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Optimized K-means routing protocol with black-winged kite algorithm for sustainable 5G/6G sensor networks☆

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ABSTRACT

Wireless sensor networks (WSNs) face critical challenges due to energy-constrained nodes, affecting their longevity, reliability, and efficiency. To improve energy effectiveness in WSNs for fifth-generation and sixth-generation (5G/6G) networks, various clustering techniques have been developed. These techniques aim to optimize energy use, ensuring better system performance. Moreover, to overcome these complications, this article proposes a K-means online-learning routing protocol optimized with the black-winged kite optimization algorithm for sustainable communication (KORP-BWKOA-SC-WSN). Initially, the input data is collected from the sink node. This data is fed to a binarized simplicial convolutional neural network for cluster formation, in which the network nodes are clustered. Next, the formed cluster is used for cluster head selection by using the hiking optimization algorithm for better data transmission. Finally, the K-means online learning routing protocol is implemented to improve node coordination and energy efficiency. The black-winged kite optimization approach is employed to enhance the system performance. The proposed KORP-BWKOA-SC-WSN achieves throughput improvements of 21.51%, 12.38%, and 21.51%, respectively, and energy consumption reductions of 15.85%, 23.37%, and 22.04% compared to existing methods The performance of the proposed technique is evaluated and is found to attain higher throughput and high network lifetime when compared with other existing methods.

1. Introduction

Modernization has profoundly transformed our reality with the advent of innovative technologies such as 5G, Internet of Things (IoT), and artificial intelligence (AI). Integrating these technologies into various environments has led to the development of more resilient and innovative designs with unique capabilities [1]. While this approach demands significantly higher bandwidth and data rates, it also offers a robust transmission range, reduced latency, and enhanced throughput. However, supporting IoT in radio access networks (RAN) is challenging as IoT services may produce many short and variable sessions, impacting the performance of mobile users sharing the same RAN [2]. A cornerstone of 5G wireless communication is massive machine-type communication (mMTC), which is essential for enabling smart communication systems, big data platforms, and advanced processing applications through the seamless integration of wireless communication technologies [3]. Wireless sensor networks (WSNs) comprise numerous spatially distributed sensor nodes that monitor and collect data from their surrounding environment [4]. These nodes are typically

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low-power devices with sensing, processing, and wireless communication capabilities. WSNs enable real-time data acquisition and transmission for applications such as environmental monitoring, industrial automation, smart cities, healthcare, and defense [5,6].

This combination, currently widely available in 5G technologies, is expected to be fully utilized in 6G technology. 6G networks are envisioned to support advanced applications such as interactive media technologies towards extended reality (XR), mapping, and ultra-high-speed mobile services, fulfilling the high requirements of quality of service (QoS). WSNs, which serve as active components for communication, are essential to 5G telecommunications. Future 6G networks will provide faster, reliable, and seamless connectivity for a wide range of devices and applications. With features such as higher data rates, ultra-low latency, extensive device connectivity across coverage areas, and dynamic network slicing, 6G networks will significantly enhance wireless communication capabilities. Moreover, WSNs can further improve their communication efficiency by leveraging the robust connectivity infrastructure of 5G and 6G networks, particularly for long-distance communication and network integration. As more and more sensor devices rely on mobile connectivity, it is essential to enhance and ensure flawless data delivery. The challenges in routing for WSN in IoT systems include developing a scalable addressing mechanism to accommodate new sensor nodes, providing reliable data transmission to the sink node, and creating efficient strategies to manage and transmit similar data from multiple sensors. These issues impede optimal communication and data management. The motivation behind this article is to improve the routing mechanism in WSN for IoT systems and to enhance communication efficiency, scalability, and reliability. As IoT applications continue to grow, efficient data transmission and energy optimization become increasingly crucial. Effective routing ensures seamless data delivery, maximizing network performance and longevity. The novelty of the work lies in the integration of a binarized simplicial convolutional neural network (CNN) with the black-winged kite optimization approach (BWKOA) to enhance K-means clustering for online-learning routing protocols (KORP) in 5G/6G WSN. This approach improves data routing, energy efficiency, and throughput by adapting to real-time network conditions. By leveraging 5G/6G technologies, it ensures high-speed, low-latency communication, thereby offering a sustainable solution for future WSNs. The major contributions of this article are:

- Optimized the sustainable communication algorithm in 5G/6G WSN (KORP-WSN) to ensure better system performance.
- Enhanced energy efficiency achieved through clustering based on a binarized simplicial convolutional neural network (BSCNN).
- Improved data transmission is facilitated by selecting the cluster head (CH) based on the hierarchical optimization algorithm (HOA).
- Facilitating cooperative as well as energy-efficient routing using KORP, followed by the utilization of BWKOA to enhance system effectiveness.

The rest of the manuscript is arranged as follows: Section 2 presents the literature review; Section 3 discusses the proposed method; Section 4 covers the results and discussion, and finally Section 5 concludes the paper.

