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Original Article

A Fuzzy Inference System and Elephant Herding Optimization for Increasing Survivability in Wireless Sensor Network

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Abstract *- Wireless Sensor Networks (WSNs) are networks of embedded systems that can sense and transmit data about environmental factors. These sensors, sometimes called as sensor nodes, have a number of drawbacks, including limited data processing capabilities and, most critically, low battery energy. As a result, one of the major challenges in WSNs is developing techniques, hence increasing the networks' survivability. Based on Fuzzy Inference Systems and Elephant Herding Optimization (EHO), this study provides a new way to assist In order to choose the optimum route, multi-path routing protocols are used. The Fuzzy System determines the low survivability level among the nodes that make up the route and is used to determine the degree of route performance. A comparison is made with various Ant colony methods, such as Relay clustering-based algorithms that have already been investigated on the same topic. Our proposed algorithm, EHO, can obtain more consistent and precise locations, according to simulation findings. The EHO algorithm is used to modify the fuzzy system's rule base in order to improve the route's identification strategy and network survival. The simulations demonstrated that the approach is beneficial in terms of Network Survivability when compared to alternative methods, the number of receiving data, and the cost of information received.*

Keywords *- Routing, Fuzzy inference systems, WSN, Elephant Herding Optimization, Sensor.*

1. Introduction

A ground station and a node form a Wireless Sensor Network (WSN), heat and other physical environmental factors are monitored by these networks, light, pressure, and sound, and then send data to a central location over the network. Wireless modems and reduced Radio Frequency (RF) designs are being developed. Frequently used in sensor nodes as well as national security, Wireless Sensor Networks (WSNs) have already piqued interest due to their widespread application in monitoring systems, mass transit, and disaster recovery [1, 2]. The WSN differs from traditional networks in several respects, such as the fact that it consists of a large number of nodes, each with limited power, processing capacity, and memory for wireless sensor networks; we adopt a fuzzy-based technique to save energy. We must calculate the eligibility index of each node in a fuzzy-based approach, and then find the threshold value after that shown in Figure 1.

A Wireless Sensor Network (WSN) is a network infrastructure comprised of many small, reduced sensors and autonomous devices known as sensor nodes that monitor and detect the surroundings in order to assemble data [3]. The installation of WSNs faces several obstacles, including node localization, coverage, sensor node energy usage, data routing issues, and so on. Despite all of these concerns and challenges, the most pressing is establishing the location of sensor nodes. The positions of all sensor nodes must be known and valid in order to enable data to be collected from the surroundings properly. This is due to the fact that fuzzy inference systems have the potential to Qualitative information that can be expressed and analyzed in a variety of ways. Fuzzy inference techniques are used in this paper to Examine some of the sensor network's properties, such as power and hop speed, to choose the best-suited sink node. The variables and their enrollment functions are described in the fuzzy database, and the fuzzy rule base stores the text syntax of all fuzzy steps.

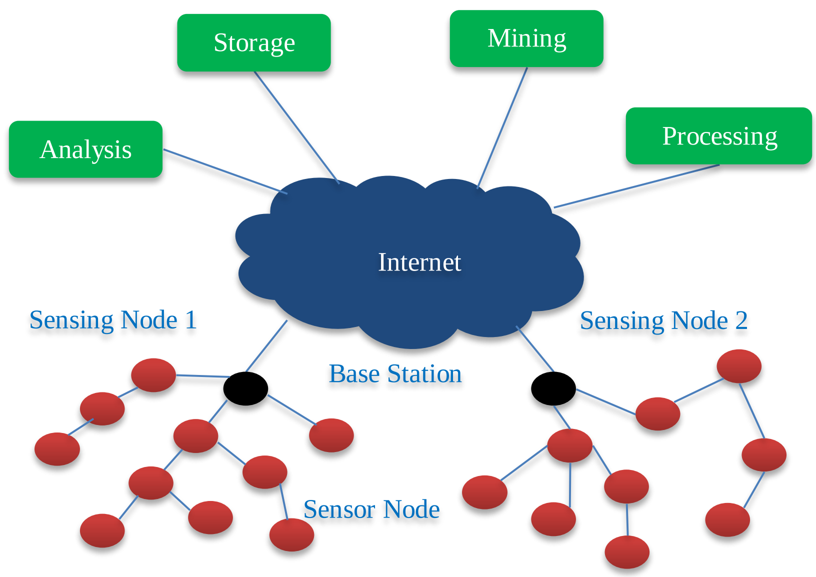

Fig. 1 Wireless sensor network architecture

The identified data, interest, gradient, and reinforcement elements all play a role in the execution of the procedure for directed diffusion. The information is labelled with a pair (feature, quantity) and reflects a detected event by the sensor nodes. The network is credited with the hunt for the natural environment. The gradient is a pointer that points to the sink node's backward direction. Depending on the network configuration, one or more sink nodes can send out interest signals. As a result, this study will focus on the In order to lengthen the wsn's lifetime, as well as the power and load on the sensor nodes, must be lowered. To achieve the desired result, a load of sensor nodes must be uniformly distributed. The suggested technique spreads the load across nodes with more processing and communication capacities. WSN [4-6] is a network of smart sensor nodes that gather data from a variety of sources and send it to a base station for processing analysis. It also adds to the amount of data that users must download for analysis.

This project aims to use a fuzzy inference rule-based mechanism to assist the directed diffused routing protocol in determining the best route for communications between any nodes in the network. The rule base holds the behaviour strategy applied to the fuzzy system. Depending on Fuzzy Logic - based Systems and Elephant Herding Optimization (EHO), to assist inter-routing mechanism in choosing the best route. It will increase the survivability of the network.

2. Related Work

Many studies regarding the use of fuzzy logic techniques in wireless sensor networks to increase survivability will be discussed here.

Brante, G. et al. [1] proposed a paper Innovative Relay selection technique based on fuzzy logic aimed at both the lifetime of the network and final throughput. The approach takes into account the relay-destination link's channel condition as well as the battery's residual energy. It is shown that the suggested technique can transfer a bigger amount of data over the network's lifetime.

