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Multi-Objective Approach to Improve Network Lifetime and Congestion Control Routing for Wireless Sensor Networks

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The wireless sensor networks (WSNs) and their extensive characteristics and applicability to a wide range of applications attract researchers attention. WSN is an emerging technology where the sensor nodes are its major elements used to monitor and control physical and environmental systems. Clustering in wireless sensor networks groups all the nodes in a region, uses a single node as a cluster head, and communicates with the sink. However, the resource-constrained nodes' lifetime reduces in the communication process. To improve the network lifetime, an efficient cluster head selection process is widely adopted. Similarly, identifying energy-efficient routing reduces the node energy requirements and enhances the network lifetime. Considering these two characteristics as objective, this research work proposes a fuzzy neural network-based clustering with dolphin swarm optimization routing and congestion control (FNDSCC), where an energy-efficient cluster head selection using a deep fuzzy neural network (DFNN) model and an energy-aware optimal routing using an improved dolphin swarm optimization (DSO) enhance the network lifetime by reducing the energy consumption of the nodes. Moreover, novel rate adjustment techniques to overcome the congestion inside the network are introduced. Proposed model performance is experimentally verified and compared with conventional methods such as genetic based efficient clustering (GEC), hybrid particle swarm optimization (HPSO), and artificial bee colony (ABC) optimization and rate-controlled reliable transport (RCRT) protocol in terms of latency, reliability, packet delivery ratio, network lifetime and efficiency. The results demonstrate that the proposed multi-objective approach performs better than conventional models.

Keywords: deep fuzzy neural network, network lifetime, wireless sensor network, dolphin swarm optimization (DSO), cluster head selection, energy-aware routing.

1. Introduction

Internet paves the way for many wireless communications, making it possible for new technologies to emerge. People share their data more instantly. In this modern world, people expect new technologies and faster communication with no interruption. Many wireless communication technologies were developed, and some are still under development. Each of these has its unique features and possesses different standards for communications. Wireless communications play a vital role in transmitting information from one place to another without any cables and wires within a specified distance. In wireless communications, all the nodes have to run for longer periods of time without any substitute for any energy resources. So, there is a need for optimizing the energy in the network. For this, a greater number of resources are added to increase the network lifetime. Energy sources may be recharged and replaced at any time within a conventional network. So, energy consumption is not a problem. All the sensor networks are constrained oriented for some resource limitations. So, if the power is increased in these criteria, it will be more useful. To minimize power consumption, various algorithms and techniques are used.

WSNs comprise of small sensor devices with limited battery power. Moreover, after their deployment they become unnoticeable, which leads to difficulty in recharging. Every node has different computational capabilities. These nodes with the limited available power process the received data and forward the information to the nearest possible node. Most wireless network systems, situated in remote locations, monitor the environment and military surveillance, and deal with the communication and coverage hole problems. In such situations, the exhaustion of the battery takes place in the sensor nodes. It consumes more power, and the battery drains fast when the sensor node is placed near the sink node. The conservation of power resources, the exclusion of the network life-time during the process of the sensed data reporting task and sensing the network are tedious tasks in conserving the energy. As these issues shorten the network lifetime, sink relocation is introduced to WSN to avoid these problems. It is an efficient method of extending the network lifetime in WSN, and also helps to avoid excess battery consumption. An efficient method for preserving the network lifetime is energy-aware sink relocation. In this method, sensor nodes undergo unequal energy depletion because of multiple nodes. So, they release their energy very fast and finally go down. Moreover, the sensor nodes face a problem in transmitting. In this situation, there is no proper replacement for batteries in such environments. Moreover, the residual battery provides low performance after completing the rounds of relaying the message and sensing the environment task. So, if the transmission range is reduced, there is less energy consumption.

In WSN, routing holds a significant part in decreasing energy consumption. The distance between the two nodes (i.e., source and destination nodes) is considered inversely proportional. It uses the routing protocol such as maximum capacity path (MCP) to maintain the network lifetime for WSN by taking the routing protocol as an underlying message relaying. This also may affect the performance because of the algorithm variations due to the parameters. Many approaches have been used to save power in sensor nodes by allowing more energy-intensive mobile sensor nodes, where power is transferred to the place where there are low-level nodes. This has been achieved by controlling the energy distribution in WSNs. Mobile sensors are often used via sensor relocation to manage energy consumption and improve network lifetime, and these mobile nodes are used as relays for long-distance communication. The following summary provides an overview of the contributions presented in this work:

- an energy-efficient cluster head selection method using a DFNN,
- an energy-aware optimal routing using improved DSO to enhance the network lifetime and minimize energy consumption,
- a novel rate adjustment technique to overcome network congestion,
- an thorough experimental analysis to demonstrate the proposed method enhanced performance,
- performance comparative analysis of the proposed approach with existing ones such as GEC, HPSO, ABC optimization, and RCRT algorithm.

The remaining part of the article is organized as follows. Section 2 presents a brief literature analysis of existing works. Section 3 presents the proposed methodology and Sec. 4 presents the results and discussion. The features of the proposed work are concluded in Sec. 5.