2. Literature survey

Numerous related works suggested in the literature were based on Sustainable Communication in 5G/6G WSN; a few of them are reviewed here.

Kakisim A.G., Turgut Z., [7] propose a dual-band approach utilizing 2.4 GHz and 5 GHz WiFi signals by employing a multi-channel CNN regression with an attention mechanism that aims to capture high-level correlations for each band's data and fuse high-level patterns. It achieves higher positioning performance and reduced energy consumption. Gururaj, H.L., et al. [8] have presented a collaborative energy-effective routing protocol for sustainable communication in 5G/6G WSNs. In the suggested paper, after network nodes are grouped using reinforcement learning and cluster heads are selected based on a residual energy technique, data is collected and aggregated at the sink node. The Multi-Objective Improved Seagull Approach is then applied to optimize system performance further. It provides high throughput and low network lifetime. Ioannou, I., et al. [9] have presented a new distributed artificial intelligence framework with machine learning for D2D communication in 5G/6G networks. In this suggested paper, the DAI framework utilizes Belief-Desire-Intention agents enhanced with machine learning, deployed autonomously on mobile devices. It provides a component-based structure for creating execution plans by organizing and adapting machine learning algorithms within the framework. It attains lower energy consumption and a low packet delivery ratio. Mao, C., et al. [10] have presented DL in physical layer communications: development and prediction in 5G/6G networks. In this suggested paper, DL has reached remarkable achievements in domains like voice recognition, language processing, and computer vision, due to its strong representation power as well as computational efficiency. The focus now shifts to exploring the latest advancements in DL-based algorithms for the physical layer of wireless communication. It provides high routing overhead and low transmission speed. Burghal et al. [11] have presented enhanced AI-based CSI prediction solutions for massive MIMO in 5G and 6G systems. Deep learning-based CSI prediction solutions are suggested using 3-Dimensional (3D) complex convolutional neural networks (CCNN). These solutions provide improved capabilities for capturing temporal and spatial correlations, enhancing CSI prediction performance. In particular, they utilize the angle delay decomposition of previously observed CSI to predict the future one. In one architecture, the network, dubbed CSI prediction network (CSI-PNet), uses small kernels with circular padding to efficiently capture the correlation between propagation paths in the angle domain. It provides high throughput and high energy efficiency.

Agrawal et al. [12] have presented adaptive hybrid genetic-ant colony optimization for dynamic self-healing and network performance optimization in 5G/6G networks. They suggest an adaptive hybrid genetic-ant colony optimization (GA-ACO) framework designed for dynamic self-healing and multi-objective performance optimization in next-generation mobile networks. The developed method combines the global optimization competencies of a genetic algorithm (GA) with the local rerouting performance of ant

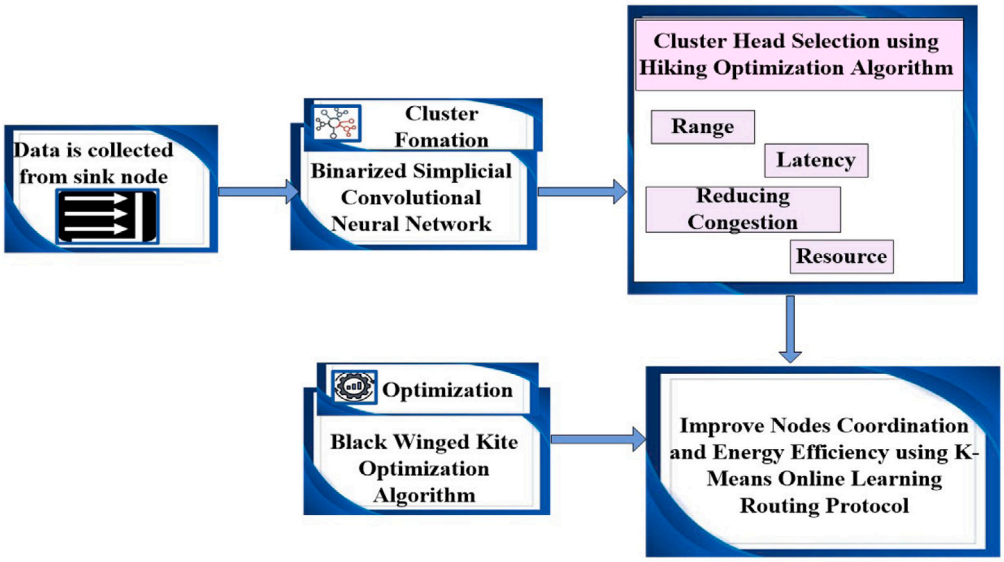

Fig. 1. Block diagram of the proposed KORP-BWKOA-SC-WSN methodology.

colony optimization (ACO), creating a dynamic switching mechanism. When no faults are detected, GA optimizes critical objectives such as latency minimization, bandwidth utilization, and energy efficiency. It provides lower latency and lower Packet delivery ratio.

