

WITHDRAWN: Multiobjective Routing Protocol Design in WBAN Using Optimized Fuzzy Clustering and Hybrid Deep Learning for Optimal Path Selection

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MULTIOBJECTIVE ROUTING PROTOCOL DESIGN IN WBAN USING OPTIMIZED FUZZY CLUSTERING AND HYBRID DEEP LEARNING FOR OPTIMAL PATH SELECTION

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Abstract

Real-time monitoring of patients' health conditions is now possible because to wireless body area networks (WBANs). In WBANs, nodes are placed inside, on, or around the human body to collect a range of physiological data, such as body temperature, heart rate, and blood pressure. The routing of data packets in WBANs, however, confronts a number of difficulties because of the dynamic nature of the body, including limited power, interference, and movement. Data packet routing can be made more efficient by using a multiobjective routing protocol architecture to handle these problems. In this research work, WBAN's multiobjective routing protocol architecture is made possible by two phases as clustering and optimal path selection. To group nodes based on several objectives, such as energy consumption, transmission delay, and network longevity, the proposed multiobjective routing protocol design in WBAN uses an optimised Fuzzy C-means clustering method. The membership function in Fuzzy C-means clustering is determined using a novel hybrid optimization model HBWBF that combines the Black Widow Optimization (BWO) and the Bacterial Foraging Optimization Algorithm (BFOA). The hybrid deep learning approach for determining the optimal path between clusters combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The proposed model is implemented in MATLAB. To validate the efficiency of the proposed model, a comparative evaluation is performed.

Keywords-*Multiobjective Routing; WBAN; Fuzzy C-means Clustering; HBWBF; CNN; RNN.*

NOMENCLATURE

Abbreviation	Description
WBAN	Wireless Body Area Networks
WIoT	Wearable Internet of Things
DECR	Distributed Energy-Efficient Clustering and Routing Protocol
MAC	Medium Access Control
TAEO	Temperature Aware and Energy Optimized
TSs	Time Slots
EH	Energy Harvesting
ISM	Industrial, Scientific, and Medical
TCR	Two-Hop Connectivity Ratio
ESR	Energy Aware and Stable Routing Protocol
AODV	Ad hoc On-Demand Distance Vector routing
DSDV	Destination Sequenced –Distance Vector routing
DSR	Dynamic Source Routing
IoMT	Internet of Medical Things
EF	Energy Factor
NSF	Node Stability Factor

1. Introduction

The development of wireless communication technology and intelligent electronic sensors has led to the emergence of numerous electronic health applications [1]. WBAN are dynamic, heterogeneous networks that include sensors with a range of sizes, functions, and energy needs. WBAN has the ability to monitor bodily health. Early diagnosis is essential for disease diagnosis and treatment [2]. Users are exhibiting a remarkable interest in actually wearing these devices, which is something that wearable's can do better than a Smartphone alone [3]. Wearables can be anything from smart watches to jewellery to skin patches to glasses to electronic clothing. In ways that smartphones cannot, wearable technology can sense, collect, and store physiological data while also improving human life [4]. Wearable technology makes

many micro-level tasks easier and more realistic, such as validating incoming messages and processing crucial data immediately [5]. The monitoring of one's physical and mental well-being, along with indoor localization and navigation, is one of the value-added services that wearable's can provide [6].

In WBAN, the human body is not thought to be the best medium for wireless network signal propagation [7]. Variable dielectric constants, thicknesses, and impedances in the components of the human body may not be ideal for communication. Depending on the frequency of operations, the human body may experience a variety of impairments and losses, including intake, attenuation, refraction, etc [8]. WBAN has grown in popularity in terms of health monitoring. Using a variety of wearable sensors and actuators, its objective is to create a larger network. It consists of surgically implanted gadgets that deliver precise and thorough data about a person's health. In reality, WBAN calls for continued research in a variety of fields, including network, physical, and MAC. Additionally, crucial components like independent usage and affordability encourage wearable device usage without the need for significant involvement from medical professionals, opening the door for their widespread adoption [9,10]. The ability of WBAN, a cutting-edge wireless communication technology, to offer consistency and energy competence is driving up interest in it in the modern world. WBANs are quickly overtaking other technologies as the go-to solutions for a wide range of uses [11]. Due to the potential health risks associated with changing batteries, energy conservation is given top priority in WBANs [12]. By preserving the sensor node's energy, the patient can be watched without interruption for the longest period of time. The sensors may use energy as they collect, analyse, compare, and transmit data from the human body from one location to another. The sensor node uses the most energy during the transmission process, though.

