Energy and Lifetime Efficient Routing Technique for Wireless Sensor Networks using optimal Clustering

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Abstract -Wireless Sensor Networks (WSN) is one of the most technologically advanced technologies used in advanced applications. However, the network lifetime of the WSN is very short due to the low power of the sensor network. Therefore, energy efficiency and network reliability are considered to be the main challenges of WSN. Most WSN applications in real-time scenario need to provide vital information on energy efficiency. In this study, we investigate the joint optimal problems of energy and lifetime efficient routing technique in WSN routing protocol using optimal clustering (ELR-OC). The proposed ELR-OC routing technique aimed to provide optimal clustering using multi-objective flower optimization (MOFO) algorithm which ensures the energy efficiency in overall performance. Based on trust degree, we calculate cluster head (CH) using numerous design metrics. Finally, we illustrates the cat hunting with feed-forward neural network (CH-FFNN) for multi-hop routing between CHs and sink nodes to optimizes both energy efficiency and network lifetime. The simulation results showed that our proposed ELR-OC routing technique efficiency over the existing routing methods based on energy and network lifetime metrics.

Keywords: cluster head (CH), network lifetime, energy efficient, multi-hop routing, sensor node

1. Introduction

The sensor node has small devices that can detect transceivers called sensors, computers, and sensors [1]. These small devices are best used to accurately understand the environment, store data, and process required data [2][3]. A group of similar or other sensor nodes is called a WSN. WSN is growing rapidly, although certain issues are unavoidable. Sensor battery life, communication performance, routing efficiency, QoS, fault tolerance, and security features are challenges for WSN applications [4].Network runtime and data power consumption are the main responsibilities of WSN services. The WSN environment is often put together to make it easier to deal with such commitments. WSN QoS performance is influenced by the distance between sensor nodes and the number of clusters in the circuit [5]. The designer's puzzle revolves around the ability of the sensor nodes to strike a balance between the limited residual power and the need for longer network performance [7]. Any inconsistencies in the management of such targets may complicate the allocation and operation of the QoS due to power failure of the sensor terminal or the high-value atmosphere [8]. The low-energy adaptive clustering hierarchy (LEACH) is a distribution system designed to meet such challenges. Since the power consumption of a sensitive terminal is directly proportional to the square of the distance between that sensitive terminal and the base station (BS) [6], nodes farther away from BS rapidly reduce their power. The area with the nodes farthest from the BS will be excluded from the region of interest [9]. To overcome these problems, the direct data transmission can be supplanted with a multi-hop connection, which results in significant energy savings over a small range of contacts.

Therefore, power consumption is an important choice for a terminal used to improve power consumption and network performance [10].

The article remaining sections are: Sec.2 discusses recent literature works. The problem research methodology and the network design are described in Sec.3. Sec.4 demonstrates the proposed research methodology in detail. In Sec.5 describes the simulation results and the comparative analysis of proposed and existing routing techniques. Sec.6 summarizes the research.

2. Related works

Over the past few years, there has been a lot of research into energy and network lifetime aware routing technique for WSNs around the world. The literature is compiled in various aspects and presented in Table 1.

Panchal et al. [11] have proposed energy aware distance-based cluster head selection and routing (EADCR) protocol based on FCM technology recommended Euclidean distances from BS and energy-sensitive distances to extend the service life of WSN using a cluster centroid. To avoid this, the authors present a clustering method here, where the choice of CH is based on the newly suggested exercise activity because the nodes use more energy during the clustering phase. They offer a pocket routing technique using a short routing method between the node and its destination that lessens the CH energy consumption using multi-hop communication. Naeem et al. [12] have proposed the remaining energy conservation protocol is based on stable election protocol (DARE-SEP) which combines the characteristics of sustainable energy efficiency with residual energy. This protocol aims to ensure the optimal transmission path from the sensor nodes to the CH based on the network dynamics. A multi-jump path between the CH and sink nodes is used to decrease power consumption. Abdullah et al., [13] extended the service life of sensor assemblies. These protocols are designed to improve network routing. Because multi-jump routes are energy efficient, root optimization techniques need to be used to improve the service life of the WSN in a multi-jump route environment. Modified distance-based energy-aware routing protocol (MTPEA) that lessens sensor terminal energy usage and extends network lifetime.