Despite advancements in 5G/6G WSNs, several gaps persist. Existing protocols tend to emphasize energy efficiency or throughput but neglect trade-offs with latency, reliability, and network lifetime. Most are based on static clustering or traditional optimization, which hampers adaptability to dynamic networks. Machine learning and deep learning-based methods tend to have high computational complexity and routing overhead. Security, resilience, and multi-metric optimization tend to be under-explored, especially in large-scale deployments. Scalability and end-to-end communication under dense sensor networks are also constrained. These limitations indicate the demand for a strong, adaptive, and smart framework. The proposed methodology resolves these constraints by fusing advanced optimization and learning principles for better energy efficiency, reliability, and performance.

3. Proposed methodology

In the proposed section, the KORP-WSN is described. The input data are collected from the sink node. To optimize energy consumption, sensor nodes are grouped using BSCNN. Cluster head selection is determined by HOA, which enhances data transmission and increases the network's lifespan. The integration of a KORP further improves routing strategies, while routing optimization is realized through BWKOA. The description of the KORP-WSN is given below, and the proposed block diagram is represented in Fig. 1.

3.1. Data acquisition

The simulation utilizes the healthcare dataset [13]. The research on software defects in medical applications and faults in various medical apps was taken into consideration when creating the dataset for healthcare systems. In this healthcare dataset, Boolean classifications labeled as damaged and non-defective are present. It contains a total of 5,432 records with 12 input features describing both functional and non-functional aspects of medical software modules. After the data is collected, it is transmitted to the sink node (S.N.) for clustering. The proposed system model includes a source node, a destination node, and many intermediate nodes. The collection of information is split into two separate training and testing information sets, with 70% of the data being used to educate the recommended strategy and 30% being used to test the suggested model.

3.2. Cluster formation using binarized simplicial convolutional neural network

In this part, the cluster formation using BSCNN [14] is discussed. Binarized weights enhance computational efficiency, allowing faster processing and reducing memory usage. In the realm of cluster formation within WSNs, BSCNN utilizes Binarized principles to arrange sensor nodes into clusters dynamically. Initially, the BSCNN begins by gathering raw data like node IDs, connectivity, and spatial information from the sink node. These data are processed through a binarization step, where weights are reduced to binary values to minimize memory usage and accelerate computation. Then, the simplicial convolutional layer examines both local and

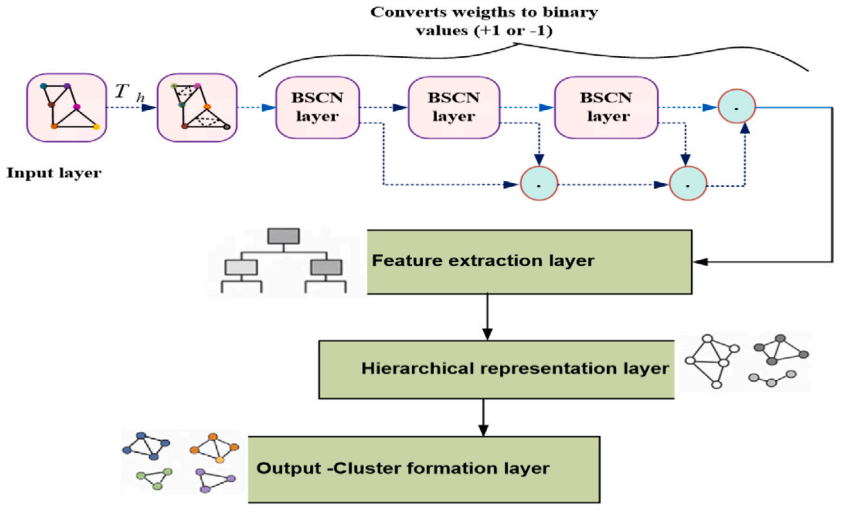

Fig. 2. Architecture diagram of BSCNN.

global characteristics of the network, detecting higher-order relations between nodes. From this, essential patterns like connectivity and energy status are learned and formatted into a hierarchical structure for scalable examination. Last but not least, the network establishes clusters through the grouping of nodes with like attributes and nearness, setting them up for the next level of cluster head selection. As shown in Fig. 2, BSCNN employs a multi-level hierarchical architecture for effective feature extraction from the data, integrating local and global contexts from the topological data, as given in Eq. (1).

$$T_h = V_h \lambda_h V_h^N \tag{1}$$

where, T_h denotes the topological node, V_h indicates the number of identify node, λ_h signifies the eigen value matrix, V_h^N indicates the variations of number of the nodes. The Binarized convolution operations used to process the formation of clusters by applying convolutional layers that capture key features from the data, distinguishing between conditions of the simplicial convolution layers, are given in Eq. (2).

$$y_{h,q+1} = \vartheta\left(\sum_{a=1}^{b_a} T_h^b \, y_{h,q} \, \tau_{h,a}\right) \tag{2}$$

where, $y_{h,q+1}$ denotes the simplicial convolution architectural analysis from the node, ϑ indicates the scalar valued functions of node, $\tau_{h,a}$ represent the arbitrary of node. Then, the formed cluster node is fed to the cluster head selection process.