2. Related works

Nowadays, researchers pay more attention to develop a model that enhances the WSN lifetime. In this section, various research works are considered to present different methodologies, advantages, and further enhancement possibilities. WSN consists of various factors such as energy-efficient operations, the energy dissipation among nodes, temporal and spatial variations of node operations, routing and network unbalance. Among these, routing algorithms are the major factor that improves the network lifetime by selecting appropriate cluster heads for the shortest path to transmit data and reduce energy consumption. The modified ad-hoc on-demand distance vector (AODV) routing protocol for wireless sensor networks reported in [1] reduces the jamming and the energy depletion issues by maintaining the desired energy level for each node.

The two-phase routing model, reported in [2], explores the available energy in the non-hotspot network to create routes between the nodes and source. Min-hop routing is used to obtain the node energy consumption and a diffusive routing phase is introduced to estimate the remaining node energy. This routing process enhances network lifetime along with security. Distributed energy-aware routing algorithm based on fuzzy logic [3] is reported to resolve the energy balancing and efficiency issues in the wireless sensor networks. To obtain the shortest path routing, energy metrics are converted into respective cost values, and by using fuzzy logic the path is identified in the fuzzy-based energy-aware approach. Q-learning based routing [4] is introduced to achieve reliable routing where a weighted agent approach is used to adapt to the changes in the network. The reinforcement learning concept is used to adjust the weights that improve the network lifetime, which reduces the network latency.

Similar to routing, clustering is another widely adopted approach in numerous research models. Clustering approaches introduce the cluster heads, which improves the load balancing characteristics of WSNs. Conventional methods use the round policies to select the cluster heads, but this imposes network overhead while selecting the next cluster heads. Recently, various approaches such as low energy adaptive clustering hierarchy (LEACH) protocol, power-efficient gathering in sensor information systems (PEGASIS), adaptive periodic threshold-sensitive energy efficient sensor network protocol (APTEEN), distributed energy efficient clustering (DEEC), and Het-DEEC [5, 6] have been introduced to improve the clustering performance and network lifetime. Research work, reported in [7], introduces an optimization model to enhance the performance of the LEACH protocol. Results of the LEACH protocol are optimized using PSO, which increases the network lifetime by its optimal cluster head selection process. An enhanced PEGASIS model for multi-hop routing reported in [8] reduces the latency and increases the energy efficiency by deploying the nodes and creating the individual clusters to form a chain from the sensor node.

The clustering algorithm, reported in [9], considers the node's initial energy, residual energy, and optimal cluster heads of the network to select the successive cluster heads. This energy-based approach increases the network lifetime by 66% compared to the conventional LEACH. A high-quality clustering algorithm, reported in [10], generates high-quality clusters to enhance energy efficiency. Various parameters are considered in the clustering algorithm to assess the cluster quality. This process reduces the error rate and improves the inter/intra cluster distances [11]. Hyper round policy based on fuzzy inference logic is used to compute the terms, which improves the network lifetime and reduces the overhead instead of fixing the hyper round into a fixed value [12]. The energy-efficient cluster head selection module introduced in [13] uses an adaptive clustering strategy for improved load balancing and cluster head selection. Through dedicated parameters such as mobility level, distance from the node to sink, and neighbor density the cluster heads are selected in this approach, which directly reflects on improved lifetime performance.

Fuzzy logic-based cluster head selection is widely used to select cluster heads through its decision-making characteristics. However, this model faces difficulties while handling uncertain level decisions, So, type-2 fuzzy logic is introduced in [14] to efficiently handle the decision factors and improve the network lifetime better than conventional fuzzy models. Further, an interval type-2 fuzzy logic system [15] is designed to increase the lifetime. The interval model is used for the decision-making process, which considers the transmission power allocation strategies for network lifetime enhancement. Load balanced data gathering algorithm reported in [16] achieves energy efficiency through its node deployment strategy that introduces less traffic and efficient coverage supporting the network. The multi-hop path for packet delivery reduces the network traffic. which is performed using a random bipartite graph model that obtains the deployed load boundaries. This significantly reduces the deployment cost and improves the network lifetime.

The congestion control model, reported in [17]. comprises of three modules: hop by hop flow control, prioritized medium access control (MAC), and rate limiting. The fusion process prevents packet drop in the transmission. The flow control model identifies the packets to be dropped based on the analysis of insufficient space in the nodes. The prioritized MAC confirms the congested nodes' access to the channel, and the rate limiting provides better support to the nodes distant from the sink in the transmission process. The rate-controlled reliable transport (RCRT) protocol eliminates the congestion by analyzing the data rate. All processes such as rate control, detection of congestion level and providing resource to the node are performed in the sink. However, the inability to identify the flow constraints and slow convergence rate are considered the demerits of the presented approach.

In [18], a decentralized clustering algorithm along with the game theory is presented to improve the network quality and lifetime. The non-cooperative game theory controls the node activities and the neighboring nodes in forwarding the messages. These control activities decrease the energy consumption and improve the lifetime compared to LEACH and location-based clustering models. A distributed medium access control, reported in [19], considers the limitations of cooperative-based communication in the multi-hop device selection process. The conventional cooperative communication models limit the energy consumption based on the bit, and this is overcome by the optimized transceiver operations while selecting the multi-hop devices. Minimized energy consumption and maximum lifetime are the advantages of this distributed control model.

Various optimization models are employed to obtain optimal routing, network lifetime enhancement and energy efficiency enhancement. Optimization models such as genetic algorithm, ant colony optimization, ant lion optimization, and PSO are comparatively analyzed in [20] to obtain a WSN optimal routing. The experimental analysis concluded that the best performance is observed in the ant colony optimization compared to other optimization algorithms. An ABC optimization-based optimal routing strategy presented in [21] effectively uses the characteristics of the optimization model to obtain centralized and decentralized routing decisions. Improved network performance and network lifetime are the merits of the presented work.

