Energy Prediction for Mobile Sink Placement by Deep Maxout Network in WSN

Chamandeep Kaur[1,]*, Samar Mansour Hassen[2], Mawahib Sharafeldin Adam Boush[3], and Harishchander Anandaram[4]

[1] Computer Science & Information Technology Department, Jazan University, Jizan, Saudi Arabia; Email: cgourmeat@jazanu.edu.sa
[2] Department of Management Information Systems, Jazan University, Jizan, Saudi Arabia; Email: shassen@jazanu.edu.sa
[3] Computer Science Department, Jazan University, Jizan, Saudia Arabia; Email: mboush@jazanu.edu.sa
[4] Centre for Excellence in Computational Engineering and Networking, Amrita Vishwa Vidyapeetham, Coimbatore, Tamil Nadu, India; Email: a_harishchander@cb.amrita.edu
*Correspondance: kaur.chaman83@gmail.com

***Abstract*—In a Wireless Sensor Network (WSN), Numerous cost-effective and energy-constrained sensor nodes are typically used. In a typical Wireless Sensor Network, a single Base Station (BS) gathers information from the whole network, which contributes to concerns including latency, network failure, and congestion. The overwhelming proportion of energy consumption, as well as the energy hole limitation, significantly degrades the overall system performance and network lifetime, which is owing to the sensor nodes that are near the BS consuming more energy. To tackle this problem, it's essential to determine the perfect spot for mobile sink nodes, which minimizes the power consumed and so increases the network's lifespan. In this work, an effective strategy is designed and developed to detect the location of a mobile sink considering factors such as distance, estimated energy, and fairness, using Deep learning-based energy prediction with an adjacency cell score model. In addition, the predicted energy is determined by employing the Deep Maxout Network (DMN). However, a Minimum distance of 137.364, maximal residual energy of 30.903, maximum standardized fairness of 64.426, maximum network duration of 60, and maximum standardized throughput of 60.613 was obtained using the proposed adjacency-based cell score + Deep Maxout Network.**

***Keywords*—Wireless Sensor Network (WSN), mobile sink nodes, deep Maxout network, Base Station (BS) and energy prediction**

I. INTRODUCTION

WSN has rapid development and tremendous growth in recent years [1, 2] because of its large-scale applications in various domains, like home automation, military, healthcare, and manufacturing industries, and provides some specific characteristics, like detecting certain features in the environment. WSN is comprised numerous of nodes and also consists of more BS, generally known as sinks. In general, sensor nodes are very small electronic components with a small amount of energy, like processing potential, and memory. Such nodes are normally constructed in the area to gather specific information through multi-hop interaction with BS [3]. The main purpose of the sink node is to receive the collected information [4], which is carried out by nodes and broadcast to the destination. The destination node can either be a sensor node or a personal system. Wireless networks are mainly designed for replacing the conventional wiring methods because of reasons, such as being difficult to deploy, being highly expensive, and due to accommodated in large spaces. On the other side, small size and less expensive devices permit WSNs in large-scale applications. Moreover, small devices are generally structured with small batteries, and wireless networks, and efficiently function even in absence of a network framework. Though energy consumption of the network is a significant part of wireless networks, it becomes a crucial limitation because of the energy hole problem [5].

The essential characteristic of WSN is that most of the evaluation metrics, like energy consumption, and latency of communication are mainly based on the position of the sink in which the gathered information is solved. If the location of the BS is mounted far away from nodes, the distance will provoke delay and energy utilization. However, if BSs are located as much as close to the nodes, it mitigates the latency and energy consumption [6] of the system. The major issue that lies in such networks is the placement of a single sink node inside the network [7]. Sink mobility is broadly classified into two types, such as random mobility based and controlled mobility based [8] In the former type, the sink is developed to proceed unevenly inside the zone, whereas in controlled mobility the primary issue is to organize the sink node to roam around the system to gather information. Determining the optimal placement of sinks is typically an offline issue that is mainly because of the high cost of deployment. Moreover, estimating the optimal position of BS is a major obstacle. The deployment of WSNs can be implemented either in a planned or structured manner in a semi-random pattern. In such cases, the optimal location of sink nodes cannot be solved easily and there is an immediate

Manuscript received July 2, 2022; revised August 29, 2022; accepted September 13, 2022; published February 17, 2023.

doi: 10.12720/jait.14.1.112-121

requirement to ease the reassignment of existing sink nodes to position new sink nodes in the network [9]. Optimal positioning of BS causes mitigation in the number of needed sinks and controllers and subsequently promotes the utilization of inexpensive sink nodes.

The primary objective of this research is to establish an effective approach for optimal positioning of mobile sink nodes in the WSN network using the Adjacent Cell Score-based Deep learning method. Initially, the nodes are simulated in the WSN network. Then, the simulated nodes are transformed to form a cell network utilizing the Voronoi partition. After that, the best cluster heads are selected based on the concept of Sparse Fuzzy C-means (FCM) [10]. To place the mobile sink nodes in an optimal location, an adjacency-based cell score is utilized and the optimal location is identified using the factors, such as predicted energy, distance, and fairness. The predicted energy is estimated by exploiting DMN.

The major contribution of this research is illustrated as follows:

- An effective strategy for optimal positioning of mobile sink nodes with deep learning-based energy prediction is designed to prolong the lifespan of the system and mitigate energy consumed by the entire system. The position of the mobile sink is identified depending upon the parameters, like predicted energy, distance, and fairness. DMN is utilized to estimate the predicted energy.

The rest of the section is structured as follows: The literature review of recently published papers corresponding to optimal placement of mobile sink nodes along with their merits and disadvantages are explained in Section II, which motivates the researchers to develop a new strategy for optimal placement of mobile sinks. Section III describes the developed Adjacency-based Cell Score and Deep Maxout Network. The results and discussion of the proposed scheme are elaborated in Section IV. Finally, the research concludes in Section V.

II. Motivation

This section describes the literature review of conventional mobile sink placement techniques that are collected from the recently published papers along with their advantages and limitations. This provokes the researchers to design an effective mechanism for optimally positioning the mobile sink.

A. Literature Survey

Sharafeldin *et al.* developed an eminent technique for evaluating the existing energy in the system model. In their research work, sinks were positioned based on the solution of the K-mean issue, thereby reducing the entire energy utilization of the system and prolonging the lifetime of the system [11]. The developed model disclosed a considerable profit under lifetime and energy savings. Moreover, the effect of the energy hole problem was considerably reduced when the number of sink nodes increased. Lemia Louail and Violeta Felea introduced a centroid-based single sink placement method, which was employed to provide the appropriate data about the shape of the construction field and structures of the empty fields. The major contribution of this developed approach was to mitigate the latency of interaction by positioning BS as near as possible to the geographic distance of each node. The main advantages of the developed method are that it reduced the delay in communication and minimized the energy consumption of the network [12]. However, it failed to provide accurate performance for the circle model since the sink nodes are located in the void area.