3.3. Cluster head selection using hiking optimization algorithm

The Cluster head selection using the HOA [15] technique is discussed for increasing communication efficiency and minimizing energy depletion. The probabilistic procedure is utilized to choose the best Cluster Head that chooses the ideal node from the cluster to serve as the cluster head based on a variety of parameters like range (Ra), latency (Lat), Reducing Congestion (RC), and resource (Re). Since nodes expend substantial energy during data collection, transmission, and reception, it is crucial to minimize energy usage, especially for the Cluster Head node. Then the multi-objectives are covered below.

Range (Ra): The range criterion ensures that the chosen cluster heads have sufficient coverage for effective communication with neighboring nodes. Then the range is calculated by using Eq. (3).

$$Ra = \frac{MR_a - DN}{MR_a} \tag{3}$$

where R_a represent the range, MR_a is the maxim range, DN is the distance to nearest neighbor.

Latency (Lat): Latency refers to the delay in data transmission between nodes, with lower latency being preferable for faster data transfer. Then the latency is calculated by using Eq. (4).

$$Lat = \frac{1}{Round - TT} \tag{4}$$

where, Lat represent the Latency, TT is the trip time.

Reducing Congestion (RC): Congestion reduction refers to the crucial task of cluster heads efficiently managing network traffic distribution to prevent bottlenecks. Then the Reducing Congestion is calculated by using Eq. (5).

$$RC = \frac{1}{NN * ATL} \tag{5}$$

where RC represents the Reducing congestion, NN is the number of neighbors, ATL is the average traffic load.

Resources (Re): Optimal resource utilization is essential for extending the network's longevity and guaranteeing dependable operation. Then the resources are calculated by using Eq. (6).

$$R_e = \frac{AE * AB}{TR_e} \tag{6}$$

where R_e represent the resources, AE is the available energy, AB is the available bandwidth, TR_e is the total resources.

Step 1: Initialization

A matrix can be used to represent the whole HOA population, including all different types of Hiking, and it is given in Eq. (7).

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1p} \\ P_{21} & P_{22} & P_{23} & \cdots & P_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{d1} & P_{d2} & P_{d3} & \cdots & P_{dp} \end{bmatrix} \tag{7}$$

where, P represent hiking group, and d represents the group members.

Step 2: Random generation

After the initialization process, cluster head selection is randomly performed using the aid of the HOA algorithm approaches.

Step 3: Fitness function evaluation Initialized assessments are utilized to create the random result. It is evaluated to select the optimal cluster head using Eq. (8).

$$Fitness function = [cluster\ head\ selection] \tag{8}$$

Step 4: Compute the velocity hiking

HOA takes advantage of the advantages of both the individual hikers' cognitive capacities and the group's social reasoning. As a result, the hiker's current velocity, i is expressed in Eq. (9).

$$P_{j,t} = P_{j,t-1} + \gamma_{j,t}\left(\beta_{best} - \alpha_{j,t}\beta_{j,t}\right) \tag{9}$$

where, γ is the evenly distributed count within the interval $[0, 1]$, $P_{j,t}$ and $P_{j,t-1}$ represents the existing and first hikers velocity, β_{best} denotes lead hikers location.

Step 5: Update the hiker position It impacts both the rate of convergence and the availability of workable solutions. The HOA uses the random initialization technique to initialize the locations in this specific investigation. It is given in Eq. (10).

$$\beta_{j,t+1} = \phi_i^1 + \delta_i\left(\phi_i^2 - \phi_i^1\right) \tag{10}$$

where, δ_i the evenly distribution count within the interval $[0, 1]$, $\beta_{j,t+1} = \phi_i^1 + \delta_i\left(\phi_i^2 - \phi_i^1\right)$ and ϕ_i^2 represents the lower and upper bounds.

Step 6: Termination In this step, the HOA finishes, and a better solution is obtained by each process iteration returned as output. The HOA processes are complete, from cluster head selection, which achieves optimal cluster head selection among the nodes. Afterwards, the selected cluster heads are fed to improve the nodes' coordination and energy efficiency process.