Rathore et al. [14] suggested an innovative approach to selecting cluster heads. The magnitude of CH depends on the node's distance and energy. The concept of a short circuit relay terminal is used to minimize energy usage and extend network life.. The distance between the clusters determines main role of energy consumption. The short path selection relay system allows to nominally reducing the power of every node in the line to generate a transmission with adjacent nodes in the short path between the source cluster heads. A cost-effective routing protocol is proposed by Verma et al. [15] in which CH selection is based on energy efficiency, which includes parameters such as terminal density, residual power, total network power, and distance factor. Jasim et al. [16] have proposed an energy-efficient unequal clustering scheme based on a balanced energy method (EEUCB), which uses short distances and short distances, has been proposed. The EEUCB node uses the maximum power capacity and dual-panel head mechanism with sleep and wake mechanism. EEUCB has developed a cluster rotation strategy based on two-stage, internal and intermediate clustering methods, taking into account the average power range, average distance, and BS layer terminal.

3. Proposed Methodology

This section describes the proposed ELR-OC routing technique which consist following steps are cluster formation, CH selection and optimal path selection.

3.1 Cluster formation using multi-objective flower optimization (MOFO) algorithm

Rooting a WSN is a challenging task because it's an important feature that sets WSN apart from other ad hoc wireless networks. WSN requires energy-efficient routing methods to transfer sensitive data from the sensor terminal to the BS; this will extend the network life. WSN sensor nodes are usually grouped, and this grouping method is used to access the WSN for network measurement. Efficient management of limited network resources, energy savings, and sustainable network maintenance are also guaranteed. Clustering applications are used on sensor networks to ensure efficient use of resources and communication overlays, to reduce overall computer power consumption, and to interact with sensor nodes. Clustering provides energy using inexpensive communication methods that divide a network into nodes called clusters.

The multi-objective flower optimization (MOFO) method is used for optimal clustering in this research, which ensures the energy efficiency in overall performance. In the MOFO algorithm, we first start with the rules and sensor unit design dimensions. For example, in the case of global dust mites, pollen is carried away by insect-like contaminants, and data can be transmitted over long distances as insects can often fly long distances.

$$y_j^{s+1} = y_j^s + \gamma l(\lambda)(h_* - y_j^s), \tag{1}$$

where y_j^s the dust j or solution vector t returns y_j, h_* where are the best solutions of all existing generation / recurrence solutions. γ where is the influence of scale on step size control. Where L (λ) is a parameter, especially the step size, which is similar to the breaking force. Since insects can travel long distances at different distances, an optional solution is used to effectively reflect these characteristics. That is, L> 0 is obtained from the tax distribution.

$$l \sim \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\,\frac{1}{T^{1+\lambda}}, \qquad (T >> T_0 > 0) \tag{2}$$

Here $\Gamma(\lambda)$ there is a standard gamma function, this distribution works in large steps t> 0. Theoretically it is required $|T_0| >> 0$, but in practice it can be up to 0.1. But, pseudo-random measurements that strictly adhere to this tax breach (2) often develop. Mantegna algorithm is used to estimate the step size based on two meter distributions U and V is very useful with the following modifications:

$$t = \frac{U}{|V|^{1/\lambda}},, \quad U \sim n(0,\sigma^2), \quad V \sim n(0,1) \tag{3}$$

U ~ (0, σ^2) is a sample taken from the total Gaussian distribution with mean and amplitude zero. σ^2 is compute as,

$$\sigma^2 = \left\{\frac{\Gamma(1+\lambda)}{\lambda\Gamma[(1+\lambda)/2]}\cdot\frac{\sin(\pi\lambda/2)}{2^{(\lambda-1)/2}}\right\}^{1/\lambda} \tag{4}$$

For instance, when λ = 1, the gamma meanings develop Γ (1 + λ) = 1, Γ [(1 + λ)/2] = 1 and

$$\sigma^2 = \left\{\frac{1}{1\times 1}\cdot\frac{\sin(\pi\times 1/2)}{2^0}\right\}^{1/1} = 1 \tag{5}$$

The Mantegna technique can generate random models that exactly match the desired distribution (Mantegna 1994).

