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Yellow Saddle Goatfish Optimization Algorithm based Energy Aware Multihop Routing Protocol for Wireless Sensor Networks

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Abstract: Wireless sensor networks (WSNs) can be defined as a set of independent sensor devices, which are linked by wireless channels. WSN has potential for real-time monitoring namely environment surveillance, military applications, industrial applications, health monitoring, and many more. Certain limitations of WSNs include limited storage space and node energy. Energy efficiency will be the major design problem in WSN, which is solved through clustering and routing methods. They were regarded non-deterministic polynomial (NP)-hard optimizing issues and can be solved with the utilization of metaheuristic techniques for identifying the near-optimal or optimum solutions. This article introduces a novel yellow saddle goatfish optimization algorithm based energy aware multihop routing (YSGOA-EAMHR) method for WSN. The presented YSGOA-EAMHR methodology concentrates on the recognition of optimum routes to destinations for data communication in WSN. To attain this, the proposed YSGOA-EAMHR methodology is mainly based on YSGOA, which is stimulated by the characteristics of yellow saddle goatfish. In addition, the presented YSGOA-EAMHR model derives a fitness function involving residual energy (RE) and distance to BS. The YSGOA-EAMHR model selects the nodes with higher RE and lowers the distance to BS as optimal relay nodes for data transmission. The investigational validation of the YSGOA-EAMHR technique is examined utilizing a sequence of measures. The comparison study reported that the YSGOA-EAMHR technique has gained significant performance over existing models such as FUCHAR, GWO, MOPSO, WGWO, and HMBCR techniques.

Keywords: Wireless sensor networks, Routing, Multihop communication, Yellow saddle goatfish, Fitness function, Clustering.

1. Introduction

WSNs are disseminated in nature and they can be defined as a collection of several small-sized sensor nodes (SNs) that comprises battery, microcontrollers, and sensors which were entrenched on one chip positioned in the network area of interest for sensing and collecting data from it [1]. This made the WSNs as most suitable one for applications where monitoring of the environment is carried out e.g., in case of fire in the forest then it should grant alarming signals to forest rangers to alert them. Other applications involve disaster monitoring security surveillance in the home and military, healthcare, traffic, weather monitoring, agriculture, etc. [2]. Among several units of SNs, the sensing, communication, and data processing units are the units which used the higher amounts of energy. Of these, it is observed that the communication units consume the maximum energy [3]. For reducing energy utilization in such unit's various energy preservation methods like collection tree protocols clustering, cluster-based routing protocols, data aggregation, and efficient node deployment were developed [4].

SNs function on very small batteries which have little communication and processing ability and it is tough to recharge them [5]. Thus, energy utilization of such SNs must be to have a longer network lifespan. Such SNs even inhibited in terms of storage, energy, transmission range, and computational power but from them [6]; the energy of SNs was the major constraint while devising WSNs. A great deal of work was made in this domain for the past few years to solve overcome this problem and it is noted that cluster related routing was the method by which energy consumption of SNs is proficiently minimized and provided greater network lifetime as compared to other techniques such as direct communication [7]. Clustering offers two- or three-times better network lifespan than others. In clustering, grouping of SNs occurs for cluster formation which leads to energy saving due to the number of long-distance communications of SNs being reduced. CH inside all the clusters takes responsibility for all cluster members' SNs which again leads to energy saving [8]. Data aggregation at CH also resulted in saving SN energy through a reduction of the number of data transferred. The most energy-efficient and widely used techniques in WSN are Hierarchical routing protocols [9]. Any of the structures that split the network into groups are known as clusters, with each cluster including a head, and a central node, termed cluster heads (CHs). Such heads get the sensed data from local nodes and accumulates the data and report to the BS over a multi-hop (MH) communication method depending on the distance from the BS [10].

This article introduces a novel yellow saddle goatfish optimization algorithm based energy aware multihop routing (YSGOA-EAMHR) method for WSN. The presented YSGOA-EAMHR methodology concentrates on the recognition of optimum routes to destinations for data communication in WSN. To attain this, the proposed YSGOA-EAMHR methodology is mainly based on YSGOA, which is stimulated by the characteristics of yellow saddle goatfish. In addition, the presented YSGOA-EAMHR model derives a fitness function involving residual energy (RE) and distance to BS. The YSGOA-EAMHR model selects the nodes with higher RE and lowers the distance to BS as optimal relay nodes for data transmission. The investigational validation of the YSGOA-EAMHR technique is examined utilizing a sequence of measures.