Van, N.T., et al. [2], a paper proposed for sensor networks, a power strategy fuzzy-based is being developed to not only lengthen network lifetime but also improve data transfer efficiency. The suggested protocol is shown to be better energy efficient than existing protocols already in use using OMNeT++.

Leal, L.B. et al. [3] proposed routing decisions in WNSs with an evolution fuzzy system (GFS) used to connect many sensing and sink nodes. To demonstrate the viability of the implementation of this system, route selection was used in conjunction with computer simulations.

Beitollahzadeh J.et al. [5] proposed a power routing system that is used to reduce power usage while uniformly spreading power consumption among devices using a fuzzy neural network (ERFN). This study extends the lifetime of the WSN by creating fuzzy rules, sets, and class labels to calculate next-hop selection decisions based on overall remaining energy.

Leal, L.B. et al. [6] proposed and introduced a new algorithm based on a method enabling energy-aware routes in sensor networks, which enables us to save energy and prolong the life of the network. The approach we suggest raises the mean residual energy. In the same settings, LEACH and LEACH-C were compared.

Pattnaik, S. and Sahu, PK [18] proposed a base. Only a specified circular course can be followed by the facility, making it more practical. The simulation findings are compared to those of a static base station method. The mobility of the ground station employs fuzzy logic, and this technique has proven to be effective in increasing the base station's duration.

Kamgueu, P.O. et al. [19] proposed a Segment approach based on Advanced Neuro-Fuzzy Inference Engine Swarm Optimisation and the combination Moth-Flame Cuttlefish Optimal (MFO-CFO) approach. It is proposed for WSN routing efficiency.

Rabelo, RA, et al. [11] proposed that to aid the Directed Diffusion routing protocol; fuzzy systems are being Route quality is estimated using this method. Depending on the number of hops and the distance travelled the fuzzy approach is used to determine the degree of route efficiency metabolic rate of the hubs that make up a route.

Juang, CF and Bui, T.B., [12] proposed in the RNFS-MEO that the colony of FCs is maintained until a colony of effective FCs is found, based on RNFS parameter estimates or objective function values following genuine evaluations.

Shen, Y. and Ju., [13] proposed a cluster heads are chosen using a fuzzy logic technique. The cluster heads are picked using three fuzzy numbers: chance, distance from the ground station, and the sum of lengths between the node as well as the other node.

3. Proposed Method

This paper provides a fuzzification system to help the directional diffused routing protocol figure out the optimum path for connection between any devices in the system. Based on Fuzzy Inference Systems and Elephant Herding Optimization (EHO). This research provides a new method for assisting multi-way routing protocols in selecting the best path. The Fuzzy Systems are used to assess path reliability. A comparison was done with other Ant colony approaches, such as Relay clustering-based algorithms, that have previously been studied on the same subject. The EHO methodology is used to increase the route's methodology and, hence, the network's survival by modifying the fuzzy system's rule base. The simulations demonstrated that the approach is effective in terms of Network Survivability, number of receiving data, and cost of knowledge and help when compared to other existing methods (Figure 2).

Configured data can be used to depict exceedingly complicated procedures, and fuzzy inference systems can handle them. The majority of the time, fuzzy inference is applied. In which fuzzy option is used as well as fuzzy logic to supply the required information, a mathematical foundation for dealing with qualitative data information, as well as the laws of linguistic.

3.1. System of Fuzzy Inference

A fuzzy inference system usually consists of four parts (Figure 2).

3.1.1. Interface for Fuzzification

The fuzzification interface is in charge of converting the numerical input vector to the fuzzy domain, which represents the allocation of nominal attributes (main terms) to the input variables using membership function parameters.

3.1.2. Base of Knowledge

The database and the number of rules are the two components that makeup knowledge and understanding. The similarity measure linked with each major word, as well as the main terms for each variable investigated in the rule base, are stored in a database. The rule is made up of language rules that establish influence strategy and choice procedures. The fuzzification system's findings are generated by the rule base, which performs the mappings from the input data to the output sphere (Figure 3).