$$y_j^{s+1} = y_j^s + \in (y_j^s - y_k^s), \tag{6}$$

Where y_j^s and y_k^s are the pollen of various flowers of the same plant. It mainly reflects the stability of the flowers in the defined environment. Mathematically, y_j^s and y_k^s originated from the same species or was selected from the same population. If [0, 1] is taken from the integrated distribution, it becomes an equally localized random sample. In general, floriculture activities can take place domestically and around the world. However, in reality, nearby flowers or nearby flowers are polluted by local pollen rather than by distance. To clarify this characteristic, the conversion potential or proximity probability p can be effectually used to convert from a standard universal crusher to an active local crusher. Initially, the absolute value q = 0.5 can be used as the initial value. Preliminary research of the parameters shows that q = 0.8 works best in most applications. The problem of multiple objective optimization scan usually written as,

$$Minimize \quad F_1(y), F_2(y), \ldots\ldots F_M(y), \tag{7}$$

Which subject to the nonlinear fairness and inequality restrictions,

$$g_i(y) = 0, \quad (i = 1, 2, \ldots\ldots, I) \tag{8}$$

$$h_k(y) \le 0, \quad (k = 1, 2, \ldots\ldots, k) \tag{9}$$

There are various ways to achieve this, either with single objective optimization techniques or with multiple lens adjustment techniques. The easiest way to use weight is to combine multiple goals into one goal:

$$F = \sum_{j=1}^{M} w_j F_j \tag{10}$$

$$\sum_{j=1}^{M} w_j = 1, \qquad w_j > 0, \tag{11}$$

M means number of goals w_j (j = 1... M) is the negative weight.

The weighted strategy serves as a choice for many of these needs. The process of optimizing a particular set ($w_1, w_2, \quad w_M$) will create a point in front of the problem. For the next set w_j , Barre to can create another point ahead. The weight can then be calculated by normalization.

$$w_j = \frac{u_j}{\sum_{j=1}^{M} u_j} \tag{12}$$

So that $\sum_j w_j = 1$ can be satisfied. For example, for three purposes $F_1, F_2, \; and \; F_3$, three random numbers/loads can be formed from the same distribution [0, 1] which can sample flow event.

4.3 Optimal path selection CH-FFNN

In this section, we discuss the multi-hop option for cat hunting via the feed-forward neural network (CH-FFNN). A better approach between CH and relationships was chosen to improve energy efficiency and network life. Cat Hunting Optimization (CHO) was developed by focusing on cat behavior and using two types of cat behavior, namely tracing mode and search mode. Depending on the magnitude of the difference, different strategies change the function of the difference.

$$R_K = \frac{1 - (\sqrt{C_K + 1}) \cdot rand \cdot j}{C_K \cdot MaxIter}, \qquad K = 1, 2, \; j < \frac{MaxIter}{2} \tag{41}$$

To optimize particle mass after processing:

$$R_K = \frac{1 - (\sqrt{C_K + 1}) \cdot (1 + rand) \cdot j}{C_K \cdot MaxIter}, \qquad K = 1, 2, \; j \ge \frac{MaxIter}{2} \tag{42}$$

If the initial values of C_1 and C_2 are relatively small, add them to control negative values formation to evade negative numbers.

$$R_1 = R_2 = rand, \qquad R_1 \le 0, \; R_2 \ge 0. \tag{43}$$

At the initial stage of the filtering process, the search can be increased globally to improve local purity and clarity in the next iteration. However, when the distance y_j^D and q_{best}^D between them is small, dive out. Item value is determined by the following sizes:

$$V_j^D(s+1)=\omega\cdot V_j^D(s)+C_1\cdot R_1\cdot(q_{best}^D(s)-y_j^D(s))$$
$$+C_2\cdot R_2\cdot(h_{best}^D(s)-y_j^D(s))+F\cdot f_j+E\cdot e_j, \quad (44)$$

$$\begin{cases} F=0.1-j\cdot\left(\dfrac{0.2}{MaxIter}\right) \\ E=2\cdot rand, \\ f_j=h_{best}^D(s)-y_j^D(s) \ \ dist2hbest\le radius, \\ e_j=q_{best}^D(s)+y_j^D(s), \ \ dist2qbest\le radius \end{cases} \quad (45)$$

F and E individually show the weight drawn for the best global solution and the weight separated by the best local solution. And describe j-th unity and j-th enemy.

$$y_j^D(s+1)=\frac{1}{2}(x\cdot y_j^D(s)-(1-x)\cdot y_j^D(s-1)+x\cdot V_j^D(s+1)+(1-x)\cdot V_j^D(s)) \quad (46)$$