3.4. Improve nodes coordination and energy efficiency using k-means online learning routing protocol

In this section, the KORP [16] technique is discussed. KORP is used to improve node coordination and energy efficiency. Nodes coordinate to ensure efficient task execution by synchronizing activities and communication in a distributed network. KORP starts by randomly selecting cluster centroids from network nodes and assigning nodes to the nearest centroid using Euclidean distance. This process facilitates efficient data transmission among nodes. Energy levels are monitored to optimize energy usage throughout the system. Then the Euclidean distance is calculated in Eq. (11).

$$|Z_b| = \sqrt{(zs_b - zs_a)^2 + (zv_b - zv_a)^2 + (zu_b - zu_a)^2} \tag{11}$$

where $|Z_b|$ represent the wireless ad hoc network, $(zs_b), (zv_b), (zu_b)$ is the 3D coordinates relative nodes, $(zs_a), (zv_a), (zu_a)$ is the point coordinates. Then the coverage distance is calculated in Eq. (12).

$$U(D) = \sum_{h=1}^{w}\sum_{s=1}^{S} U(D)(Z_b, \vartheta_b) \tag{12}$$

where $U(D)$ represent the exposure volume of entire network, $\sum_{h=1}^{w}$ is the minimum coverage area, $\sum_{s=1}^{S}$ is the efficient communication, Z_b is the learnable parameter, ϑ_b is the sigmoid representation of coverage volume. Then the distance between the nodes as well as the centroid is calculated in Eq. (13).

$$U\left(Z_b, \vartheta_b\right) = \left(\left|zb_s - \vartheta b_s\right| + cs\right) * \left(\left|zb_m - \vartheta b_m\right| + cm\right) * \left(\left|zb_\delta - \vartheta b_\delta\right| + c\delta\right) \tag{13}$$

where, $U\left(Z_b, \vartheta_b\right)$ represent the volume influenced by coverage volume and sigmoid coverage volume, zb_s, zb_m, zb_δ is the Cartesian coordinates, ϑb_s, ϑb_m, ϑb_δ is the lengths in each direction of node, cs, cm, $c\delta$ is the coverage interval in every axis depending upon distance among node as well as centroid. ϑb_m is the learnable scalar function. Finally, the node's coordination and energy efficiency are improved by using KORP. The BWKOA is considered to optimize the KORP optimal routing paths Z_b and ϑb_m, also tuning the weight, bias parameter of KORP.

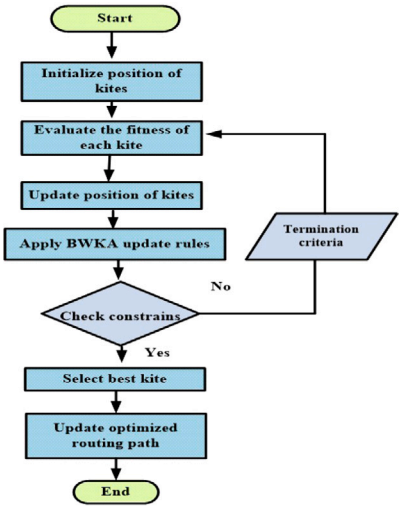

Fig. 3. Flowchart of BWKOA.

3.5. Optimization utilizing black-winged kite optimization algorithm

The proposed BWKOA [15] is utilized to enhance routing paths Z_b and ϑb_m. The routing paths Z_b are optimized to maximize the throughput, and ϑb_m is optimized to minimize the energy consumption. It optimizes routing paths to enhance overall system performance. The BKOA combines the Leader method with the Cauchy mutation approach to increase the approach's global search ability with speed of convergence. The step-by-step process for achieving suitable values using KORP is defined. To create an evenly distributed population for optimizing the ideal KORP variables. The entire step method is presented below.

Step 1: Initialization

$$bl = \begin{bmatrix} bl_{1,1} & bl_{1,2} & \cdots & \cdots & bl_{1,Dim} \\ bl_{2,1} & bl_{2,2} & \cdots & \cdots & bl_{2,Dim} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ bl_{Pop,1} & bl_{Pop,1} & \cdots & \cdots & bl_{Pop,1} \end{bmatrix} \tag{14}$$

In Eq. (14), bl is the ith side of the black-winged kite in jth; Pop is the total amount of possible outcomes in BWKOA; and Dim represents dimension of the problem.

Step 2: Random generation

The input routing paths Z_b and ϑb_m developed randomness via the BWKOA approach.

Step 3: Fitness function

From the initialized values, it creates an arbitrary solution. It is computed by optimizing routing paths Z_b and ϑb_m. Then the formula is derived in Eq. (15).

$$Fitness\ function = optimizing\ route\ path\left[Z_b\ and\ \vartheta b_m\right] \tag{15}$$

Step 4: Attacking behavior for optimizing Z_b

The quick-witted black-winged kite hunts insects and small grassland animals. After silently studying their prey and changing their wings as well as tail angles to the speed of the wind, they quickly dive and attack. An arithmetical approach for the attack performance of black-winged kites is given as Eq. (16)

$$c_{T+1}^{i,j} = \begin{cases} c_T^{i,j} + N(1+\sin(rand)) \times c_T^{i,j} & s < rand \\ c_T^{i,j} + N \times (2rand - 1) \times \dfrac{c_T^{i,j}}{P^*} & \text{else} \end{cases} \tag{16}$$

where $c_{T+1}^{i,j}$ and $c_T^{i,j}$ identify the location of the ith black-winged kites in the jth size during the T and $(T+1)^{th}$ iteration steps; $rand$ is an arbitrary value range among 0 and 1; s represents the BWKOA constant value; T represents overall count of completed iterations up to this point in time. The flowchart of BWKOA is given in Fig. 3

Step 5: Migration behavior for optimizing ϑb_m

Table 1
Estimated cost associated with necessary hardware and software.