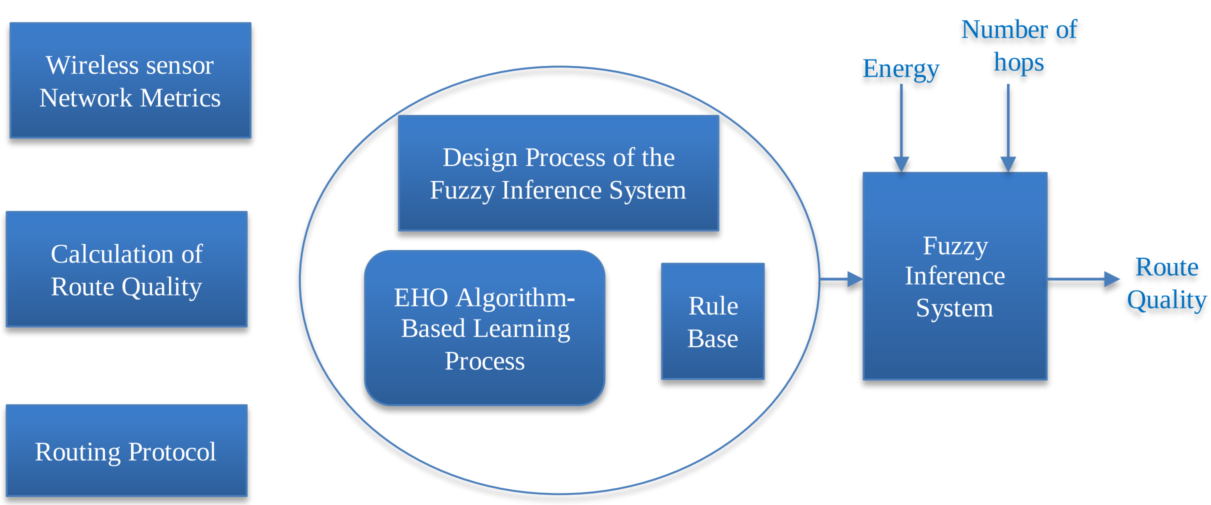

Fig. 2 Overall block diagram of fuzzy inference system

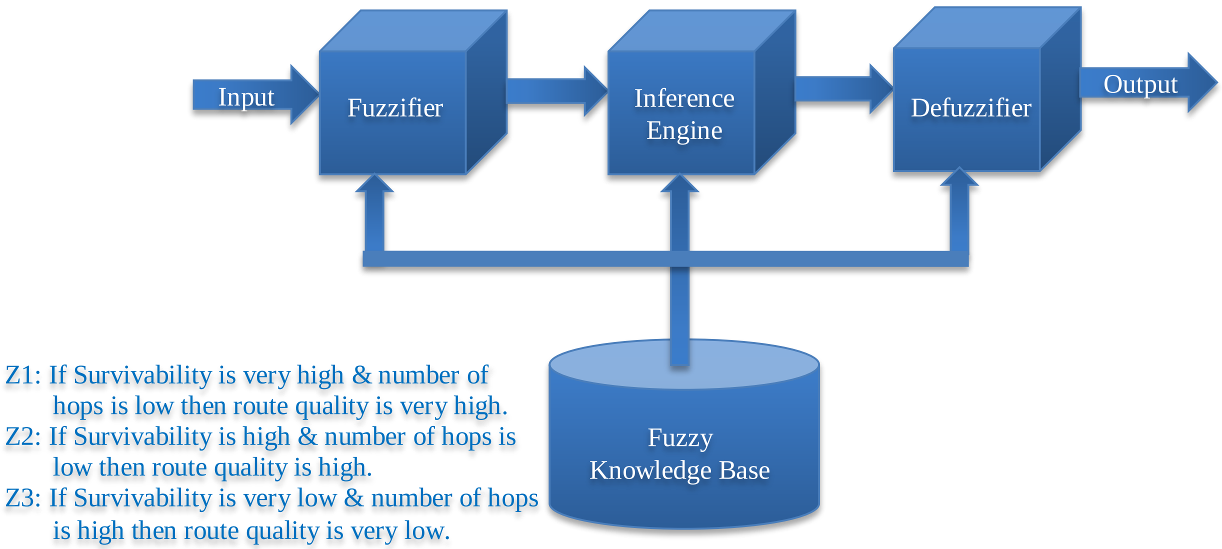

Fig. 3 Architecture of fuzzy inference system

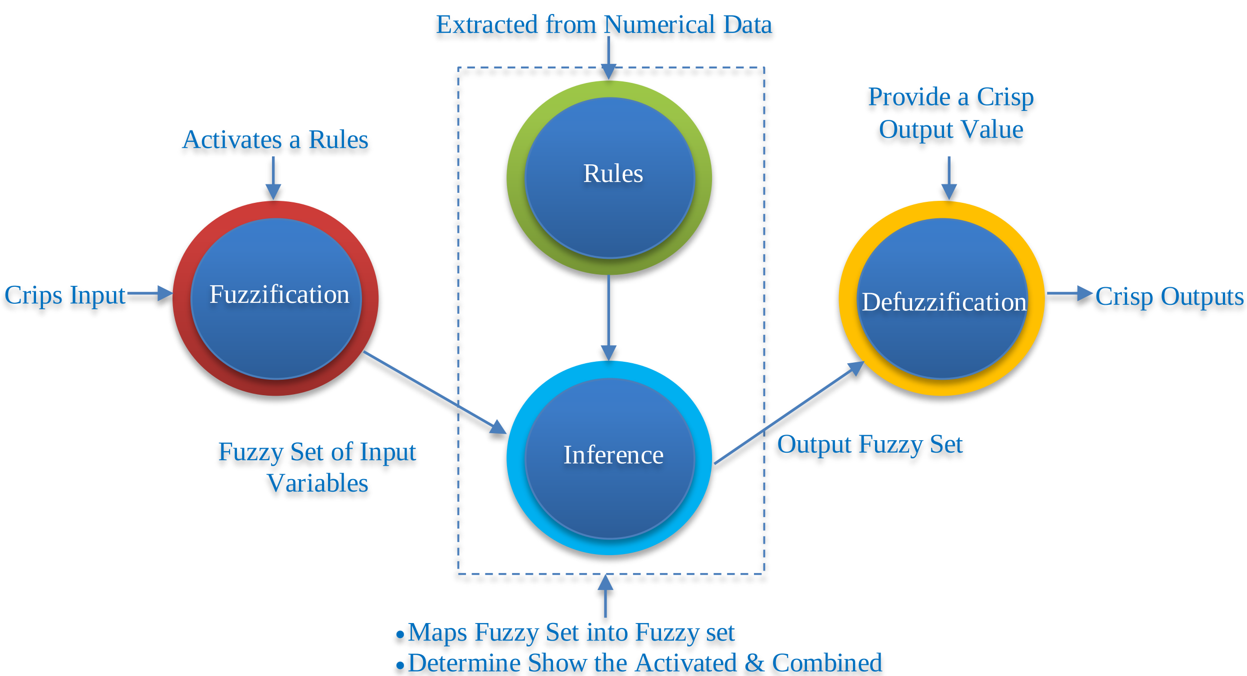

Fig. 4 Fuzzy inference system design process

3.1.3. System of Inference

Evaluating the main terms of the input parameters using the rule base's language production rules in order to get the inferences system's fuzzified value. As a result, the fuzzified performance is a measure of the provided rule base.

3.1.4. Interface for Defuzzification

Consists of assigning value to the resulting fuzzy value. As a result, feature reduction can be thought of as a numerical value-based synthesizing of the final fuzzified set.

