The Fuzzy-IAVOA Energy-Aware Routing Algorithm for SDN-based IoT Networks

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***Abstract*—The Internet of Things (IoT) has rapidly grown in the past decade as an emerging technology. Due to the heterogeneity and energy limitations of IoT devices, adopting efficient management practices for developing IoT applications and managing IoT networks is a challenging task. One of the most critical IoT challenges that needs to be considered is routing due to its significant impact on energy consumption. Software Defined Networking (SDN) is a novel approach that decouples the control plane from the data plane, enabling network administrators to program and manage their networks more efficiently. This paper proposes an energy-aware routing mechanism for IoT networks by leveraging the capabilities of SDN. In the proposed method, the SDN controller has a global view of the network devices and establishes several optimal clusters in the IoT environment using Fuzzy logic. Then, the controller computes optimal routes by combining the Fuzzy logic system and the Improved African Vulture Optimization Algorithm (IAVOA). Applying this mechanism enables data packets to be routed through IoT devices with sufficient energy, leading to prolonged network lifetime and improved Quality of Service (QoS). Simulation results confirm that the proposed solution significantly improves energy efficiency and QoS in terms of packet delivery ratio.**

***Index Terms*—AVOA, Energy-aware routing, IoT, Qos, Routing, Software-defined networks.**

I. Introduction

With the rise of electronic circuits and the Internet, the Internet of Things (IoT) has become an integral component of modern society. IoT applications are widespread, spanning areas such as healthcare [1], security [2], smart home [3], exploration of unknown underwater areas [4], transportation, and industrial systems [5]. In IoT networks, overcoming the heterogeneity of devices and enabling gadget cooperation using Software Defined Networking (SDN) is feasible. This technology enables simultaneous communication between various communication technologies, as the entire network is managed and monitored by an SDN controller [6]. Thus, using an SDN controller, it is possible to manage the system uniformly and plan for the network (e.g., routing). The centralized position of the SDN controller provides a global view of the topology and network conditions, enabling adequate control of the system, such as guiding and controlling Quality of Service (QoS). In fact, the main role of the network layer is to realize communication among IoT devices, efficient data routing, and collaborative measurement. IoT routing protocols must meet network performance parameters, including energy efficiency, heterogeneity, mobility, scalability, reliability, and convergence. Their main function is to establish an efficient, reliable, and energy-aware path to provide the longest lifetime for the entire IoT network [7].

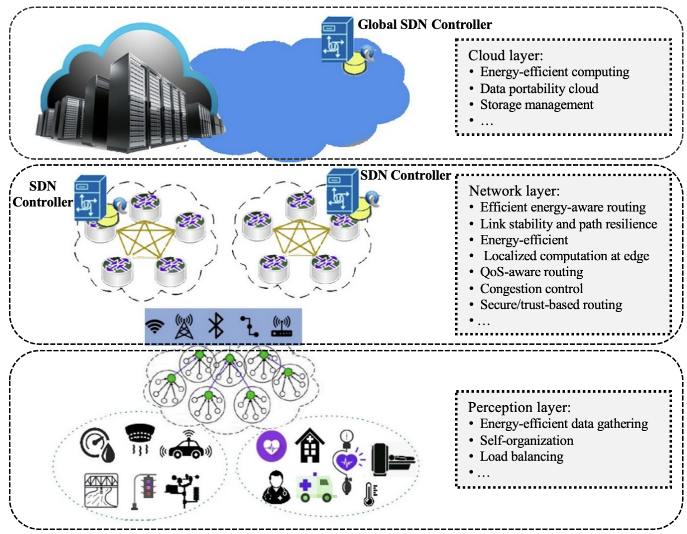


Fig. 1: Energy-aware layered architecture for SDN-IoT.

According to Cisco's projections, the number of internet-connected devices is expected to reach 41 billion by 2025 [8]. Such devices generate massive amounts of data that require real-time processing. The International Data Corporation forecasts that the volume of data produced by IoT devices will reach 73 zettabytes by 2025 [9]. Despite their numerous advantages, IoT devices, such as sensors, have limitations in terms of computing power, storage capacity, and energy sources, thereby posing significant challenges to their development [10], [11]. To overcome these challenges, many studies have proposed the use of cloud computing and edge computing to process the data generated by IoT devices [12], [13]. However, it is crucial to develop specialized protocols to reduce energy consumption in these networks. Clustering is a widely used and effective method for reducing energy consumption by aggregating data and preventing the transmission of duplicate information [14]. To handle heterogeneous nodes, a flexible layered architecture is necessary. In addition, SDN is a modern approach that can increase network flexibility [15]. SDN separates the control plane from the data plane, allowing for dynamic network control, better QoS, and network management simplicity [16]. SDN is a promising approach in IoT that enables controllers to detach from sensor nodes. The SDN controller determines the various parts of the network and applies current input rules based on information received from the network. As such, SDN has the potential to optimize resource usage and enhance network performance in IoT environments. SDN enables network administrators to manage network services without evaluating low-level details.

A. Motivation

IoT enables the connection of various devices to the internet. IoT sensors can automatically track, process, and route data, allowing for the execution of various applications in real-time. The IoT enables the transfer of information over the internet without human intervention. This dramatically changes people's lifestyles and allows for more proactive device behavior in response to reactive triggers. Heterogeneous devices will be deployed to locations that were previously inaccessible. The IoT is composed of extensive heterogeneous networks with varying capacities, processing power, and platforms. Routing protocols are required to facilitate communication between different devices to meet these requirements. Various issues slow down the communication process in the IoT. The heterogeneous network refers to devices with different capacities, geographic locations, speeds, and energy consumption. There is no unique identification for each device in the environment. Most devices in the IoT are low-power and have lower computational capabilities. Energy consumption plays an important role in data transmission in the network. Recently, SDN has emerged as an evolving technique in IoT networks. SDN enables IoT networks to dynamically and efficiently manage network functions through programmable control. In IoT applications, intelligent sensors suffer from low battery life, and they are usually deployed in network environments where recharge is often not feasible. In addition, SDN integration with an IoT-enabled sensor network presents numerous challenges, such as selecting control nodes, load balancing, and optimization.

