and is acceptable for any network scale, later this way developing the lifetime of the entire IoT organization.

Transforming associated objects into IoT devices requires tiny, and modest low-density sensors, actuators, and handling equipment as parts for the robot's complex practices, incorporating components for social communications, automated route, and item examination, among others.

AI approach is reasonable for IoT and makes typical robots comprised of the advanced robots whose epitome and stateliness on the earth bring out practices that prohibit consistent human guidance [4]. Robots on fit acting individually, exhibiting some level of AI levels. Certain M2M and robotics-robots present to execute a combination of exhaust work during this manner moving up as of now a reality, deciding the subsequent phase of development, the Internet of Intelligent Things (IoIT) [5].

An IoT standard model for a significant move from a late sensor network into a network of intelligence sensors authorized with operated instruments. In future networks that comprise the 'Internet of Intelligent Things' [6]. This model with the following stage in system administration development, it design intelligence of a universal, and wise, living, internet. It emerged from the necessity to enable typical items to understand their environmental factors and choose decisions individually [7]. Henceforth, decisions should not be sent to center dynamic nodes, by offering intelligence to sensors, enabling them to think as indicated by the intelligence sensors motive, designing the IoIT to improve to time-critical circumstances that alternatives are made in a distributed way.

As yet the first research trial on IoT is directed essentially from the purpose of super view objects and resources, going from object recognition, and information access to item control [8]. IoIT extracts insight and knowledge focusing on the connection of objects and individual things. Instead of concentrating on associating and controlling intelligent items, it takes attention and improvement in smartness in the IoIT framework by breaking down the collaborations among people and smart items (e.g., conveying cell phones, passing by road cameras, and driving in savvy vehicles).

More clearly, the aim is to concentrate on how the IoIT acknowledges 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 analyzing the performance follows (e.g., signal strength, data size, transmission route) collected by the devices while cooperating with the IoT. High-level intelligence can't be acquired directly from IoT devices; rather, it's gotten by determining information and employing advanced data mining and AI strategies. It calls the knowledge gained from human-IoT connection "Embedded Intelligence (EI)" [9], [10] that indicates the knowledge about human life, bounded elements, and social association. A significant collection of original applications is often entitled EI-improved IoT, in zones, for instance, knowledge search, point-to-point, and intelligence communication, network detecting, etc [11].

The Internet of Things (IoT) and its applications are now a focus of a growing field of research, however, there remains an obvious gap in the integration of advanced energy-efficient routing technologies that can handle a large and complex IoT network. Many of the current approaches are still based on centralized frameworks, which have inherent inefficiencies and limitations. In addition, the importance of efficiently integrating AI is not fully addressed in current works in order to integrate with the modern age of IoIT. Secure advances, effective data collection, and load balancing are yet to be tested. Utilizing the opportunities of cloud and edge computing and understanding how they interact with IoT is an industry that is still in its infancy. Therefore, the objective of this research is to bridge these gaps by trying to develop IoT systems that are not only effective and scalable but also reliable and accessible to all.

This paper consequently proposes a network scheduling with a load balance technique that employs an efficient intelligence algorithm and cloud resources for any scale I-IoT network. The technique is utilized from the GA approach that optimizes heterogeneous IoT nodes clustering in the physical layer for MS to collect data over an enormous data-collecting field. The prime objective of this effort is to optimize the energy usage in the system that normalizes the load of I-IoT devices and MS scheduling, and the network into sleep/awake mode as needed. Subsequently, the work increases the system lifetime and minimizes energy distributed in devices. The proposed system maintains complex technique calculations from the system framework and executes them using the SDN controller that makes use of edge computing for network operation. The data is accumulated using a MS and it is forwarded to the SDN controller for network processing. Besides, the cluster's load-balanced set, global O_{DG}, and the MS optimal path are effectively decided by the cloud based SDN-AI. Firstly GA gathers data from the sensing area and forwards it to its cluster head of a heterogeneity cluster. PSO and ABC, to collect the CHs data and to find the optimal path for data transfer. Later, the SDN controller forms the cluster's optimal points set, global O_{DG}, the MS optimal path, and MS network scheduling messages that is broadcast to the entire network.

The proposed work contributions are as follows:

- Introducing an SDN-AI network's construction, that implements the energy-efficient routing technique for load balancing of the network.
- GA method that optimizes heterogeneous nodes clustering and balances node's energy consumption.
- SDN controller is responsible for cluster's formations as well as determining the O_{DG} and the O_{MSpath} using the functionality observed from I-IoT devices.
- Identifying the O_{MSpath} from ABC to gather data from all O_{DG} at a scheduled time.
- Designing an energy-efficient system, that interfaces the O_{MSpath} decisive cost with the cluster formation procedure to identify an optimized routing technique applicable for different I-IoT networks range.
- The performance of proposed energy efficient routing with SDN-AI algorithms is validated by comparing against existing optimized mobile sink with load balancing (OMS-LB), and random move with load balancing (RM-LB) algorithms.

The paper remains organized as a pursuit. Section II paper in brief analyzes literature related to this research issue later Section III characterizes the problem focused on in this paper. The technique for the proposed energy-efficient optimized routing approaches with distributed SDN-AI is exhibited in Section IV and the shortest path with an ABC also being imported in this section. In Section V, the gained simulation results and validation are inspected. Finally, Section VI gives a paper conclusion and future scope.

II. RELATED WORKS

IoT with various types of communication techniques that combine D2D, a device to nature or living things and vice-versa, and a device to distributed storage. Communication in homogeneous systems (intra-domain) or up heterogeneous systems (inter-domain). Moreover, D2D communication can often without human interference and the process in single or multiple hops. In single-hop communication, the connected devices try to communicate by means of a network framework, which might be a transition point or a network's base station. In multi-hop, devices hand off data to accomplish end-to-end communication between any two devices.

According to a recent research trend, using artificial intelligence techniques with bioinspired inspiration in IoT networks provides substantial enhancements in QoS routing. A centralized routing framework utilizing SDN for IoT is offered by Janabi et al. [12] in order to reduce IoT device energy usage and extend network lifespan. AI-driven PSO and GA are used in the IoT network to produce energy-efficient routing. The outcomes show that the proposed work increases the network's lifetime by reducing latency in IoT. The proposal fails to take other QoS factors like throughput, jitter, etc. into consideration.

In a mobile sink-supported Internet of Things (IoT) network, the author Bandarupalli Rakesh et al. [13] proposes a unique authentication and secure trust-based RPL routing approach. The objective of the proposed strategy is to address the RPL protocol's faults and constraints, which include excessive power utilization, inefficient authorization, and extensive packet losses. The proposed SecRPL-MS technique includes a data transmission authentication process, a mobile sink deployment for reducing the frequent death of IoT nodes, a registration process, and secure routing employing the sail-fish optimizing algorithm. The Network Simulator 3 (NS3) is used to evaluate the performance of the recommended strategy in terms of packet delivery ratio, delay, energy consumption, key generation time, and precision in malicious node detection. In terms of malicious node identification accuracy, the proposed SecRPL-MS technique exceeds current technologies, offering excellent safety against attacks like rank attacks, Sybil attacks, blackhole attacks, and man-in-the-middle attacks. These constraints address challenges with loss of packets during data transfer, opposed nodes available, and IoT network loss of energy.

The author [14] proposed a methodology for describing vulnerabilities in devices and proposes a Deep Learning solution using Pointer Networks. The proposed approach scales higher than the existing AI approach and produces high-quality diverse outcomes. The paper also mentions the use of the Normal Constrained Method (NCC) to frame the final solution set and compares the proposed scheme with other AI algorithms. Experimental results show that the proposed work is more efficient in terms of time and solution quality. The author concludes by mentioning future work and the need to test the proposed approach in real conditions.

To minimize data collection delay time, the study [15] proposes a mobile data-acquiring technique with multi-hop transmission. To enhance the process further, it includes a constrained relay combining-reduction ability. In addition, the authors give a modified mixed frog jump algorithm with delay constraints which makes use of an adaptive step modifying method and chaos techniques. Furthermore, a data-gathering approach based on Bayesian Compression Detection (BCD) is created. In addition, an energy-efficient routing method based on PSO and GA is proposed for large-scale IoT networks using cloud architecture.

A proposed technique for mobile sink-based data gathering in wireless sensor networks (WSNs) with constraints is termed DAOSVM (Data Acquisition through Mobile Sink for WSNs with Obstacles using Support Vector Machine), and it is explored in the paper [16]. The two phases in the DAOSVM algorithm's execution are path development and visiting point selection. A support vector machine is used in the path selection and a spanning tree technique is utilized in the visiting point selection. The objective of the suggested strategy is to solve the issue of providing an obstacle-aware path in WSNs so that the mobile sink can collect data. In order to minimize unwanted packet transmissions between sensor nodes (SNs) and rendezvous points (RPs), the work does not include the virtual rendezvous point (VRP) selection process. The study further points out that, like earlier approaches, the distance traveled by the mobile sink can be optimized and dynamically developed.