In a WBAN, a sensor node is utilised for data detection, management, and processing in accordance with default settings and for comparison-based analysis of the results prior to transmission to the base station. The mode may on occasion take the place of a node [13]. A WBAN uses a person's body to gather and send physiological, environmental, and medical data [14], which can then be used to carry out a number of tasks, such as patient monitoring, fitness tracking, and healthcare monitoring. The devices in a WBAN typically use low-power, low-data-

rate communication technologies like ZigBee, Bluetooth, or ANT+ and operate in the ISM frequency band [15].

This study's major contribution is exemplified below:

- To decrease energy consumption and optimize routing in WBAN, partition the sensors into clusters. This can be achieved by utilizing optimized Fuzzy C-means clustering to generate the clusters, while taking into account the multi-objectives of energy consumption, transmission delay, and network lifetime.
- To improve the accuracy and efficiency of determining the membership function in Fuzzy C-means clustering, a novel hybrid optimization model called HBWBF is utilized. This model is a combination of two optimization algorithms, Black Widow Optimization (BWO) and the Bacterial Foraging Optimization Algorithm (BFOA).
- To optimize the transmission of data between clusters, a novel hybrid deep learning approach is being utilized. Convolutional neural networks (CNNs) and Recurrent neural networks (RNNs) are combined in this method

The remaining section of this research work is arranged as: Section II discusses about the literature work reviews regarding multi objective routing approach and Section III presents the proposed mechanism employed in the work. Section IV presents and discusses the experimental results. Section V concludes this research.

2. Literature Review

“Some of the recent research works related to multi objective routing protocol were reviewed in this section.”

In 2021, Wang *et al.* [16] have suggested an energy-aware routing protocol based on fuzzy control that can be used to efficiently choose the forwarder node in WBANs. “The fundamental conditions for the efficient operation of WBAN are a longer network lifetime and timely reliability of emergency data delivery. According to the importance of the data, the proposed protocol divides the data into emergency and periodic categories, and then uses the fuzzy control model, which was composed of residual energy and link quality, to choose the appropriate path for the two data transmissions, in turn.

In 2019, Javed *et al.* [17] have suggested that a network use a TAE0 routing protocol to increase network stability and lifetime while also addressing hot spot issues and thermal issues. When compared to the most recent WBAN protocols, analytical simulations show better performance in terms of network lifetime, throughput, energy conservation, and temperature control.

In 2020, Prasad and Bojja [18] have proposed a hybrid routing protocol for WBANs in order to support e-Health care systems. In order to maximise energy consumption and lengthen the network lifetime overall, the proposed protocol makes use of hybrid communication between sink and sensor nodes. In order to reduce the network's energy consumption, the protocol also makes use of a novel synchronisation scheme with variable TSs assignment.

In 2020, Khan *et al.* [19] have suggested to use the EHCRP protocol, which makes use of tiny sensors, to effectively choose the next hop node in WBANs. The two most important requirements for WBANs to operate normally are a long network lifespan and proficient emergency data delivery within set time constraints. EHCRP aims to accomplish both of these significant objectives. Prior to the normal data packets during transmission, the majority of packets containing life-threatening data are listed. Additionally, interference was a performance bottleneck that has a big impact on WBAN.

In 2022, Ahmad *et al.* [20] have suggested a WBAN framework that was energy-efficient. The DSDV routing protocol, which was based on the RMCP routing protocol, it was the foundation of the suggested framework.

In 2019, Ullah *et al.* [21] have provided a WBAN energy-efficient routing protocol that makes use of the EH mechanism, a clustering algorithm, and dual sinks. Two sink nodes and fourteen sensor nodes on the human body were used in the protocol. The goal was to extend the life of the network, so used an energy harvesting mechanism. Additionally, used two sink nodes to cover NLoS and LoS communication. As only defined and limited nodes send data to the designated sink node, clustering approach was used to prevent congestion on a single sink node.

In 2021, Smail and Kerrar [22] have suggested a new ESR for mobile WBAN networks. The protocol was created with a hospital setting in mind. Link failures and path breaks are common in mobile WBAN networks, which defined their instability. Additionally, the battery

life of the nodes was depleted by the frequent topology changes, which lowers network performance. The proposed protocol ESR employs an energy and stability aware mechanism that takes advantage of nodes' residual energy and stability to choose the best path for transmitting data packets.