The remaining sections of the article is arranged as. Section 2 offers the related works and section 3 portrays proposed model. Then, section 4 elaborates the output evaluation and section 5 completes the work.

2. Related works

The authors in [11] introduced a multi-objective MH routing (MOMHR) protocol for optimum data routing for obtaining the network's life duration. In the initial stage, the K-means technique was implemented for node segmentation into k clusters. Later, the ABC optimization technique was implemented for acquiring the best probable CH in every cluster and then implementing a multi-objective function lastly the MH routing protocol identifies a MH route with lesser transfer cost from node to the base stations (BS). Elhoseny et al. [12] suggest an innovative swarm intellectual–related clustering and MH routing protocol for WSN. At first, an enhanced PSO method was enforced to select the CHs and systematizes the clusters effectively. After that, for choosing the optimum paths in the network, the GWO technique–related routing process is executed. The presented enhanced PSO–GWO method integrates the benefits of both routing and clustering processes.

Altowaijri et al. [13] modelled an efficient MH routing protocol (EMRP) for effective distribution of information in IoT-based WSNs in which ranking-related energy-effective routing was utilized. It is considered a rank-related next-hop selective system. For every device, for choosing the path for data interchange, the RE was considered. The author made an extraction of the RE at all nodes and assessed it depending on the connection degree for validating the maximal rank. The authors in [14] devised a potential lightweight security solution for mitigating security problems relevant to MH routing in WSN. A point-to-point verification method, symmetric encryption, and additive perturbation utilizing a new key distribution and troubles generation approaches for assuring data integrity and confidentiality at the time of MH routing were involved in this solution. Augustine and Ananth [15] modelled a multi-path routing technique that relies upon the optimized method. The CH selection and multi-path routing are the 2 significant stages of the presented routing model. Firstly, the CH selection can be executed by the kernel FCM method. Afterwards, using the formulated rider salp swarm optimization (RSSO) method, the combination of the salp swarm algorithm (SSA) and rider optimization algorithm (ROA), multipath routing is accomplished. The FF of the devised RSSA was devised by taking the various elements into account like trust, energy, and QoS.

3. The proposed model

In this article, an effectual YSGOA-EAMHR technique for optimal selection of route in the WSN

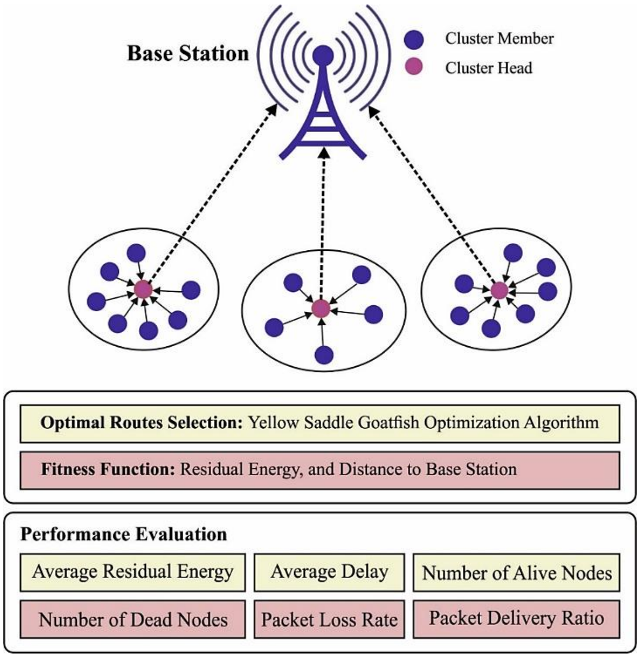

Figure. 1 Working process of YSGOA-EAMHR approach

is introduced. The proposed YSGOA-EAMHR technique focused on the recognition of maximal rutes to destinations for data transfer in WSN. The projected YSGOA-EAMHR technique is mainly based on YSGOA, which is stimulated by the characteristics of yellow saddle goatfish. Fig. 1 showcases the working procedure of the YSGOA-EAMHR algorithm.