The best edge is selected using a feed forward neural network (FFNN). This is a server configuration that involves a lot of connections. In this section, we describe how to use the CH-FFNN method to find a reliable and common solution:

$$y^M x^N(y)=f(y,x(y),x^{'}(y)), \quad (47)$$

The stations specified in I Z, x ∈ R and D ⊂ R represent the category, and x (y) are the proximal solutions. $x_s(y,q)$ is the variable parameter represents the experimental answer using q, this problem will be changed to the specified type.

$$\min_q \sum_{y_j\in \vec{d}} f(y_j,x_s(y_j,q),x_s^{'}(y_j,q)) \quad (48)$$

According to the regulations are issued by using the BS. In our unique system, the CH-FFNN test model is used with a parameter that is appropriate for the weight and background of the vascular system. For the screening process $x_s(y)$, we select the type of tail filling.

$$x_s(y_j,q)=B(y)+H(y,n(y,q)), \quad (49)$$

The CH-FFNN output unit has a parametric of input units, where N is the vector y. There are no parameters that can solve this problem and fill the station. The second G word is designed to satisfy them $x_s(y)$, without help at the tail end. For y input, the output of CH-FFNN

$$n=\sum_{j=1}^{g}\nu_j\sigma(w_j), \qquad where\, w_j=\sum_{i=1}^{N}w_{ji}y_i+a_j \quad (50)$$

w_{ji} Input unit j represents the load that connects the hidden unit to j, ν_j the input unit j represents the load that connects j to the output unit, and a_j the hidden unit represents the dependence of j, and $\sigma(w)$ is a sigmoid transfer function (tansig.). The slope of CH-FFNN based optimal path selection process is described as follows:

$$\frac{\partial n}{\partial \nu_j}=\sigma(w_j), \quad (51)$$

$$\frac{\partial n}{\partial a_j}=\nu_j\sigma^{'}(w_j), \quad (52)$$

$$\frac{\partial n}{\partial \omega_{ji}}=\nu_j\sigma^{'}(w_j)y_i, \quad (53)$$

Fig. 2 depicts the proposed ELR-OC routing architecture.