The paper [17] introduces a light-weight data fusion and AI-driven network load optimization method tailored for IoT usage. This method employs MiniMax stratified sampling to mitigate correlation and redundancy in data. Furthermore, to ensure network traffic balance, it integrates a real-valued Genetic Algorithm and Discrete Particle Swarm Optimization. A dynamic service migration strategy is also recommended for even load distribution among edge servers. However, the approach has limitations: the data fusion depends on fixed thresholds unsuitable for all cases; the load optimization overlooks the differences in resource processing speeds; and the migration strategy, while based on current resource usage, neglects potential overload scenarios.

The paper [18] introduces an Intelligent-IoT (I-IoT) architecture tailored for healthcare applications, anchored on a deep learning Artificial Intelligent System (AIS) that acts as a controller. This AIS is based on the EG-CRNN structure, a hybrid of DL-RNN and EleAttG, aiming to optimize packet flow by intelligently selecting cluster heads and their members. Furthermore, an associated training algorithm is presented to expedite weight updates and training. While the EG-CRNN demonstrates faster training and reduced error compared to conventional CNN-based structures, the paper does not discuss potential limitations, leaving room for queries on scalability, real-world adaptability, and robustness against varying IoT traffic.

The paper [19] introduces two algorithms aimed at enhancing energy efficiency in WSNs. The first divides the network into clusters, selecting a cluster head based on proximity and residual energy, while the second employs a genetic algorithm to dictate routes for a data-collecting mobile sink. Despite these innovative approaches, the paper falls short in detailing performance metrics and outcomes, and it doesn't address scalability concerns or the algorithms' performance in large-scale WSNs, necessitating further exploration and validation in real-world contexts.

The paper [20] introduces an LED lighting control system leveraging wireless remote controls and Android-based applications, integrating devices such as a human-machine interface and an infrared learning module. Through the PSO algorithm, the system analyses data to maximize energy efficiency and refines the LEACH protocol for optimized data routing in wireless sensor networks (WSN). However, the work falls short in detailing the system's implementation, experimental outcomes, scalability, and robustness. It also overlooks security implications and the system's adaptability with diverse LED fixtures, necessitating further research for real-world validation.

The author [21] proposed a novel deep-learning approach for load balancing and selecting the partially overlapped channel to maximize channel usage in SDN-IoT. Convolution Neural network (CNN) is made to train the model in a centralized control system for regular and best IoT traffic and for allocating the channel with less interference. This approach exhibits better results correlated to the typical path in consideration of throughput, packet loss and increase in the node number. The QoS flow concern is not considered while allocating the channel.

Mobile-sink improved energy-efficient PEGASIS-based routing algorithm (MIEEPB) was designed by [22]. The system prolongs the WSN lifetime by giving a multi-chain with a multi-head technique to the mobile sink. Moreover, the path, sojourn, and its effort on the MS are static, the protocol experiences improved energy consumption by the CHs while moving device MS data or to the sojourn station. Additionally, the effect of this subject builds the larger the dimensions of the network area.

The author [23] proposed the Virtual Grid-based Dynamic Routes Adjustment method (VGDRA) to limit the value of IoT sensor nodes diversion by providing the simplest course to the present MS coordinates. The system consists of a review of correspondence guidelines that affect the IoT system methodology, so just confined total devices that are vital to re-adjust network data towards the MS.

The work carried out in [24] has proposed energy-efficient routing algorithm SDWSNs. Here, CN uses that are used to allocate various tasks actively to achieve the network's actual functioning. The routing technique uses PSO and they have considered CN distant numbers and it shows that the network lifetime is maximized.

Qixun et al. [25] proposed a low latency routing algorithm with efficient network coverage architecture. This work is on restricted space data and a system of network connectivity. Whereas coverage of the furthest reaches of every node in the higher surface IoT is controlled by the power supply, a few higher surface nodes help out one another to ensure complete coverage to down-layer IoTs.

Verma et al. [26] proposed an optimal path routing algorithm from on ant clustering technique in WSNs. The clustering algorithm is used to handle a huge amount of data on large-scale networks. The combination of clustering and ACO has achieved a higher probability of finding the optimum path with a high coverage rate. Results show that individual QoS parameters are used to enhance performance. The capabilities of the SDN controller can be explored with the proposed technique to achieve higher performance to meet QoS requirements.

The work of [27] has proposed a forward aware factor to energy balanced routing method (FAF-EBRM). In FAF-EBRM, according to the recognition of connection load and energy amount, the next hop node is selected. On considering different algorithms like LEACH and EEUC, a comparative study is made with FAF-EBRM. The proposed work has reduced the probability of successive node failure. This method doesn't focus on the trade-off between QoS parameters.

Furthermore, an optimized routing protocol Ad-Hoc on Demand Distance works better in a powerful topology. AODV performance analysis in particular mobility and models proposed by Simaremare et al. [28] to analyze the performance of packet reaching speed, waiting period, and energy consumption. The drawbacks of this research are low processing, high operation cost and interruption or delay. Also, link failure affects route discovery which leads to additional latency, and bandwidth and maximizes the network scale. The reactive-greedy-reactive (RGR) technique was enhanced by Biomo et al. [29] based on AODV. A flexible routing system like OLSR is not effective in dynamic networks because speed of IoT nodes. At the time, the AODV routing protocol was also not suitable for the reactive routing protocol, which caused more time consumption before each process of data transmission.

The work in [30] gives the optimizing multi-path routing with secured fault tolerance. The proposed system applies the Particle Multi Swarm Optimization (PMSO) method to ensure connectivity among IoT things. Further while pleasing QoS, the proposed method selects K-disjoint paths to tolerate the failure. However the author claims the average improvement in routing performance. Since it is a centralized network difficult to transfer the data between nodes because of load shedding queuing delay.

Tang et al. [31] suggested a novel deep-learning approach for load prediction and partially overlapping channel practice in SDN-IoT. Convolution Neural network is used to train the model in a centralized control system for periodic and bursty IoT traffic and for allocating the channel with less interference. This approach has better results compared to the conventional approach in terms of throughput, packet loss, and when there is a node number increase. The QoS requirement of flows is not taken into consideration while allocating the channel.

Kumar et al. [32] presented the Green Routing algorithm using the Fork and Join Adaptive Particle Swarm Optimization (FJAPSO) model that increases the lifespan of automatic reconfigurable SDWSNs by minimizing the energy consumption of sensors. FJAPSO uses a two-level optimizer approach by optimizing the control node number during the network execution, and by selecting the best suitable position for all the control nodes to increase the network lifetime. The simulation shows the enhanced lifespan of the network using the FJAPSO.

Sendra et al. [33] implemented the use of an intelligent algorithm using reinforcement learning for distributed routing in SDN. They have considered QoS parameters like delay, jitter, and packet loss for routing. This scheme is compared with the traditional OSPF routing method. The proposed method shows a better result compared to the traditional method. The main disadvantage is the rule capacity constraint is not considered for switches.

Jing et al. [34] proposed a novel method that is the combination of both a genetic algorithm and an ant colony for routing in a power communication network using SDN. The proposed scheme takes advantage of both algorithms to find the best path efficiently with minimum execution time. While finding the best path parameters like delay, link utilization is not considered.

III. PROBLEM DESCRIPTION AND OBJECTIVES

The prime objective of the proposed system is to design an energy-efficient routing technique for I-IoT networks. Due to physical layer constraints regarding battery, processing systems, storage and communication range. Balancing the physical things factor is non-trivial, and providing an optimization method to tackle the heterogeneity clustering and in the data aggregation process, a clustering technique is used to control the energy in the network. The cluster construction starts by selecting the CHs location subjected to gathering CMs data and forwarding it to the sink. Therefore, CHs drain their energy even more quickly than the CMs due to: the unstable cluster system that drives some CHs to consume more energy compared to others, managing data aggregation points, and forwarding the information to the mobile sink. Moreover, in a large-scale IoT network, it is technically difficult to manage the entire network from a static sink. Also, sink usage in large-scale network systems prompts high power consumption in the CHs and raises the hot-spot issue scheduled to the network with the sink. To design and develop an energy-efficient routing approach with AI to prolong the lifespan of the network for Intelligent-IoT the following objectives are considered:

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.

IV. PROPOSED SYSTEM

One active solution to decrease the amount of energy wasted in the nodes is the use of a clustering process for dynamically organized heterogeneous nodes using GA that forms a platform to organize multiple heterogeneity network and cluster factors, namely residual energy, network locality, active time usage, expected energy consumption and search of optimal distance to reach CHs and dynamic network for heterogeneous IoT. Later MS use intern reduces the CH load. The I-IoT network performance presents huge difficulties, for instance: MS optimal path identification and O_{DG}, coordination among the CHs and MS, and technical

TABLE 1. Existing techniques advantages and its disadvantages.