3.1 Energy model

The major issue relevant to WSN is energy consumption. Seemingly, the process of re-energization was not accessible within the WSN battery, so whenever the battery was down, the energy distribution is not accessible [16]. In general, the data communication to BS from whole SNs made effectively through the additional energy. Therefore, energy consumption was highly essential for communication purposes. Seemingly, more energy was used by the network of different functions namely transmission, sensing, aggregation, and reception. Hence, the need for energy for the overall data communication was described in Eq. (1). In this study, E_{et} expressed the electronic energy relevant to multiple modules including filtering, spreading, and digital coding, and defined in Eq. (2) and $E_{TM}(N\colon di)$ indicates the whole utilized energy that was significant to transfer N packet bytes on distance di. The method for electrical energy can be described in Eq. (2), here E_{ea} illustrates the energy employed during data accumulation. The overall energy E_{RP} that can be significant to get N packet bytes at a distance di was specified in Eqs. (3) and (4) portray the required energy for amplifying E_{om}.

$$E_{TM}(N\colon di) = \begin{cases} E_{et} \times N + E_{rs} \times N \times di^2, if\ di < di_0 \\ E_{et} \times N + E_{pw} \times N \times di^2, if\ di \geq di_0 \end{cases} \tag{1}$$

$$E_{et} = E_{TM} + E_{ea} \tag{2}$$

$$E_{RP}(N\colon di) = E_{et}N \tag{3}$$

$$E_{amp} = E_{fr}di^2 \tag{4}$$

$$di_{0=}\sqrt{\frac{E_{fr}}{E_{pam}}} \tag{5}$$

In Eq. (1), di_0 designates the threshold distance assessed in Eq. (5), mandatory energy when using the free space technique was delineated as E_{fr} power amplifier energy can be described as E_{pam}. In general, the aggregate network energy is specified in Eq. (6), whereas E_1 symbolizes energy that are in need for the entire idle state and E_C shows the energy cost for the general sensing procedure. The aggregate energy minimized can be expressed in Eq. (6).

$$E_{total} = E_{TM} + E_{RP} + E_1 + E_C \tag{6}$$

3.2 Algorithmic steps of YSGOA

The YSGOA is a new metaheuristic optimization approach motivated by the behaviour of yellow saddle goatfish [17]. This technique considers the individual population separated into various classes, in which every sub-population is made of a k-means method. Individuals in every group might play two dissimilar roles: blocker and chaser. In addition, change zone operators and exchange roles are incorporated into the search process of YSGOA.

Chaser behavior

In each sub-populace, individuals with the better fitness value are the chaser Φ_1. These particles lead the group through search, and the behaviours are modelled by random Lévy Flight (LFs) method. The LD is sudden drift's initializing process scientifically. The LFs is a random walk procedure where the search task's step length gets greater with sudden drift, as:

$$Levy(\alpha) \sim t^{-1-\alpha}, 0 < \alpha < 2 \tag{7}$$

In Eq. (7), t, α represents the arbitrary parameter ranges within (0, 1], and the index of stability. In the proposal of LD in the search area, it is considered as:

$$Levy(\beta) = \frac{u \times \phi}{|v|^{1/\beta}} \tag{8}$$

In Eq. (8), u and v indicate the value of uniform dispersal, β denotes levy exponent:

$$\phi = \left[\frac{\Gamma(1+\alpha)\times\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{(1+\alpha)}{2}\right)\times\alpha\times2^{\left(\frac{\alpha-1}{2}\right)}}\right]^{\frac{1}{\alpha}} \tag{9}$$

In Eq. (9), α is equivalent to 1.5, and u and v show the arbitrary value. Therefore, the position of the chaser can be determined by:

$$\Phi_l^{t+1} = \Phi_l^t + \alpha\left(\frac{u}{|v|^{\frac{1}{\beta}}}\right)\left(\Phi_l^t - \Phi_{besi}^t\right) \tag{10}$$
$$0 < \beta \leq 2$$

Whereas α indicates the step size whose value is 1. u and v values are evaluated from the uniform distribution:

$$u \sim N(0, \sigma_u^2)$$
$$v \sim N(0, \sigma_v^2)$$

Consider Γ as the Gamma function, σ_u and σ_v are determined by Eq. (11):

$$\sigma_u = \left\{\frac{\Gamma(1+\beta)\sin\frac{\pi\beta}{2}}{\frac{\Gamma\left(\frac{1+\beta}{2}\right)\beta 2(\beta-1)}{2}}\right\}^{\frac{1}{\beta}}, \sigma_v = 1 \tag{11}$$

The Lévy index β will be controlling the tail of likelihood distribution:

$$\beta = 1.99 + \frac{0.001t}{t_{\max}/10} \tag{12}$$

In Eq. (12), $t_{\max}$ and t depicts the maximal and existing iteration count. The better chaser amongst ensembles is the global optimal particle Φ_{best}. Hence, the global optimal location is updated as:

$$\Phi_{besi}^{t+1} = \Phi_{best}^t + \alpha\left(\frac{u}{|v|^{\frac{1}{\beta}}}\right) \tag{13}$$