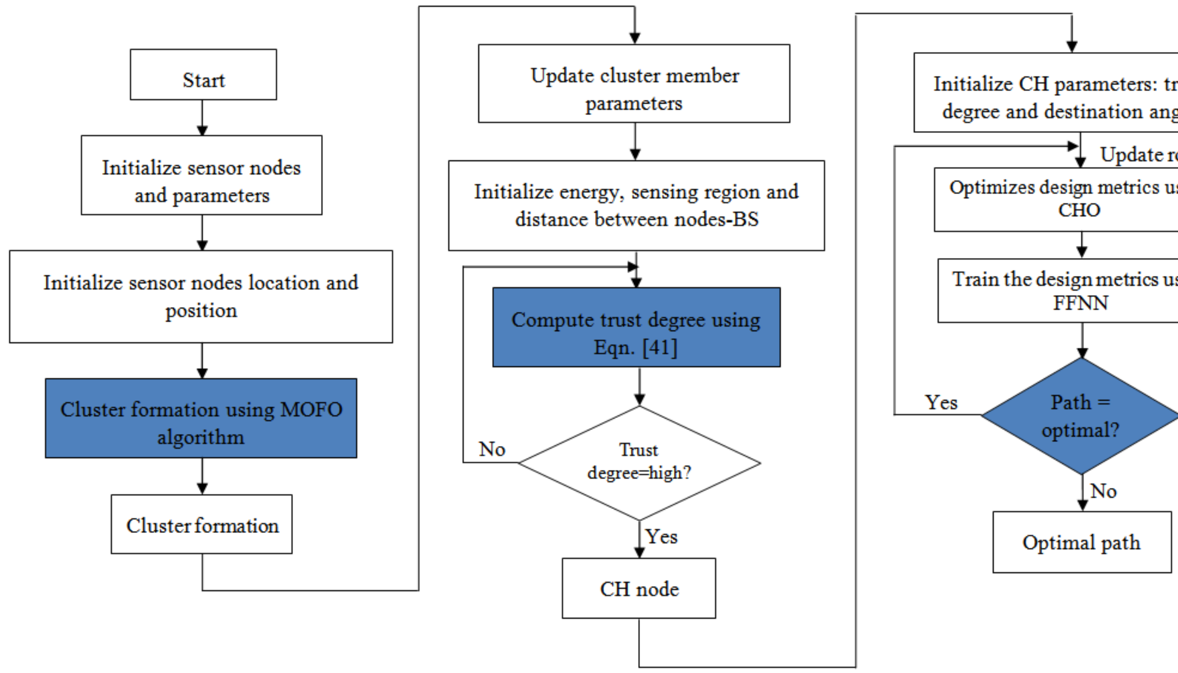


Fig. 2 Proposed ELR-OC Routing Technique Flow Diagram

5. Results and Discussion

In this section, we validate and evaluate our proposed ELR-OC routing using two simulation scenarios. We performed the simulations of proposed ELR-OC routing technique using network simulator (NS2) tool. For comparison, ELR-OC routing obtained results are compared to existing routing techniques such as LEACH, DAREP, SEP, and DARE-SEP.

5.1 Simulation parameters

For evaluating the proposed ELR-OC routing technique, the portable WSNs are tested using the NS-2 simulator (NS-2 version 2.35 in Linux Mint). NS-2 enables device re-enactment from the radio transmission physical channel to the application layer. A conventional network test system with many sensor nodes has been used for this testing. The base station is maintained far away from the target area to broaden the protocol's application. The nodes are randomly distributed in a $100\times100m^2$area. Initial energy is 0.5J. Every sensor node has a 100m communication range. Each sensor node mayaccumulate10 data packets in its memory. A data packet length is 200bytes. We consider 200 seconds run time to execute the entire simulation. The energy consumption of both transmission and receiving node is 50 and 5 nJ/bits respectively. Further, Table 2 presents the simulation parameters.

Table 2 Simulation parameters

Parameters	Values
Number of sensor nodes	200, 400, 600, 800 and 1000
Network size	100×100 m^2
Simulation time	200sec
Standard	IEEE 802.11

Propagation model	Two-way propagation model
Traffic type	CBR
Sensor maximum communication range	100m
Average sensor initial energy	0.5J
Data packet length	200bytes
Number of rounds	0-2000
Routing protocol	AODV

5.2 Comparative analysis of proposed and existing routing techniques

This section compares proposed and existing routing techniques based on performance measures such as number of alive, dead, and stable nodes, average energy consumption, end-to-end delay, throughput, and packet delivery rate.