Ref. No	Technique	Outcomes	Advantageous	Disadvantageous
[12]	Centralized routing using SDN, Particle Swarm Optimization, Genetic Algorithms	Increased network lifespan with reduced delay	Energy-efficient routing, longer network lifespan	Other QoS parameters not considered
[13]	SecRPL-MS using Sailfish optimization	Improved malicious node detection accuracy, security against several attacks	High security, efficient performance metrics	Energy depletion, presence of malicious nodes, packet losses
[14]	Deep Learning with Pointer Networks and NCC	Efficient in terms of time and solution quality	Scales better than existing AI solutions	Need for real-world testing
[16]	DAOSVM with SVM and spanning tree	Obstacle-aware data collection path for mobile sinks	Efficient path construction in the presence of obstacles	Did not address certain optimization techniques
[17]	AI-driven load optimization, MiniMax, GA, DPSO	Balanced network traffic with data fusion	Effective load distribution and network traffic balance	Data fusion depends on fixed thresholds; load optimization and migration strategy issues
[18]	Intelligent-IoT (I-IoT) with EG-CRNN structure	Faster training, reduced error	Faster training, reduced error compared to conventional methods	Scalability and real-world adaptability not discussed
[20]	LED lighting control with PSO and LEACH protocol refinement	Efficient LED lighting control system	Energy efficiency and refined data routing	Implementation details missing, overlooks security and adaptability
[21]	Deep Learning (CNN) for load balancing	Improved throughput, packet loss, and node number performance	Efficient channel allocation with less interference	QoS flow concerns not considered
[22]	MIEEPB	Extended WSN lifetime, reduced energy consumption by CHs	Longer network lifetime, energy-efficient	Effect increases with the size of the network area
[23]	VGDRA	Limited sensor node diversion	Efficient route adjustment based on current MS coordinates	Only a limited number of devices adjust routes to MS
[27]	FAF-EBRM	Reduced probability of successive node failure	Efficient routing based on connection load and energy	Doesn't focus on QoS parameters trade-off
[28]	AODV performance analysis	Analysis of packet speed, waiting period, energy consumption	-	Low processing, high operational cost, delay, other drawbacks
[29]	Reactive-greedy-reactive (RGR) based on AODV	Improved AODV routing	Enhanced AODV routing	Ineffectiveness in dynamic networks because of node speeds
[30]	Optimizing multi-path routing with PMSO	Average improvement in routing performance	Ensured connectivity among IoT devices with QoS	Centralized network issues like queuing delay
[31]	Deep Learning (CNN) for load prediction	Improved throughput, packet loss, and node performance	Efficient channel allocation with less interference	QoS flow concerns not considered
[33]	Reinforcement learning for distributed routing in SDN	Better results than traditional OSPF	Improved QoS parameters like delay, jitter, packet loss	Rule capacity constraint not considered for switches
[34]	Combined genetic algorithm and ant colony for SDN-based routing	Efficient path discovery with minimized execution time	Efficient combination of two algorithms for path discovery	Parameters like delay, link utilization not considered

overheads for CHs path detection at sending collected data to the mobile sink. In the proposed work, an energy-efficient routing technique for IoT from SDN-AI [12], that deals with raised solving idea, with the concept of decreasing the energy used by the network's CMs and CHs and prolonging its lifetime. In the proposed system, forming distributed SDN reduces network complexity, thus successfully moderating the overheads produced by the device's path discovery. Moreover, the cloud-based SDN use AI methods to characterize load-balanced cluster groups that recognize the O_{MSpath} effect as the CHs select procedure. The proposed method offers a sequenced procedure in the CHs and MS that grants the network to sleep and awake technique when feasible, in turn decreasing the power used by them.

The proposed technique is fragmented into 4 related stages: cluster construction, O_{DG} point determination, O_{MSpath} identification and MS network schedule.

A. NETWORK ARCHITECTURE

The system is constructed in line to minimize the average network energy consumption. The proposed technique is developed from optimized algorithms and the latest technologies, including Cloud-based SDN with edge computing. From Fig. 1, the proposed system architecture is formed into 3 prime layers: (i) perception layer, (ii) operation layer and (iii) application layer. The perception layer is parallel with the data-link layer from SDN and incorporates two sub-layers: the data gathering and sensing layers. Initially, the sink or gateway collects the sensor's data and either make a cloud to store the data or the data is forwarded and processed to the SDN to prepare perceptive route based decisions.

SDN controller is carried over the cloud and its working is: cluster formation by AI with cloud methods, GA based heterogeneous clustering, O_{DG} identification by PSO algorithm, O_{MSpath} determination from ABC technique, and network scheduling. The proposed system reduces the network complexity. Moreover, the processing and storing of data and spotting of SDN over the cloud add vital benefits to the network. For example, in the implementation of the optimized algorithms proposed in the system, the SDN controller utilizes the data center as a prime resource for computation in the network. The developed proposed system gives a productive framework and efficient mapping in the selection of CHs and sink nodes, avoids congestion at the sink and reduces the redundant paths provided at the sink node failure.

B. CLUSTER FORMATION

The proposed technique employs the cloud using distributed SDN to construct an optimal routing technique for I-IoT systems. This segment, gives details of some objectives specifically, the CM and CH current energy level, the distance between CM and CH, and CH degree for efficient cluster construction. After selecting the CH, the remaining nodes join the respective CH in the network by affiliating with an effective CH and they are authorized by the CH based on the SDN use. The architecture of the SDN-based routing system is proposed as shown in Fig. 1.

The cluster-based routing technique is designed for data-efficient routing that maps the sensor device to the cluster heads with the cluster member nodes or straightforwardly. The proposed method gives the shortest path by applying an SDN based GA algorithm 1 and continues the path for performing efficient routing of the data packets. The proposed system finds an optimal route from the source CM to its connected CH. The GA chromosomes are noted for the path from source CM → CH.

The optimal route is the total CMs number length in the routing path. The initial genetic population is placed through the random generation set and it calculates from *FF* (Fitness Function). The best are selected from the definitive fitness values and it cooperates for the next formation. The selected optimal path from CM → CH, lower the node energy usage and enhance any system lifetime. The fitness function gives the best optimal path. Here each chromosome represents a precise path from CM → CH. Alg. 1 proposes the enhanced CH selection process from GA and chromosome length depends on TN_{CM}.

$$Fit\_Func(pos) = AVG(CM, CH) + \frac{TN_{CM}}{N} + NO_{ofpart} + NCN \tag{1}$$

$Fit\_Func(pos)$ gives the i_{th} chromosome value, $AVG(CM, CH)$ is the average distance from the cluster member → CH and TN_{CM} is the total number of cluster member in the route, NCN is the total cluster member.

The system gives an AI-based intelligent energy-efficient routing technique by coupling the MS moving cost that collects cluster construction processed data, the energy used when data is sent over the network is decreased. The cluster formation is controlled with cloud-based SDN that is processed along with edge computing and forms the CT by implementing a load-balanced PSO method. In the initial round, the SDN constructs the CT table only from the device coordinates. For later rounds, the SDN process with collected data is based on remaining energy and the distance to select the CHs best set. Also, in each round, an obtained CT process is executed, if any new device is trying to connect to the network, a CH drains its energy or a new device gains more energy using an energy harvesting technique. In the proposed work devices are heterogeneous, with various energy levels and additional energy is not going to be added to any device in the system during the execution procedure. The above organized data around the clusters, the CMs set and the CHs connected to surrounded CH as shown in Fig. 1. Also, the MS communicates the CT to all the devices.

From Fig. 1, PSO is processed by creating a cluster of stochastic particles (*GSP*), with each of its particles (*p*) being a *D* distance vector measured by the *Fit_Func*. Henceforth, only after a positive number of iterative rotations the solution of PSO is obtained. From this, every *p* within the swarm ensures its global best (G_{best}) value and personal best (P_{best}) value. Here SDN considers the device's remaining energy that is alive from each round and its data is retained with the higher energy value being greater than CH's average value, as the number of CHs (*NCH*) in a matrix. Additionally, PSO maximizes the cost of the following function:

$$cost = \alpha \frac{\sum_{j=1}^{k} E_{ng(CH_{(i,j)})}}{\sum_{i=1}^{N} E_{ng_{(ni)}}} + \beta \sum_{j=1}^{k} \frac{NA_r}{\sum_{i=1}^{NC_{p,i}} dist_{CH_{(p,i),ni}}} + \tau \frac{(LB_{avg})^2}{\delta + \sum_{j=1}^{k}(NC_{(p,j)} - LB_{avg})^2} + \gamma \frac{S_{DG}}{O_{MSpath}} \tag{2}$$