In the analysis, it is observed that efficient cluster head selection, congestion control and routing are the major parameters considered in existing research work to reduce energy consumption and increase the network lifetime. In existing congestion techniques such as RCRT and the hop-by-hop-based congestion control technique were used based on normal routing, and they were not used for cluster-based routing. Most existing congestion techniques do not support cluster-based routing.

Considering these observations, an optimal cluster head selection algorithm and deep learning approach for efficient routing are proposed, and for congestion control we introduce a rate optimization congestion control scheme that maximizes the network lifetime as much as possible by measuring the congestion levels using the intensity of traffic. This measurement is based on queue buffer allocation in the link.

2.1. Objective of the research

The objectives of the proposed research work are set based on the analysis given in Sec. 2, and they are summarized as:

- to obtain an efficient cluster head selection algorithm for a balanced network,
- to obtain an optimal routing model for enhanced network lifetime and reduce the latency,
- to obtain the rate adjustment technique to overcome the congestion inside the network to reduce the packet loss.

To achieve the above objectives, a deep learning model is introduced for the efficient cluster head selection and the dolphin swarm optimization model is presented intended for the optimal energy-efficient routing.

3. Proposed work

The multi-objective model presented in this section initially selects the optimal cluster heads and identifies the optimized routing path along with congestion control. This section provides a detailed description of the presented objectives. The nodes in WSN generally communicate with the sink through cluster heads. Various statistical and mathematical models evolved to identify suitable cluster heads. However, the performance of conventional systems can be increased by introducing deep learning models in the cluster head selection and election process.

In the efficient cluster head selection process, the DFNN model is introduced, combining the characteristics of fuzzy logic and deep neural network. Initially, the clusters are generated using the Bayesian fuzzy clustering approach in which the nodes are categorized based on the location and the energy levels. The combined nodes are considered as the clusters and node factors are estimated as a probability function:

$$P(L_y^x, v^*, g^*) = P(L_y^x|v^*, g^*)P(g_*)P(v_*|g_*), \tag{1}$$

where the prior distribution of the Gaussian function is denoted as $P(g^*)$, the fuzzy clustering is denoted as $P(v_*|g_*)$ and the likelihood distribution of nodes is represented as $P(L_y^x|v^*,\ g^*)$. Based on the likelihood distribution, the cluster model is derived as:

$$P(L_y^x|v^*, C^*) = \sum_{n=1}^{m} P(L_n|g_n, C), \tag{2}$$

where the node likelihood information is denoted as L_y^x, the relationship function for fuzzy is denoted as v^* and cluster information based on the Gaussian function is denoted as g_n. The total number of nodes is represented by n, and the cluster is represented by C. The clusters are obtained based on the likelihood function, and the same principle is followed for all the clusters and is represented as:

$$P(L_y^x|v^*, C^*) = \sum_{n=1}^{m} \frac{1}{\rho(g_n, \delta, C)} \sum_{i=1}^{j} N(L_n|\mu = k_i,\ b = C_{ni}I), \tag{3}$$

where $\rho(g_n, \delta, C)$ represents the normalization constants, the total number of clusters is represented as j, and the cluster number is represented as i. The fuzzifier function is represented as δ and C represents the cluster. The performance of the clustering model is evaluated similar to the fuzzy c-means algorithm and it is expressed as:

$$P(v^*|C^*) = \sum_{n=1}^{m} P(L_n|C^*). \tag{4}$$

The fuzzy clustering has two factors including a Dirichlet function $(L_n|\mu)$ and $\rho(g_n, \delta, C)$, $\sum_{i=1}^{j}\left(C_{ni}^{m/2}\right)$ and it is expressed as:

$$P(v^*|C^*) = \sum_{n=1}^{m} \rho(g_n, \delta, C)\left[\sum_{i=1}^{j}\left(C_{ni}^{m/2}\right)\right]\mathrm{Dir}(L_n|\mu), \tag{5}$$

where C_{ni} represents the membership function for the cluster i and μ is used to obtain the mean function. In order to obtain a high membership function, the initial factors in the cluster stabilization points are neglected. This process increases the clustering proficiency, and the distribution probability of the cluster is expressed as:

$$P(C^*) = \sum_{i=1}^{j} N\left(k_i|\mu_b, \sum k\right), \tag{6}$$

where $\mu_b = \frac{1}{g}\sum_{n=1}^{m} L_n$ is the mean for the clusters and the cluster coverage is defined as the $\sum k = \frac{1}{g}\sum_{i=1}^{j}(L_n - \mu_b)(L_n - \mu_b)^T$.