As the majority of energy consumption in IoT networks occurs during packet transmission and reception, multi-hop routing has been introduced as an effective method for reducing energy consumption in these networks [16]. Therefore, in this study, we aim to simultaneously consider clustering and multi-hop routing to reduce energy consumption in IoT networks. We have used various criteria for clustering and selecting the appropriate cluster head. Since the IoT environment is dynamic and uncertain and the criteria for selecting cluster heads are in conflict with each other, the use of a fuzzy system can be promising for creating suitable clusters in these environments. In addition, we have used another fuzzy system to select the best intermediate node among the available nodes, which considers both the energy of the nodes and their distance. The main contributions of this study are listed below.

- We improved the AVOA algorithm for solving clustering problems by applying an objective function based on the fuzzy system.
- We considered different criteria such as distribution and load balance of clusters and centrality and residual energy of nodes in selecting the cluster head. We defined new criteria to measure the degree of distribution for the cluster heads in the environment and the load balance of clusters.
- We increase the scalability by reducing control packets using cluster structure and routes in SDN architecture.

This paper is organized as follows: Section II outlines the related work and motivation for the research. Section III discusses previous work and key concepts. The proposed method is discussed in Section IV. Simulation results are presented in Section V, and Section VI concludes with future work and conclusions.

II. Related Work

In this section, recent routing protocols and methods for IoT networks have been reviewed. Nazari *et al*. in [3] introduce an SDN-based clustering approach with an intelligent algorithm for energy conservation in the IoT. Their method utilizes an evolutionary algorithm based on virtual grids to ensure load balancing and cluster distribution in the environment. SDWSN is a software-defined sensor network that combines SDN and WSN to create a more flexible system [17]. In SDWSN, the next hop determination is carried out using a fuzzy system that employs various criteria, such as remaining power (RP), node cost (NP), nearest neighbor (NN), and queue length (QE). Eghbali et al. propose a multilayer SDN-based system for monitoring data and load balancing in IoT devices [18]. Their proposed architecture prevents the controller from becoming a bottleneck and facilitates the use of management mechanisms. Experimental findings show that their technique improves system performance by reducing costs and waiting times. In [19], the authors introduce an SDN-based load balancing service (SBLB) that minimizes response time and resource usage for cloud service customers. SBLB components include an application module, an SDN-based network controller, and cloud servers. Other sub-modules are also used for active load balancing, service monitoring, and categorization. In this system, all incoming communications are processed immediately, and the controller monitors the available server set. The algorithm also reduces response time.

In [20], a cluster-based traffic control strategy is proposed to reduce the control message load in SDN networks. This method combines the old decentralized routing and controlled SDN routing and makes it a hybrid. The induced overhead of the SDN controller communication is reduced by this approach. An exploratory algorithm for optimizing routing in SDN has been proposed in [21]. This algorithm is developed based on maximizing the utilization of bandwidth in active links. The authors aim to reduce energy consumption by increasing the use of network links and reducing the use of network equipment. In [22], a cluster-based routing method is presented for efficient routing in IoT sensor networks. This modeling uses energy-aware network management and energy consumption to effectively route packets while minimizing energy consumption. The network lifetime has increased due to the use of convolutional neural networks and fuzzy rules for load balancing.

MHC-RPL is a multi-hop clustering-based routing protocol for RPL, which has been proposed to reduce energy consumption in the IoT networks [23]. At the first level, it reduces the number of control messages sent in the RPL network. In the next stage, network traffic is routed using SDN and Q-learning algorithm. Performance results show that it outperforms ordinary protocols in terms of global delays, packet transfer rate, and energy consumption. In [24], a dynamic algorithm for efficient energy-relay node selection in variable environments over time has been proposed. The next relay node is selected based on link cost and reward, using the nodes' location and transition probability (calculated by Markov chain). Simulation results show that DRA-EERS consumes less energy compared to the existing Dijkstra algorithm. One limitation of this algorithm is that its algorithm complexity increases as the network size increases. In the future, the ability to move to nodes can be added to the dynamic network. In [25], more inactive links are created to improve routing in SDN. Here, edge network devices are loaded with more traffic to create more idle links. For this purpose, a link-based genetic algorithm (LBGA) has been proposed. Although this strategy may provide sufficient energy efficiency in some time periods, overall energy consumption may increase. However, increasing energy efficiency by creating less active links can be an effective solution for managing delay and bandwidth, which needs to be focused on. Additionally, the authors emphasize reducing active links for packet exchange between switches and controllers to satisfy controller load constraints.

In [26], an algorithm-based optimization method is proposed to increase system lifetime. The method considers intra-cluster energy consumption, inter-cluster energy consumption, and energy consumption of non-clustered nodes. The article uses a layered system for clustering, with nodes closer to the base station assigned less radio range to reduce cluster size and conserve energy. The goal is unequal clustering, where cluster heads close to the base station have more energy for relaying data. In [27], the objective is to minimize energy consumption and maximize network lifetime in IoT. The Butterfly Optimization Algorithm selects optimal cluster heads based on several criteria, including remaining node energy, distance, node degree, and centrality. After clustering, data is sent to cluster heads for aggregation and routing towards the base station, and Ant Colony Optimization is used to optimize the path based on distance, remaining energy, and node degree criteria. As explained above, SDN-based methods have been used to reduce energy consumption in various applications and to develop QoS-aware routing protocols for the Internet of Things. The expansion of these methods can lead to more energy-efficient and reliable IoT systems.