Component	Estimated cost (USD)
Sensor Nodes (500 units)	500 ×$25 = $12,500
Sink Node/Base Station	$500
Processing Unit	$1,200
Software Tools	$800
Networking Equipment	$600
Maintenance & Upgrades	$400
Total Estimated Cost	$16,000

Table 2
Simulation parameters of the proposed model.

Parameter	Value	Parameter	Value
Number of sensor nodes	500	Simulation rounds	1200
Area of deployment	500 × 500 m^2	K-means iterations	100
Initial energy per node	2 Joules	black-Winged kite population	30
Data packet size	500 bytes	Hiking Optimization Factor	0.5

Climate and food availability are two of the many environmental factors that influence the complex behavior of bird migration. The leader will resign from leadership and adopt the migrating populace behavior using Eq. (17).

$$c_{T+1}^{i,j} = \begin{cases} c_T^{i,j} + X(0,1) \times \left(c_T^{i,j} - k_T^j \right) & P_i < P_{randi} \\ c_T^{i,j} + X(0,1) \times \left(\dfrac{k_T^j - M \times c_T^{i,j}}{V_M^{tX}} \right) & \text{else} \end{cases} \tag{17}$$

where k_T^j indicates the black-winged kites' highest scorer in the jth size of the Tth iteration thus far; E_i depicts the current location in the jth size that was attained through any black-winged kite during the T iteration; P_{randi} represents value of fitness obtained from any black-winged kite in the T iteration for the random position in the jth dimension; X represents the mutation brought about by Cauchy and V_M^{tX} is the temporally altered feature vector of each layer.

Step 6: Termination

The routing paths value of $Q^{(m)}$ *and* ϑ from KORP is optimized utilizing BWKOA; or else repeats step3 until it satisfies its halting condition $bl = bl+1$. Finally, the KORP-WSN method enables sustainable communication in 5G/6G WSNs, achieving high throughput and low energy consumption.

4. Results and discussion

In this section, the experimental outcomes of the proposed method are examined. The KORP-WSN approach is executed in Python and analyzed using various performance metrics, including throughput, energy consumption, and network lifetime. The KORP-WSN model is tested against several performance metrics. The result of the KORP-WSN method is analyzed with existing techniques like CEERP-SC-WSN [8], D2DC-DNN-WSN [9], and PLC-RNN-WSN [10], respectively.

Table 1 represents the estimated cost associated with the necessary hardware and software. The estimated cost to deploy the KORP-BWKOA-SC-WSN model is approximately $16,000. High-cost items are sensor nodes at $12,500, the processing unit at $1,200, along with the sink node, networking devices, software tools, and maintenance. This indicates that though the approach enhances performance, deployment also comes with high hardware and software expenses.

Table 2 represents the simulation parameters of the proposed model. The network consisted of 500 sensor nodes over a 500 × 500 m^2 area, each with 2 Joules of initial energy, data packet size of 500-byte packets, and simulated for 1,200 rounds. Algorithm-specific settings included 100 K-means iterations, a black-winged kite population of 30, and a hiking optimization factor of 0.5.

4.1. Performance measures

The proposed approach is evaluated based on metrics such as throughput, energy consumption, and network lifetime.

4.1.1. Throughput

Throughput is measured by the number of successful packets transmitted from the starting place to the target over time. It is determined by Eq. (18).

$$Throughput = \frac{T_s}{t} \times 100 \tag{18}$$

where, T_s is the amount of successfully transmitted packets, t is the time.

4.1.2. Energy consumption

This metric assesses total energy used by each node during the course of operation. It is represented in Eq. (19).

$$C_E = \dot{\eta} - \breve{\alpha} \tag{19}$$

where, C_E represents the consumption of energy, $\dot{\eta}$ represents the initial energy, $\breve{\alpha}$ denotes remaining energy.

4.1.3. Network lifetime

The total amount of time a network may function before it becomes unusable due to various limitations, including energy depletion or node failure. It is evaluated by using Eq. (20).

$$Network\ lifetime = \frac{\sum_{b=1}^{q} N_{ba} * g_b}{P_a} \tag{20}$$

where, P_a is the power consumption of transmission energy usage, N_{ba} signifies overall number of nodes in the network, g_b is the total initial energy at each node.

4.1.4. Latency

Latency refers to the average time taken for a data packet to travel from the source node to the destination node. It is calculated as shown in Eq. (21).

$$Latency = \frac{\sum_{i=1}^{N} \left(T_{recv}^{i} - T_{send}^{i}\right)}{N} \tag{21}$$

Here, T_{recv}^{i} denotes the reception time of the ith packet, T_{send}^{i} denotes the transmission time of the ith packet, and N is the total number of successfully received packets.