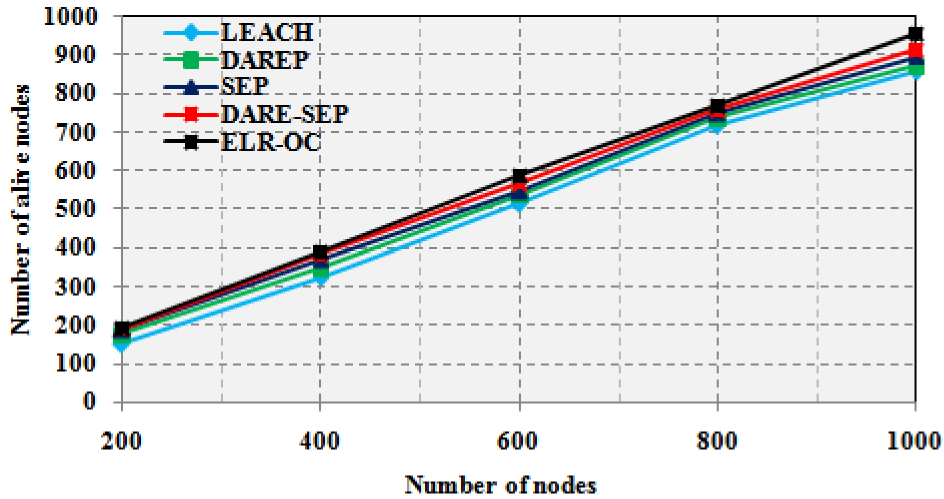


Fig. 3 Number of alive nodes comparison with nodes

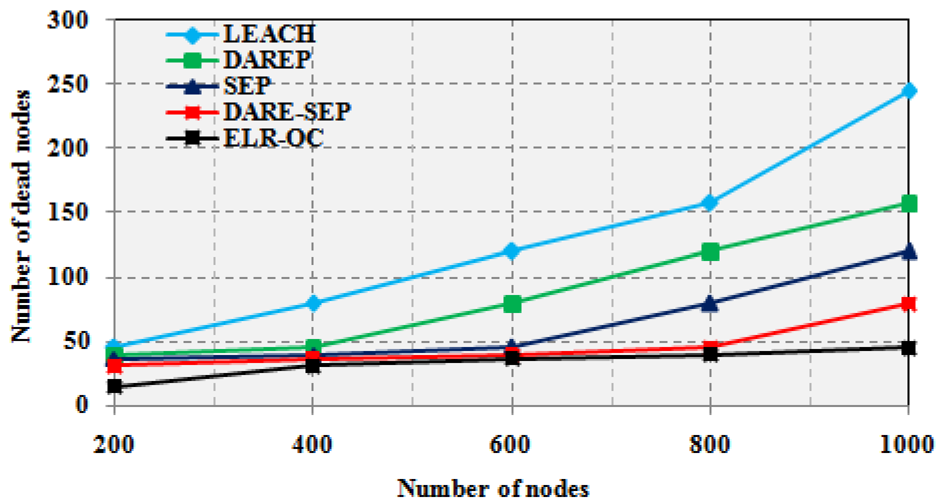


Fig. 4 Number of dead nodes comparison with nodes

5.2.1 Number of sensor nodes

In this study, we consider the number of nodes varied as 200 to 1000 with the fixed network size as 100×100m^{2}area. Fig. 3 depicts the number of alive-nodes comparison of the proposed and existing routing techniques. It clearly describes the number of alive-nodes of proposed ELR-OC routing is 11.52%, 7.69%, 5.17% and 2.79% efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively. Fig. 4 describes the number of dead nodes comparison of the proposed and existing routing techniques. The number of dead nodes in the proposed ELR-OC routing is 74.07%, 62.08%, 47.83% and 27.90 efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively. Fig. 5 describes the stable period's comparison of the proposed and existing routing techniques. It clearly describes the stable period's of proposed ELR-OC routing is 11.29%, 7.54%, 5.07% and 2.74% efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively.