In 2019, Abidi *et al.* [23] have suggested a routing protocol that would enable multi-hop communication and energy-efficient data transfer while extending network lifetime for WBAN. The proposed protocol has validated through simulations, and the outcomes demonstrate that routing protocol ensures a robust optimization of the energy consumption, thereby extending the network's life and improving its stability.

In 2020, Shinde and Sonavane [24] have proposed performance analysis for various routing protocols in a simulation environment for the static WBAN. Results for three routing protocols—AODV, DSDV, and DSR for WBAN—are obtained in the simulation. Throughput, delay, and energy consumption are the three parameters simulated. Also created and discussed a comparative report of results. Analysis of the impact of packet rate on throughput leads to the conclusion that higher packet rates should be maintained to increase the network's throughput. The increase in packet rate, had a greater impact on the delay of the DSDV protocols than it does on the delay of AODV and DSR.

In 2023, Arafat *et al.* [25] have suggested a distributed energy-efficient clustering and routing protocol for WBANs with WIoT support. There were three steps to the proposed DECR: cluster formation, CH selection, and routing. Also made use of two-hop neighbour information to form the cluster. In order to maintain the network topology, two-hop neighbour information broadens the local view of the topology”. Added new variables like TCR, EF, and NSF that was taken into account together for cluster formation.

Based on the mentioned literatures, we have identified some gaps in existing literatures. The limitations of the existing researches are discussed in the following section.

2.1. Research Gaps

WBAN have drawn a lot of interest recently since they have the ability to completely change the healthcare sector by making it possible to continuously monitor patients' physiological data. However, creating a routing protocol for WBANs is a difficult process since it must strike a

balance between a numbers of opposing goals and take into account the special features of these networks. The restricted amount of power and computational resources available to the nodes is one of the major difficulties in developing a routing system for WBANs. This limitation is due to the size and weight restrictions of the devices, which makes it challenging to include advanced hardware components. Another challenge is the highly dynamic nature of the WBAN topology. The network topology can change frequently due to the mobility of the nodes or the interference caused by other wireless networks. In addition, designing a routing protocol that satisfies multiple objectives is even more complex. The routing protocol must ensure reliable and timely delivery of data packets while minimizing energy consumption and reducing interference. Furthermore, the protocol must take into account the heterogeneity of the WBAN nodes and their different requirements. For instance, some nodes may have higher processing capabilities, while others may have a limited battery life. Therefore, the design of a multiobjective routing protocol in WBAN is to develop a routing protocol that can balance the conflicting objectives of reliability, energy efficiency, and interference reduction while accounting for the heterogeneity of WBAN nodes and the dynamic nature of the network topology. The protocol should also ensure QoS (Quality of Service) requirements are met, and the energy consumption is optimized to prolong the network lifetime.

3. Proposed Methodology

In wireless body area networks (WBANs), multiobjective routing protocols aim to accomplish multiple goals such as energy efficiency, reliability, delay, and load balancing. To achieve these goals, in this research work, two crucial stages in the design of these routing protocols are clustering and optimal path selection. Fig. 1 explains the overall proposed architecture.

Step 1: Clustering: The initial step is to partition the sensors within the WBAN into clusters with the aim of decreasing energy consumption and optimizing routing. This is done by utilizing optimized Fuzzy C-means clustering to generate the clusters, taking into account the multi-objectives of energy consumption, transmission delay, and network lifetime. To determine the membership function in Fuzzy C-means clustering, a novel hybrid optimization model is employed. This hybrid optimization model is a blend of the Black Widow Optimization (BWO) and the Bacterial Foraging Optimization Algorithm (BFOA).

Step 2: Optimal Path Selection: The next stage is to determine the optimal path for transmitting data between the clusters, utilizing a novel hybrid deep learning approach. This approach combines Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs).