4.1.5. Packet Delivery Ratio (PDR)

PDR measures the reliability of data transmission, defined as the ratio of packets successfully delivered to the destination to those sent by the source, and it is calculated in Eq. (22).

$$PDR = \frac{P_{recv}}{P_{Sent}} \times 100 \tag{22}$$

Here, P_{recv} is the number of packets successfully received and P_{Sent} denotes the total number of packets transmitted.

4.1.6. Energy Efficiency (EE)

Energy efficiency refers to the effectiveness with which the protocol delivers data per unit of energy consumed. It is given by Eq. (23).

$$EE = \frac{P_{recv}}{E_{consumed}} \tag{23}$$

P_{recv} denotes the number of packets successfully received and $E_{consumed}$ represents the total energy consumed by the network during transmission.

4.2. Performance analysis

Figs. 4–6 display the simulation results of the KORP-BWKOA-SC-WSN method. The performances are analyzed in comparison with the existing CEERP-SC-WSN, D2DC-DNN-WSN, and PLC-RNN-WSN methods. Fig. 4 shows the performance analysis of throughput. It involves measuring the rate at which a system processes or handles tasks, requests, or data within a given timeframe. The KORP-BWKOA-SC-WSN method attains 22.65%, 25.79%, and 24.83% higher throughput at 100 nodes; 28.39% and 23.41% higher throughput at 300 nodes; and 19.67%, 25.24%, and 16.36% higher throughput at 500 nodes when analyzed against existing techniques such as CEERP-SC-WSN, D2DC-DNN-WSN, and PLC-RNN-WSN, respectively.

Fig. 5 shows the analysis of energy consumption performance. The routing protocol reduces unnecessary transmissions by selecting energy-efficient paths, while the AGNN adapts to changing network conditions to optimize data flow, minimizing redundant energy consumption. The KORP-WSN method achieves 12.25%, 10.19%, and 11.71% lower energy consumption at 100 nodes; 21.36%, 15.69%, and 11.25% lower energy consumption at 300 nodes; and 16.35%, 17.56%, and 12.45% lower energy consumption at 500 nodes, respectively, when compared with existing techniques such as CEERP-SC-WSN, D2DC-DNN-WSN, and PLC-RNN-WSN.

Fig. 6 shows the performance analysis of network lifetime. The count of nodes in the WSN is a key factor influencing communication overhead, energy consumption, and overall network performance. Here, KORP-WSN attains 17.75%, 24.55%, and 12.66% higher network lifetime at nodes 100; 21.01%, 14.08%, and 17.33% higher network lifetime at nodes 300; and 28.02%, 11.56%, and 13.67% higher network lifetime at nodes 500, compared to the existing CEERP-SC-WSN, D2DC-DNN-WSN, and PLC-RNN-WSN, respectively.

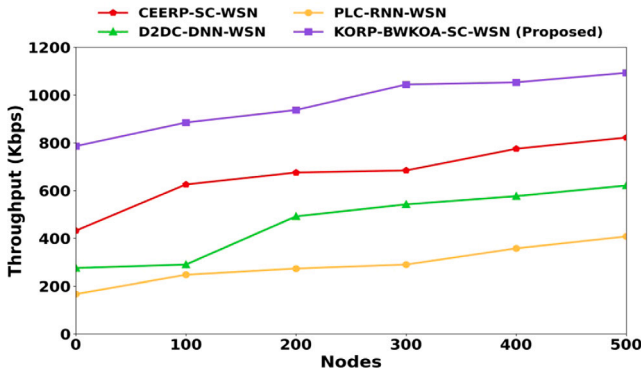

Fig. 4. Performance analysis of throughput.

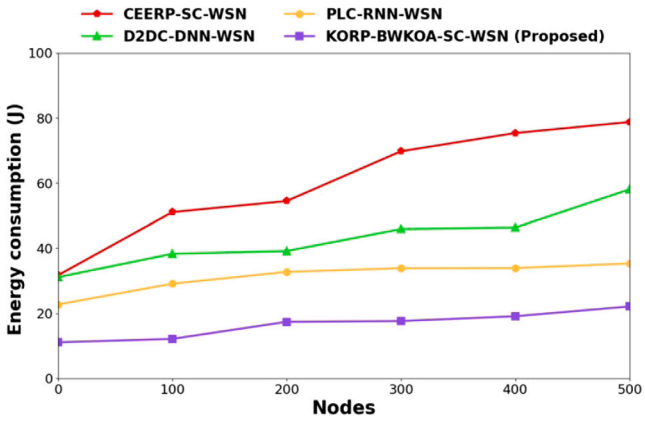

Fig. 5. Analysis of energy consumption performance.