3.1.5. Design Process of Fuzzy

The lower survival and/or related with a sensor network along a predefined route and the number of sensor nodes required to convey the message to the sink node are the two input variables for the suggested fuzzy reasoning system. For each partition, the partition's meaning is uncertain. The nodes that should receive data are defined by gradients connected to the interests that have been disclosed, and then there is the sink node that receives inputs in the form of reward events, which are transmitted at a slow rate. It goes along a number of different paths before deciding on one. One of these pathways increases the rate of transmission for the activity to be notified via this method at a later time increased rate of transfer (Figure 4).

3.1.6. Directed Diffusion

Sensor networks in the property slope to each interested received data after broadcasting the interest signal, building as shown in Figure 5, there are pathways between the sink and the multiple data node. The directional diffusion protocol interacts with dynamic networks through a trading system that uses the to allow the network to converge before any topological changes, and the attention and incentive paths should be spread out. The sink node sends an interesting message over the network including the wishes to receive named data (variable, values) from data at this initial moment.

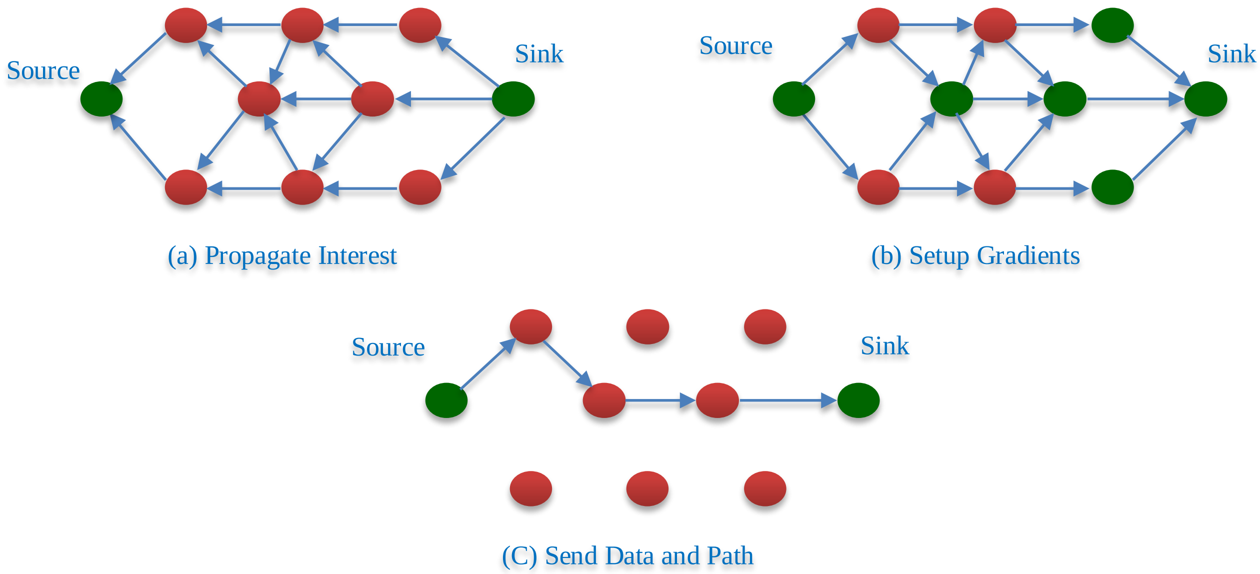

Fig. 5 Directed diffusion

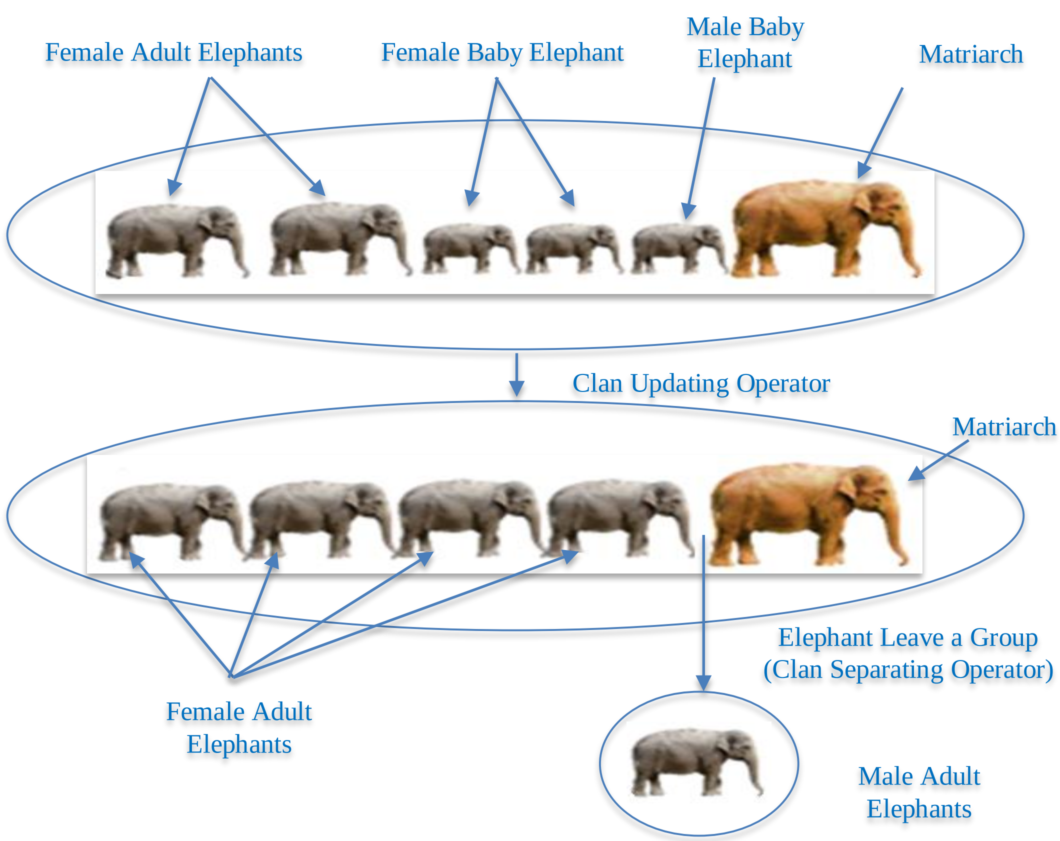

Fig. 6 EHO generation

3.2. Elephant Herding Optimization

The EHO method is a metaheuristic optimization focus of this work derived from natural elephant herding behaviour modelling, which is basically an SI technique. The following is a summary of this particular behaviour shown in Figure 6.