After the clustering process, the cluster heads are selected using a DFNN model. Figure 1 depicts the cluster head selection model in the proposed ap-

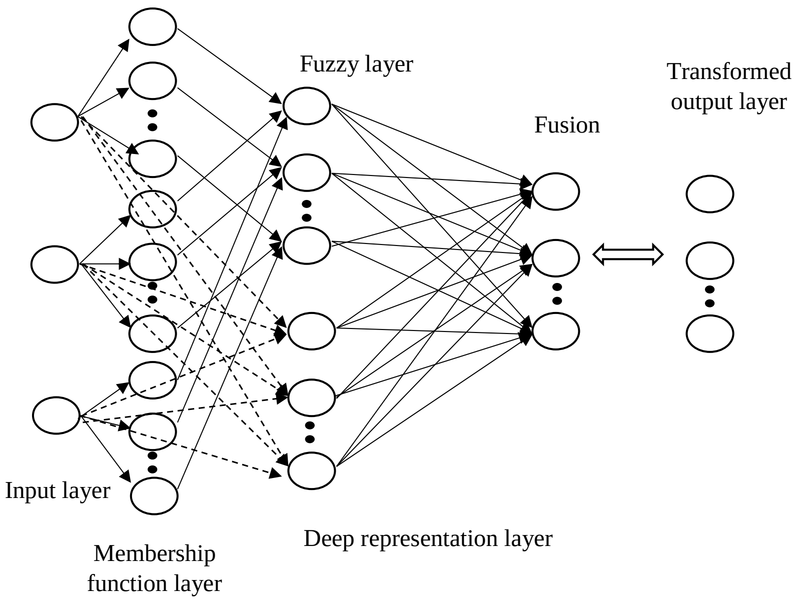

FIG. 1. DFNN for cluster head selection.

proach using the DFNN approach. The inputs of the networks are the clusters and these process the nodes based on the energy levels. Fuzzy logic is used to obtain logical decisions to select and elect the nodes as the cluster heads. Initially, the membership function is obtained based on the average mean value of residual energy of the nodes, and then it is compared with all the other nodes to select the cluster heads for all the clusters. In the DFNN model, each cluster with its nodes is connected to multiple membership functions. This process provides labels for the inputs and is based on fuzzy logic. The function is expressed using the mean, variance, and Gaussian membership function, and it is given as:

$$C_n^{(i)} = e^{-\frac{\left(L_n^{(i)} - \mu_b\right)^2}{\varphi_i^2}}, \tag{7}$$

where μ represents the mean, and φ_i^2 indicates the variance function. Next to the fuzzy representation, the neural network model provides the high-energy level nodes as cluster heads. A fully connected neural network model is used in the proposed approach, which is mathematically expressed as:

$$h_n^{(i)} = w_n^{(i)} h^{(i-1)} + b_n^{(i)}, \tag{8}$$

where $w_n^{(i)}$ denotes the weight function used to define the energy level of the nodes, and $b_n^{(i)}$ represents the connected bias factors. The results are combined in the fusion process where the dense layer is expressed as:

$$d_n^i = w_{d_n}^{(i)} h_d^{(i-1)} + w_{f_n}^{(i)} h_f^{(i-1)} + b_n^{(i)}, \tag{9}$$

where the deep network and fuzzy logic for cluster head selection are denoted as h_d and h_f respectively, and their corresponding weight functions are denoted as w_d for deep network and w_f for fuzzy logic. Finally, the node with the highest energy has the possibility to provide maximum data aggregation, which is obtained by using the SoftMax function. This is expressed as the final layer as below:

$$C_h^i = \frac{e^{w_n \pi_{\Theta(f_n)} + b_n}}{\sum_k e^{w_n \pi_{\Theta(f_n)} + b_n}}, \tag{10}$$

where the cluster heads are selected based on the network bias coefficient and regression coefficient denoted as b_n and w_n, respectively. Based on the selected nodes, the cluster heads are assigned for each cluster in an efficient manner, which improves the network lifetime. The summarized pseudocode for the efficient cluster head selection process is given in Algorithm 1.

Algorithm 1: Cluster head selection using a DFNN.

Initialize the nodes in wireless sensor networks
Initialize deep fuzzy parameters
Initialize Bayesian fuzzy clustering
Start
{{
Estimate probability function for clusters $P(L_y^x, v^*, g^*)$
Derive the cluster model using $P(L_y^x|v^*, C^*)$
Evaluate the performance for $P(v^*|C^*)$
Improve the clustering probability distribution using $P(C^*)$
}
{
Derive the fuzzy layer function using $C_n^{(i)}$
Derive the deep neural network layer function $h_n^{(i)}$
Fuse fuzzy and deep neural network layer as d_n^i
Estimate the cluster heads C_h^i
}}
End

Optimal route selection is another factor considered in this research work to improve network lifetime. To achieve this, the improved dolphin swarm optimization is proposed providing optimal solutions based on the food searching behavior of dolphins. Compared to other optimization algorithms, dolphin optimization provides fast convergence and avoids local optimal better than other optimization algorithms. Moreover, it does not require any specific benchmark functions to obtain the optimal solution, which is the major merit of the DSO algorithm. The significant characteristics of dolphins are categorized into four features: echolocation, information exchange, coordination, and diversity of labor. The artificial neural network model is used to classify the cluster heads, and the results are further optimized through a swarm intelligence model. Mathematically, the proposed optimization model characteristics are derived for the four operations. In echolocation, the distance estimation characteristics of dolphins are formulated to estimate the location and prey size. The intensity of the echo helps the dolphins to predict the environment easily. In the cooperation and labor division phase, the predatory nature of dolphins is utilized to attack the large prey. The coordination process helps to track the prey movements and the dolphins. The information exchange phase helps the dolphins to communicate by producing different frequency sounds either to update the position information about the prey or to call others. The three-stage process includes four operations in which dolphins make use of sounds to predict the environment and prey, exchange information, and identify the food source.