III. Background

A. SDN and Routing Protocols for IoT Networks

In IoT networks, overcoming device heterogeneity and enabling gadget collaboration using SDN is achievable. This technology allows simultaneous communication among various communication technologies. Since the entire network is managed and monitored by an SDN controller, unified system management and planning for the network (e.g., routing) can be performed using the SDN controller. The centralized position of the SDN controller provides a global view of the network topology and conditions, allowing for appropriate system control, such as traffic steering and QoS control. In fact, the main role of the network layer is to achieve communication between things, efficient data routing, and collaborative sensing. IoT routing protocols must meet network performance parameters, including energy efficiency, heterogeneity, mobility, scalability, robustness, and convergence. Their main function is to create an efficient, reliable, and energy-aware path to provide the longest lifetime of the entire IoT network. In this section, recent protocols and methods for routing in IoT networks have been reviewed. The energy-aware layered architecture for SDN-IoT is divided into three layers, which are shown in Fig. 1. *Perception Layer* collects data from various sources such as smart devices, RFID, cameras, and sensors. The Perception Layer is responsible for energy-saving data collection, self-organization, load balancing, static control, and more. Data is dynamically collected and effectively sent safely to the Network Layer. Using *Network Layer*, data is directed from the Perception Layer to the Application Layer. It is also called the Transmission Layer. The Network Layer includes routing, addressing, energy awareness, QoS, reliability, and IoT gateway devices that transfer sensor data to the internet. *Cloud Computing and Storage Processing Layer* is responsible for monitoring the entire IoT system, including services and applications. It can create business models, diagrams, and reports based on information received from the lower layers. Additionally, it makes precise decisions about the company's strategy and monitors the performance of the lower layers [28].

TABLE I: Main notations

Symbol	Meaning
R	The optimal position of the vulture
F	The hunger level of the vultures
t/T	The current/total iteration number
$V(i)$	The position of the vulture
PS_i	The probability of selecting node i
$d(t)$	Difference between current and optimal positions
pow	The power of the Vultures-leader
nc	The number of members in cluster
E_i/E_{avg}	The current/average energy
N_{alive}	The number of alive nodes
k_{opt}	The optimal number of clusters
LB	Lack of load balancing
LD	Lack of distribution

B. Fuzzy System

Computational intelligence techniques provide a promising approach for routing algorithms in computer networks. One of these techniques is fuzzy logic, which was first proposed by Zadeh [29] for control systems. A fuzzy logic system uses IF-THEN rules to describe the relationship between discrete inputs and output variables, which consists of three parts:

fuzzification, inference engine, and defuzzification. Input variables are represented by fuzzy sets through the fuzzification process. While the inference engine calculates fuzzy output based on IF-THEN rules, defuzzification uses a mathematical formula to convert fuzzy output into crisp values. Fuzzy controller design imitates human reasoning. Fuzzy logic is suitable for control problems that face difficulties in converting them to mathematical models or complex environments with uncertainty (such as IoT environments) [30].

A fuzzy system is a type of artificial intelligence that uses fuzzy logic to approximate and reason about complex, uncertain, and imprecise information. Fuzzy logic allows for the representation of uncertain and vague concepts in a more human-like way, by assigning degrees of membership to various sets or categories. These degrees of membership range from 0 (not a member) to 1 (fully a member), with intermediate values representing degrees of partial membership. Fuzzy systems can be used in a variety of applications, including control systems, decision-making systems, pattern recognition, and data analysis. In a control system, fuzzy logic can be used to control a process based on imprecise input data or uncertain environmental conditions. In decision-making systems, fuzzy logic can be used to evaluate different alternatives based on multiple conflicting criteria. In pattern recognition and data analysis, fuzzy logic can be used to extract meaningful information from complex and noisy data sets. The key advantages of fuzzy systems are their ability to handle uncertainty and complexity, their ease of implementation and interpretation, and their ability to mimic human decision-making processes. Fuzzy systems can be designed using various methodologies, including rule-based systems, neural networks, genetic algorithms, and fuzzy clustering.

C. AVOA Algorithm

The AVOA algorithm, short for *African Vultures Optimization Algorithm*. It simulates African vultures' foraging and navigation behaviors and is used for solving optimization problems [31].The algorithm stages are as follows:

1) Initialization Stage: After forming the initial population, the objective function is calculated for all individuals. Then, the first and the second best solutions are selected as the best Kruskal and suboptimal Kruskal. Eq. (1) is used to transfer all other solutions in the population to the optimal and suboptimal solutions.

$$R(i) = \begin{cases} BestVulture_1, & \text{if } p_i = \alpha \\ BestVulture_2, & \text{if } p_i = \beta, \end{cases} \tag{1}$$

where $R(i)$ indicates the optimal position of the vulture in the current iteration. $BestVulture_1$ and $BestVulture2$ represent the optimal and suboptimal solutions, respectively. α and β lie in the interval $[0, 1]$. The value of p_i is obtained for choosing the best solution using the roulette wheel and based on Eq. 2.

$$p_i = Fit_i / \sum_{i=1}^{n} Fit_i. \tag{2}$$

2) Vulture Hunger Calculation Stage: African vultures have two feeding patterns. When their energy level is high, they fly to more distant areas to find prey. But when they get hungry, their energy drops, thus they hunt for prey alongside stronger vultures. Eq. (3) shows the level of hunger of the vulture. If the value of F is high, AVOA applies exploration, or else it uses exploitation.

$$F = (2 \times rand_1 + 1) \times z \times (1 - (t/T)) + u. \tag{3}$$

$$u = H \times (\sin^w (\pi/2 \times t/T) + \cos (\pi/2 \times t/T) - 1). \tag{4}$$

F represents the hunger level of the vultures, t denotes the current iteration number, and T represents the total number of iterations. $rand_1$, z, and H are random values, which will be different for each iteration. To avoid getting stuck in local optima, u is used, thus increasing the exploration. As w increases, the probability of optimization operations entering the exploration phase increases. As w decreases, the probability of optimization operations entering the development phase increases. In fact, Eq. (4) simulates the rotational movement of the vulture.