$$LB_{avg} = \frac{(NA_r - k)}{k} \tag{3}$$

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

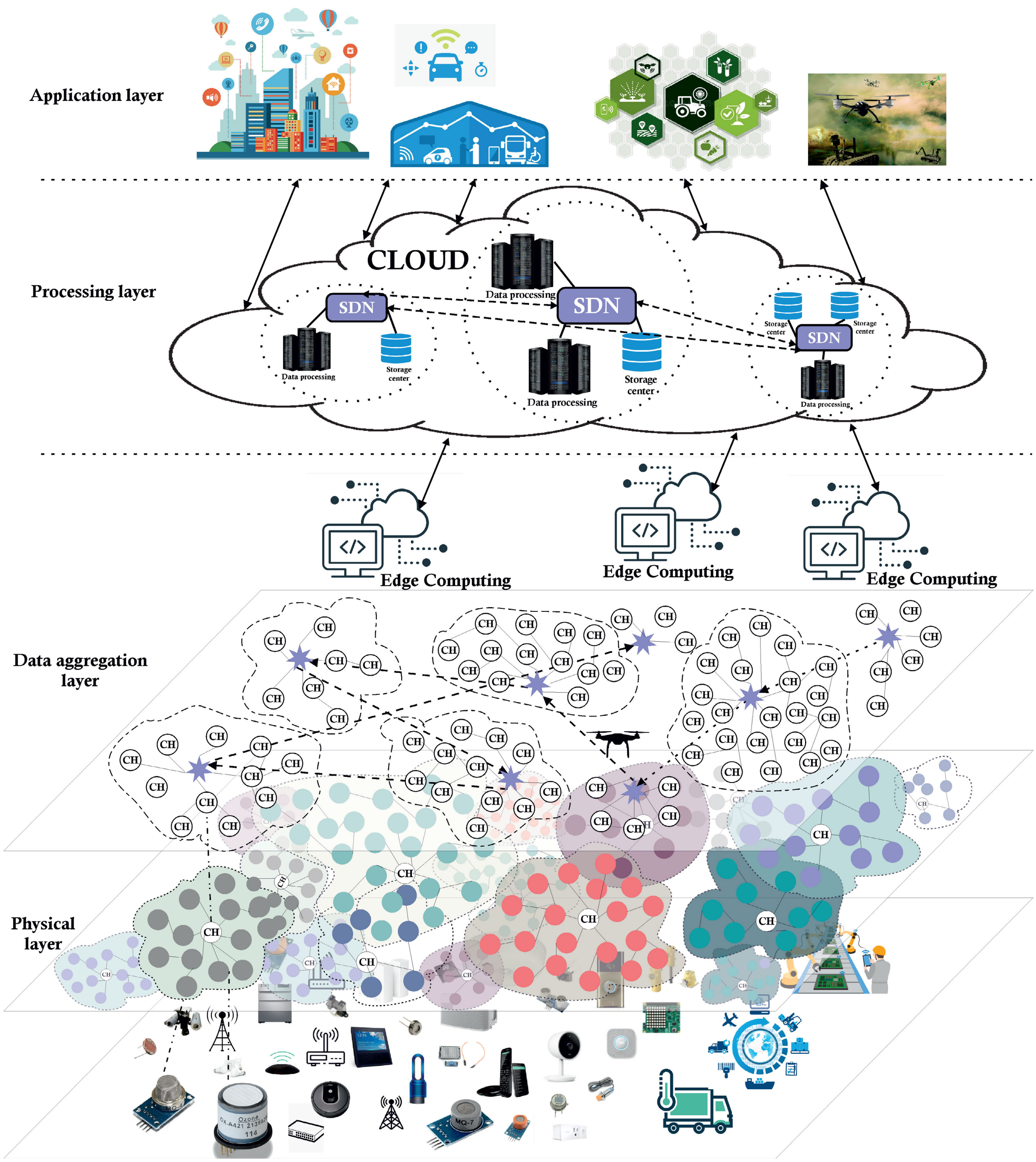

FIGURE 1. A system framework based SDN-AI.

been constant, for instance, the energy, communication range, load balance and O_{MSpath}, are mentioned in Table 1. From Eq. 2 the system analyzes the CHs gathered with a CHs high energy rate, determines the cluster with less communication costs between the CMs and CHs(dist) and chooses the cluster sets with highest load-balance rate. The δ in Eq. 2, is a stable value that implements a technique to leave the PSO process from local maxima and N, K and NC are the IoT devices number, CMs and CHs, respectively. The SDN executes a load-balancing approach by selecting a cluster's set from applying Eq. 2. The value LB_{avg} from Eq. 3 is the CM's mean value of every cluster, and NA_r is the total number of IoT devices alive throughout the round r. O_{DG} and O_{MSpath} refers to the MS optimal path. As appeared in Fig. 2, on deciding the routing technique the cluster formulates in the proposed method with optimized MS operation.

C. DATA AGGREGATION POINTS

The O_{DG} is characterized by the PSO algorithm. At first, the number of O_{DG} during the proposed system is as $(DG \times K)$,

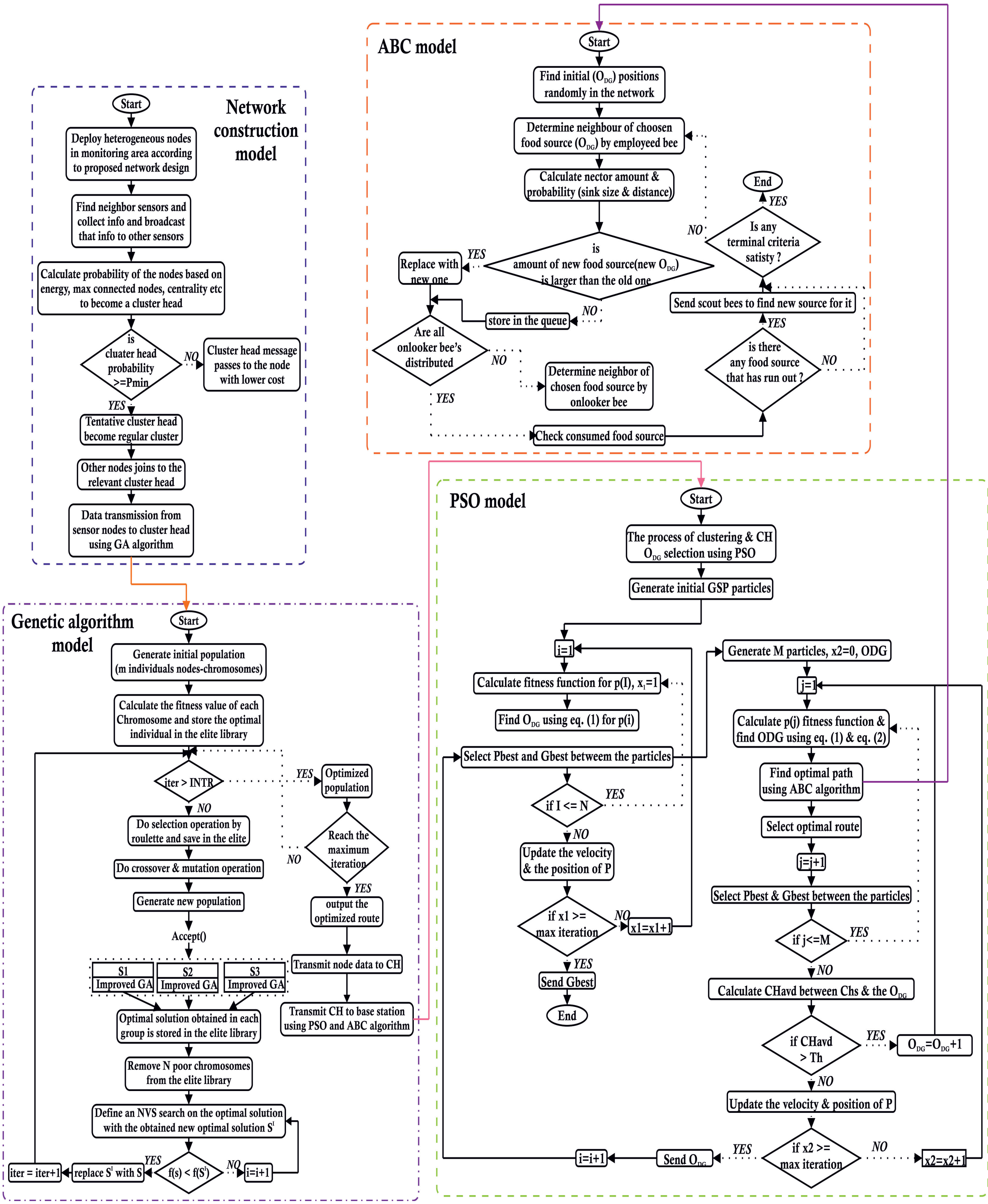

FIGURE 2. The system flow diagram.

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 IoT_N 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 O_{DG} selected in the range of 0 to 1. Moreover, the optimal O_{DG} from PSO method by increasing the FF cost value:

$$cost = \Phi f_1 + \psi f_2 + \mu f_3 \tag{4}$$

$$f_1 = \sum_{O_{DG}}^{i=1} \frac{\sum_{j=1}^{k_i} CH_{s_{i,j}}}{O_{DG}} \tag{5}$$

$$f_2 = \sum_{O_{DG}}^{i=1} \frac{k}{\sum_{j=1}^{k_i} dist_{(CH_{(p,i)}, O_{DG})}} \tag{6}$$

$$f_3 = \frac{O_{DG}}{optimaldistance} \tag{7}$$

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 & S_{DG} 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 S_{DG} is equal to ($DGxK$), here DG is the selection S_{DG} percentage range (0, 1)
18: Optimal S_{DG} 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 i_{th} 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 S_{DG} point
28: Continue → the process till the MAX Iteration

Table 2 provides the constant value of Φ, ψ and μ. From Eq. 5 f_1 is to select the O_{DG} that holds the maximum number of CHs. Later, the Eq. 6 f_2 determine the O_{DG} consist of the shortest distance from the CHs and its data aggregation points, the Eq. 7 f_3 select the O_{DG} with the MS shortest route. Additionally, the shortest route from the final iteration of MS_{Opath} shortest way found within the last cycle that employed the fraction of O_{DG} and O_{MSpath}. The optimal path is recognized by the ABC and its advantages of minimizing the network delay, which decreases the CHs energy while waiting for the MS. Each CH and its closest O_{DG} are connected, and the proposed method has been constructed and the maximum average distance from CH to its closest O_{DGi} (named as CH_{avd}) is not higher of the threshold (Th) value. If the distance is greater than Th, a further aggregation point is combined in the routing method to satisfy a CHs high level of energy preservation.