Blocker behavior

Each group has a single chaser individual. Thus, the residual particles in every group are regarded blocker ϕ_g. The blocker location is upgraded based on the logarithmic spiral determined by:

$$\phi_g^{t+1} = D_g \cdot e^{b\rho} \cdot \cos 2\pi\rho + \Phi_l \tag{14}$$

In Eq. (14), ρ depicts a random value inside [a, 1], whereby a is declined serially from -1 to -2. The b parameter value is 1. The distance D_g between the corresponding chaser and the blocker is evaluated by:

$$D_g = \left|r \cdot \Phi_l - \phi_g^t\right| \tag{15}$$

The random integer r is amongst [1, 1].

Exchange of roles and change of zone

The exchange of roles helps block individuals from being chaser particles. This is a simple technique which upgrades the chaser if a blocker is better than the fitness values. At the same time, the zone change is an approach for jumping out of the local optimum. Once the best solution is not found in a specified time, the change of zonal process is executed depending on the succeeding equation:

$$p_g^{t+1} = \frac{\Phi_{best} + p_g^t}{2} \tag{16}$$

This formula will be updating the location of each particle p_g^t in the populace without regarding the roles. Even though YSGOA performs LFs in its search process, as do other approaches like cuckoo search (CS), there exists a critical variation amongst them. For instance, CS applies a global population of host nests for the search. In contrast, YSGOA applies a sub-population of search agents with a blocker and a chaser in every sub-population. In addition, the primarily upgraded method in CS is LFs, whereas the upgraded mechanism in YSGOA is LFs (for exploration) and a logarithmic spiral path for utilization. In addition, the CS approach involves a selection operator that rejects the worst solution with a specific probability of replacing them with a new one. On the other hand, YSGOA performs other operators, namely the exchange of roles and the zone change. This operator helps to increase the solution, so they don't want to be detached from the population by a selection process. Moreover, the exchange of roles stimulates diversity in each sub-population, whereas the zone change evades stagnation in the local optimum. Fig. 2 illustrates the steps utilized in YSGOA.

3.3 Process involved in route selection technique

The presented YSGOA-EAMHR model derives an FF consisting RE and distance to BS. For determining an optimum group of routes, let us, $\theta^i = (\theta_1^i, \theta_2^i|\theta_{p+1}^i)$ is an i^{th} goatfish, $\theta_{n_i}^i$ signifies the real value lies between [0, 1]. Later, the offered function has been implemented for determining the ensuing

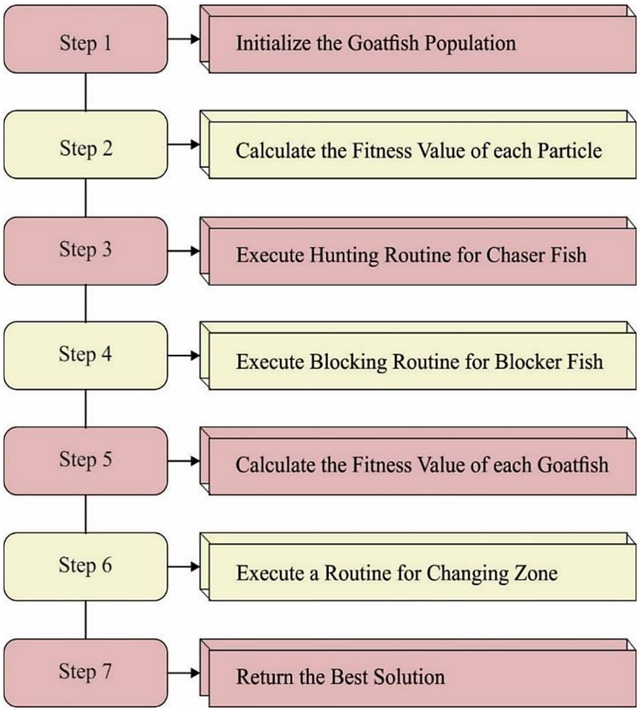

Figure. 2 Steps involved in YSGOA

hop to BS and was stated as [18]:

$$f(x) = \{i, for\ which \left|\left(\frac{i}{k} - X_{i_f j}\right)\right| is\ minimum, \forall_i 1 \leq i \leq k \quad (17)$$