3) Exploration Stage: When $|F| \geq 1$, AVOA enters the exploration phase. AVOA applies two strategies for exploration. C_1 and $rand_{C_1}$ are used for selecting one of the strategy (C_1 and $rand_{C_1}$ are random values in the interval [0, 1]). When C_1 is greater than or equal to $rand_{C_1}$, the vulture updates its position according to Eq. (6). When C_1 is less than $rand_{C_1}$, the vulture updates its position according to Eq. (7).

$$V(i+1) = \begin{cases} Eq.(6), & \text{if } C_1 \geq rand_{c_1} \\ Eq.(7), & \text{if } C_1 < rand_{c_1} \end{cases} \tag{5}$$

$$V(i+1) = R(i) - |X \times R(i) - V(i)| \times F, \tag{6}$$

$$V(i+1) = R(i) - F + rand_2 \times ((Up - Low) \times rand_3 + Low), \tag{7}$$

where $V(i+1)$ represents the position of the vulture in the next iteration. X is calculated by the formula $X = 2 \times rand$, which represents the position vector where vultures move randomly to protect their prey from other vultures. $V(i)$ is the position of the vulture in the current iteration. In Eq. (7), $rand_2$ and $rand_3$ are random values, and Up and Low are the upper and lower bounds of the vulture's search domain, respectively.

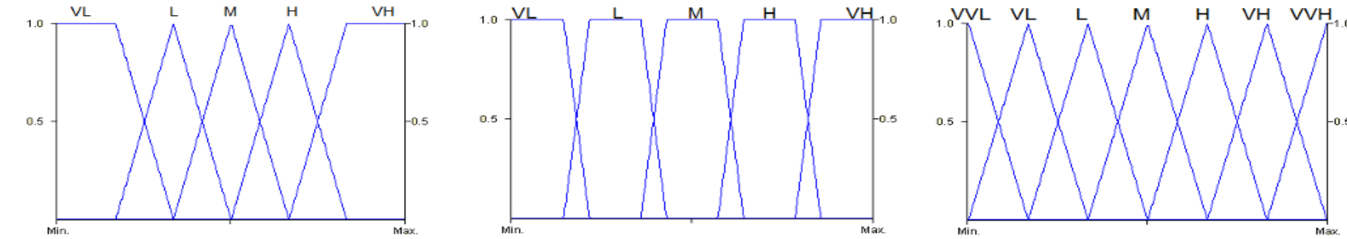
4) Development Phase 1: When $0.5 < |F| < 1$, AVOA enters the first stage of development. The parameter C_2 is randomly determined for strategy selection. According to the result of comparing C_2 and $rand_{C_2}$, the Vulture updates its position according to Eq. (9) or Eq. (12).

$$V(i+1) = \begin{cases} Eq.(9), & \text{if } C_2 \geq rand_{c_2} \\ Eq.(12), & \text{if } C_2 < rand_{c_2} \end{cases} \tag{8}$$

$$V(i+1) = |X \times R(i) - V(i)| \times (F + rand_4) - d(t), \tag{9}$$

$$d(t) = R(i) - V(i). \tag{10}$$

$d(t)$ represents the difference between the current position of the Vulture and the optimal position. Eqs. (11) and (12)



(a) Membership Functions of Number of Neighbors (b) Energy Membership Functions (c) Output functions

Fig. 2: Fuzzy ranking.

create a spiral equation between all current Vulture and one of the best Vulture for modeling the Vulture's spiral flight.

$$\begin{aligned} S_1 =& R(i) \times \Big((rand_5 \times V(i))/2\pi \Big) \times \cos(V(i)), \\ S_2 =& R(i) \times \Big((rand_6 \times V(i))/2\pi \Big) \times \sin(V(i)), \end{aligned} \tag{11}$$

$$V(i+1) = R(i) - (S_1 + S_2). \tag{12}$$

5) Development Phase 2: When $|F| < 0.5$, AVOA enters the second phase of development. It means that the dominant vultures are weak and hungry. Therefore, the other vultures will surround them and engage in quarrels and fighting amongst themselves. The parameter C_3 is randomly selected for strategy selection. According to the result of comparing C_3 and $rand_{C_3}$, the Vulture updates its position according to Eq. (15) or Eq. (16).

$$V(i+1) = \begin{cases} Eq.(15), & \text{if } C_3 \geq rand_{c_3} \\ Eq.(16), & \text{if } C_3 < rand_{c_3} \end{cases} \tag{13}$$

When the energy of a Vulture is insufficient, its hunger increases, and it competes for the same prey. Eqs. (14) and (15) model this behavior.

$$\begin{aligned} A_1 =& BestVulture_1(i) - |X \times R(i) - V(i)| \times F, \\ A_2 =& BestVulture_2(i) - |X \times R(i) - V(i)| \times F, \end{aligned} \tag{14}$$

$$V(i+1) = (A_1 + A_2)/2. \tag{15}$$

At this time, other Vultures compete with it and move in different directions for hunting. This behavior is modeled as in Eqs. (16) and (17).

$$V(i+1) = R(i) - |d(t)| \times F \times Levy(d), \tag{16}$$

$$Levy(d) = 0.01 \times (u \times \sigma)/(|v|^{\frac{1}{\beta}}). \tag{17}$$

$Levy$ is a probability distribution function used to generate random values that can further explore the search space. $Levy(d)$ is used to enhance the efficiency of AVOA. In Eq. (17), d represents the problem dimension, u and v are random values in the range $[0, 1]$, and β is a fixed default value of 1.5.