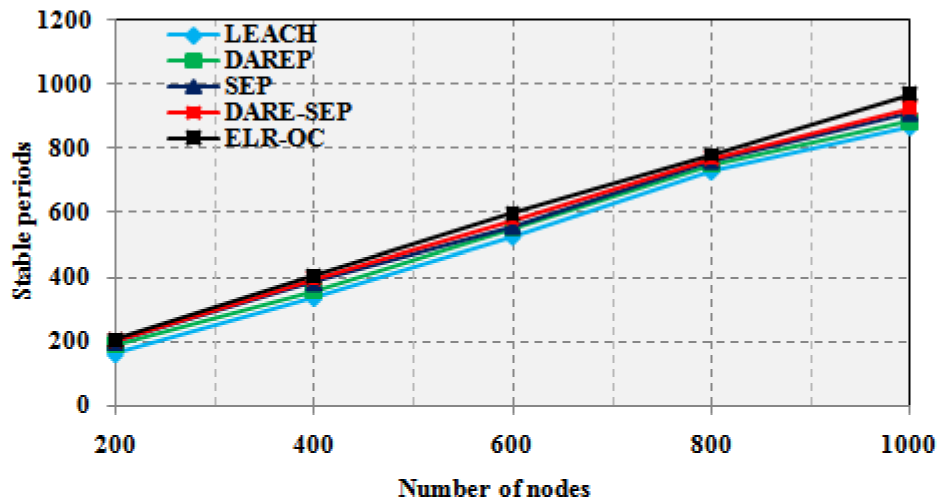


Fig. 5 Stable periods comparison with nodes

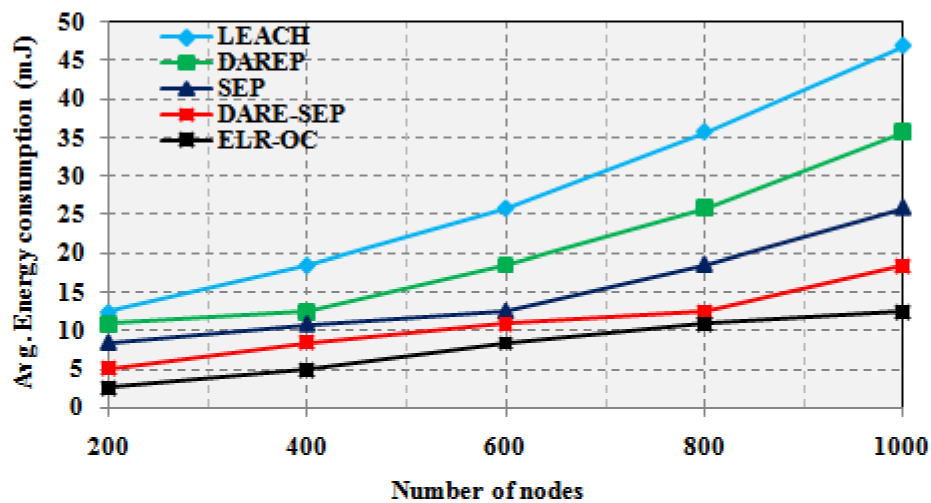


Fig. 6 Average energy consumption with nodes

Fig. 6 describes the average energy consumption of alive-nodes comparison of the proposed and existing routing techniques. It clearly describes the average energy consumption of proposed ELR-OC routing is 71.75%, 61.93%, 48.29% and 28.82% efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively. Fig. 7 illustrates the proposed and existing routing systems' end-to-end delay. It clearly describes the end-to-end delay of proposed ELR-OC routing is 83.82%, 76.64%, 64.76% and 42.38% efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively.

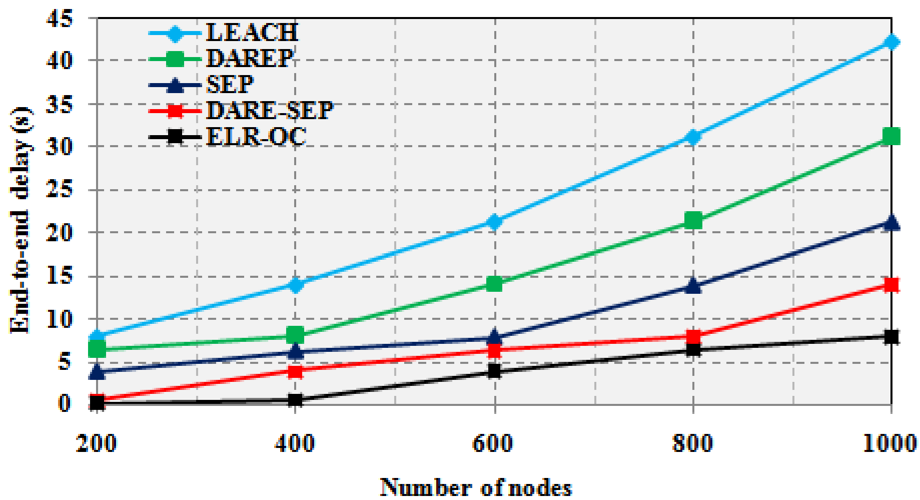


Fig. 7 End to end delay with nodes

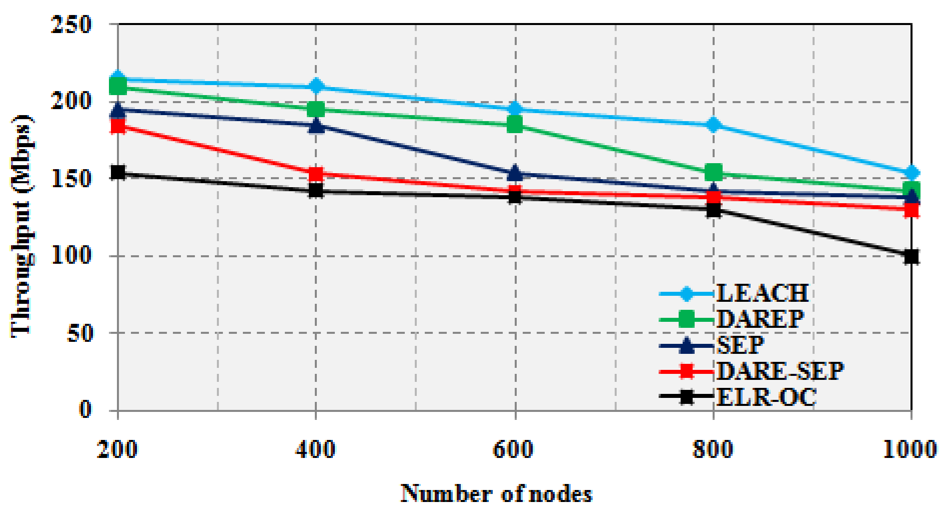


Fig. 8 Throughput with nodes

Fig. 8 compares proposed and existing routing techniques based on throughput. It clearly describes the throughput of proposed ELR-OC routing is 30.76%, 25.06%, 18.43% and 11.35% efficient than the existing state-of-art LEACH, DAREP, SEP and DARE-SEP routing techniques respectively. Fig. 9 compares the proposed and existing routing strategies' packet delivery rates.It clearly describes the proposed ELR-OC routing packet delivery rate is 9.00%, 5.73%, 3.31% and 1.41% efficient than the existing state-of-art