Similar to the dolphin characteristics, the cluster heads are identified for each cluster and analyze the nearby cluster cooperative status to obtain optimal path in the wireless sensor networks. The details of the cluster heads are obtained from the DFNN model, and privilege to act as cluster head is obtained through an artificial neural network model. It classifies the cluster heads as active and passive ones using a training and testing dataset. Consider the cluster heads in a wireless sensor network where each cluster head is considered as dolphin $D = [d_1, d_2, d_3, ..., d_n]$. The fitness function of each dolphin is $F = [f_1, f_2, f_3, ..., f_n]$. To obtain the available cluster head details in the network search process is initiated, which analyzes the characteristics using fitness function and distance, and it is expressed as:

$$H_{m,n,t} = F(D + u_n t), \tag{11}$$

where D represents the dolphin and $u_n t$ indicates the sound produced in the search phase. The minimum fitness ($F_{\min}$) and the maximum fitness ($F_{\max}$) values are obtained based on the characteristics and are expressed as:

$$F_{\min} = \left[\min(H_{1nt}), \min(H_{1nt}), ..., \min(H_{mnt})\right], \tag{12}$$

$$F_{\max} = \begin{cases} F_{\min} & \text{if } F_{\min} < F_{\max}, \\ F_{\max} & \text{otherwise.} \end{cases} \tag{13}$$

In the call phase, the nearby clusters are analyzed for route formation. For this, the distance ($d_{m,n}$) and the energy (E) of the cluster heads are considered, and we have:

$$S_{m,n} = \begin{cases} \left(\frac{d_{m,n}}{E}\right) & \text{if } F_{k,n} < F_{k,m}, \\ S_{m,n} & \text{otherwise.} \end{cases} \tag{14}$$

The next phase in the route selection is the incepted phase, which eliminates the cluster heads unsuitable for path selection. This is expressed as:

$$F_{k,m} = \begin{cases} F_{k,n} & \text{if } S_{m,n} = 0 \text{ and } F_{k,n} < F_{k,m}, \\ F_{k,m} & \text{otherwise.} \end{cases} \tag{15}$$

Finally, the hunting phase is related to the path selection process, which is the optimal path from source to sink, and it is expressed as:

$$N_{CH} = \begin{cases} S_{m,n} > \left(\frac{d_{m,n}}{E}\right) & \text{if } d_{k,n} < d_{k,m}, \\ S_{m,n} = 0 & \text{otherwise.} \end{cases} \tag{16}$$

The movement of dolphins to their new position is depicted in Fig. 2. This process is proceeded continuously along with a fitness function new position while identifying the shortest path to reach the sink. The pseudocode for the optimized path selection is summarized in Algorithm 2.

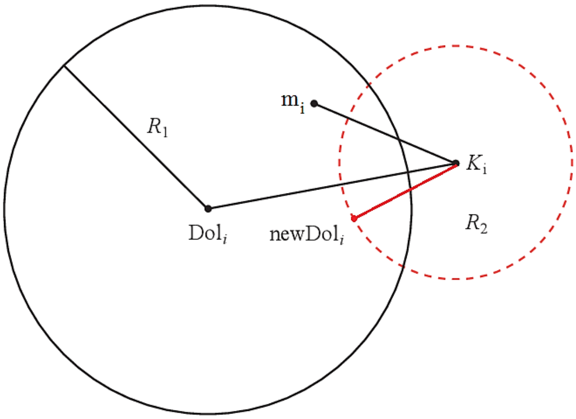

FIG. 2. Movement of dolphins in DSO.

Algorithm 2: Optimal routing using improved DSO.

Initialize the cluster heads
Initialize optimization parameters D, F
Start
{
Estimate the available cluster heads $H_{m,n,t}$
Derive the maximum and minimum fitness function $F_{\min}$, $F_{\max}$
Evaluate the neighbor clusters $S_{m,n}$
eliminates the unsuitable cluster heads $F_{k,m}$
Select the optimal cluster head N_{CH}
}
Repeat the process to reach sink
End

The improved DSO incorporates the results of the Bayesian fuzzy clustering-based deep learning approach for cluster head selection to reduce energy consumption and enhance the network lifetime.

3.1. Congestion detection

According to the queue buffer presented in the link, the overall traffic intensity is computed. Traffic intensity in and among the clusters is monitored by the network. Once the cluster formation becomes complete, the congestion level in all the local clusters is estimated. To perfectly fine-tune the source node transmission rate and overall congestion level are estimated and provided to the source nodes. Hence, computing the intensity of congestion present in the clusters and among the clusters is quite significant.

3.2. Computing the cluster traffic intensity

Considering a sensor node i that is alive and its traffic flow queue length is BL_{si}, BL_i indicates the node queue length in total. The ratio BL_{si}/BL_i is the caching queue of the node, which is termed ω_{si}. For each N distinct queue, considering the packets δ in a queue, the probability of traffic flow is mathematically formulated as:

$$P(\delta_1, \delta_2, ..., \delta_M) = \prod_{i=1}^{M} (1 - \omega_{si})\omega_{si}^{\delta_i}. \tag{17}$$

Computing the intensity of traffic in each cluster σ is the likelihood at which minimum of one sensor contains complete queue:

$$\sigma = 1 - P(0, 0, ..., 0) = 1 - \prod_{i=1}^{M} 1 - \omega_{si}. \tag{18}$$

Hence, every sensor i computes the neighborhood load ω_{si} at the specified time gaps, and the same is notified to the cluster head via neighbor transmission. To gather the ω_{si} value of every sensor, the cluster head computes the σ in every cluster through Eq. (18).