Elephants are divided into elephant are divided into clans, each of which possesses a number of elephants. Each clan is led by a matriarch, with a small number of mature male elephants leaving the herd to live independently.

3.2.1. Elephants' Herding Behaviour

Elephants have more social structures, are larger, and have a more regimented personality. Elephants live in groups, such as a mother elephant and her calves or a group of related woman elephants. The tribe is the name given to this group. The matriarch is indeed the clan's leader.

Evenly spaced circles are formed by an elephant herd led by a matriarch. Male elephants prefer to live alone and separate from their parents as they grow up, but female elephants prefer to remain in a family group. Following his departure, the male elephants form a small group with a few other male adult elephants.

3.2.2. Clan Updating Operator

According to the elephant's behaviour, each clan has a matriarch who leads the elephants. The elephant j in clan zp may be computed using the updated position of each elephant zp (1).

$$Q_{new,zp,k} = Q_{zp,k} + \alpha \times \left(Q_{good,zp} - Q_{zp,k}\right) \times y \qquad (1)$$

The new and existing positions for elephant k in clan zp are represented by $Q_{new,zp,k}$ and, $Q_{zp,k}$ respectively. $Q_{good,zp}$ is the matriarch of the clan, and she represents a good elephant. A scale factor, y ∈ [1,0], is indicated by α ∈ [0,1]. Equation (2) can be used to determine the optimal elephant for each clan.

$$Q_{new,zp,k} = \beta \times Q_{medium,zp} \qquad (2)$$

Where, β ∈ [1,0] is a component that defines the $Q_{medium,zp}$ on $Q_{new,zp,k}$ .The new member is $Q_{new,zp,k}$ Clan zp's medium member is $Q_{medium,zp}$. Equation (3) can be used to calculate it for the d-th level.

$$Q_{medium,zp,r} = \frac{1}{n_{zp}} \times Q_{zp,k,r} \qquad (3)$$

Where, 1≤ $r \leq R$ and n_{zp} Estimate how many elephants are in a clan zp, $Q_{zp,k,r}$ represents r th dimension of the elephants' individuals $Q_{zp,k,r}$. $Q_{medium,zp,r}$ it is the zp clan's epicentre, and the equation can be modified (3).

3.2.3. Separating Operator

When tackling optimization problems, the separate process by which male elephants depart their family group can be modelled as a separation operator. As seen in an equation, trying to separate the elephant with the weakest athleticism in each production is integrated as the operators (4).

$$Q_{low,zp,} = Q_{min} + Q_{max} - Q_{min} + 1) \times pan \qquad (4)$$

Where, Q_{max} denotes the individual's upper bound and Q_{min} denotes the individual's lowest bound. $Q_{low,zp,}$ denotes the worst member of clan ci. Pan [1,0] is a probabilistic range with values ranging from 1 to 0.

The foundation of EHO is summarised based on the descriptions. In Figure 7, the tribal operator and the separation operator are both members of the clan-updating operator. The flowchart that corresponds is as follows.

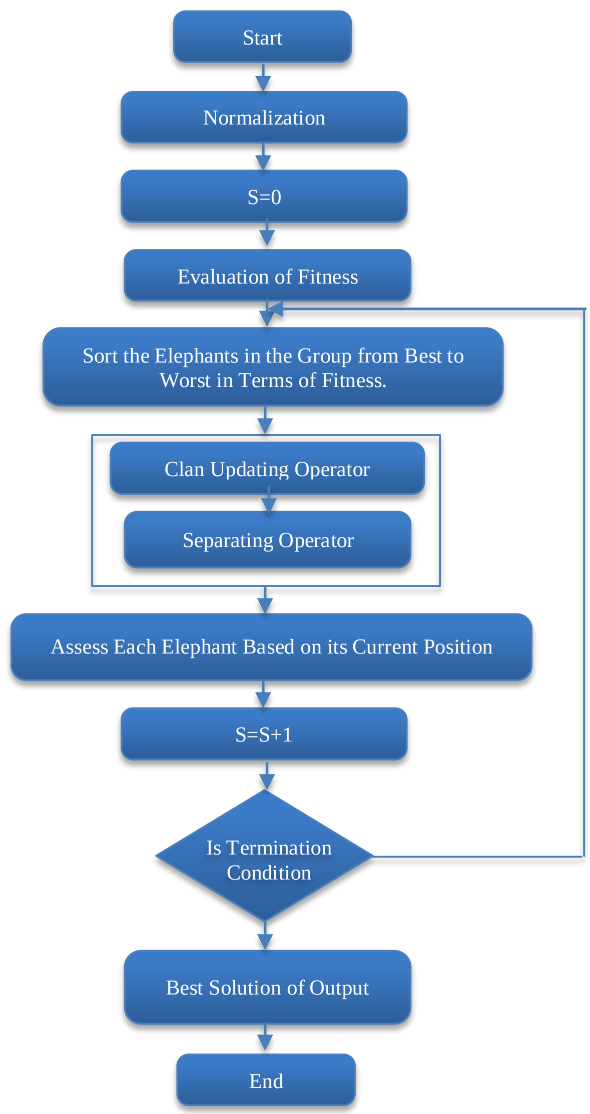

Fig. 7 Flow chart of EHO Algorithm

Algorithm 1. Elephant herding optimization

Start

Normalization. Set the number of iterations S=1, the population to P at random, and the maximum growth to MaxGrow.