Mir Md. Sajid Sarwar and Punyasha Chatterjee modeled a distributed algorithm for the effective determination of a deployed minimum number of sinks. In this mechanism, the system was k-covered and the delay was covered by M-hop. It was evaluated that the count of BSs varied inversely with the broadcasting limit of the nodes and the network delay. Moreover, the number of sinks was directly proportional to the fault tolerance stage, but it failed to integrate the energy effectiveness of the network and it only considered the value of K as 1 to 4, which surpasses the lifetime of the network. Govind P. Gupta and Binit Saha developed a novel hybrid meta-heuristic strategy for solving the node clustering problem. The dynamic placement of the mobile sink nodes was accomplished using an Artificial Bee Colony algorithm and further optimized the load balancing and energy consumption [4]. The uniform selection of CH and load distribution between the CHs saved energy utilization. In addition, the lifespan of the system was improved by dynamic adjustment of mobile sink placement. The method was not suitable for underwater wireless sensor networks. The approach, on the other hand, was not suitable for a wireless sensor network submerged in water. Authors proposed a strategy for geographically segmenting the network into a few cells, and then using two mobile sinks to collect the data that is being sensed by these cell nodes [13] The NS2 software was used to perform simulations of the strategy that was suggested. The application of EGRPM results in a large drop in average energy consumption and data delivery delay and causes a substantial increase in packet delivery rate and network lifetime, as shown by a comparison between the performance of EGRPM and that of conventional approaches. Sachan *et al.* [14] proposed a study of a new probabilistic algorithm for analyzing network connectivity by using characteristics like network probability, detection area, individual node radius, and the total detection area, this study proposes. Free space propagation takes place in the intended area. A workable mathematical network model has been discovered through the use of probability theory [13]. We've taken a look at how sensor nodes vary across the detecting region in this model. The connectivity factor can be increased in a new algorithm to improve energy efficiency and preserve connectivity. The proposed model's simulation graph is also shown to verify the mathematical network model. Hajipour *et al.* [15] analyzed the Energy-Efficient Layered Routing Protocol (EELRP). The network is divided into a few concentric circles with various radii using the suggested method. Eight equally sized sectors are created within the circles. Crossovers between sectors and layers result in sections. Each segment has a few nodes, and the agent is chosen from among them based on its circumstances. Each section's nodes communicate the sensed information to their agent. The outcomes revealed that EELRP's performance is superior to conventional approaches when compared to the network lifetime, energy consumption, packet delivery rate, and path hop count. Fu *et al.* [16] suggested a study on an energy-efficient data gathering mechanism (BIIE) to increase network lifetime by balancing inter-cluster and inner-cluster energy. They created a better hierarchical clustering technique for the proposed BIIE to cut down on communication expenses. By creating an effective system to choose the best Rendezvous Node (RN) for each cluster and by using particle swarm optimization to create the mobile sink's trip path, they were able to balance the energy between clusters (PSO). Additionally, simulated studies were performed that demonstrate that, in comparison to other widely-used algorithms, the proposed BIIE can extend network lifetime by roughly 46% and reduce the path length of the mobile sink by roughly 7%. (i.e., WRP and EAPC). Srivastava *et al.* proposed a genetic algorithm-based approach to plan the path for the mobile sink. All the basic intermediate operations of genetic algorithms, i.e., chromosome representation, crossover, and mutation are well explained with suitable examples. The proposed algorithm showed its efficacy over the randomly generated path [16].

B. *Challenges*

Some of the limitations faced by conventional optimal sink placement techniques are deliberated as follows,

- The number of fixed sink nodes in a given set of mobile nodes was hard to determine as the mobile sink nodes collaborated with the fixed BSs to gather the sensor's information [17].
- This method effectively tackled the limitation of node positioning to offer target coverage and connectivity in WSNs with various sink nodes [18]. However, it failed to ensure the upper bound of the approximation ratio.
- Design distributed online algorithms rather than using a centralized optimal algorithm as it enhances the execution speed in large-scale networks and provides accurate results while testing in real-world applications [19].

III. Optimal Placement of Mobile Sink Using Proposed Adjacency-Based Cell Score

The major challenging issue lies in WSN is the optimal placement of mobile sinks without deteriorating the performance of the network and reducing energy consumption [20]. Thus, this research proposes an adjacency-based cell score be designed and developed to achieve optimal positioning of the mobile sink. Initially, the nodes are simulated in the WSN network. After that, the simulated nodes are converted into a cell employing the Voronoi partition [21]. Once the cell transformation is completed, the cluster head selection is performed utilizing sparse FCM. Finally, the optimal position of the mobile sink node is effectively carried out using an adjacency-based cell score based on certain factors, such as predicted energy, distance, and fairness. Besides, the predicted energy is effectively determined by adopting DMN. Fig. 1 represents a block diagram of the optimal placement of the mobile sink.

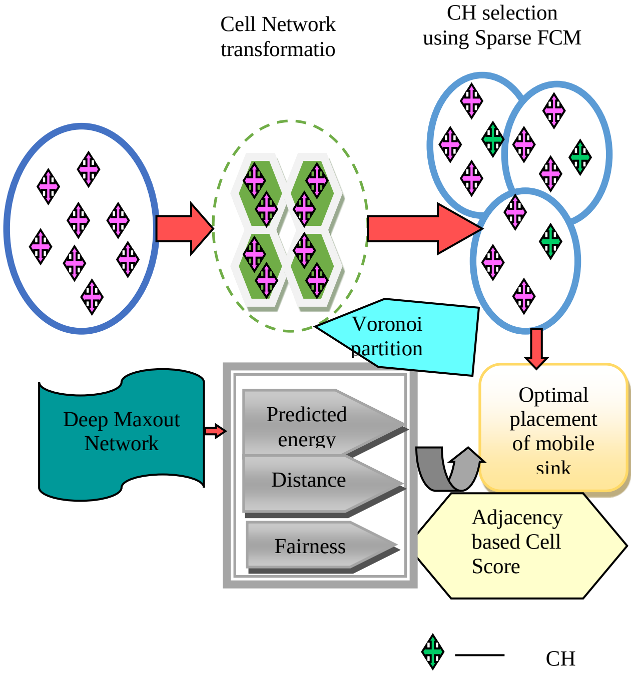


Figure 1. Block diagram of optimal placement of the mobile sink.

A. *Transformation of Cell Network Using Voronoi Partition*

To transform nodes in the cell network, the simulated nodes in WSN are initially grouped and the simulated nodes in the network are transformed into different cells by exploiting the Voronoi partition, which is mainly utilized to find the optimal partitioning of the cells in WSN. The group of various cell regions is indicated as R_n, such $n \in (1 \le n \le p)$. However, p represents the number of partitioned cell regions in the wireless sensor network [22, 23]. Such partitioned cell regions are created depending on the nodes $N_1, N_2, \ldots, N_m$. Moreover, the transformed network using the Voronoi partition is generally referred to as a cell network. After the completion of cell network transformation, the transformed cell is subjected to the CH selection process to choose the optimal cluster head.