IV. Proposed Approach

In this section, a proposed protocol is presented that includes two main phases of clustering and routing. The clustering phase includes sub-sections of ranking, configuration, and stability. Initially, node information is collected at the base station, and the controller ranks them based on their remaining energy and the number of neighbors using a fuzzy system. Then, using the AVOA algorithm and a fuzzy objective function, the final clusters are selected based on the distribution criteria and cluster balance. Subsequently, the base station broadcasts a message to all nodes. After receiving information about the clusters, nodes connect to their nearest cluster in the stability phase to deliver information to their respective clusters. In the stability phase, sensor data is collected and sent to the clusters, and after accumulating the information, clusters prepare them for transmission to the base station. The transmission of information from the clusters to the base station is done through intermediate nodes and in a multi-hops manner using a routing algorithm.

It is assumed that nodes are randomly scattered in the environment, and after the nodes are deployed, a message is sent from the base station to all nodes in the form of a broadcast, informing them of the position of the base station. It is also assumed that nodes are aware of their own location. The nodes are considered stationary during the simulation and all have the same initial energy.

A. Fuzzy Ranking

Initially, the nodes are ranked using a fuzzy system with two inputs: the number of neighbors and the energy of the node. Fig. 2 (a) shows the membership functions for the number of neighbors, and Fig. 2 (b) shows the membership function for the energy. The higher the energy and the number of neighbors, the more deserving a node is to become a cluster head. The node characteristics are given as inputs to the fuzzy system, and the degree of membership for each of the fuzzy variables is calculated. Then, using the total set of rules specified in Table II, fuzzy inference is performed and the output of the system is determined in the form of fuzzy variables with different degrees of membership. The output membership function, which models the output fuzzy variables, is shown in Fig. 2 (c). These variables indicate the level of eligibility of a node to become a cluster head. The fuzzy variables are mapped to a numeric value between zero

TABLE II: The set of Ranking Inference Rules

Energy \ Neighbors	VL	L	M	H	VH
VL	VVL	VVL	VL	VL	L
L	VVL	VL	VL	L	L
M	VL	VL	M	H	H
H	L	L	H	VH	VH
VH	L	M	H	VH	VVH

and one for better use. The closer the obtained value is to one, the more deserving the node is to become a cluster head.

$$Z = (X_i - X_{min})/(X_{max} - X_{min}). \tag{18}$$

It should be noted that all numerical inputs are mapped to the range of zero to one using Eq. (18) and then given to the fuzzy system.

B. Improved AVOA Algorithm

We have developed the AVOA algorithm for the custom clustering problem. For this purpose, we introduce two new operators to improve the accuracy of clustering and create optimal clusters. By optimal clusters, we mean balanced clusters. The operators used to improve AVOA are based on the social life of animals and competition among them in mating and survival. To do this, we consider each cluster as a *Vultures-leader* that leads other Vultures (IoT devices) in the cluster. The leader receives power from its group members and competes with neighboring leader Vultures to find better positions. If a *Vultures-leader*'s power is less than a threshold, it is dethroned, and its members connect to neighboring leaders. The power of the *Vultures-leader* is calculated as:

$$Pow_i = nc_i \times (E_i/E_{avg}), \tag{19}$$

where nc_i represents the number of members in cluster i. E_i is the current energy of the Vulture-Leader node i. E_{avg} represents the average energy of Vulture-Leader nodes. If the power of a Vulture is less than the normal power, it loses its legitimacy. Therefore, the threshold for removing the leadership of a Vulture is calculated by Eq. (20).

$$Th_1 = \overline{Pow}_{init}/\alpha, \tag{20}$$

$$Pow_{init} = (N_{alive}/K) \times (E_i/E_{avg}), \tag{21}$$

where Pow_{init} represents the initial and essential power for leadership. N_{alive} indicates the number of alive nodes, and k represents the total number of leader Vultures. The value of k can be obtained based on the formula in Eq. (22).

$$k_{opt} = (\sqrt{N/2\pi}) \times (\sqrt{\epsilon_{fs}/\epsilon_{mp}}) \times (M/d^2_{toBS}). \tag{22}$$

The next operator is performed based on the clustering of Vulture groups. When the number of cluster members exceeds the threshold, the cluster is divided into two separate clusters, and the Vultures will compete with each other for leadership. The threshold for dividing a group is calculated based on:

$$TH_2 = \beta \times \overline{X}. \tag{23}$$

Algorithm 1 IAVOA-Fuzzy

Input: Whole network information, k_{opt}, IAVOA parameters.
Output: Clusters Heads and Routes.

```
Calculate k_opt by Eq.(23).
Rate all IoT devices by Fuzzy-Ranking.
Set a probability for each IoT device based on the rate.
Cluster-Heads = IAVOA(Input)
Routes = FuzzyRouting(Input, Cluster-Heads)
return Clusters Heads and Routes =0
```

Algorithm 2 IAVOA

Input: Whole network information, k_{opt}, IAVOA parameters
Output: Clusters Heads

```
Generation initial population.
while (stop condition not reached) do
    Calculate LB and LD for individuals.
    Evaluation vultures by Fuzzy-Clustering.
    Set V_FirstBest and V_SecondBest by Eq.(1).
    for (each vulture(V_i)) do
        Calculate p_i and F
        if (|F| ≥ 1) then
            Update V_i by Eq.(6) or Eq.(8).
        end if
        if (|F| ≥ 0.5) then
            Update V_i by Eq.(10) and Eq.(13).
        else
            Update V_i by Eq.(16).
        end if
        Extract leaders from V_i.
        for (each leaders(L_j)) do
            Calculate Pow_j.
            if (Pow_j < Th_1) then
                Remove L_j.
            end if
            if (Pow_j > Th_2) then
                Generation L_j.
            end if
        end for
    end for
end while=0
```

Algorithm 3 Fuzzy-Routing

Input: Whole network information, k_{opt}, Cluster-Heads.
Output: Routes.

```
Cluster Heads=V_FirstBest.
for (each Cluster-Heads(CH_i)) do
    for (each CH_j ∈ Neighbours CH_i) do
        Calculate fitness_j by Fuzzy-Routing (Sec.4-5).
    end for
    CH_i^{Next-Hop}=max(fitness)
end for=0
```

In the case of removing the leadership of a Vulture and dividing the cluster, a leader is assigned to each new cluster. The criterion for competition to gain leadership among cluster members is based on the remaining energy of the node.