While doing something, if the stopping requirement is not satisfied.

Sort division into groups based on individual ability.

for zp performs over all clans.

for something for elephant k in the clan zp.

for Equation generates $Q_{new,zp,k}$ and updates$Q_{zp,k}$ (1).

if $Q_{new,zp,k} = Q_{good,zp,k}$ then

Generate $Q_{new,zp,k}$ and update $Q_{zp,k}$ by Equation (2).

end if

end for

end for

for all clans, zp do

Equation is used to replace the lowest individual zp (4).

end for

Evaluate each elephant based on its present position.

H = H + 1.

end while

end.

4. Results and Discussions

The Sinalgo simulators have been utilized to test the applicability of the proposed technique. Sinalgo is a Java framework that enables the simulation of wireless networks by extracting the protocol stack's lowest layers.

The proposed method compares to the fuzzy inference system-based directed diffusion and directed diffusion routing, both of which were manually built. With a topology of 11×11 sensor nodes, the simulated situation was created to give a didactic understanding of the proposed algorithm. The original energy Survivability storage system was assumed to be equal to 1 to 0.

Since the cost of survivability usage is associated with fuzzy processes because sink hubs are not fuel-limited, the cost of survivability usage related to fuzzy processes is not taken into account (defuzzifier, inferences, and fuzzified).

At all sensor nodes, the cost of collecting, processing, and sending communications, on the other hand, is taken into account.

Approach (DD-EHO-Fuzzy) to the manual methods DD (directed dispersion) and DD-Fuzzy, the authors employed the following four metrics: the amount of collected signals, survivability rises, number and information obtained vs. time simulation, and the cost of receiving a message (directed diffusion with fuzzy).

The quantity of incoming messages vs the time simulation recorded in rounds refers to the number of information received (time scale of the simulator). After transmitting the leftover signals to the sink node survival checks how much is left in the sensor network.

The cost of new messages is calculated as the ratio of wasted resources to the number of received messages in the sink node. The number of accepted signals into the sink node utilizing the suggested approach in this work is more than the DD and DD-Fuzzy approaches, as shown in Figure 8.

In this way, the suggested technique. In the same period of time, increase the quantity of messages sent. This means that you can send as many texts as you like benefits the sensor nodes' scarce funds.

The time required for the other methods to have the same quantity of signals as the DD-EHO-Fuzzy is shown in Figure 9, which compliments Figure 10. During the simulation, the suggested approach delivers a greater total the least quantity of messages sent to the sink nodes amount of time to receive a particular message.

The proportion between the spent power and the amount of accepted messages into the sensor nodes is the cost of incoming messages. With the DD-EHO-Fuzzy technique, the remaining survivability of the size of the sensor nodes once they send signals from the sink node is larger, as shown in Figure 10.

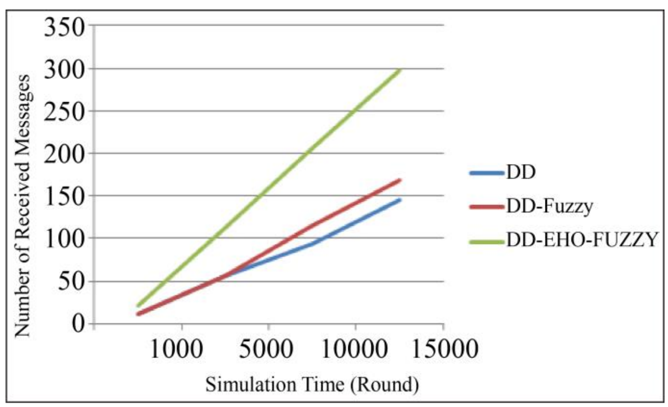

Fig. 8 The number of received messages is a function of time in the sink node

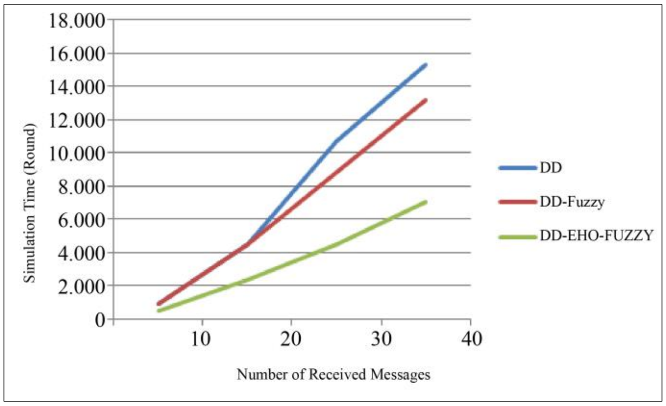

Fig. 9 Required simulation time for a certain amount of received messages

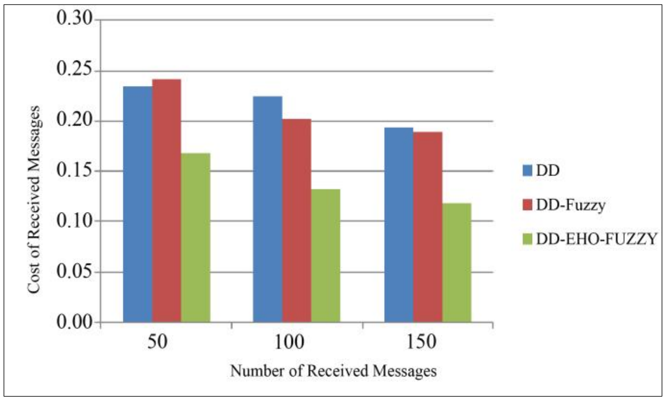

Fig. 10 Incoming message costs

This is accomplished because the suggested method ensures a high delivery performance by intelligently choosing the route with the fewest base. The sensors show that residual survival is greatest along the path. As a result, the routing protocol relies on information such as route quality, which is calculated depending on the number of hops and sensor node residual survivability. When network circumstances (metrics) change, the route quality changes as well. Any changes in the fuzzy level of the sensor nodes, for example, this modification improves the route quality's reliability.