B. *Sparse FCM for Effective CH Selection*

After the transformation of the cell network, it is necessary to choose optimal CH in every area to achieve the effective positioning of mobile sink nodes [24]. The Ch selection mechanism is performed by exploiting sparse FCM. However, the sparse FCM is derived by the integration of the FCM algorithm and sparse regularization. The Sparse-FCM has the potential to tackle the limitations related to data clustering. The Sparse-FCM generates cluster-centroids and it is expressed as,

$$C = \{C_1, C_2, \ldots C_j, \ldots C_\alpha\} \tag{1}$$

where the available number of cluster centroids in the system is denoted as α. Let us consider the data matrix

$D_g = X_{rs}{}^g = \alpha^{u\times v}$ u as a count of data points and v as a number of values. Thus, it is represented as $(1\le r\le u)$ and $(1\le s\le v)$. Here, $[u\times v]$ specifies the dimension of g^{th} matrix and the columns of D_g is expressed as $X_s{}^g \in \alpha^u$ and rows of D_g is indicated as $X_r{}^g \in \alpha^v$. Generally, the Sparse-FCM chooses the optimal CH depending on the minimum distance among the specific data point and center of clusters [25]. Algorithm 1 illustrates the pseudo-code of Sparse-FCM. The algorithmic procedure followed by the Sparse-FCM is elaborated as follows,

Step 1: Initialization

Let us consider attribute weights and it is denoted as, $W = W_1^b = ... = W_x{}^b = \frac{1}{\sqrt{x}}$ and initialize the population.

Step 2: Update the matrix of partition

Let us assume the attribute weight as W, and C is specified as cluster center such that α is reduced utilizing the below condition and it is expressed as,

$$Q_{fh} = \begin{cases} \frac{1}{Z_f} & ; M_h = 0, and\, Z_f = card(k) \\ 0 & ; M_h \neq 0 \; but \; M_{ft} = 0 \\ \frac{1}{\sum_{t=1}^{e}\left(\frac{M_h}{M_{ft}}\right)\left(\frac{1}{d-1}\right)} & ; \; otherwise \end{cases} \tag{2}$$

here, $card(k)$ indicates the cardinality set k. The computed distance between cluster center and data values is accomplished using the below equation and the distance determined in sparse FCM is expressed as,

$$M_h = \sum_{f=1}^{e} H_l \left(L_{hl} - L_{fl}\right)^2 \tag{3}$$

Step 3: Update the cluster center

Let W and α be the group and $\varepsilon(C)$ is reduced if it follows the below condition,

$$C = \begin{cases} 0 & ; if \; W_l = 0 \\ \frac{\sum_{t=1}^{e} Q_{fh} - L_{hl}}{\sum_{f=1}^{e} Q_{fh}} & ; if \; W_l \neq 0 \end{cases} \tag{4}$$

Step 4: Estimate the class

The class attribute is determined according to Q and C. The class E_i is denoted as $\max \sum_{i=1}^{x} W_i.E_i$ such $\|W\|_2{}^2 \le 1, \|W\|_y{}^y \le c$ and determined W^*. However, the tuning parameter is denoted as c.

Step 5: Termination

The aforementioned explained process is continued till the optimal solution is attained or until satisfying requirements. The cluster centroid attained utilizing the Sparse-FCM is specified as,

$$\frac{\sum_{i=1}^{x}\left|W_i{}^* - W_i{}^b\right|}{\sum_{i=1}^{x}\left|W_i{}^b\right|} \langle 10^{-4} \tag{5}$$

Algorithm 1. Pseudo code of Sparse-FCM	
1	Input: a cluster, and data matrix as $D_g = X_{rs}^g = \alpha^{u\times v}$
2	Output: cluster centroid $C = \{C_1, C_2, ...C_j, ..., C_a\}$ and W^b
3	Begin
4	Initialize $W = W_1^b = ... = W_x{}^b = \frac{1}{\sqrt{x}}$
5	Compute Q
6	Specify C
7	Fix Q and C calculate E_i
8	Compute W^*
9	Terminate

C. Optical Placement of Mobile Sink

After the selection of CH using Sparse FCM, the best positioning of the mobile sink is carried out in the WSN network [26, 27]. The adjacency-based cell score plays a significant role in placing the mobile sink, such that the lifetime of the network is prolonged and also it considerably reduces the consumption of energy [28]. However, the best position of the mobile sink is identified by utilizing factors, such as predicted energy, distance, and fairness. The predicted energy is determined by applying the energy as an input to the DMN and this classifier determines the predicted energy, which is considered one of the factors in optimally placing the mobile sink node.

Let us assume V number of cells and V CHs in the WSN network and it is expressed as,

$$B = \{B_1, B_2, ...B_o, ...B_V\}; 1 \le o \le V \tag{6}$$

The location of the mobile sink from B_o to B_s depends on the adjacency-based cell score and it is expressed as,

$$A_s = K_s{}^p + G_s + (1 - F_s) \tag{7}$$

where the predicted energy $K_s{}^p$ and the distance G_s are specified by the following equations,

$$K_s{}^p = \frac{1}{t}\sum_{\beta=1}^{t} K_{loss}{}^{product}(\sigma) \tag{8}$$

$$G_s = G\left(Loc_o, Loc_s\right) \tag{9}$$

where the Euclidean distance is represented as $G(\cdot)$ the position of BS at the o^{th} cell is specified as Loc_o and Loc_s indicates the position of the sink at the s^{th} cell. The fairness F_s is expressed as,

$$F_s = \frac{V^q}{V} \tag{10}$$

where V^q indicates the maximum number of nodes that equally distribute its resources.

1) Structure of deep Maxout network

DMN is a type of trainable activation factor and is mainly included with a multi-layer structure [29]. Here, an efficient activation function known as Maxout allocates a non-zero slope to both positive terms and negative terms. In general, Maxout assists steps to solve the optimization problem by partially protecting the hidden components from transiting to an abnormal mode [30−32]. Though the Maxout plays like a trainable activation parameter, it does not play the role of arbitrary function approximator. The energy K_s is subjected to DMN and the output obtained from the Deep Maxout Network is represented as $K_s^{\,P}$. Fig. 2 represents the structure of DMN. The activation of the hidden unit is determined as follows:

$$T_{w,z}^{\;1} = \max_{U\in[1,I_1]} \gamma_{J_{\ldots wz}}^{\;tt} + \phi_{wz} \tag{11}$$

$$T_{w,z}^{\;2} = \max_{U\in\lfloor 1,I_2\rfloor} T_{w,z}^{\;1} J_{\ldots wz} + \phi_{wz} \tag{12}$$

$$\vdots$$

$$T_{w,z}^{\;mm} = \max_{U\in[1,I_{mm}]} T_{w,z}^{\;mm-1^{tt}} J_{\ldots.wz} + \phi_{wz} \tag{13}$$

$$\vdots$$

$$T_{w,z}^{\;nn} = \max_{U\in[1,I_{nn}]} T_{w,z}^{\;nn-1^{tt}} J_{\ldots wz} + \phi_{wz} \tag{14}$$

$$Y_w = \max_{U\in[1,I_{nn}]} T_{w,z}^{\;nn} \tag{15}$$

here, I_{mm} represents the count of units in mm^{th} the layer and nn is the overall layers in the Maxout network [33, 34].

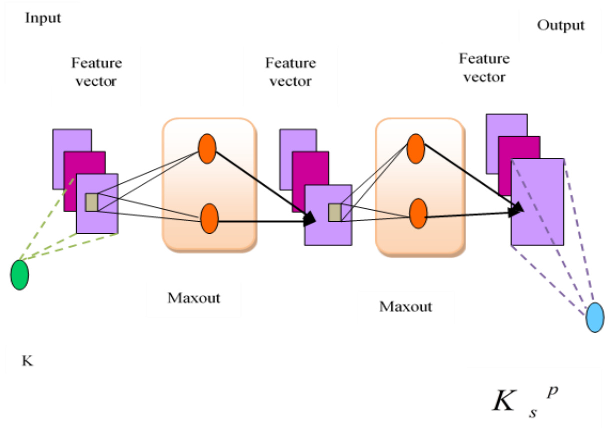


Figure 2. Structure of deep Maxout network.