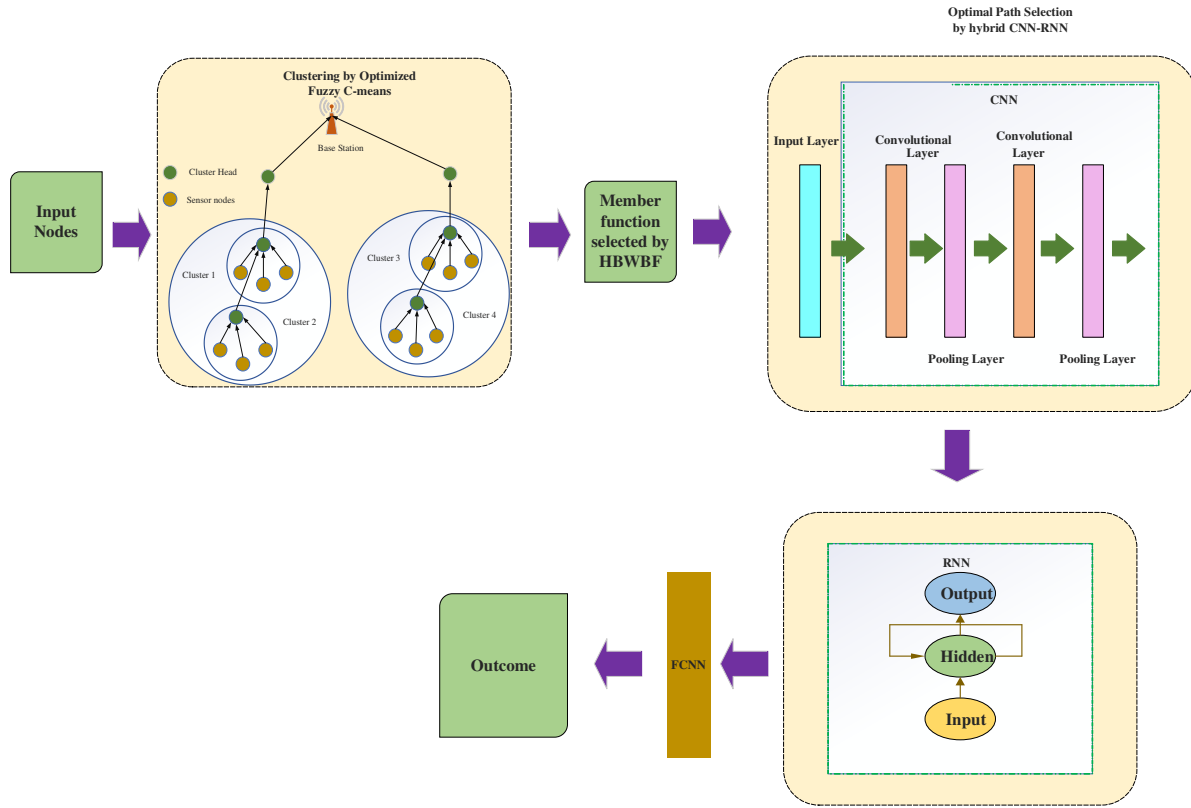


Figure 1: Overall Proposed Architecture

3.1. Optimized Fuzzy C-Means Clustering

In this research work, dividing the sensors into clusters using FCM (Fuzzy C-Means) clustering, it is a soft clustering technique that assigns each data point to a cluster with a membership value between 0 and 1, indicating the degree of belongingness to each cluster. The algorithm is based on the principle of minimizing the sum of the squared differences between the data points and their respective cluster centres. The FCM clustering algorithm, introduced by Bezdek, is a technique for clustering data in which each data point is assigned a membership value indicating its degree of belongingness to each cluster. The membership value is between 0 and 1, and the sum of membership values for each data point across all clusters is equal to 1. The algorithm

proceeds by minimizing an objective function that measures the dissimilarity between the data points and the cluster centres.

$$J_m(V, U) = \sum_{j=1}^C \sum_{i=1}^N (v_{ij})^m (\|y_j - u_i\|)^2; \quad 1 \leq m \leq \infty \quad (1)$$