3.3. Computing the intensity of traffic among the clusters

Correspondingly, the overall traffic intensity computation can be performed by modifying the λ value among the cluster head, and σ_i can be represented as the value σ of the cluster i. Besides, the computations of the source and sink in the available cluster are obtained from the next cluster. By integrating σ_{j-1}, the overall traffic intensity obtained by the cluster head is formulated as:

$$\sigma_j = 1 - \left[(1 - \sigma_{j-1}) \prod_{i=1}^{N} 1 - \omega_{si} \right]. \tag{19}$$

3.4. Rate optimization

Assuming that the traffic flow s passes along the link l, we consider $\eta_{ls} = 1/CP_l$ (where CP_l is the transmitting capacity of wireless networks), else η_s

will be considered as "0". Similarly, the transmitting link presence is indicated as $Y_{nl} = 1$, else it is considered as "0". Consider the node data forwarding rate as χ_s; hence, to assure the MAC protocol applicability, the MAC protocol bounding conditions are obtained using matrices Y and η. Thus, $\eta Y \chi \leq 1 - \vartheta$, where the efficiency factor $\vartheta = (\vartheta_j \epsilon [0, 1])\, j \epsilon N$. The node utility function is considered elastic [19]. which expands the transmitting rate monotonously. In view of resource allocation, the obtained utility factor is used to define the available resources in the network. This helps to realize the distribution using suitable weight factors. So the weight factor based on the utility parameter is formulated as:

$$\varphi_s(\chi_s) = w_s \log(\chi_s). \tag{20}$$

Further, we consider the issue of maximizing the utility of the Internet [19] and denote the issue of congestion control in WSNs as a non-linear optimization issue. The total traffic is optimized to select the transmission rate through which every node present in the cluster maximizes the overall utility. Hence, the following problem has to be solved:

$$\max_{x} \varphi_s(\chi_s) = \max_{\chi} \sum_{s \in S} w_s \log(\chi), \tag{21}$$

where the condition of constraint $GA\chi \leq (1 - \varepsilon)$. The theory of optimization states that the formula to compute utility function (21) is a rigid concave continuous function where the practicable segment is convex in any case:

$$P(\chi : G, A) = \sigma^T (GA\chi - (1 - \varepsilon)). \tag{22}$$

Hence, we employ the Lagrange function in order to solve

$$L\,(\chi, \beta) = \sum_{s \in S} w_s \log(\chi) - \sigma^T (GA\chi - (1 - \varepsilon)), \tag{23}$$

where the Lagrange factor σ denotes the traffic link '1' of the overall traffic level computation. Further, it is realized that the traffic control in the network changes the utility factor. Since the practicable segment in the optimization problem is programmed convex and the utility function is continuous, an optimal solution must be derived. As per the theory of optimization, the actual problem (21) will contain two-fold problem. The optimal solution can be derived as a two-fold problem, and it is formulated as:

$$D : \min_{\sigma \geq 0} D(\chi), \tag{24}$$

where the objective function is

$$D\,(\chi) = \max_{\chi} L(\chi, \sigma). \tag{25}$$

The two-fold problem solution is obtained using the steepest descent approach by considering the input and output links of traffic flow that passes through the nodes $li(n, r)$ and $lo(n, r)$, respectively. The rate has been adjusted by adapting the updated process, and therefore we can obtain the cluster nodes:

$$\chi_s(t+1) = \chi_s(t) + \alpha\left(-\frac{\partial D(\chi)}{\partial \chi_s}\right)$$

$$= \chi_s(t) + \alpha\left[-\frac{w_s}{\chi_s} + \sum_{j\epsilon A(s)}\left(\frac{\sigma_j}{c_{li}(n,s)} + \frac{\sigma_j}{c_{lo}(n,s)}\right)\right], \quad (26)$$

where the constant step is represented as α. Optimal convergence will be obtained for smaller step values. The above function, expressed in Eq. (25), denotes the varying direction of rate $\chi_s(n)$ with respect to the node and it is reverse to the varying direction of the considered objective function. In other words, the varying rate across the negative descent of the objective functions is used to realize the desired objective function. The proposed algorithm computes the overall degree of traffic to obtain the congestion information present in the network through the Eq. (19). Then, it computes $\chi_s(n)$ and it is considered source node transmission rate based on Eq. (26). Thus, the proposed algorithm is capable of justifying the network state by fine-tuning the source node transmission rate. Hence, the presented procedure transforms the network with responsiveness to real-time and better adaptability.

4. Performance analysis

The proposed multi-objective model is experimentally verified to demonstrate the improved performance. Network simulator version 2.35 is used to experiment with the model, and Table 1 depicts the simulation parameters used in the experimentation process. The performance is evaluated using the parameters such as latency, packet delivery ratio, network lifetime, reliability, efficiency, and throughput.

Table 1. Simulation parameters.