The idea is to define an optimal path group in CHs to BS implementing an FF consisting 2 parameters like energy and distance. Principally, the RE of the next-hop node has been determined and the node with superior energy is denoted as the node of relay. Hence, the node comprising maximum RE was referred to as the subsequent-hop node. The initial sub-objective $f1$ was presented as:

$$f1 = \sum_{i=1}^{m} E_{CHi} \quad (18)$$

Additionally, euclidean distance was performed for determining the distance between CHs to BS. In the event of a lesser distance, the energy can be accumulated substantially. When the distance was enhanced, an additional energy count can be consumed. Therefore, a node with minimal distance has been referred to as the relay node. Hence, the subsequent sub-objective utilizing distance is $f2$, and is expressed as:

$$f2 = \frac{1}{\sum_{i=1}^{m} dis(CH_i, NH) + dis(NH, BS)} \quad (19)$$

The aforesaid sub-objectives can be briefed as to FF as offered whereas the α_1 and α_2 signify the weight assigned to each sub-objective.

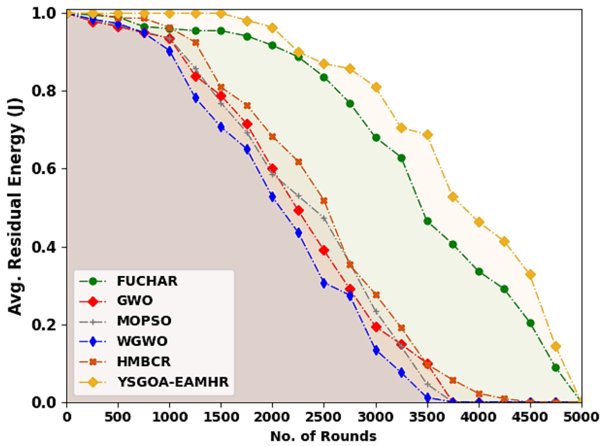

Figure. 3 AVRE evaluation of YSGOA-EAMHR model under changing rounds

$$Fitness = \alpha_1(f1) + \alpha_2(f2), where \sum_{i=1}^{2} \alpha_i = 1 \alpha_i \varepsilon (0,1); \quad (20)$$

4. Results and discussion

In the following, an elaborate investigational validation of the YSGOA-EAMHR methodology is performed under various measures. Table 1 and Fig. 3 demonstrate a relative average residual energy (AVRE) study of the YSGOA-EAMHR methodology with other existing methods [19]. The outputs implied that the WGWO approach has obtained minimal AVRE values while the GWO, MOPSO, and HMBCR approach have shown certainly improved values of AVRE. At the same time, the FUCHAR technique has managed to report reasonable values of AVRE. However, the YSGOA-EAMHR technique has demonstrated better performance with maximum AVRE values.

The outputs show that the WGWO methodology has obtained minimal NOAN values while the GWO, MOPSO, and HMBCR methods have shown certainly improved values of NOAN. Simultaneously, the FUCHAR method has managed to report reasonable values of NOAN. But, the YSGOA-EAMHR method has illustrated better performance with maximum NOAN values.

Table 2 and Fig. 4 portray a relational No. of alive nodes (NOAN) inspection of the YSGOA-EAMHR technique with other current methods.

In Table 3 and Fig. 5, an average delay (ADEL) investigation of the YSGOA-EAMHR technique with other optimization algorithms is demonstrated. The obtained values illustrated that the GWO algorithm has demonstrated poor accomplishment with higher ADEL values. Next, the FUCHAR and

Table 1. AVRE evaluation of the YSGOA-EAMHR approach with other models under varying rounds

Avg. Residual Energy (J)						
Number of Rounds	**FUCHAR**	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
250	0.9954	0.9793	0.9820	0.9847	1.0000	1.0000
500	0.9900	0.9658	0.9685	0.9739	0.9874	1.0000
750	0.9658	0.9497	0.9524	0.9497	0.9874	1.0000
1000	0.9605	0.9363	0.9363	0.9040	0.9632	1.0000
1250	0.9551	0.8395	0.8583	0.7830	0.9255	1.0000
1500	0.9551	0.7884	0.7696	0.7077	0.8099	1.0000
1750	0.9416	0.7158	0.6943	0.6513	0.7642	0.9820
2000	0.9175	0.6002	0.5868	0.5276	0.6836	0.9640
2250	0.8879	0.4927	0.5303	0.4362	0.6190	0.9012
2500	0.8368	0.3905	0.4738	0.3072	0.5196	0.8702
2750	0.7696	0.2910	0.3582	0.2749	0.3529	0.8576
3000	0.6809	0.1942	0.2346	0.1351	0.2776	0.8109
3250	0.6298	0.1485	0.1432	0.0760	0.1916	0.7058
3500	0.4658	0.1001	0.0464	0.0114	0.0975	0.6878
3750	0.4066	0.0000	0.0000	0.0000	0.0571	0.5286
4000	0.3367	0.0000	0.0000	0.0000	0.0222	0.4637
4250	0.2910	0.0000	0.0000	0.0000	0.0087	0.4140
4500	0.2050	0.0000	0.0000	0.0000	0.0000	0.3280
4750	0.0894	0.0000	0.0000	0.0000	0.0000	0.1439
5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. NOAN evaluation of the YSGOA-EAMHR approach with other models under varying rounds