When comparing the DD-EHO-Fuzzy technique to the directed diffusion and direct diffusion fuzzy approaches, Figure 10 indicates that the cost of incoming messages increases performance by around 89% when employing the DD-EHO-Fuzzy approach. As a result, the suggested technique achieves the lowest price for information transmission. This suggests that the highest level of survivability will be available, resulting in the wireless sensor network's longest life period.

As a result, the proposed approach achieves the lowest cost for message communication. This means that the maximum amount of survivability will be accessible, resulting in the longest possible life for the wireless sensor nodes.

Table 1. The survival method is compared (N=10-150)

Node	RNFS-MEO	OMNeT++	MFO-CFO	DD-ACO-FUZZY	DD-EHO-FUZZY
10	11.77	22.25	34.5	45.5	82.8
50	41.11	30.01	51.42	70.56	88.5
100	20.56	32.14	33.4	77.55	84.25
150	40.77	55.33	60.11	55.12	82.47

Table 1 compares certain parameters between prior approaches and the EHO method now in use. When the values are compared, we may conclude that the DD-EHO-FUZZY approach is superior to other ways, as shown in Table 1.

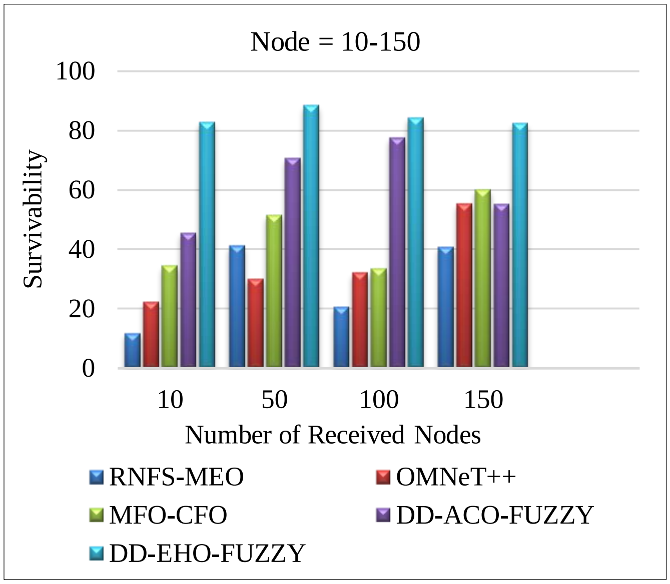

Fig. 11 The performance of survival in the method is compared (N=10-150)

The performance of the various nodes' survivability is increasing at various time intervals, as shown in Figure 11. When the nodes are 10, 50, 100, 150, the survivability performance is determined. When compared to the RNFS-MEO, OMNeT++, MFO-CFO, and DD-ACO-FUZZY, the suggested DD-EHO-FUZZY consumes a 20.15 percent increase in survivability performance.

Table 2. The survival method is compared (N=200-350)

Node	RNFS-MEO	OMNeT++	MFO-CFO	DD-ACO-FUZZY	DD-EHO-FUZZY
200	44.2	32.5	33.4	60.12	85.55
250	20.12	40.52	44.14	70.8	84.5
300	15.12	60.15	50	79.45	88.7
350	22.45	44.7	32.15	56.22	80.01

Table 2 compares certain parameters between prior approaches and the EHO method now in use. When the values are compared, we may conclude that the DD-EHO-FUZZY approach is superior to other ways, as shown in Table 2.

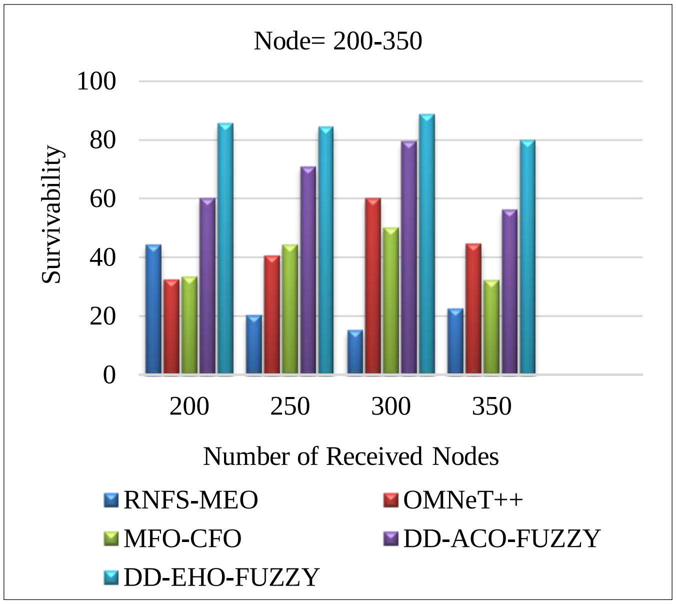

Fig. 12 The performance of survival in the method is compared (N=200-350)

The performance of the various nodes' survivability is increasing at various time intervals, as shown in Figure 12. When the nodes are 200, 250, 300, and 350, the survivability performance is determined. When compared to the RNFS-MEO, OMNeT++, MFO-CFO, and DD-ACO-FUZZY, the suggested DD-EHO-FUZZY consumes a 20.31 percent increase in survivability performance.

Table 3. The survival method is compared (N=400-550)

Node	RNFS-MEO	OMNeT++	MFO-CFO	DD-ACO-FUZZY	DD-EHO-FUZZY
400	41.4	50.5	36.01	55.12	80.2
450	12.55	26.2	47	65.4	85.8
500	35.5	55.7	44	72.12	85.09
550	30.2	47.4	43.4	66.4	89.77

Table 3 compares certain parameters between prior approaches and the EHO method now in use. When the values are compared, we may conclude that the DD-EHO-FUZZY approach is superior to other ways, as shown in Table 3. The performance of the various nodes' survivability is increasing at various time intervals, as shown in Figure 13. When the nodes are 400, 450, 500, and 550, the survivability performance is determined. When compared to the RNFS-MEO, OMNeT++, MFO-CFO, and DD-ACO-FUZZY, the suggested DD-EHO-FUZZY consumes a 20.75 percent increase in survivability performance.