IV. RESULTS AND DISCUSSION

This section deliberates the results of the developed Adjacency-based Cell Score + DMN in terms of performance measures.

A. Experimental Setup

The experimentation of developed Adjacency-based Cell Score + DMN is carried out in Network Simulator-2 (NS-2) using 200 nodes, 300 nodes, and 400 nodes by changing the number of rounds.

B. Evaluation Metrics

The performance enhancement of developed Adjacency-based Cell Score + DMN is evaluated using performance measures, such as distance, residual energy, normalized fairness, network lifetime, and normalized throughput.

C. Comparative Methods

The performance of the developed scheme is analyzed with that of conventional approaches, like Ant Colony Optimization-based Mobile Sink Path determination (ACO-MSPD), Multi-Objective Particle Swarm Optimization (MOPSO) F-ROA, and Adjacency-based Cell Score.

D. Comparative Analysis

This part explains the comparative assessment of Adjacency-based Cell Score + DMN concerning the evaluation metrics by changing the number of rounds.

1) Analysis using 200 nodes

Fig. 3 represents the assessment of the proposed Adjacency-based Cell Score + Deep Maxout Network based on 200 nodes concerning the evaluation measures by increasing the count of rounds.

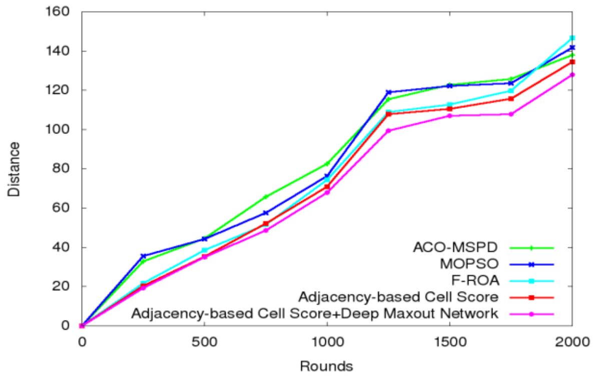
Fig. 3(a) illustrates the assessment of distance by increasing the count of rounds. If rounds are 2000, the proposed Adjacency-based Cell Score + DMN achieved a distance of 127.826, whereas the existing techniques attained the distance of 138.080 for ACO-MSPD, 141.885 for MOPSO, 146.619 for F-ROA, and 134.470 for Adjacency-based Cell Score. The performance enhancement of the developed approach while comparing it with the traditional approaches are 7.426%, 9.908%, 12.817%, and 4.940% for ACO-MSPD, MOPSO, F-ROA, and Adjacency-based Cell Score, respectively.

Fig. 3(b) represents the analysis of residual energy concerning the count of rounds. If the number of rounds=100, energy attained by Adjacency-based Cell Score + DMN is 70.713, which shows the performance development of the proposed technique with that of the conventional schemes, such as ACO-MSPD is 7.569%, MOPSO is 4.572%, F-ROA is 3.933%, and Adjacency-based Cell Score is 4.681%. However, the residual energy achieved by traditional techniques, like ACO-MSPD is 65.361, MOPSO is 67.481, F-ROA is 67.932, and Adjacency-based Cell Score is 67.403.

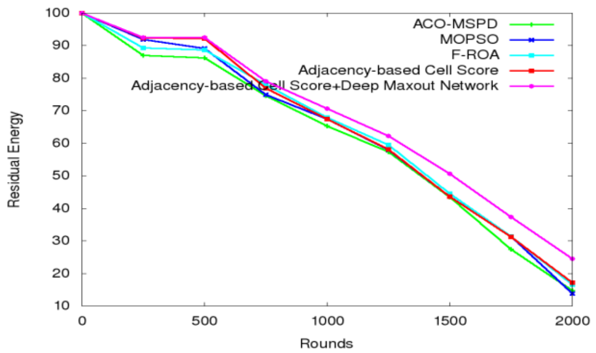
The analysis of normalized fairness in terms of the count of rounds is represented in Fig. 3(c). If the number of rounds=2000, fairness achieved by conventional approaches, such as ACO-MSPD, MOPSO, F-ROA, and Adjacency-based Cell Score is 50.684, 44.759, 43.342, and 51.734, respectively. However, the proposed Adjacency-based Cell Score + Deep Maxout Network attained the fairness of 54.601 that outcomes the performance enhancement of 7.174% for ACO-MSPD, 18.024% for MOPSO, 20.620% for F-ROA, and 5.250% for Adjacency-based Cell Score.

Fig. 3(d) shows the analysis of network lifetime. If the count of rounds=2000, the network lifetime obtained by the proposed Adjacency-based Cell Score + DMN is 20 results in the performance enhancement of the designed method with that of the classical schemes, such as ACO-MSPD is 15%, MOPSO is 10%, F-ROA is 15%, and Adjacency-based Cell Score is 5%. However, the network lifetime obtained by conventional schemes, such as ACO-MSPD is 17, MOPSO is 18, F-ROA is 17, and Adjacency-based Cell Score is 19.

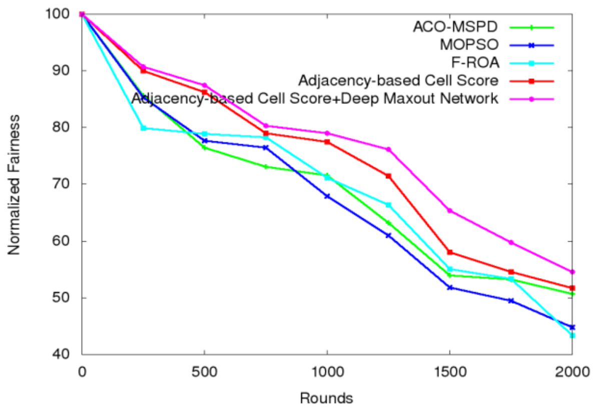
The analysis of normalized throughput is depicted in Fig. 3(e). By considering the number of rounds is 2000, the normalized throughput attained by existing methods, like ACO-MSPD is 52.156, MOPSO is 53.490, F-ROA is 53.259, and Adjacency-based Cell Score is 54.255. However, the proposed Adjacency-based Cell Score + Deep Maxout Network attained the normalized throughput of 56.605 that resulting in the performance enhancement developed with that of traditional methods, like ACO-MSPD, MOPSO, F-ROA, and Adjacency-based Cell Score is 7.860%, 5.503%, 5.910%, and 4.152%, respectively.