Simulation no.	Parameters	Range
1	Total number of nodes	500
2	Packet size	1024 bytes
3	Simulation area	5000*5000 sq. units
4	Initial energy	0.5 nJ
5	Transmission rate	1 packet/sec

Existing methodologies such as GEC, HPSO, ABC optimization models and RCRT protocol are compared with the proposed model. Figure 3 depicts the latency comparison for all the algorithms considering the nodes. Results show that the proposed multi-objective optimization model introduces a smaller delay compared to that of the other models, due to its efficient cluster head selection and the optimal routing process.

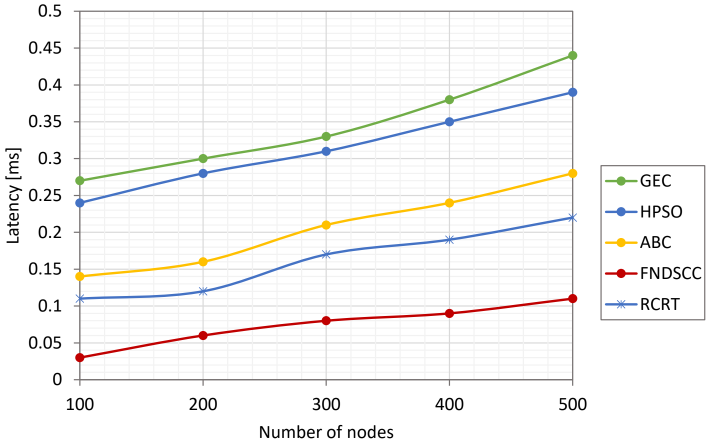

Fig. 3. Latency analysis.

Next, the proposed approach performance is evaluated based on the packet delivery ratio. The efficient clustering approach supports the deep neural network model to select the cluster heads, providing clusters to the optimization model. These cluster heads are used to obtain the optimal path so that the packet delivery ratio increases for the proposed model more than for other approaches. Figure 4 depicts a comparative analysis for the algorithms in which maximum

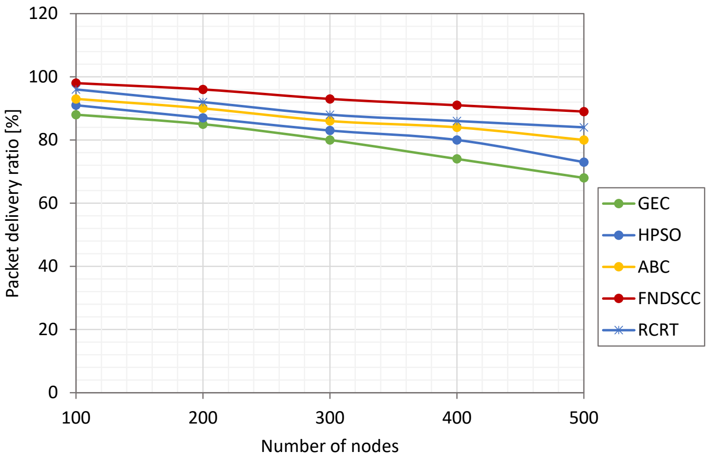

Fig. 4. Comparison of packet delivery ratio.

performance is exhibited by the proposed approach for all values. The shortest path and the efficient cluster heads allow the proposed system to transmit more packets. Besides the conventional techniques, the HPSO approach performs better. However, compared to the proposed model, almost 10% increased performance is observed. The genetic based energy efficient (GEC) model exhibits lesser performance than all the other models.

The next parameter considered for analysis is throughput obtained based on the number of nodes employed in the network. The obtained values are compared and depicted in Fig. 5. This proposed model exhibits maximum throughput because of the high-energy cluster heads and the shortest path. The lesser distance helps the nodes to transmit data quickly and efficiently, whereas the conventional models exhibit lower performance due to their longest path length.

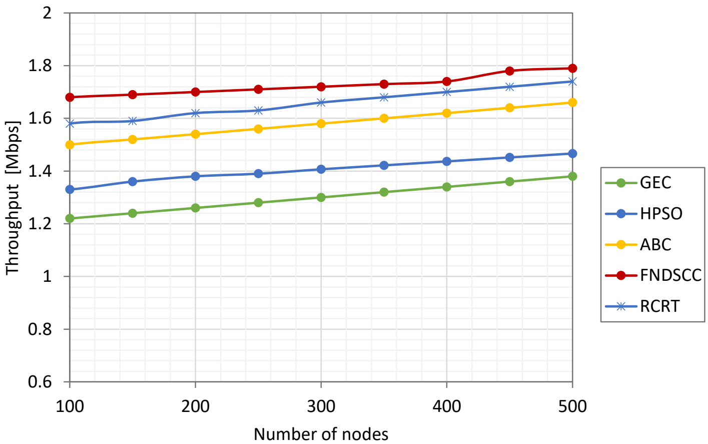

Fig. 5. Comparative throughput analysis.

The network reliability with respect to the number of nodes is depicted in Fig. 6. It is observed in the above figure that the proposed approach attains higher reliability when compared to the existing methods. The energy efficient cluster head selection and the optimal routing improve the network reliability by reducing the node failure. Since the proposed approach measures the energy level of nodes and selects the cluster heads, the successive selected cluster heads are ready to process the data to sink when the primary cluster head fails or disappears. This process extensively improves the network reliability of the proposed approach.