TABLE III: The set of clustering rules

LB \ LD	VL	L	M	H	VH
VL	VVH	VH	H	M	L
L	VH	VH	H	H	L
M	H	H	M	L	VL
H	M	M	L	VL	VVL
VH	L	L	VL	VVL	VVL

TABLE IV: The set of inference rules

Energy \ Dist2BS	VL	L	M	H	VH
VL	L	L	VL	VL	VVL
L	M	L	L	VL	VL
M	H	M	M	M	L
H	VH	H	H	M	M
VH	VVH	VH	H	H	M

C. Fuzzy Clustering - IAVOA

The final clustering is performed using the improved binary AVOA algorithm and a fuzzy objective function. For this purpose, the initial population is created based on the ranking performed in the previous step. In other words, the higher the node's fitness, the higher its chance of being selected. Eq. (24) shows the probability function. The initial population is formed based on the probability function and using the roulette wheel selection according to Eq. (2).

$$PS_i = \begin{cases} FS(Energy, NoNeighbours) & \text{if } E_i > 0 \\ 0 & \text{else,} \end{cases} \tag{24}$$

where PS_i represents the probability of selecting node i. FS is the output of the fuzzy system that determines the degree of fitness of node i. In the objective function, clusters are formed based on the centroids selected by the population. Then, two criteria for cluster distribution and balance are calculated based on Eqs. (25) and (26).

$$LD = \sum N_{uncovered}/N_{alive}. \tag{25}$$

LD represents the number of nodes without a cluster. N_{alive} represents the number of alive nodes. The smaller the value of LD, the better the distribution has been done. LD always has a value between zero and one.

$$LB = \sum |X_j - \overline{X}|/(\alpha \times N_{alive}), \tag{26}$$

where $\overline{X} = N_{alive}/k$ represents the number of members in cluster j, and k indicates the number of clusters. The smaller the value of LB, the better the balance between clusters will be. To ensure that LB always has a value between zero and one, we have used the coefficient α. The fuzzy system used in the objective function has two inputs that receive the distribution and balance values of clusters and determine the fitness of a chromosome. The membership functions of these criteria are similar to Fig. 2 (a), and the rules used are also considered in Table III. Each cell in the table indicates a rule. For example, the second row and the second column of Table III shows that if the value of LB is equal to L and the value of LD is equal to L, the fitness will be equal to VH.

The goal of the proposed method is to reduce the number of nodes that are left without a cluster. However, there may be a very small number of nodes without a cluster in each round. To manage these nodes, three different approaches are available. The first approach is to turn off the node during the rounds in which it is left without a cluster. This method will result in losing information. The second approach is multi-hop routing within the cluster, in which the data node sends its data to the nearest node connected to the cluster. The third approach is to use the transmission to the base station directly, which increases energy consumption. This method pays more attention to energy and also prevents packet loss. Therefore, the intra-cluster routing method is also used here.

D. Routing Phase

Since energy consumption is directly proportional to the square of the distance, sending data through intermediate nodes significantly reduces energy consumption and increases the network lifetime. Therefore, in addition to determining the clusters, the controller is responsible for determining the path for each cluster. To do this, the next step for each cluster needs to be identified. The next step should be one of the selected clusters in the previous phase. To prevent loops in routing, the intermediate node should always be closer to the source node than the base station. Among the candidate nodes, the node with more energy and a closer distance to the source node has a higher suitability for selection as the intermediate node. Therefore, the fuzzy system used in the routing section has two inputs: distance and node energy. By receiving these two inputs, the fuzzy system produces an output that represents the suitability of the node for selection as the next step.

The membership functions for distance are similar to the shape in Fig. 2 (a) and the membership functions for energy are similar to the shape in Fig. 2 (b). The total rules used in Table IV are provided. The output membership function that models the fuzzy output variables is similar to the shape in Fig. 2 (c). It is worth mentioning that we use the center of gravity method to convert fuzzy output to numerical output.

V. Performance Results

In this section, we evaluate the performance of our proposed method in two different scenarios. We also compare our proposed method with several new methods. Since our proposed method uses a metaheuristic algorithm for solving the clustering problem, we have used related new algorithms for comparison. For this purpose, we have used BFA-ACO [27], IWO [26], ICA [32], and GA-SDN [3]. To evaluate a comprehensive simulation, it has been performed in MATLAB software under identical hardware and software conditions and was evaluated using the following performance metrics.

- Number of live nodes: indicates the number of IoT devices whose energy has not run out at any given moment in the simulation.
- Energy consumption: shows the average energy consumed by IoT devices at each moment.