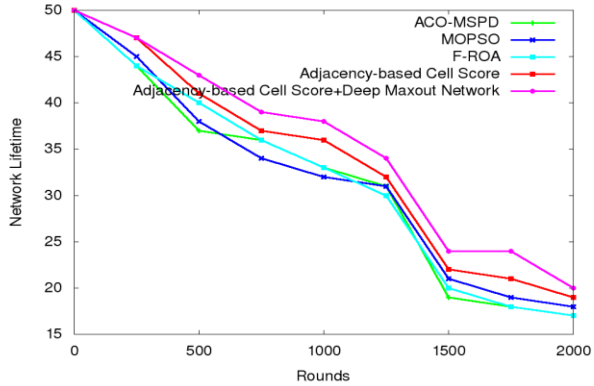
(a) Distance



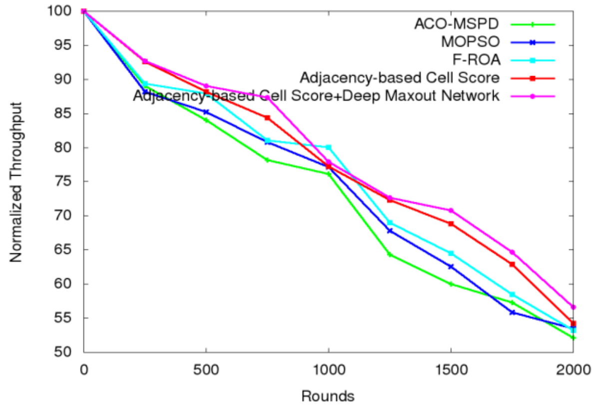
(b) Residual energy



(c) Normalized fairness



(d) Network lifetime



(e) Normalized throughput

Figure 3. Analysis using 200 nodes a) distance b) residual energy c) normalized fairness d) network lifetime e) normalized throughput.

2) Analysis based on 300 nodes

Fig. 4 illustrates the assessment of developed Adjacency-based Cell Score + DMN following the performance metrics using 300 nodes.

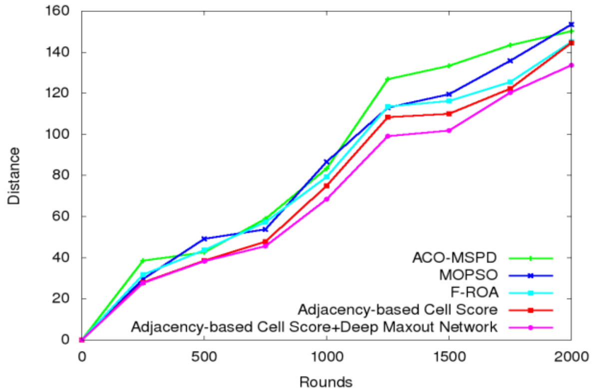
Fig. 4(a) represents the analysis of distance by changing the count of rounds. When the number of rounds=2000, the distance achieved by the proposed Adjacency-based Cell Score + DMN is 133.701, and the conventional schemes of ACO-MSPD are 150.194, MOPSO is 153.429, F-ROA is 145.030, and Adjacency-based Cell Score is 144.474. However, the proposed approach outcomes the performance development of 10.982% for ACO-MSPD, 12.859% for MOPSO, 7.812% for F-ROA, and 7.457% for Adjacency-based Cell Score.

The analysis of residual energy in terms of the count of rounds is depicted in Fig. 4(b). By changing the number of rounds=2000, residual energy attained by developed Adjacency-based Cell score + DMN is 24.244, whereas existing methods achieved the residual energy of 14.436 for ACO-MSPD, 16.544 for MOPSO, 16.795 for F-ROA, and 19.600 for Adjacency-based Cell Score.

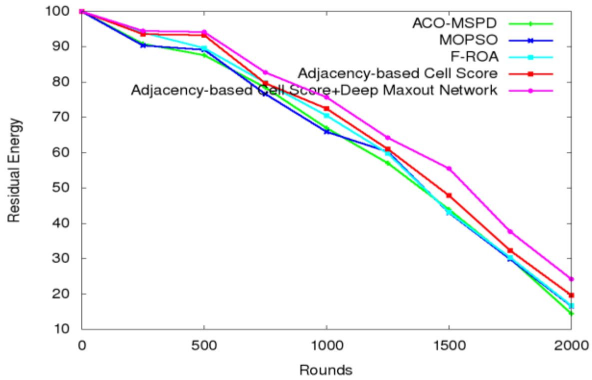
Fig. 4(c) portrays the analysis of the proposed Adjacency-based Cell Score using normalized fairness for the count of rounds. If the count of rounds=2000, normalized fairness attained by the developed approach is 61.457 which shows the performance enhancement of the developed scheme with that of conventional schemes, such as ACO-MSPD is 17.978%, MOPSO is 16.350%, F-ROA is 9.547%, and Adjacency-based Cell Score is 6.379%.

The analysis of the network lifetime of the proposed approach to the count of rounds is illustrated in Fig. 4(d). By considering the number of rounds as 2000, the lifetime attained by Adjacency-based Cell Score + DMN is 44, whereas the conventional techniques show the lifetime for methods ACO-MSPD is 32, MOPSO is 33, F-ROA is 33, and Adjacency-based Cell Score is 36.

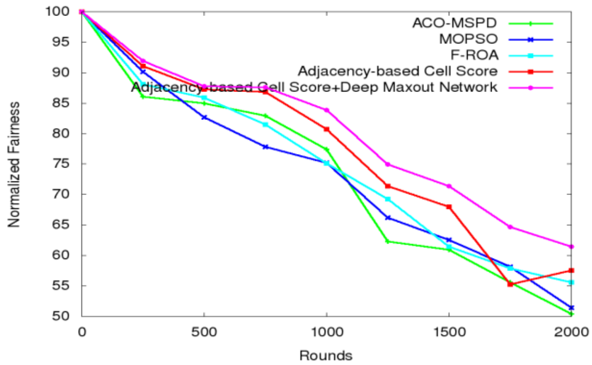
Fig. 4(e) represents the analysis of normalized throughput by changing the count of rounds. If the number of rounds=1000, the throughput obtained by Adjacency-based Cell Score + DMN is 83.952 reveals the performance development of developed with that of the traditional techniques like ACO-MSPD is 9.757%, MOPSO is 3.921%, F-ROA is 4.179%, and Adjacency-based Cell score is 2.417%. However, the normalized throughput attained by the traditional approaches, such as 75.761 for ACO-MSPD, 80.660 for MOPSO, 80.444 for F-ROA, and 81.923 for Adjacency-based Cell Score.



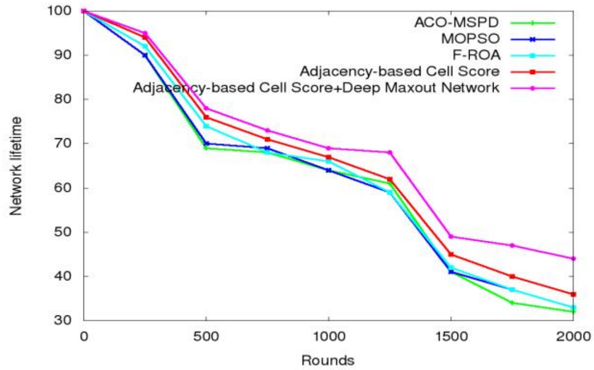
(a) Distance



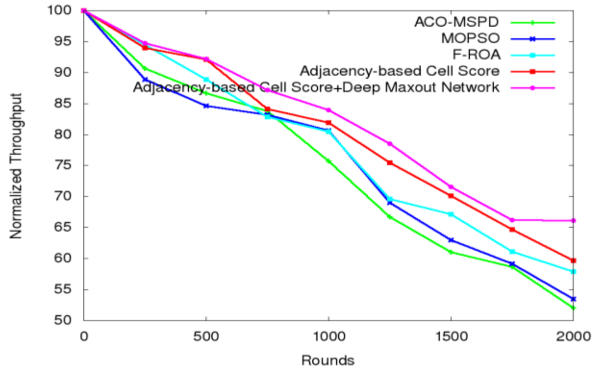
(b) Residual energy



(c) Normalized fairness



(d) Network lifetime



(e) Normalized throughput

Figure 4. Analysis using 300 nodes a) distance b) residual energy c) normalized fairness d) network lifetime e) normalized throughput.