D. OPTIMAL MOBILE SINK PATH DETERMINATION

This subsection focuses on finding the MS optimal routing path in search space. The SDN recognizes the O_{DG} from PSO, later it executes the bio-inspired ABC method to determine the O_{MSpath}, that moves over each data aggregation point for O_{DGs} and gathers CHs data and sends to the MS in single-hop transmission.

The intellectual and associated nature behaviour particularly with the honey bees is definitive in finding food and mating forms. The methodology of the natural behavior of a bee hive in finding their food is often associated and planned from the collective pattern of CHs in I-IoT network communication effective the restrictions for instance, Packet Error Rate (PER), transfer delay and energy levels. These designs are often highly reached in the contributed networking and correspondence frameworks like I-IoT and need energy-efficient communication in each phase. The study continued its mathematical design by methods for executing an optimized ABC method to ease cluster-based routing and its scenarios in I-IoT. The bee swarm intelligent thing is imitated during the computing and the entire swarm bee is characterized into 3 distinct divisions employee honey bee, onlooker and Scouts.

The study has also found that the self-organizing behavior of bee swarm can be applied in a distributed system like IoT with a higher degree of interactions among the local and global level components of the system. The system is mechanized in a way that a set of procedures on the basis of interactions get executed in the local level components that determine which CH should be chosen at each round of communication so that route optimization can effectively take place.

The increasing intelligence of swarm bee nature is mimicked in the IoT network and energy shows a very crucial approach as food sources. The swarm's forging behavior in the real sense operates with two distinct modes of activities i) requirement to a nectar/ food source and ii) discarding a food source that is of no use. Alg. 3 shows the detailed ABC based optimized routing modeling execution flow.

During the implementation of the I-IoT communication framework, the active IoT nodes are sent originally with an arbitrary pattern of distributing things of food sources. Centrality factors, energy and proximity are randomly produced in the mathematical computing progression. In the communication stage in each round a new food source is chosen accessible and related to the previous one and abuses the employee honey bees/CH IoT nodes (XIoT), onlooker honey bees/part IoT nodes (nIoT), total IoT nodes(IoT). The new food source nectar amount for energy level, closeness for IoT correlate search. CH is often determined by constructing the following numerical statement.

$$\Delta(ij) = XIoT_{ij} + \gamma_{ij}(IoT_{ij} - nIoT_{jk}) \tag{8}$$

Here $\Delta(ij)$ specify to food source nectar amount, $XIoT_{ij}$ specifies the employed bees/CH IoT nodes, $nIoT_{jk}$ refers to onlooker bees/IoT member and IoT_{ij} be the total bees number/IoT nodes. The food source nectar amount is directly correlated with the fitness probabilistic factor. An onlooker bee or in this context the unemployed bee/ the IoT members evaluate the fitness of each solution based on the computation of probabilistic factor $P(i)$, $fitness(i)$ is the global best fitness value, $fitIoTn$ is the fitness solution of particular I-IoT node and the corresponding data about the food sources by the employed bees. The fitness of the solution can be evaluated with the following mathematical Eq. 9.

$$P(i) = \frac{fitness(i)}{\sum_{n=1}^{numIoTn} fitIoTn} \tag{9}$$

E. NETWORK SCHEDULING

This method is used to preserve energy while using the pipeline or in a queue for an opportunity to forward its data the network exhausts higher energy. In the proposed system, this strategy is organized by the SDN and is proposed as a network scheduling message (NSM). Here, information is employed to program the CHs sleep/awake time, based on MS reach time. Besides, the data transmission duration is additionally organized by the SDN with Time Division Multiple Access (TDMA) schedule. With reference to the TDMA, each CMs sends its ID, remaining energy, and data to its connected CH during its defined time slot and power-off signal above all others to save network energy.

Each CMs and CHs can stop its signal to preserve energy when MS has not arrived yet; and from NSM, the things can turn on its radio signal once it's done. The system's total delay corresponds to the time needed by the MS to perform one round.

where G_i is the MS time used at O_{DG} to gather data from K_i CHs number, that apply to i aggregating point. Additionally, G_i is determined as ensure:

$$G_i = \sum_{j=0}^{K_i} \sum_{M=0}^{N_j} T_{slot(j,M)} + AllocatedTime_i \tag{10}$$

N_j is the CM number connected to CH_j and is recognized by the SDN as the process of the TDMA. $T_{slot(j;M)}$ produce to device M time slot to data send to CH_j. the price $D_{i,i+1}$,

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 S_{DG} points in the network

```
Collect Probability, Priority, Distance and Residual energy of the clusters from from SDN controller
Deploy Aggregation points with random orientation
Initially → ABC parameters
Initiate ABC() routing based on shortest path passing
for (each(iteration)) do
    for each employee bee do
        Compute→[food, range & lower bound]
        Compute → fitness(soln) and food collected distance from nectar
        Apply the greedy selection technique
        Forward the values to an onlooker
    end for
    for each onlooker bee do
        Sort fitness(soln) in descending order
        Choose the global best depends on the local best value
        Produce new best fitness(soln)
        Select the optimized O_DG point based on the fitness values
        Forward MS to all the fitness values and collect data

        Apply the greedy selection technique
    end for
    Obtain the best optimized routing of O_DG and compute the energy
    Memorize the best fitness solution achieved so far
end for
Repeat iterations until the optimization criteria are met.
```

in Eq. 11 the MS delay is moving from O_{DGi} to O_{DGi+1} and is decided as ensure:

$$D_{i,i+1} = \frac{D_{ed_{i,i}}, i+1}{V_{MS}} \tag{11}$$

$D_{ed_{i,i}}, i+1$ is from euclidean distance between O_{DGi+1} and O_{DGi}, and V_{MS} 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 O_{MSpath} 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 O_{MSpath}, CT and the MS speed, the system gets the MS data next arrival time. For the consecutive rounds, the collected data from nodes is sent to the CHs in predefined TDMA time allotment.

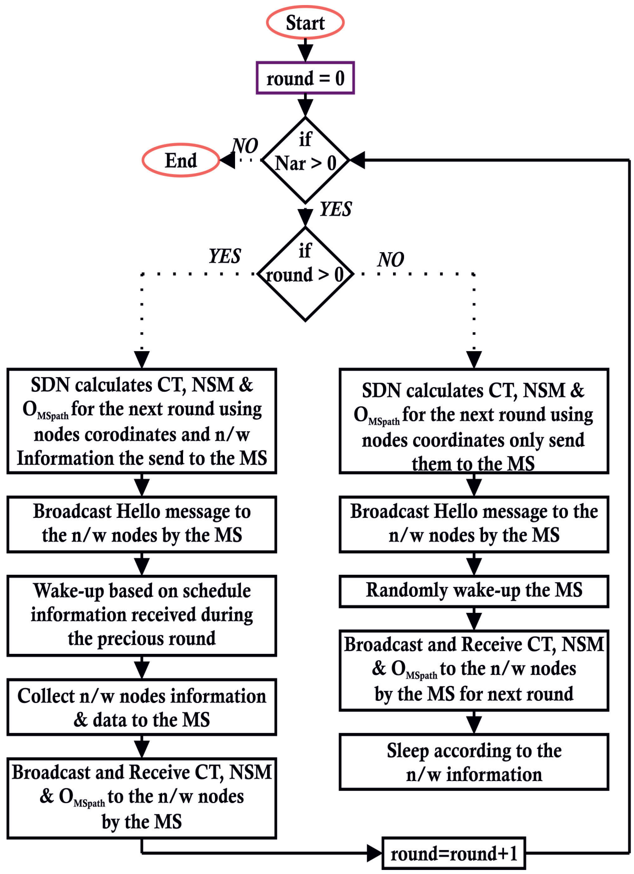

FIGURE 3. MS & network nodes schedule.

TABLE 2. Notations used the proposed work.