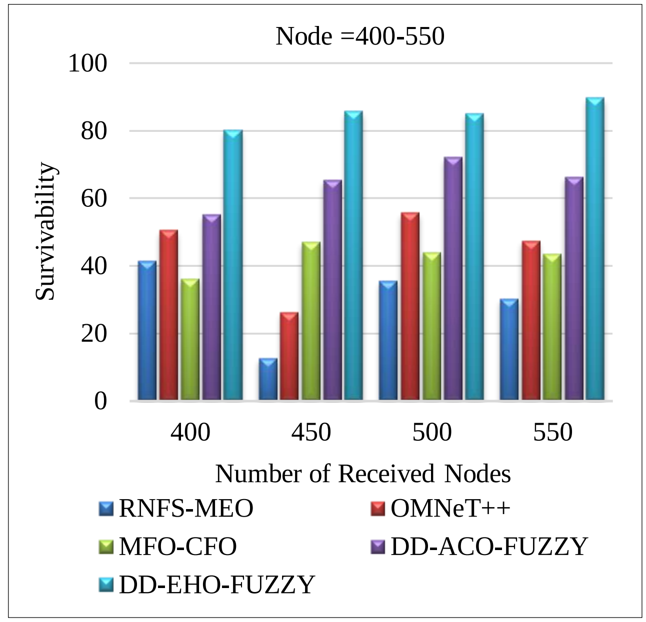

Fig. 13 The performance of survival in the method is compared (N=400-550)

Table 4. The survival method is compared (N=600-750)

Node	RNFS-MEO	OMNeT++	MFO-CFO	DD-ACO-FUZZY	DD-EHO-FUZZY
600	35.1	55.12	33.25	45.66	80
650	45.01	69.8	55.02	71	82.47
700	29.35	51	44	67.45	87
750	30.22	60	42	54	80.15

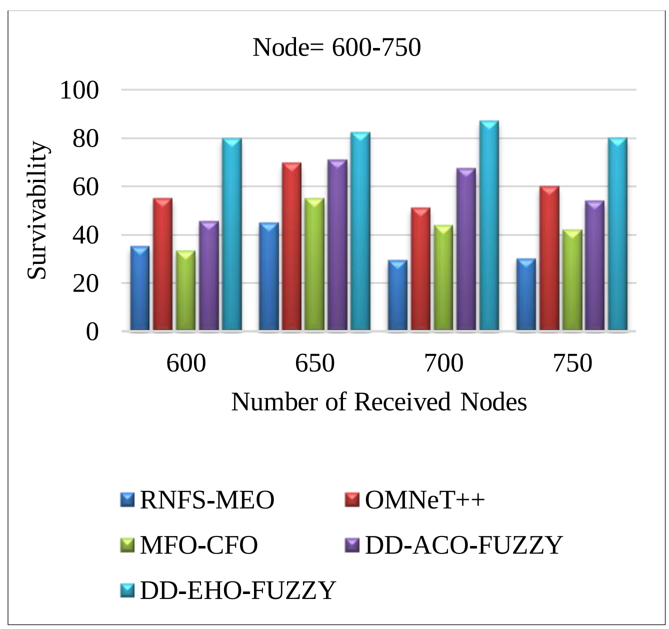

Fig. 14 The performance of survival in the method is compared (N=600-750)

Table 4 compares certain parameters between prior approaches and the EHO method now in use. When the values are compared, we may conclude that the DD-EHO-FUZZY approach is superior to other ways, as shown in Table 4. The performance of the various nodes' survivability is increasing at various time intervals, as shown in Figure 14. When the nodes are 600, 650, 700, and 750, the survivability performance is determined. When compared to the RNFS-MEO, OMNeT++, MFO-CFO, and DD-ACO-FUZZY, the suggested DD-EHO-FUZZY consumes a 20.83 percent increase in survivability performance.

In Figure 14, existing methods for improving the survival of fuzzy logic in wireless sensor network systems are compared. The proposed Fuzzy EHO method's performance is evaluated in a real-time environment using a laboratory experimental setup. The suggested Fuzzy EHO algorithm was created in MATLAB M-Script and then converted to C using a compiler before being applied to a wireless sensor network.

5. Conclusion

This paper provides the directed diffusion routing protocol that uses a fuzzy inference mechanism to choose a communication channel between any nodes in a network. The EHO method performs the fuzzy system for route categorization automatically. The EHO algorithm is used to update the fuzzy inference system's rule basis. The activity approach used on the fuzzy system is stored in the rule base. As a result, an optimal rule base update must outcome in a cost-effective plan for coping with the WSN's resource constraints. The EHO algorithm was modified in this paper to solve the Wireless Sensor Network problem.

The rule base holds the behaviour strategy applied to the fuzzy system. Therefore, the best rule-based adjustment must result in a cost-effective way to deal with the restricted resources of wireless sensor nodes. Though the use of a trial-and-error modified fuzzy system (DD-Fuzzy) makes better use of tools to determine paths, it is not as powerful as the automatic control using EHO. When it comes to solving the localization problem in WSN, EHO provides a reliable and effective metaheuristic.

As a result, incorporating a fuzzy reasoning system can help a wireless sensor network make better use of its limited functionality. The DD-ACO-Fuzzy approach saves about 60% of the time. Survivability performance has improved by 29% over the previous method. In this EHO, adopting a wireless sensor network improved performance by 89 percent. Further issues in this area, such as WSN coverage and better survivability performance, could be solved with the EHO algorithm. In future work, the authors want to use EHO algorithms to change both the simultaneous fuzzy rule base.

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