LEACH, DAREP, SEP and DARE-SEP routing techniques respectively.

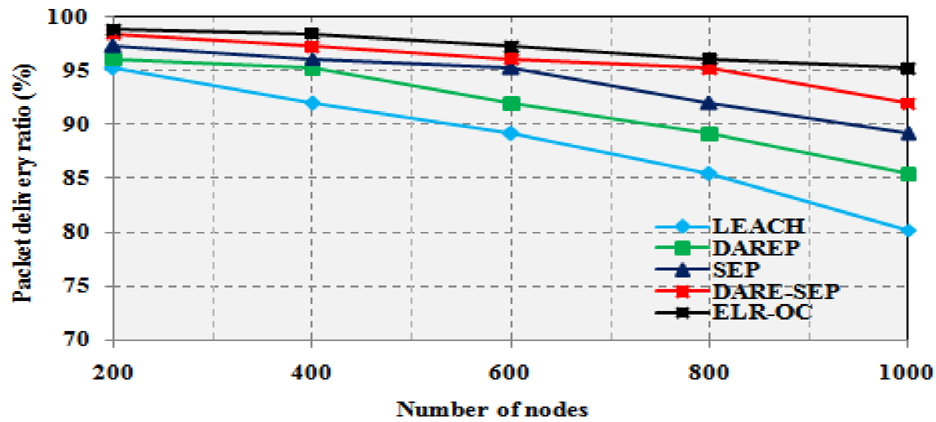
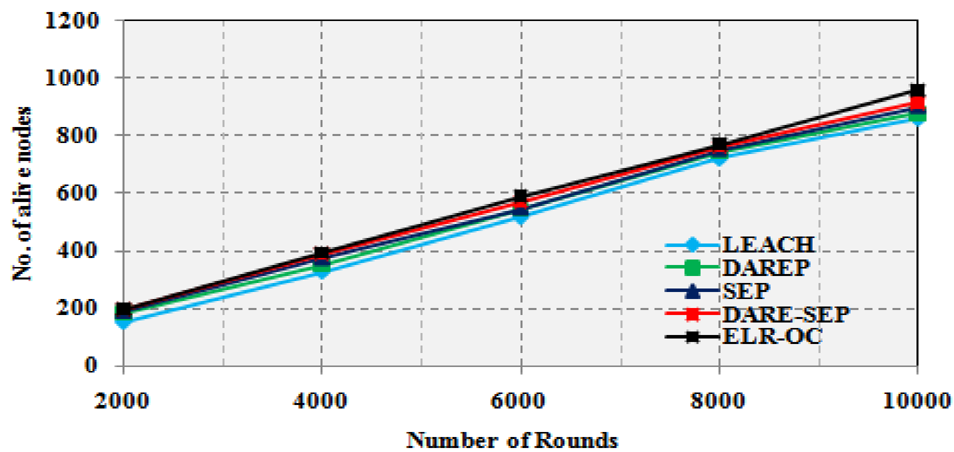


Fig. 9 Packet delivery rate with nodes



6. Conclusion

This study investigated the joint optimal energy and lifetime efficient routing problems in WSN using optimal clustering (ELR-OC). The optimal cluster formation is done by multi-objective flower optimization (MOFO) algorithm which ensures energy efficiency in overall performance. The multiple design metrics to compute the CH among multiple nodes based on trust degree. The cat hunting with feed-forward neural network (CH-FFNN) is used for multi-hop routing between CHs and sink nodes to optimize both energy efficiency and network lifetime. From simulation results, we observed that effectiveness of proposed ELR-OC routing technique over the existing routing techniques. The average energy consumption of proposed ELR-OC routing technique is 6.79525% and 6.749% efficient than the existing routing methods for the number of sensor nodes and simulation rounds scenarios respectively.

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