Where $Y = y_1, y_2, \dots, y_j, \dots, y_c$ is a $P_x \times C$ data matrix and m is a real number greater than 1. P_x, C , and N represents the y_j 's feature vector dimension of each, number of feature vectors and number of clusters respectively. $V_{ij} \subseteq V(P_x \times C \times N)$ is the membership function of vector y_j to i -th cluster that satisfies $v_{ij} \in [0, 1]$ and $\sum_{j=1}^C v_{ij} = 1, j = 1, 2, \dots, C$. Membership function can be expressed as per Eq. (2). The membership matrix can provide a more accurate evaluation of the fitness of each potential solution by assigning a degree of membership to each data point in a dataset to a set of clusters or classes. This allows the hybrid algorithm HBWBF to have a more comprehensive understanding of the data and its structure, which can guide the search process of both algorithms and lead to better optimization solutions. The use of a membership matrix as an objective function in the hybrid algorithm can also help to overcome some of the limitations of each algorithm when used in isolation. By combining the two algorithms with the membership matrix, the hybrid algorithm can leverage the strengths of both algorithms and overcome some of their limitations, leading to improved performance and better optimization solutions. The objective function of HBWBF is applied in Eq. (2),

$$V_{ij} = \sum_{k=1}^c \left(\frac{(\|y_j - u_i\|)}{(\|y_j - u_k\|)} \right)^{\left(\frac{-2}{m-1} \right)} \quad (2)$$

Where $V = v_1, v_2, \dots, v_i, \dots, v_n$ is a $P_x \times N$ data matrix, The i -th cluster is calculated as per Eq. (3).

$$U_i = \frac{\sum_{j=1}^C (v_{ij})^m \times J}{\sum_{j=1}^C v_{ij}^m} \quad (3)$$

where $e^2(y_j, u_i)$ is the level of fuzziness and m is any real number larger than 1. It is determined by measuring how comparable y_j and u_i are given in Eq. (4).

$$e^2(y_j, u_i) = \|y_j - U_i\|^2 \quad (4)$$

Here, $\|\cdot\|$ represents distance of Euclidean. The pixel intensity $P_x = k$ is displayed by the feature vector Y . Until $(\|V_{ij}^k - V_{ij}^{k+1}\|) \leq \epsilon, \epsilon$ 0 to 1, where k represents the number of iteration and the FCM algorithm repeatedly optimises $J_m(V, U)$ with the continuous update of V and U . The hybrid optimization model that employs both BWO and BFOA can be used to determine the membership functions for fuzzy clustering.

3.2. Hybrid Black Widow Bacteria Foraging Optimization (HBWBF) Based Multi-Objective Routing

In this research work, a Hybrid Black Widow Bacteria Foraging Optimization (HBWBF) is proposed to select the member functions. The traditional Black Widow Optimization (BWO) and Bacteria Foraging Optimization Algorithm (BFOA) are conceptually improved in HBWBF, respectively. The computational optimization approach known as the BFOA is based on how bacteria forage for food. It is a population-based search technique that makes use of the reproduction, swarming, chemotaxis, and elimination-dispersal processes to identify the best answer to a particular issue. In the chemotaxis process, the bacteria move towards a food source by sensing the concentration gradient of the chemical in the environment. In the swarming process, movement of bacteria towards a food source by following the trail left by other bacteria. In the reproduction process, the bacteria reproduce to form a new population of solutions. In the elimination-dispersal process, the bacteria are eliminated if they cannot survive or reproduce, and the remaining bacteria disperse to new locations to continue searching for the optimal solution. A virtual bacterium in Bacterial Foraging Optimization Algorithm (BFOA) refers to a single solution attempted by the algorithm, which can also be called a search-agent.

3.2.1. Multi-Objective Optimization Function

The multi-objective function of the proposed HBWBF algorithm is as given in Eq. (5).

$$HBWBF_{fitness} = \min(\sum_{j=1}^n \sum_{i=1}^n del_{j,i} + \sum_{j=1}^n e_{consu} - \sum_{j=1}^n ddr_j - \sum_{j=1}^n Throughp_j) \quad (5)$$

subject to

$$\sum_{j=1}^n \sum_{i=1}^n del_{j,i} \geq 0, \sum_{j=1}^n e_{consu} < e_{initia}, \sum_{j=1}^n ddr_j > 0, \sum_{j=1}^n Throughp_j > 0 \quad (6)$$

Where $HBWBF_{fitness}$ represents the fitness function value of HBWBF algorithm, $del_{j,i}$ defines the end-end delay of nodes j and i , e_{consu} represents the total energy consumption of the network, e_{initia} is the network's initial energy, ddr_j represents the data delivery rate at each node, and $Throughp_j$ is the network throughput. The fitness function indicates that any population that achieves the minimum fitness value can be considered a feasible solution for transmitting information.