3) *Analysis based on 400 nodes*

Fig. 5 represents the assessment of developed Adjacency-based Cell Score + DMN concerning evaluation metrics.

Fig. 5(a) depicts the assessment of developed Adjacency-based Cell Score + DMN in terms of distance. If the count of nodes=2000, the distance obtained by the proposed Adjacency-based Cell Score + DMN is 137.364 reveals the performance enhancement proposed with that of the traditional approaches, such as ACO-MSPD is 16.365%, MOPSO is 11.915%, F-ROA is 11.439%, and Adjacency-based Cell Score is 6.483%. Moreover, the distance measured by traditional techniques, such as ACO-MSPD, MOPSO, F-ROA, and Adjacency-based Cell Score is 164.242, 155.945, 155.107, and 146.887, respectively.

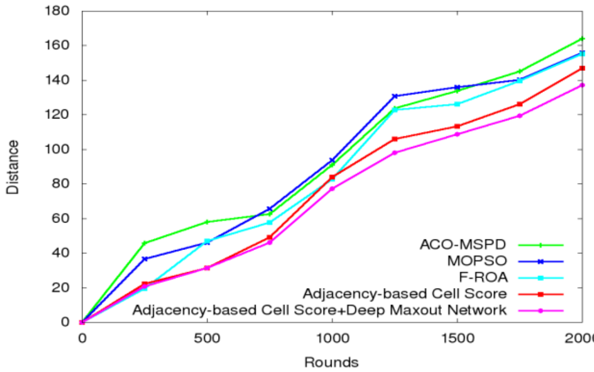
The assessment of residual energy by changing the count of rounds is represented in Fig. 5(b). For round=1000, residual energy attained by the Adjacency-based Cell Score + DMN is 77.942 showing the performance enhancement of the developed method with that of the conventional schemes, like ACO-MSPD is 11.038%, MOPSO is 10.649%, F-ROA is 9.982%, and Adjacency-based Cell Score is 3.313%.

Fig. 5(c) depicts the analysis of normalized fairness. By varying the count of rounds to 2000, the normalized fairness attained by the proposed Adjacency-based Cell Score + DMN is 64.426 results the performance increment developed with that of the conventional approaches, such as ACO-MSPD is 12.275%, MOPSO is 14.509%, F-ROA is 12.645%, and Adjacency-based Cell Score is 10.110%.

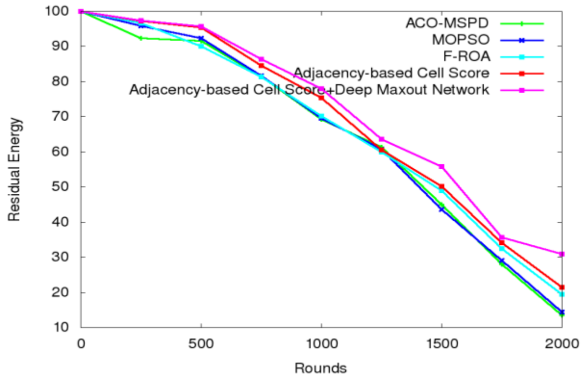
However, the existing methods attained the normalized fairness of 56.518 for ACO-MSPD, 55.078 for MOPSO, 56.279 for F-ROA, and 57.912 for Adjacency-based Cell Score.

The analysis of network lifetime by an increasing count of rounds is shown in Fig. 5(d). If the count of rounds=2000, the lifetime obtained by existing methods, such as ACO-MSPD is 50, MOPSO is 49, F-ROA is 49, and Adjacency-based Cell Score is 52 and the performance improvement of the existing techniques is 16.667%, 18.333%, 18.333%, and 13.333% for ACO-PSMD, MOPSO, F-ROA, and Adjacency-based Cell Score.

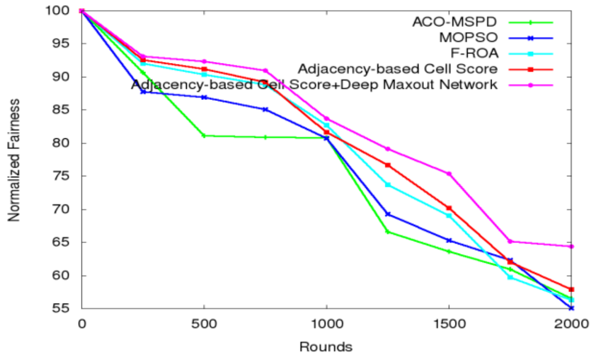
Fig. 5(e) represents the assessment of normalized throughput in terms of the count of rounds. By varying the number of rounds=2000, the proposed Adjacency-based Cell Score + Deep Maxout Network obtained the normalized throughput of 60.613 that outcomes the performance enhancement developed with that of conventional approaches like ACO-MSPD is 9.715%, MOPSO is 6.714%, F-ROA is 4.554%, and Adjacency-based Cell Score is 4.207%.



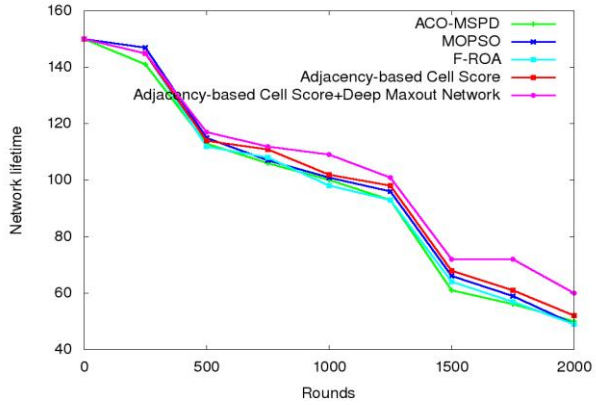
(a) Distance



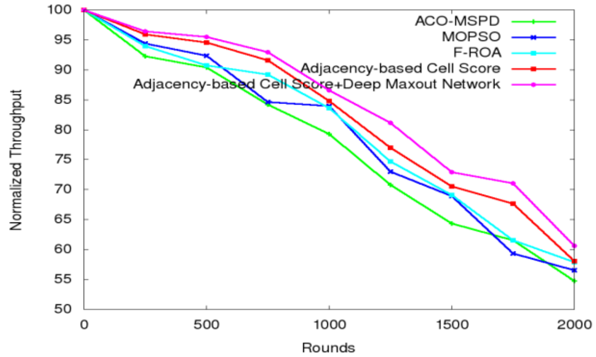
(b) Residual energy



(c) Normalized fairness



(d) Network lifetime



(e) Normalized throughput

Figure 5. Analysis using 400 nodes a) distance b) residual energy c) normalized fairness d) network lifetime e) normalized throughput.