Alive Node Numbers						
Number of Rounds	**FUCHAR**	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
0	1000	1000	1000	1000	1000	1000
250	961	969	985	974	998	1000
500	918	913	915	923	926	963
750	888	870	875	864	891	939
1000	832	856	808	819	846	859
1250	771	789	714	747	765	816
1500	725	730	709	688	738	805
1750	613	639	645	626	682	739
2000	562	586	546	580	597	678
2250	495	455	406	508	597	659
2500	455	315	334	350	503	592
2750	345	216	238	275	468	517
3000	270	155	189	171	380	458
3250	179	88	128	149	310	378
3500	58	21	69	88	165	222
3750	0	5	31	23	66	141
4000	0	0	15	7	13	93
4250	0	0	5	5	2	72
4500	0	0	0	0	0	61
4750	0	0	0	0	0	53
5000	0	0	0	0	0	0

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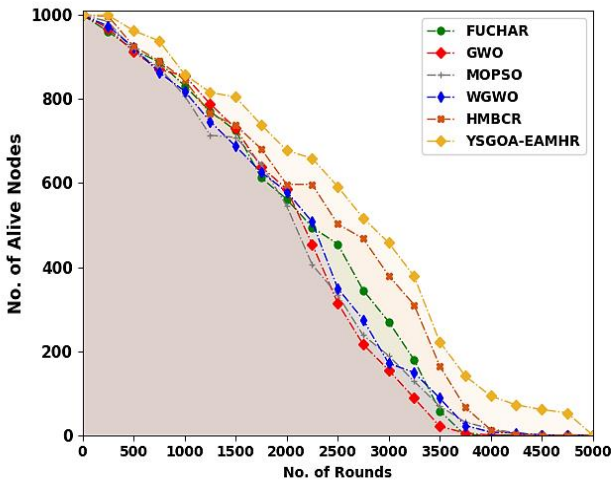