Notation	Meaning
NCN	Member in a cluster
cost	Objective function variable
α	O_{MSpath} weight parameter
β	Distance calculation parameter
τ	Load balancing parameter
γ	Constant load balance
Φ	Total number of CHs covered
ψ	Distance measure
μ	Route length calculation
δ	Nectar amount of food source
XIoT	Data aggregation point
nIoT	IoT CH nodes
L	Time slot to send data
CT	Cluster table

V. PERFORMANCE EVALUATION RESULTS

The proposed system model comprises N dynamic IoT devices randomly set up in a 500m × 500m sq. meter network space. Moreover, the system is designed by different levels of device heterogeneity, For example: 1-50% of dynamic devices and the remaining ordinary devices. The standard devices set with 0.5 J of initial energy and advanced nodes set with 1J and the MS are assumed to be resource acceptable. In each round, K is to be 1-15% of all the surviving devices (NA_r) and therefore the O_{DG} is initially set to 50% of K. Besides, the O_{DG} number keeps on increasing until it fulfills the average constraints specified in the work. All the compatible network simulation parameters are introduced in Table 2.

Proposed simulations are applied to utilize the MATLAB simulator to establish the presence of effective clustering method performance and the O_{MSpath} with AI. To enhance the efficiency of the proposed clustering method based optimization, the proposed approach is contrasted with two notable clustering based routing strategies: OMS-LB [12] and RM-LB [24].

1) Alive node: Network lifetime is the total number of alive devices after a round repetition from the beginning of execution waiting for the final device dead. Additionally, the network lifetime is ordered into two stages: the steady stage (the statement of communicating before the death of the first device in the network) and therefore the unstable stage (the death of the first to the last device).

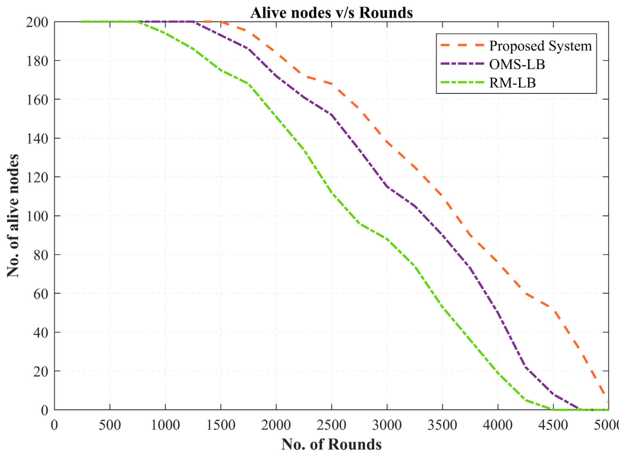

FIGURE 4. Life time of the network.

Fig. 4 exhibit the network lifetime. It's obvious from the results, that the proposed method automatically enhanced the overall lifetime of the system network in comparison with other routing protocols. The development within the general system network lifetime and the long steady stage validated by considering load-balancing, O_{DG}, network scheduling of sleep/awake technique and the O_{MSpath} by PSO method over the cluster development process. Moreover, the results present that the death of the first IoT device happens approximately at 1580th round as shown in Fig. 4. The results of the adaptable load-balancing technique and thought of the MS optimal route with ABC algorithm. It's distinct that the proposed technique shows effective energy usage and it works better efficiently for large-scale networks than different protocols. Moreover, the overall execution determined that compared with OMS-LB, RM-LB and the proposed method of the system lifetime within the main case by 17% 25% and 37% percent.

2) Remaining energy: Fig. 5 and 6 showcase the average energy remaining in the network with the system performance and distance covered. The system network starts with an identical degree of initial energy. The proposed method has more residual energy than the compared technique. Firstly, the proposed method efficiently distribute energy usage with all the devices in each round into different comparison; consequently, the entire system stays alive for an extended period.

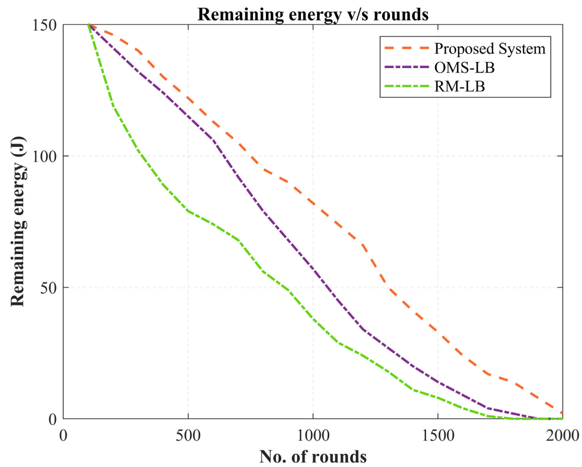

FIGURE 5. Remaining energy of the network.

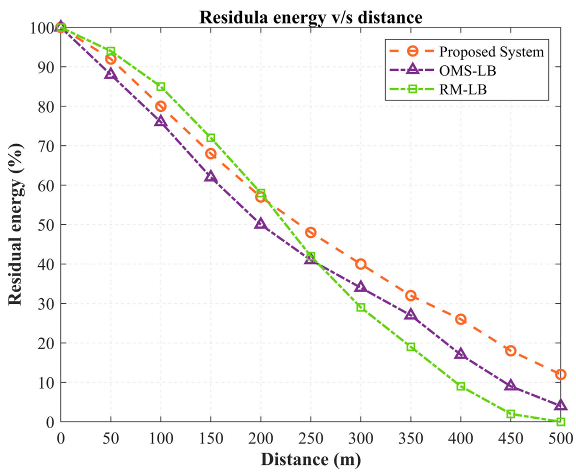

FIGURE 6. Residual energy with respect to distance.

Such effective propagation is due to the reasonable load-balancing procedure from SDN over the cluster construction process from Eq. 1 and 3. Also, the assistance and classification of the O_{MSpath} with AI methods progress data gathering with less distance over the system size and guarantees that all nodes reserve their energy for later transmission and system control. Moreover, the overall execution determined that compared with OMS-LB, RM-LB and the proposed system for the remaining energy of the system within the main case by 31%, 38% and 54% percent and in the distance by 35%, 40% and 51%.

3) Volume of data sent: Due to energy diffusion through the system implies that the proposed method sends eventually a greater amount of packets to the destination point compared to different protocols in Fig. 7.

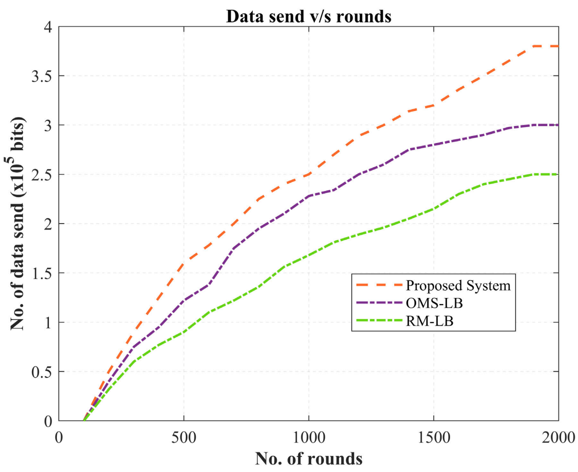

FIGURE 7. Amount of data send.

The overall data sent from the network is improved by approximately 62%, 33%, and 28% respectively in comparison with OMS-LB, RM-LB with a large-scale system network. The proposed routing method decreases the number of intermediate nodes in two different stages i) from the sensed nodes to its CH, ii) from CHs to O_{DG} points from the PSO method. It decreases the hop's count and limits system energy wastage in intermediate nodes. Besides, the system schedules the entire system using ABC, that allows the majority of the I-IoT nodes to preserve energy by passing off their radio signal. Subsequently, the quantity of data sent increased because the lifespan of the system increased.

4) End-to-end delay: Fig. 8 and Fig. 9 look at the proposed system and OMS-LB, RM-LB regarding the delay constraints. The network length in turn reduces the system delay from avoiding packet re-transmission. It's clear from the results that the MS delay used in the system has been decreased to the OMS-LB, RM-LB technique. This decrease is due to the AI effective use, i.e., PSO to differentiate the optimal set O_{DG} and path identification process with ABC. From OMS-LB, RM-LB picks CHs coordinates as an aggregation point and forwards priority to data collection, that causes less delay with a short MS path.

5) Average routing overhead: Fig. 10 and Fig. 11 represent average routing overhead. The PSO algorithm proposed cluster construction with CHs in the network and finds

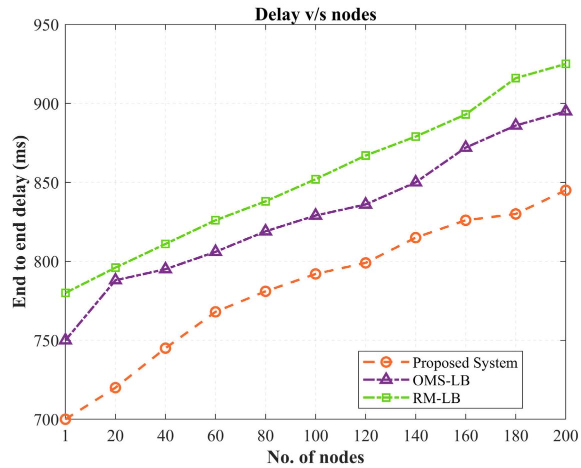

FIGURE 8. Delay with respect to nodes.