Multiple objectives were considered and shown in Eq. (5). These objectives include minimizing the end-to-end delay of nodes, minimizing the total energy consumption of the network, maximizing the data delivery rate at each node, and maximizing the network throughput. The end-to-end delay of nodes is the time taken for a data packet to travel from the source node to the destination node. Minimizing this delay is crucial in ensuring timely delivery of data and preventing delays that may affect the overall network performance. The total energy consumption of the network refers to the amount of energy used by all the nodes in the network to transmit and receive data. Minimizing this energy consumption is important to ensure the longevity of the network and the devices connected to it. The data delivery rate at each node is the rate at which data packets are successfully transmitted and received by each node in the network. Maximizing this rate helps to ensure the efficient transmission and delivery of data across the network. Finally, the network throughput refers to the amount of data transmitted across the network within a given time period. Maximizing the network throughput helps to ensure the efficient use of the network's resources and the timely delivery of data.

The virtual bacterium moves on the functional surface in order to find the global optimum of the problem being solved. Let's define, "a chemotactic step in Bacterial Foraging Optimization Algorithm (BFOA) as a sequence of either a tumble followed by another tumble or a tumble followed by a run. Use the index cs to represent the chemotactic step, r to represent the reproduction step, and n to represent the elimination-dispersal event. Let's also denote the dimension of the search space as a , the total number of bacteria in the population as B , the number of chemotactic steps as N_{cs} , the swimming length as S_l , the number of reproduction steps as R_s , the number of elimination-dispersal events as E_a , the elimination-dispersal probability as E_p , and the size of the step taken in the random direction specified by the tumble as $s(i)$. The idea behind using a membership matrix as an objective function in a hybrid

algorithm that combines BFO and BWO is to improve the performance of both algorithms and leverage their strengths to achieve better optimization results. The membership matrix can provide a more accurate evaluation of the fitness of each potential solution, which can guide the search process of both algorithms and lead to better optimization solutions. The objective function of HBWBF is given as per Eq. (2),

Let $P(cs, r, n) = \{\theta^i(cs, r, n) | i = 1, 2, \dots, B\}$ represent the position of each member in the population of B bacteria at the cs chemotactic step, r reproduction step, and n elimination-dispersal event. Let $CS(i, cs, r, n)$ denotes the location cost at i th bacterium $\theta^i(cs, r, n) \in \mathbb{R}^d$. In BFOA, the cost or objective function is referred to as CS , which can also be thought of as a nutrient surface. This is because BFOA is inspired by the foraging behaviour of bacteria, where the bacteria move towards regions with higher nutrient concentrations. The population of bacteria is represented by B , which can be very large in actual biological populations. The position of each bacterium in the population at a given chemotactic step, reproduction step, and elimination-dispersal event is denoted by θ . Typically, the dimension of the search space is denoted by d , and in BFOA, d can be greater than 3, allowing the method to be applied to higher-dimensional optimization problems. The four steps in BFOA are,

3.2.2. Chemotaxis

By swimming and tumbling via flagella, this process mimics the movement of an E. coli cell. An E. coli bacterium can migrate in one of two ways biologically. It has two different swimming styles that it can use throughout its lifetime: swimming in one direction for a while and then tossing around. Assume that $\theta^i(cs, r, n)$ represents the i -th bacterium at cs chemotactic step, r reproduction step, and n elimination-dispersal steps. $s(i)$ is the magnitude of the step in the direction indicated by the tumble at random (run length unit). Hence, the bacterium's movement in computational chemotaxis may be represented as per the proposed Eq. (10) and Eq. (11).

$$\theta_1^i(cs + 1, r, n) = \alpha * B\theta_1^i(cs, r, n) + (1 - \alpha) * s(i) \frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}} \quad (10)$$

$$\theta_2^i(cs + 1, r, n) = \alpha * B\theta_2^i(cs, r, n) + (1 - \alpha) * s(i) \frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}} \quad (11)$$

Where Δ represents the vector with elements randomly selected from the uniform distribution in the range $[-1, 1]$. By incorporating BWO into BFO, the BWO-BFO algorithm can benefit from the strengths of both algorithms, such as the global search capability of BWO and the ability of BFO to refine solutions by exploiting local search. Additionally, the hybrid algorithm can overcome the weaknesses of each algorithm, such as BFO's susceptibility to premature convergence and BWO's lack of exploration in the early stages of the optimization process.