Figure. 4 NOAN evaluation of YSGOA-EAMHR model under changing rounds

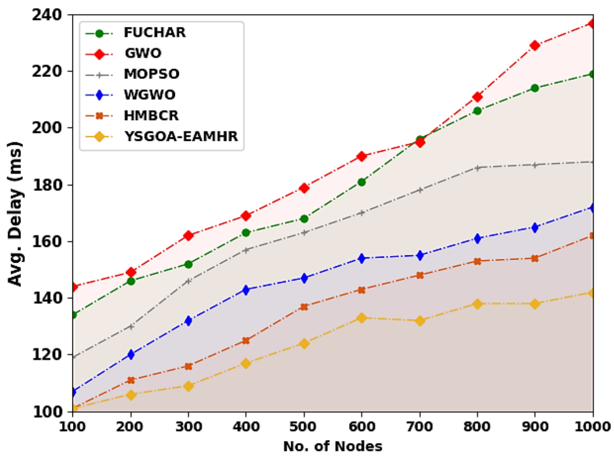

Figure. 5 ADEL evaluation of YSGOA-EAMHR model under changing nodes

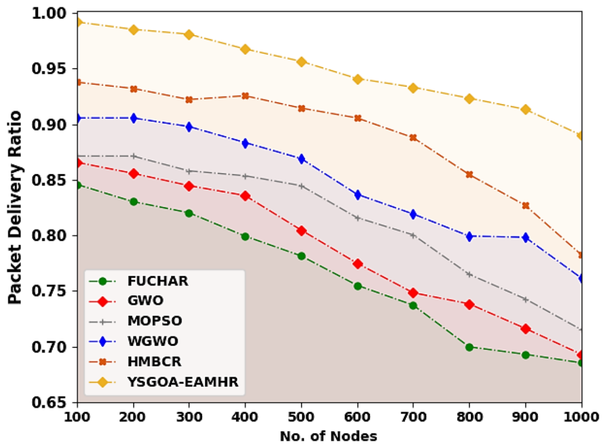

Figure. 6 PDR evaluation of YSGOA-EAMHR model under changing nodes

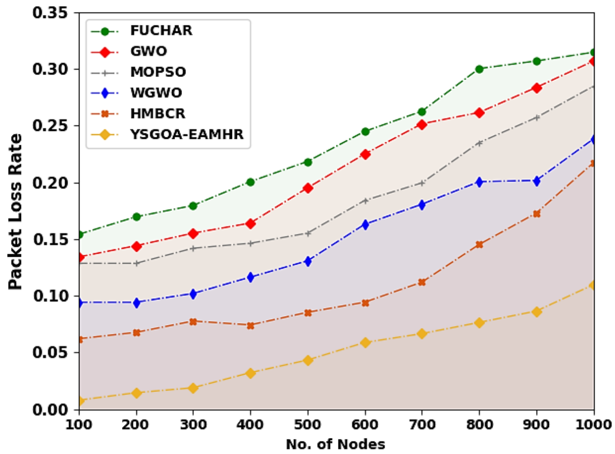

Figure. 7 PLR evaluation of YSGOA-EAMHR model under changing nodes

MOPSO models have exhibited slightly reduced values of ADEL. Moreover, the MGWO and HMBCR models have depicted somewhat considerable ADEL values. But the YSGOA-EAMHR technique has outperformed existing ones with minimal ADEL values.

Table 4 and Fig. 6 portray a relative PDR analysis of the YSGOA-EAMHR approach with other present systems. The outputs implied that the WGWO approach has acquired minimal PDR values while the GWO, MOPSO, and HMBCR methods have shown certainly improved values of PDR. Simultaneously, the FUCHAR methodology has managed to report reasonable values of PDR. But the YSGOA-EAMHR method has demonstrated superior performance with maximum PDR values.

In Table 5 and Fig. 7, a PLR investigation of the YSGOA-EAMHR technique with other optimization algorithms is demonstrated. The acquired values show the GWO technique has exhibited poor accomplishment with higher PLR values. Then, the FUCHAR and MOPSO methods exhibited slightly reduced values of PLR. Also, the MGWO and HMBCR methods have shown somewhat considerable PLR values. But the YSGOA-EAMHR method has outperformed existing ones with minimal PLR values.

Finally, Table 6 and Fig. 8 analyze the lifetime investigation of the YSGOA-EAMHR method with current models. The outputs illustrated that the YSGOA-EAMHR method can lengthen the lifetime effectually. Based on FND, the YSGOA-EAMHR approach has obtained a higher FND of 420 rounds while the FUCHAR, GWO, MOPSO, WGWO, and HMBCR models have gained lesser FND of 100, 168, 204, 248, and 264 rounds correspondingly. Meanwhile, concerning HND, the YSGOA-EAMHR approach has gained a higher HND of 4765 rounds while the FUCHAR, GWO, MOPSO, WGWO, and HMBCR methods have achieved lower HND of 2200, 2120, 2100, 2265, and 2912 rounds correspondingly.

Table 3. ADEL evaluation of the YSGOA-EAMHR approach with other models under varying nodes

Avg. Delay (ms)						
Number of Nodes	**FUCHAR**	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
100	134	144	119	107	101	101
200	146	149	130	120	111	106
300	152	162	146	132	116	109
400	163	169	157	143	125	117
500	168	179	163	147	137	124
600	181	190	170	154	143	133
700	196	195	178	155	148	132
800	206	211	186	161	153	138
900	214	229	187	165	154	138
1000	219	237	188	172	162	142

Table 4. PDR evaluation of the YSGOA-EAMHR approach with other models under varying nodes

Packet Delivery Ratio						
Number of Nodes	**FUCHAR**	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
100	0.8458	0.8657	0.8713	0.9056	0.9378	0.9920
200	0.8303	0.8558	0.8713	0.9056	0.9322	0.9854
300	0.8203	0.8447	0.8580	0.8979	0.9222	0.9810
400	0.7993	0.8358	0.8536	0.8835	0.9256	0.9677
500	0.7815	0.8048	0.8447	0.8691	0.9145	0.9566
600	0.7550	0.7749	0.8159	0.8369	0.9056	0.9411
700	0.7372	0.7483	0.8004	0.8192	0.8879	0.9333
800	0.6996	0.7383	0.7649	0.7993	0.8547	0.9234
900	0.6929	0.7162	0.7428	0.7982	0.8270	0.9134
1000	0.6852	0.6929	0.7151	0.7616	0.7826	0.8901