4) *Comparative discussion*

TABLE I. COMPARATIVE DISCUSSION

Nodes	Metrics	ACO-MSPD	MOPSO	F-ROA	Adjacency-based Cell Score	Proposed Adjacency-based Cell core + Dee Maxout Network
200	*Distance*	138.080	141.885	146.619	134.470	**127.826**
	Residual energy	14.746	13.861	16.554	17.222	**24.511**
	Normalized Fairness	50.684	44.759	43.342	51.734	**54.601**
	Network lifetime	17	18	17	19	**20**
	Normalized Throughput	52.156	53.490	53.259	54.255	**56.605**
300	*Distance*	150.194	153.429	145.030	144.474	**133.701**
	Residual energy	14.436	16.544	16.795	19.600	**24.244**
	Normalized Fairness	50.408	51.408	55.589	57.537	**61.457**
	Network lifetime	32	33	33	36	**44**
	Normalized Throughput	51.996	53.501	57.920	59.642	**66.138**
400	*Distance*	164.242	155.945	155.107	146.887	**137.364**
	Residual energy	13.516	14.502	19.494	21.410	**30.903**
	Normalized Fairness	56.518	55.078	56.279	57.912	**64.426**
	Network lifetime	50	49	49	52	**60**
	Normalized Throughput	54.725	56.544	57.853	58.063	**60.613**

Table I portrays the comparative discussion of the proposed Adjacency-based Cell Score + DMN When the count of nodes is considered as 400, residual energy yielded by the developed approach is 30.903, while the conventional techniques, such as ACO-MSPD is 13.516, MOPSO is 14.502, F-ROA is 19.494, and Adjacency-based Cell Score is 21.410. The throughput attained by the developed approach for 200 nodes is 56.605, the Network lifetime is 20, and residual energy is 24.511. From the discussion, it is clear that the proposed Adjacency-based Cell Score + DMN achieved minimal distance, maximal residual energy, Fairness, Network lifetime, and Normalized throughput.

V. Conclusion

In this research, an effective approach called Adjacency based Cell Score Network along with Deep learning is proposed to identify the optimal positioning of mobile sink nodes in the WSN network. Typically, WSNs comprise an infinite number of sensor nodes that are very affordable in terms of cost. Existing WSN methods face serious issues, like latency, energy consumption, and energy hole problem that considerably reduces the lifetime as well as the performance of the network. The cause of such issues is mainly because of the reason that the placement of sensor nodes close to the sink nodes consumes abundant energy and hence, it is significant to design an effective technique for determining the best positioning of mobile sink nodes. To overcome such limitations, this research proposes a deep learning-based energy prediction for optimal positioning of mobile sink nodes. Moreover, an adjacency-based cell score is utilized to determine the location of sink nodes employing factors, like predicted energy, distance, and fairness. The predicted energy is identified using DMN. However, the adjacency-based Cell Score + DMN attained a minimum distance of 137.364, maximal residual energy of 30.903, maximum normalized fairness of 64.426, maximum network lifetime of 60, and maximum normalized throughput of 60.613.

Conflict of Interest

The authors affirm that they don’t have any known financial or interpersonal conflicts that would have seemed to have an impact on the research presented in this study.

Author Contributions

Chamandeep Kaur: Conceptualization of proposed system, implementation, and supervision. Samar Mansour Hassen: Literature review. Mawahib Sharafeldin Adam Boush: Data collection. Harishchander Anandaram: Data analysis and implementation. All authors had approved the final version.

References

[1] S. Mawahib and C. Kaur, “A design for the Bandwidth improvement for the microstrip patch antenna for wireless network sensor,” *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, vol. 9, no. 396, 2022. 10.32628/IJSRSET2293130

[2] H. M. Mourad, C. Kaur, and D. M. Aarif, “Challenges faced by big data and its orientation in the field of business marketing,” *International Journal of Mechanical and Production Engineering Research and Development*, vol. 10, no. 3, Jun 2020.

[3] A. A. Alalmai, A. Arun, and M. Aarif, “Implementing possibilities and perspectives of flipped learning in hotel management institutions,” *Test Engineering and Management*, vol. 83, pp. 9421–9427, 2020.

[4] D. P. Kumar, A. Tarachand, A. Chandra, *et al.*, “ACO-based mobile sink path determination for wireless sensor networks under non-uniform data constraints,” *Appl. Soft Comput.*, vol. 69, pp. 528–540, 2018.

[5] A. K. Adava, I. A. Khan, P. Pandey, *et al.*, “Impact of marketing communication and information sharing on the productivity of India’s small and medium-sized businesses (SMEs),” *International Journal of Health Sciences*, vol. 6, pp. 12745–12755, 2022. https://doi.org/10.53730/ijhs.v6nS2.8352

[6] P. Chopra, V. S. Gollamandala, A. N. Ahmed, *et al.*, “Automated registration of multiangle SAR images using artificial intelligence,” *Mobile Information Systems*, 2022.

[7] M. Aarif and A. Alalmai, “Importance of effective business communication for promoting and developing hospitality industry in Saudi Arabia,” *A Case Study of Gizan (Jazan)*, 2019.

[8] M. Naghibi and H Barati, “EGRPM: Energy efficient geographic routing protocol based on mobile sink in wireless sensor networks,” *Sustainable Computing: Informatics and Systems*, vol. 25, 2020.

[9] A. Anjum, C. Kaur, S. Kondapalli, *et al.*, “A mysterious and darkside of the darknet: A qualitative study,” *Webology*, vol. 18, no. 4, 2021.

[10] M. Naghibi and H. Barati, “EGRPM: Energy efficient geographic routing protocol based on mobile sink in wireless sensor networks,” *Sustainable Computing: Informatics and Systems*, vol. 25, 100377, 2022.

[11] S. Sachan, R. Sharma, and A. Sehgal, “Energy efficient scheme for better connectivity in sustainable mobile wireless sensor networks,” *Sustainable Computing: Informatics and Systems*, vol. 30, 100504, 2021.

[12] Z. Hajipour and H. Barati, “EELRP: Energy efficient layered routing protocol in wireless sensor networks,” *Computing*, vol. 103, no. 12, pp. 2789–2809, 2021.

[13] A. Kaswan, V. Singh, and P. K. Jana, “A multi-objective and PSO based energy efficient path design for mobile sink in wireless sensor networks,” *Pervasive Mob. Comput.*, vol. 46, pp. 122–136, 2018.

[14] M. M. S. Sarwar and P. Chatterjee, “Optimal sink placement in wireless sensor networks to increase network performance,” in *Industry Interactive Innovations in Science, Engineering and Technology*, Singapore: Springer, 2018, pp. 423–433.

[15] P. Pardesi and J. Grover, “Improved multiple sink placement strategy in wireless sensor networks,” in *Proc. IEEE International Conference on Futuristic Trends on Computational Analysis and Knowledge Management*, February 2015, pp. 418–424.

[16] M. Aarif, “A study on the role of healthcare industry in the promoting of health Tourism in India,” *A Case Study of Delhi-NCR*, 2018.

[17] X. Fu and X. He, “Energy-Balanced data collection with path-constrained mobile sink in wireless sensor networks,” *AEU-International Journal of Electronics and Communications*, vol. 127, 153504, 2020.