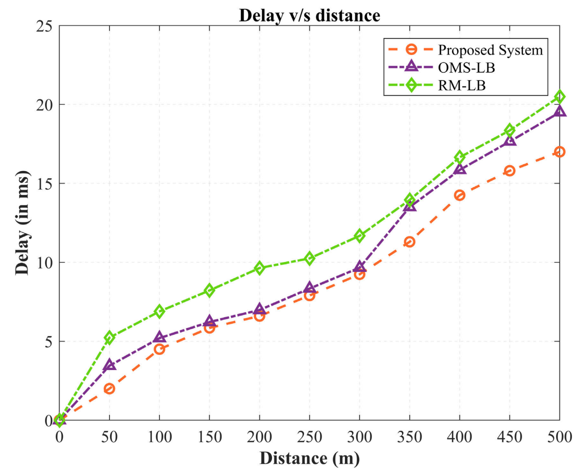

FIGURE 9. Delay with respect to distance.

the O_{DG} optimal set to collect a large amount of data for MS and it is meant to forward to the base station, with the proposed ABC MS is traversed to all the O_{DG} points in the network with scheduled by SDN-AI controller during the path recognition process, through the OMS-LB, RM-LB the ABC intern gives the optimal path for data transmission in the proposed network and it reduces routing overhead with ABC intelligent routing selection with its technique.

Moreover, the overall execution demonstrates that compared with OMS-LB, RM-LB and the executed system for the average network routing overhead with the main case by 21%, 26% and 32% percent and in the distance by 20%, 24.5% and 31%.

6) Average throughput: Fig. 12 and 13 shows the overall throughput of all the proposed algorithms of the I-IoT nodes with the network performance and distance covered. The network performance increases with high throughput by the sink usage that collects the high data which flows to the CHs in the network and increases the CHs lifetime by reducing

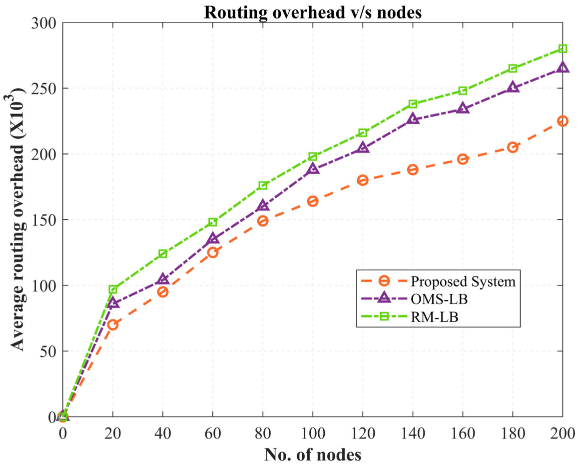

FIGURE 10. Routing overhead with respect to nodes.

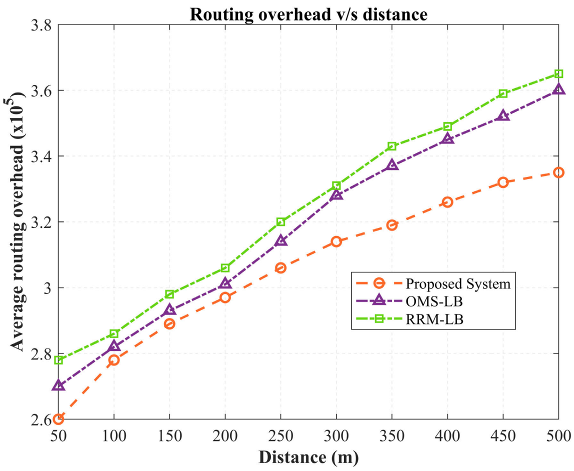

FIGURE 11. Routing overhead with respect to distance.

the CHs congestion and having an efficient MS movement in the network with ABC the maximum throughput is achieved and it is compared with OMS-LB, RM-LB and the proposed method of the system within the main case by 74%, 79% and 86% and in the distance by 70%, 75% and 81%.

7) Average bandwidth consumption: Fig. 14 shows the average bandwidth consumption of the I-IoT nodes with the network performance. The SDN-AI use constructs the network and the defined functionality of the network with minimal parameters. The concept of intelligence in the network and proper control of the network with SDN which upgrades its performances with less resources that in turn, reduces the use of network bandwidth is compared with OMS-LB, RM-LB and the proposed system within the main case by 88%, 82% and 74%.

8) Network complexity overhead: Fig. 15 and 16 shows the network complexity overhead of all the proposed algorithms of the I-IoT nodes with the network performance and distance covered. Network complexity intern represents the

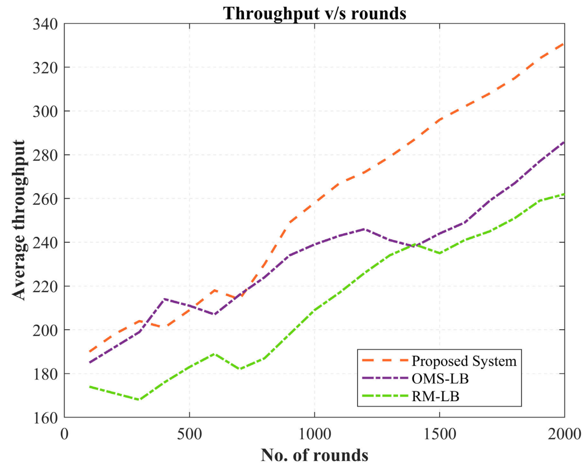

FIGURE 12. System average throughput.

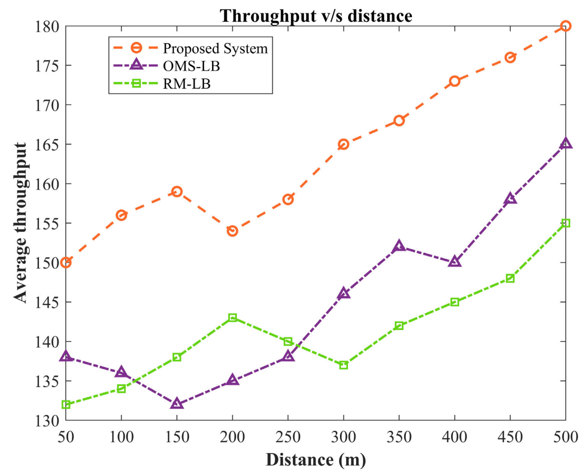

FIGURE 13. System average throughput with respect to distance.

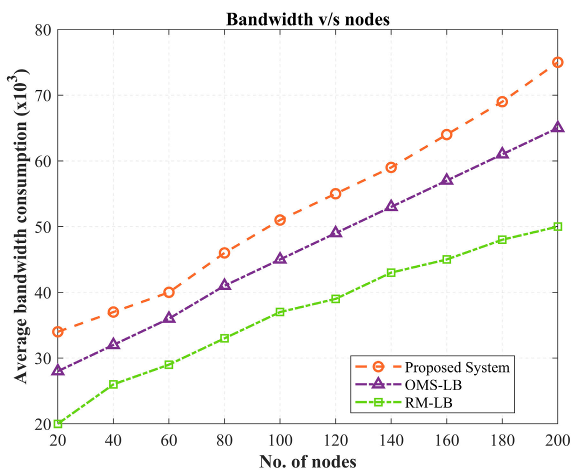

FIGURE 14. Bandwidth consumption in the network.

number of nodes and alternative paths that exist within a network. Choosing an efficient path and conserving less energy to transfer the data reduces the network complexity.

The efficient path is selected using AI of different algorithms in different stages of the network. GA gives the efficient path between the sensor nodes its CHs, PSO gives CHs to CHs data transmission and optimal data gathering points and MS with the help of ABC gives an efficient path for MS in the network and load balance is achieved and 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%.

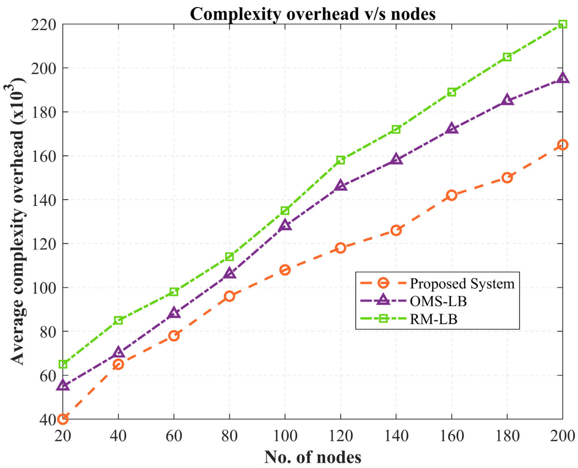

FIGURE 15. Complexity of the network.

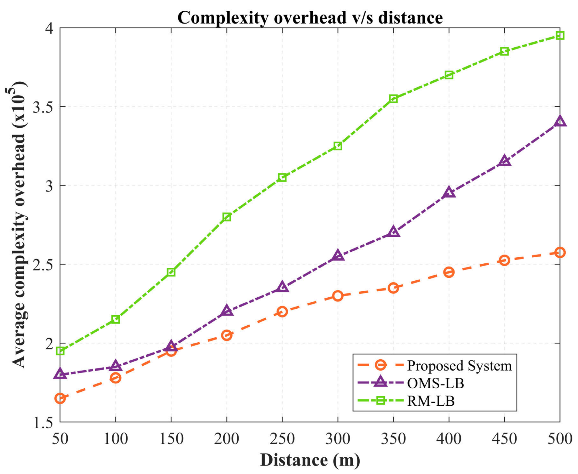

FIGURE 16. Complexity with respect to distance.