Table 5. PLR evaluation of the YSGOA-EAMHR approach with other models under varying nodes

Packet Loss Rate						
Number of Nodes	**FUCHAR**	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
100	0.1542	0.1343	0.1287	0.0944	0.0622	0.0080
200	0.1697	0.1442	0.1287	0.0944	0.0678	0.0146
300	0.1797	0.1553	0.1420	0.1021	0.0778	0.0190
400	0.2007	0.1642	0.1464	0.1165	0.0744	0.0323
500	0.2185	0.1952	0.1553	0.1309	0.0855	0.0434
600	0.2450	0.2251	0.1841	0.1631	0.0944	0.0589
700	0.2628	0.2517	0.1996	0.1808	0.1121	0.0667
800	0.3004	0.2617	0.2351	0.2007	0.1453	0.0766
900	0.3071	0.2838	0.2572	0.2018	0.1730	0.0866
1000	0.3148	0.3071	0.2849	0.2384	0.2174	0.1099

Table 6. Lifetime analysis of YSGOA-EAMHR model with other techniques

	FUCHAR	**GWO**	**MOPSO**	**WGWO**	**HMBCR**	**YSGOA-EAMHR**
FND	100	168	204	248	264	420
HND	2200	2120	2100	2265	2912	4765
LND	3750	3940	3989	4000	4300	5000

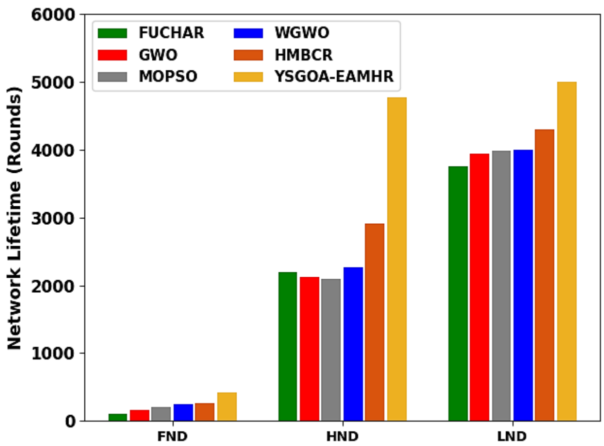

Figure. 8 Lifetime evaluation of the YSGOA-EAMHR approach

These outputs depicts that the YSGOA-EAMHR approach has offered maximal energy efficacy and lifetime of the WSN.

5. Conclusion

In this article, we have introduced an effective YSGOA-EAMHR technique for optimal route selection in the WSN. The projected YSGOA-EAMHR technique concentrated on the recognition of optimum routes to destinations for data transfer in WSN. The presented YSGOA-EAMHR methodology is mainly based on YSGOA, which is stimulated by the characteristics of yellow saddle goatfish. In addition, the presented YSGOA-EAMHR methodology derives a FF consisting residual energy and distance to BS. The YSGOA-EAMHR technique selects the nodes with higher RE and lowers the distance to BS as optimal relay nodes for data transmission. The investigational validation of the YSGOA-EAMHR technique is examined utilizing a sequence of measures. The comparison study reported that the YSGOA-EAMHR technique has gained significant performance over other models concerning distinct measures. In the future days, the energy effectiveness of the YSGOA-EAMHR approach can be enhanced by unequal clustering techniques by resolving hot spot problems.

Conflict of interest

The authors hereby provide confirmation on no conflict of interest.

Author contributions

Conceptualization, Deena Sivakumar and Suganthi Devi; methodology, Deena Sivakumar, Suganthi Devi, and Nalini; software, Deena Sivakumar and Suganthi Devi; validation, Deena Sivakumar and Suganthi Devi; formal analysis, Deena Sivakumar, Suganthi Devi, and Nalini; investigation, Deena Sivakumar, Suganthi Devi, and Nalini; resources, Deena Sivakumar, Suganthi Devi, and Nalini; data curation, Deena Sivakumar and Suganthi Devi; writing-original draft preparation, Deena Sivakumar and Suganthi Devi; writing-review and editing, Deena Sivakumar, Suganthi Devi, and Nalini; supervision, Deena Sivakumar, Suganthi Devi, and Nalini; project administration, Deena Sivakumar and Suganthi Devi; funding acquisition, Deena Sivakumar, Suganthi Devi, and Nalini. All authors have recited and accepted the final manuscript.

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