[18] C. Kaur. (2022). The influence of the hybrid staging environment of internet of things and cloud computing on healthcare. [Online]. Available: http://hdl.handle.net/10603/378260

[19] S. Sachan, R. Sharma, and A. Sehgal, “Energy efficient scheme for better connectivity in sustainable mobile wireless sensor networks,” *Sustainable Computing: Informatics and Systems*, vol. 30, 2021.

[20] C. Kaur, M. S. A. Boush, S. M. Hassen, *et al.*, “Incorporating sentimental analysis into development of a hybrid classification model: A comprehensive study,” *International Journal of Health Sciences*, vol. 6, no. S1, pp. 1709–1720, 2022. https://doi.org/10.53730/ijhs.v6nS1.4924

[21] A. K. Srivastava, A. Sinha, R. Mishra, *et al.*, “EEPMS: Energy efficient path planning for mobile sink in wireless sensor networks: A genetic algorithm-based approach,” in *Advances in Computational Intelligence and Communication Technology*, Singapore: Springer, 2021, pp. 101–108.

[22] G. P. Gupta and B. Saha, “Load balanced clustering scheme using hybrid metaheuristic technique for mobile sink based wireless

sensor networks," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–12, 2020.

[23] L. Louail and V. Felea, "Centroid-Based single sink placement in wireless sensor networks," *Wireless Personal Communications*, vol. 108, no. 1, pp. 121–140, 2019.

[24] D. Kaur, H. M. Mourad, and S. S. Banu, "Security and challenges using clouds computing in healthcare management system," *International Journal of Trend in Scientific Research and Development*, vol. 3, no. 6, 2019.

[25] G. Tsoumanis, K. Oikonomou, G. Koufoudakis, *et al.*, "Energy-efficient sink placement in wireless sensor networks," *Computer Networks*, vol. 141, pp. 166–178, 2018.

[26] H. R. Faragardi, M. Vahabi, H. Fotouhi, *et al.*, "An efficient placement of sinks and SDN controller nodes for optimizing the design cost of industrial IoT systems," *Software: Practice and Experience*, vol. 48, no. 10, pp. 1893–1919, 2018.

[27] N. T. Hanh, P. L. Nguyen, P. T. Tuyen, *et al.*, "Node placement for target coverage and network connectivity in WSNs with multiple sinks," in *Proc. IEEE 15th Annual Consumer Communications & Networking Conference*, January 2018, pp. 1–6.

[28] W. Sun, F. Su, and L. Wang, "Improving deep neural networks with multi-layer maxout networks and a novel initialization method," *Neurocomputing*, vol. 278, pp. 34–40, 2018.

[29] H. A. Hashim, B. O. Ayinde, and M. A. Abido, "Optimal placement of relay nodes in wireless sensor network using artificial bee colony algorithm," *Journal of Network and Computer Applications*, vol. 64, pp. 239–248, 2016.

[30] P. Chatterjee and N. Das, "Multiple sink deployment in multi-hop wireless sensor networks to enhance lifetime," in *Proc. IEEE Applications and Innovations in Mobile Computing (AIMoC)*, February 2015, pp. 48–54.

[31] C. M. Angelopoulos, S. Nikoletseas, and T. P. Raptis, "Wireless energy transfer in sensor networks with adaptive, limited knowledge protocols," *Computer Networks*, vol. 70, pp. 113–141, 2014.

[32] D. R. Dandekar and P. R. Deshmukh, "Energy balancing multiple sink optimal deployment in multi-hop wireless sensor networks," in *Proc. 3rd IEEE International Advance Computing Conference*, February 2013, pp. 408–412.

[33] Y. Gu, Y. Ji, J. Li, *et al.*, "ESWC: Efficient scheduling for the mobile sink in wireless sensor networks with delay constraint," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 7, pp. 1310–1320, 2012.

[34] J. Flathagen, O. Kurez, and P. E. Engelstad, "Constrained-Based multiple sink placement for wireless sensor networks," in *Proc. IEEE Eighth International Conference on Mobile Ad-Hoc and Sensor Systems*, October 2011, pp. 783–788.

Dr. Chamandeep Kaur has been working as a Lecturer in the Department of Computer Science and Information Technology at Jazan University, Saudi Arabia. She received her Ph.D. in Computer Science and Engineering from JJT University, Rajasthan, India in the year 2022, and her MCA from Punjab Technical University, Jalandhar, India in 2006. She has over 15 years of experience in teaching, research, education, industry, and consulting.
Her research areas include IoT, cloud computing, computer networks, data security, machine learning, and big data. She has made several innovative and outstanding contributions to academic research. She has contributed over 20 publications in Scopus, SCIE, Elsevier, WoS, and International peer-reviewed impact journals, several patents, and books. She is a member of the Institute of Electrical and Electronics Engineers (IEEE) and the International Association of Engineers. She has been awarded teaching and research merits by Jazan University, Saudi Arabia. Her most recent publication is "Impact of Hybrid Staging Environment of IoT & Cloud Computing on HMS: Opportunities, Challenges and Deceptive Problems", Lambert Academic Publication.

Dr. Samar Mansour Hassen has been working as a Lecturer in the Department of Computer Science and IT at Jazan University, Saudi Arabia. She also serves as a Vice Dean at Sabya College under Jazan University. Currently she is working as Lecturer in the Department of Management Information Systems. She has received her Master's Degree from Alzaim Al-Azhari University, Sudan in the year 2012. She has over 7 years of experience in teaching and research.
Her research area is Big Data, IoT, Cloud Computing, and Artificial Intelligence. She has contributed almost 10 publications in Scopus, SCIE, and International peer-reviewed journals.

Dr. Mawahib Sharafeldin Adam Boush has been working as an Assistant Professor, Department of Computer Science, Jazan University, Saudi Arabia. She receives her Ph.D. from Omdurman Islamic University, Sudan in 2016, and her Master's Degree in 2012. She has almost 6 years of experience in teaching and research.
Her research area includes Computer Networks, IoT, Artificial Intelligent, and Cloud Computing. In Scopus, SCIE, and International peer-reviewed journals, she has contributed nearly 6 research papers.

Dr. Harishchander Anandaram completed a Ph.D. in bioengineering, an M.Tech, and a B.Tech in bioinformatics from the Sathyabama Institute of Science and Technology, Chennai, in 2020, 2011, and, 2009. In his bachelor's and master's thesis, he worked on analyzing resistance in HIV protease inhibitors based on molecular mechanics and machine learning studies, a collaborative project with IIT Madras. In his Ph.D. thesis, he worked on pharmacogenomics and miRNA-regulated networks in psoriasis, a collaborative project with Georgetown University, USA, JIPMER, INDIA, CIBA, INDIA, and ILS, INDIA. His thesis illustrated a multi-disciplinary approach by combining computational biophysics and molecular biology machine learning. While doing a Ph.D., he had the opportunity to collaborate with international researchers and have publications in reputed international journals in bioinformatics and systems biology. He has received the prestigious "Young Scientist Award" from "The Melinda Gates Foundation" for his research abstract on "The Implications of miRNA Dynamics in Infectious Diseases". To date, he has reviewed more than 200 manuscripts in systems biology. He is currently working on predicting novel lead molecules and biomarkers using computational techniques to target inflammatory pathways associated with infectious and autoimmune disorders.