TABLE V: Simulation Parameters

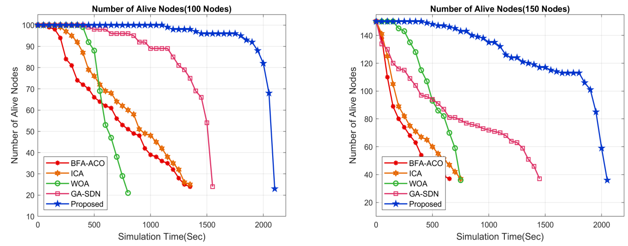
Parameters	Values
Data Pack size	4000 Bits
Hello Pack size	256 Bits
E_{fs}	$10pJ/bit/m^2$
E_{mp}	$0.0013pJ/bit/m^4$
E_{DA}	$5nJ/bit$
ETx	$50nJ/bit$
ERx	$50nJ/bit$
Initial energy	0.5 J

TABLE VI: Simulation Scenarios

Scenario	Network Area	BS Location	Number of Nodes
#1	$200 \times 200\ m^2$	$(100, 210)$	100
#2	$300 \times 300\ m^2$	$(150, 310)$	150

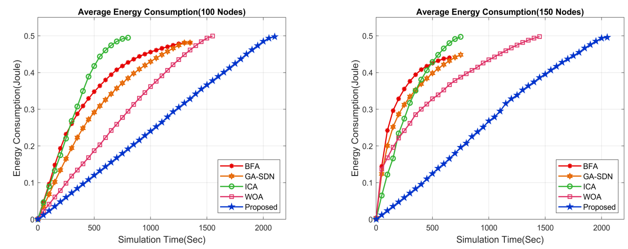
- Time of death of the first node: indicates the time when the energy of the first node runs out.
- Network lifetime: various criteria have been proposed for the lifetime of a network. Some consider the time of death of the first node, some the time when the network loses its connectivity, and some the time when the network loses 20% of its nodes as the network lifetime. Here, we use the third criterion, which is the death of 20% of the nodes, as the network lifetime.
- Packet delivery ratio: indicates the ratio of sent packets to received packets.
- Routing overhead energy: specifies the percentage of energy consumed by control packets.

Table V shows the simulation parameters for IoT devices, and Table VI presents the features of different scenarios and the position of BS. Moreover, the simulation time for all algorithms has been set equal to the time when 75% of the total nodes die. To further evaluate the parameters of first node death time, network lifetime, packet delivery ratio and energy overhead, both scenarios were implemented and evaluated with 100 and 150 nodes.



(a) Scenario 1 (b) Scenario 2

Fig. 3: Number of alive nodes.



(a) Scenario 1 (b) Scenario 2

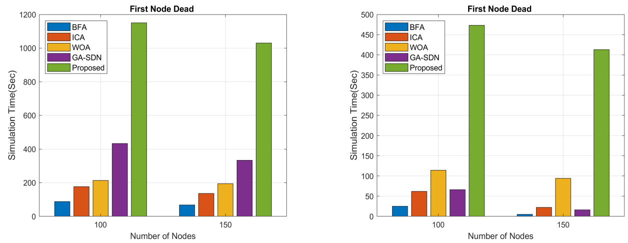
Fig. 4: Average energy consumption.

A. Results

*1) **Alive Nodes**:* The number of active nodes at any given time is a measure of network reliability and stability. If the nodes run out of energy, network cohesion and connectivity are compromised. Disruptions in network connectivity lead to loss of information as a section of the network becomes disconnected from the base station, making it difficult for some IoT devices to transfer their data. Fig. 3 illustrates this measure in various scenarios. As evident, the proposed method outperforms other methods as it takes into account the energy criterion in both the clustering and routing phases.

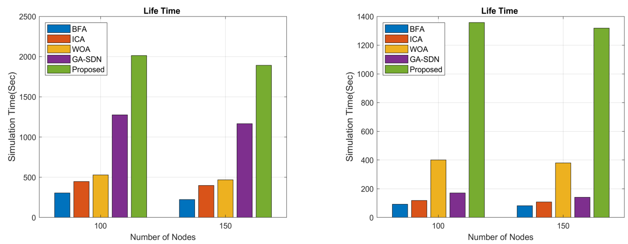
Additionally, instead of broadcasting all control packets, the proposed method sends them to the controller via the identified routes in the routing phase. Avoiding the broadcast of control packets saves energy and prolongs the lifetime of the nodes. In contrast, the BFA-ACO and ICA methods use a centralized approach for clustering and require the collection of network-wide information at the base station. These methods do not provide any mechanism for managing control packets. WOA increases the stability phase to reduce the number of control packets, but it employs asymmetric clustering, which leads to increased energy consumption in sub-clusters in large clusters. However, control traffic management has been largely addressed in GA-SDN. GA-SDN increases the stability phase as much as possible and sends control packets only during specific time periods.

*2) **Average Energy Consumption**:* One of the most significant challenges and limitations of the Internet of Things is the constrained energy resources of its devices. Therefore, reducing energy consumption is the primary motivation in designing routing protocols for these networks, as the majority of energy consumption is associated with packet transmission and reception. The average energy consumption for all IoT devices is presented in Fig. 4. According to this figure, the proposed method has better performance than the compared methods. The fuzzy system used in the ranking phase gives nodes with more energy and neighbors a better chance of becoming cluster heads. In the routing phase, the fuzzy system selects the best next hop based on distance and energy. Using a fuzzy system on one hand, and preventing the dissemination of control packets on the other hand, has led to a reduction in energy consumption in the proposed method. In the ICA, WoA, and BFA-ACO methods, energy has also been considered in selecting the appropriate cluster head. The main problem with these methods is the lack of attention to control packets. WoA attempts to reduce control packets by increasing the duration of the stability phase. However, on the other hand, increasing the radio range to reduce the number of uncovered nodes leads to the creation of asymmetrical clusters. In contrast, the proposed GA-SDN method attempts to distribute clusters uniformly in the environment to reduce the number of nodes. Additionally, the proposed method uses intra-cluster routing to retrieve data from uncovered nodes, while direct transmission or sleep/awake mechanisms are used in other methods to