VI. CONCLUSION

This work has given flexible and adaptable intelligent routing for large-scale I-IoT networks. The proposed system organizes a distributed SDN deployment coordinates the functions in I-IoT, and uses AI to point the effective formation of clusters and hence the O_{MSpath} for data collection I-IoT network. SDN uses a system that services the MS development impact in the cluster construction process. The proposed system uses GA, PSO and ABC technique methods to set up the O_{DG} optimal point and O_{MSpath} and accordingly, scale down the CHs energy consumed and increase the network lifetime. Also, this structure assures that the proposed method is more versatile and can be adapted to scope networks. Furthermore, SDN handles a cost-effective load-balanced approach along the PSO to maintain network clusters in the network. The large-scale network development exhibits that correlation with OMS-LB and RM-LB the proposed technique enhances the amount of data sent to the MS by parts of 82%, 86% and 95% respectively, and increases the lifetime of the network by up to 44%, 53% and 63% respectively decreases the energy consumed by the network by up to 62%, 69% and 78% respectively and furthermore the network's delay is reduced to 55%, 61% and 69%. To determine the balance between the techniques executed by the SDN controller and the network nodes, further research is necessary. Further investigation of SDN's effects on I-IoT networks is also required, particularly in terms of various controller types like Floodlight and NOX. Additional research is also needed in this scenario regarding the coordination and efficiency of automated AI systems, specifically those based on deep learning.

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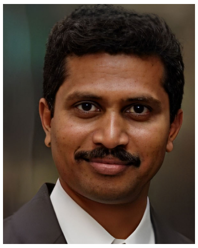
P. K. UDAYAPRASAD received the B.E. degree from Visvesvaraya Technological University, in 2018, and the M.Tech. degree from the Department of Computer Science and Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bengaluru, in 2021. He is currently an Assistant Professor with the Department of Artificial Intelligence and Machine Learning, Global Academy of Technology, Bengaluru, India. He is involved in research, and teaching B.E. and M.Tech. students of computer science and engineering and he has more than three years of research, academia, and industrial experience. He has published more than 15 papers in international journals, including Elsevier, Springer, and Inderscience, and international conferences. His current research interests include the Internet of Things, machine learning, artificial intelligence, sensor networks, and image processing.

J. SHREYAS received the B.E. and M.Tech. degrees in computer science and engineering from Visvesvaraya Technological University, and the dual Ph.D. degree in computer science and engineering and in area of the Internet of Things and artificial intelligence from the Department of Computer Science and Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bengaluru, in 2021. He is currently an Assistant Professor with the Department of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India. He is involved in research, and teaching B.E. and M.Tech. students of computer science and engineering and he has more than eight years of research, academia, and industrial experience. He has published more than 60 papers in international journals, including Elsevier, Springer, and Inderscience, and international conferences, which are indexed by SCI and Scopus. He has filed, published and registered various patents. His current research interests include sensor networks, artificial intelligence of things, swarm intelligence, and machine learning. He has received two best paper awards in Hong Kong and Dubai each during international conferences. He has served as a Reviewer for various reputed journals, including Nature, IEEE, Elsevier, Springer, and Johnny Wiley publishers and international conferences. He also served as a guest editor, an editorial member, the session chair, and a technical committee member for various journals and conferences. He has delivered many keynote/invited talks at international conferences and chaired technical sessions worldwide. He is a valued member of professional bodies, such as ACM, IEEE, ISTE, and IAENG, contributing to the academic community in various capacities.

N. N. SRINIDHI received the Ph.D. degree in computer science and engineering. He is currently an Assistant Professor with the Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal. He has published more than 40 research articles in international journals, including Elsevier, Inderscience, Springer, and Taylor & Francis, and international conferences. He is involved in research and teaching for seven years and he has three years of industrial experience. His current interests include sensor networks, cloud computing, fog computing, edge computing, and the IoT. He served as a Reviewer for various reputed journals, including Springer, IEEE, and Elsevier and delivered expert talk on WSN, the IoT, and robotics in various colleges, including IIT, NIT, DIAT, and other premier institutions. He served as a guest editor, an editorial member, the session chair, and a TPC member for various journals and conferences. He is an international Reviewer for research projects with Sultan Qaboos University, Oman, and reviewed four different projects. He was a Project Fellow for a SERB-DST sponsored research project in the area of the IoT worth 40 lakhs.



S. M. DILIP KUMAR received the B.E. degree in computer science and engineering from Kuvempu University, in 1996, the M.Tech. degree in computer science and engineering from Visvesvaraya Technological University, in 2001, and the Ph.D. degree in computer science and engineering from Kuvempu University, in April 2010. He is currently a Professor with the Department of Computer Science and Engineering, University of Visvesvaraya College of Engineering (UVCE), Bengaluru. He is heading the Training and Placement Office with UVCE, where he is also the Head of the Department of Computer Science and Engineering, from 2020 to 2022. He is involved in research and teaching B.Tech. and M.Tech. students of computer science and engineering and he has 25 years of teaching experience. He has guided eight Ph.D. candidates and six are pursuing the Ph.D. degree in computer science and engineering under his guidance with Bangalore University. He has published 126 papers in international journals, including IEEE, Elsevier, Springer, and Inderscience, and conferences. He has received six best paper awards in IEEE International Conferences. 27 papers have appeared in best quartile SCI Rank journals out of which six papers have appeared in Q1 Journals. The number of Google Scholar citations is 916 and H-index is 11. He has published two Indian patents. He has completed two research-sponsored projects as a Principal Investigator in the areas of grid computing and the IoT sponsored by the Science and Engineering Research Board, Department of Science and Technology (SERB-DST), Government of India. He has completed two consultancy projects in the areas of mobile governance and e-FMS sponsored by the Government of Karnataka. Further, two research projects in the area of IoT each sponsored by Bangalore University are ongoing. His current research interests include the Internet of Things and fog computing. He was a recipient of the Exemplary Leadership Accolade Award in recognition of Outstanding Leadership, Vision, and Dedication to Shaping the Future at the Panchajanya Corporate-Academia-Media Ceremony, in August 2023.

P. DAYANANDA (Senior Member, IEEE) received the M.Tech. degree from RVCE, and the Ph.D. degree from VTU. He is currently a Professor in information technology with the Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education. In previous assignment, he was a Professor and the HOD with the Department of Information Science and Engineering, JSSATE, Bengaluru. His research interests include image processing and information retrieval. He has published many papers in national and international journals in the field of image processing and retrieval. He has got few research grants and consultancy into his account.

S. S. ASKAR received the B.Sc. degree in mathematics and the M.Sc. degree in applied mathematics from Mansoura University, Egypt, in 1998 and 2004, respectively, and the Ph.D. degree in operation research from Cranfield University, U.K., in 2011. He has been an Associate Professor with Mansoura University, since 2016. He has joined King Saud University, in 2012, where he has been with the Department of Statistics and Operation Research as a Professor. His research interests include game theory and its applications that include mathematical economy, dynamical systems, and network analysis.

MOHAMED ABOUHAWWASH received the B.Sc. and M.Sc. degrees in statistics and computer science from Mansoura University, Egypt, in 2005 and 2011, respectively, and the joint Ph.D. degree in statistics and computer science from Michigan State University, USA, and Mansoura University, in 2015, through a channel program. He currently holds significant academic positions at distinguished institutions, including computational mathematics, science, and engineering (CMSE), biomedical engineering (BME), and radiology with the Institute for Quantitative Health Science and Engineering (IQ), Michigan State University, East Lansing, MI, USA. He is also an Associate Professor with the Department of Mathematics, Faculty of Science, Mansoura University. His dedication to advancing knowledge transcends geographical boundaries, as evidenced by his role as a Visiting Scholar with the Department of Mathematics and Statistics, Faculty of Science, Thompson Rivers University, Kamloops, BC, Canada, in 2018. He is a Distinguished Researcher and an Academician, widely recognized for his outstanding contributions to the fields of computational intelligence, machine learning, and image reconstruction. With an illustrious career, he has published over 160 papers in esteemed journals, including notable publications, such as IEEE Transactions on Evolutionary Computation, IEEE Transactions on Medical Imaging, IEEE Transactions on Emerging Topics in Computational Intelligence, *Artificial Intelligence Review*, *Expert Systems with Applications*, *Swarm and Evolutionary Computation*, *Knowledge-Based Systems*, and *Applied Soft Computing*. In addition to his prolific research output, he has showcased his expertise by authoring several edited books published by reputable academic publishers, such as Springer, Wiley, Taylor, and Francis. His impact on the academic community is further amplified through his editorial board service in numerous prestigious journals and conferences. Throughout his illustrious career, he has received recognition for his academic excellence, notably being honored with the Best Master's and Ph.D. Thesis Awards from Mansoura University, in 2012 and 2018, respectively.