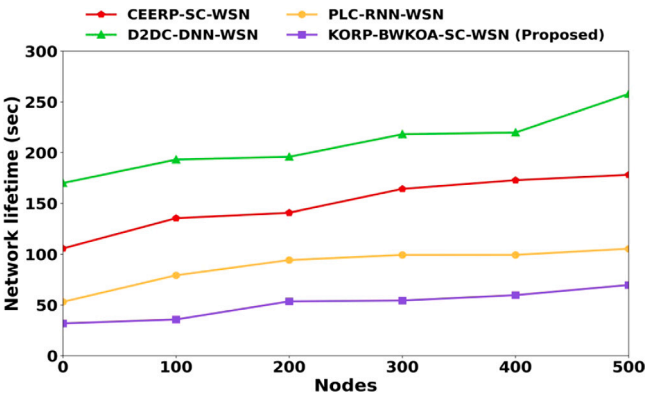

Fig. 6. Performance analysis of network lifetime.

Table 3
Performance comparison of latency, energy efficiency, and Packet Delivery Ratio (PDR)

Methods	Energy efficiency	Latency (ms)	PDR (%)
CEERP-SC-WSN [3]	0.68	125	87.4
D2DC-DNN-WSN [4]	0.71	118	88.9
PLC-RNN-WSN [5]	0.74	121	89.6
Proposed KORP-BWKOA-SC-WSN	**0.89**	**95**	**96.8**

Table 3 represents the performance comparison of Latency, Energy Efficiency, and PDR. It suggested the KORP-BWKOA-SC-WSN approach with other approaches using network performance parameters, i.e., latency and PDR. The outcomes reveal that the recommended technique had a minimum latency of 95 ms, reflecting quicker data transfer than CEERP-SC-WSN (125 ms), D2DC-DNN-WSN (118 ms), and PLC-RNN-WSN (121 ms). The proposed method also achieved a maximum PDR of 96.8%, reflecting enhanced reliability and effectiveness in packet delivery compared to other current techniques. It also achieves a higher energy efficiency of 0.89. These findings underscore the better performance of the proposed approach in improving speed and reliability in WSN communications.

4.3. Discussion

In this study, a CEERP for 5G/6G communication in WSN is created, which contains the BSCNN for cluster formation. The proposed BSCNN has increased the architecture's overall network lifespan. The cluster head from each cluster must then be chosen to carry out efficient data transfer. In this design, an effective HOA-based method is used, selecting the CH, which is recognized as the primary factor in WSN. Four main goals are considered to choose the most effective cluster head for sending the information to the descendant node. The cluster head selection considers the following criteria: range, latency, reducing congestion, and resources. The KORP-BWKOA-SC-WSN model achieves up to 28.39% improvement in throughput, a 21.36% reduction in energy consumption, and a 28.02% increase in network lifetime, demonstrating consistent superiority across different network sizes (100, 300, and 500 nodes). While the proposed model has minor restrictions, the use of multiple algorithms raises computational complexity, which is a problem for resource-restricted sensor nodes. The model is parameter-sensitive, and unfitting settings may impact performance. The proposed KORP-BWKOA-SC-WSN model improves energy efficiency by minimizing redundant transmission and extending network lifetime. The adaptive clustering using BSCNN ensures scalability and efficient feature extraction, whereas the cluster head selection using HOA ensures reliability using multi-criteria optimization. In addition, the incorporation of KORP improves node coordination with less latency, and optimization of BWKOA ensures stable routing paths with accelerated convergence.

5. Conclusion

In this work, the KORP-BWKOA-SC-WSN framework optimized with the BWKOA was developed to enhance sustainable communication in 5G/6G WSNs. By integrating BSCNN for clustering, HOA for cluster head selection, and KORP with BWKOA for routing, the proposed method achieved significant performance improvements. Simulation results show that KORP-BWKOA-SC-WSN increased throughput by up to 28.39%, reduced energy consumption by up to 21.36%, and extended network lifetime by up to 28.02% compared with existing CEERP-SC-WSN, D2DC-DNN-WSN, and PLC-RNN-WSN methods. These results confirm that the proposed approach ensures higher efficiency, reliability, and longevity, making it a strong candidate for future IoT-enabled 5G/6G deployments. Overall, KORP-BWKOA-SC-WSN significantly improves throughput, latency, PDR, energy efficiency, and network lifetime, making it a robust solution for sustainable 5G/6G WSNs. Future research will concentrate on the investigation of hybrid optimization techniques for quicker convergence and experimenting with the technique in large-scale, heterogeneous WSNs. Real-world deployment of the tested and augmented fault-tolerance mechanisms will also be pursued to confirm the practicality and robustness of the proposed framework.

CRediT authorship contribution statement

Nishu Gupta: Writing – original draft. **Mauro Mazzei:** Supervision, Formal analysis. **Jukka Mäkelä:** Visualization, Supervision, Project administration, Conceptualization. **Mikko Uitto:** Writing – review & editing, Validation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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