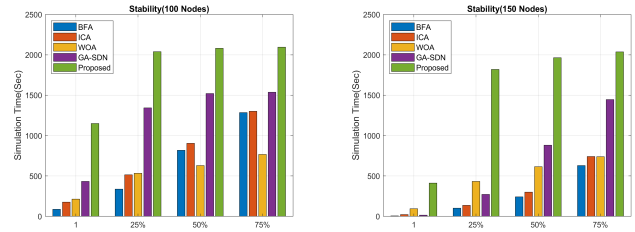
(a) Scenario 1 (b) Scenario 2

Fig. 5: Death time of the first node



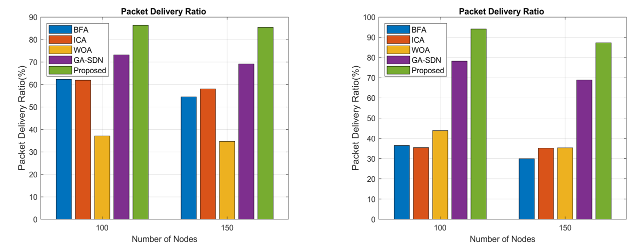
(a) Scenario 1 (b) Scenario 2

Fig. 6: Network life time.



(a) Scenario 1 (b) Scenario 2

Fig. 7: Network stability.



(a) Scenario 1 (b) Scenario 2

Fig. 8: Packet delivery rate.

manage uncovered nodes. Based on Fig. 4, GA-SDN has been relatively successful in reducing energy consumption. In this method, control packets are sent periodically, and during the cycle, if the energy of the cluster head is less than the threshold, it selects a new node as the cluster head from among the cluster members and informs other members by sending a message. This divides the tasks among the members of the cluster and prevents premature death.

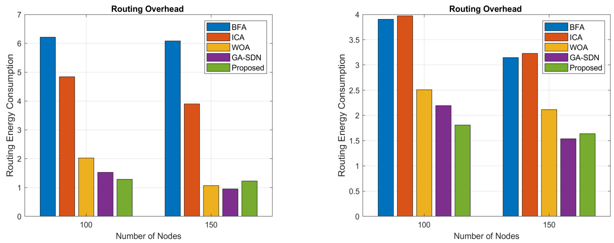
*3) **The Death Time of the First Node**:* This criterion determines whether different tasks are fairly distributed across the network or not. If a node is continuously selected as a cluster head, it consumes a significant amount of energy in collecting and aggregating data from cluster members. This will lead to the node's rapid death. Evaluation findings shown in Fig. 5 indicate that the proposed strategy is significantly better than alternative approaches because the proposed method leverages SDN architecture for selecting optimal clusters and paths. Having a comprehensive view of the network is very useful and effective in selecting the best solution. In the proposed strategy, attention to energy is one of the important criteria for selecting, which has been considered in different phases of the routing algorithm.

Additionally, the proposed algorithm selects balanced clusters using the improved AVOA algorithm, which leads to a balance in the energy consumption of cluster heads. Cluster imbalance causes a cluster with more members to consume more energy and its energy to be exhausted sooner than a cluster with fewer members. The GA-SDN and ICA methods also pay attention to cluster balance, while WOA uses asymmetric clusters. It is noteworthy that WoA is more scalable than GA-SDN in the event of the first node death. Meanwhile, the BFA-ACO and ICA methods do not perform well due to the lack of control packet management.

*4) **Network Lifetime**:* Since the death of some nodes results in the loss of network connectivity, the lifetime of the network is considered an important metric in the IoT. Fig. 6 shows the network lifetime for different algorithms in various scenarios. Additionally, in Fig. 7, we present the time of the first node death, the time of 25% node deaths, the time of half of the nodes dying, and the time of 75% node deaths. In all cases, the proposed method performs significantly better, as it prevents packet flooding. Moreover, the intra-cluster routing leads to reduced energy consumption.

*5) **Packet Delivery Rate**:* Fig. 8 displays the packet delivery rate expressed as a percentage. The proposed approach, due to its use of multi-hop routing and intra-cluster routing, prevents direct packet transmission and reduces packet loss. BFA-ACO uses the ant colony algorithm for routing, but due to the premature death of nodes, fewer packets reach the BS. GA-SDN employs greedy routing, which increases the possibility of path failure and may result in packets being trapped during routing. The WOA approach uses multi-hop data transfer to the BS, but due to the increased radio range of nodes, the likelihood of packet collision and loss is significantly increased. ICA also focuses on clustering and does not perform routing within clusters.

*6) **Routing Overhead**:* The traffic overhead determines the portion of the total energy consumption attributed to control packets. Fig. 9 illustrates the traffic overhead for different algorithms. This average energy consumption represents the transmission and reception of control packets for IoT devices and BSs. As evident, the proposed approach has been highly successful in managing control packets and preventing their indiscriminate dissemination. This has resulted in a significant improvement in energy consumption and network lifetime. SDN-based approaches are highly efficient due to the need



(a) Scenario 1

(b) Scenario 2

Fig. 9: Routing energy consumption.

for a comprehensive view to better manage the network. However, in networks such as the IoT, precautions must be taken to consider their limitations. It appears that the proposed approach has been able to address this issue.

VI. Conclusion

In this paper, we proposed an energy-aware routing mechanism for IoT environments. The proposed method leverages SDN programmability to establish optimal paths using Fuzzy logic and the IAVOA heuristic algorithm. The global view of the SDN controller is utilized to create optimal clusters in terms of energy. Comprehensive performance evaluation showed that implementing the proposed method as a routing module in the SDN controller is a feasible solution for IoT environments, leading to improved energy efficiency and QoS. Future work could explore the scalability and feasibility of the proposed method in larger-scale IoT environments.

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