The network lifetime depends on the number of alive nodes. The performance of the proposed approach in terms of alive nodes is depicted in Fig. 7. The multi-objective approach reduces the energy consumption of nodes and increases the cluster head lifetime during data transmission, which simultaneously increases the overall network lifetime. In the proposed approach, the number

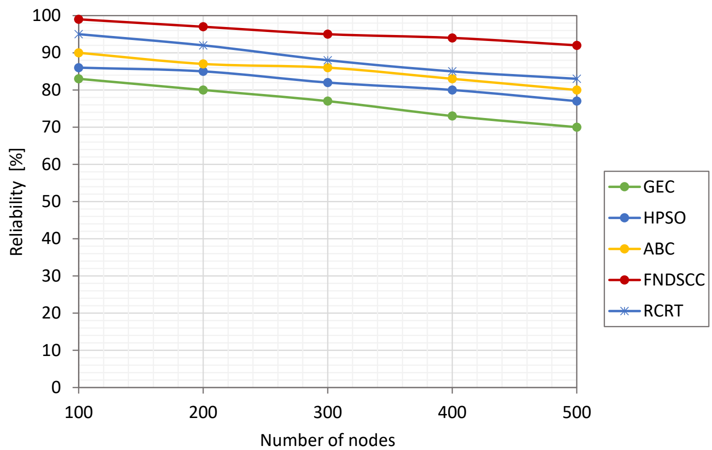

Fig. 6. Network reliability comparison.

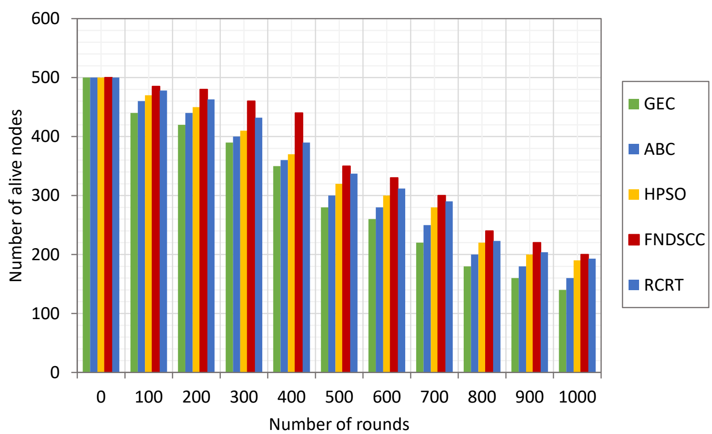

Fig. 7. Network lifetime analysis.

of alive nodes gradually decreases, which indicates the balanced energy-efficient processing characteristics. The performance of the proposed multi-objective approach is 18%, 12% and 8% better compared to the GEC approach, the ant colony optimization model and the HPSO approach, respectively.

The proposed multi-objective approach efficiency is comparatively analyzed with conventional models, as shown in Fig. 8. The efficiency is measured based on the number of alive nodes, delay, and the packet delivery ratio. The proposed model exhibits an efficiency of 98.5% compared to the other models. The efficiency attained by RCRT is approximately 96.8%, whereas the efficiency of HPSO is 96%. The proposed model performance is further verified through simulation analysis with different samples at different instances as a post-classification

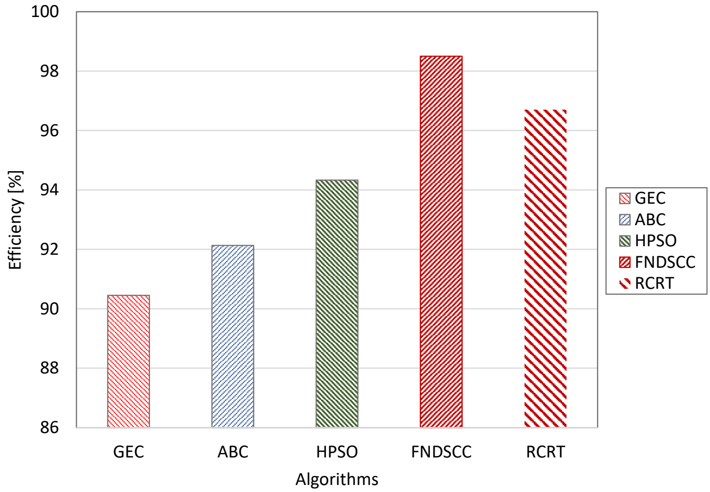

Fig. 8. Efficiency analysis.

process. It is observed that there are minor deviations that are less than 0.05% in terms of efficiency, which is acceptable. The efficiency attained by ABC and GEC is 94.5% and 93%, respectively, which is lesser than the proposed model efficiency. Results clearly show that the presented approach will be suitable for the reliable energy-efficient wireless sensor applications.

5. Conclusion

A multi-objective approach to improve the wireless sensor network lifetime and congestion control was presented in this research work. The objectives of this study were the efficient cluster head selection, the rate-based congestion control scheme and the optimal route establishment. The deep fuzzy-based cluster head selection model, cluster head congestion control scheme with rate adaption technique and the dolphin swarm optimization-based route identification process were used to achieve the objectives. To improve the efficiency of the cluster head selection process, Bayesian fuzzy clustering was used to create clusters and a DFNN approach was used to select the optimal cluster heads. Further, to improve the network lifetime, the optimal routing process was incorporated using an improved DSO model. The proposed model performances were validated experimentally and compared with the conventional models such as GEC, HPSO and ABC optimization algorithms. In the proposed model, a performance better than in the existing models was observed for all the parameters. Further, this research work can be extended by introducing hybrid deep learning approaches for optimal route selection.

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