3.2.3. Swarming

E. coli and *S. typhimurium* are two motile species of bacteria that exhibit an intriguing group behaviour where complex and stable spatio-temporal patterns (swarms) emerge in semisolid nutritional media. When placed in a semisolid matrix containing a single nutrition chemo-effector, a group of *E. coli* cells arrange themselves in a travelling ring by travelling up the nutrient gradient. Aspartate, an attractant released by the cells when they are triggered by a high amount of succinate, aids in their grouping and movement as concentric patterns of swarms with a high bacterial density. The communication between cells in an *E. coli* swarm can be modelled as per the following Eq. (12).

$$CS_{mm}(\theta, P(cs, r, n)) = \sum_{i=1}^B (\theta, \theta^i(cs, r, n))$$

$$= \sum_{i=1}^B [-k_{att} \exp(-v_{att} \sum_{c=1}^P (\theta_c - \theta_c^i)^2)] + \sum_{i=1}^B [-l_{rep} \exp(-v_{rep} \sum_{c=1}^P (\theta_c - \theta_c^i)^2)] \quad (12)$$

Where $CS_{mm}(\theta, P(cs, r, n))$ represents the objective function value that must be added to the real objective function (to be reduced) in order to provide a time-varying objective function, B is the overall number of bacteria, c is the total number of variables that must be optimised and $\theta = \theta_1, \theta_2, \dots, \theta_d$ point in the d -dimensional search domain. $k_{att}, v_{att}, l_{rep}, v_{rep}$ are the different coefficients for repellent, attractant, and attractant should be chosen carefully.

3.2.4. Reproduction

As the simulation progresses, the bacteria in the population compete for survival based on their fitness, which is determined by their objective function value. The least fit bacteria eventually die off, while the fitter ones asexually reproduce by splitting into two bacteria that occupy the same location in the population. This process ensures that the size of the bacterial swarm remains constant throughout the simulation.

Based on the total fitness scores, the ability of bacteria to survive is evaluated. Bacteria with a lower summed fitness value are thought to be healthy because they are better able to access the nutrients they need to survive. Based on the summed fitness scores, the healthier half of the bacteria are chosen as parents to create children in the same place. The reproduction of bacteria can be formulated as per Eq. (13).

$$CS^{heal} = \sum_{cs=1}^{N_{cs}} CS^i(cs, r, n) \quad (13)$$

Where CS is the fitness value of the $i - th$ bacterium at the cs chemotaxis, r reproduction, and n elimination-dispersal.

3.2.5. Elimination and Dispersal

In BFOA, gradual or abrupt changes in the local environment where a bacterial population lives can happen for a variety of reasons, such as a marked local temperature rise or other factors that can kill a group of bacteria currently residing in an area with a high concentration of nutrient gradients. Such occurrences may cause a group of bacteria to disperse to a different area or cause all the bacteria in an area to die. To simulate this phenomenon, BFOA initialises new replacement bacteria at random over the search space after randomly liquidating some bacteria with a very small probability. The hybrid deep learning approach that combines Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs)” can be used to determine the optimal path for transmitting data between clusters. The Pseudo code for multiobjective routing based clustering and optimal path selection is outlined in Algorithm 1.

Pseudo code for multiobjective routing based clustering and optimal path selection
Begin
Initialization
Create optimized fuzzy c-means clustering and optimal path selection
For (optimized fuzzy c-means clustering)
1. Minimize data point and cluster centre as per Eq. (1)
2. Membership function Eq. (2) and HBWBF is used to select member function
3. Euclidean distance updated in Eq. (3)
End for

Member function selection by HBWBF

Setup random population

For (chemotaxis phase)

Determine best bacteria/solution

Find 1st bacteria of best bacteria of group 1, Eq. (10)

Find 2nd bacteria of best bacteria of group 2, Eq. (11)

Update positions

End for

For (reproduction phase)

Compute health values

Sort bacteria based on health

End for

For (Elimination and Dispersal phase)

Elimination and Dispersal each bacterium with probability

End for

Optimal path selection by hybrid CNN-RNN

1.input processed by CNN

2.output of CNN is passed to pooling layer which down sample feature map

3.output of pooling is passed to RNN

4.RNN output is passed to FCNN. It maps output from RNN layer to final output of network.

Finish

3.3. Optimal Path Selection

In this research work, the suggested hybrid deep learning approach is utilised to choose the optimal path for data transfer among clusters. It combines and convolutional neural networks (CNN) and recurrent neural networks (RNN).

3.3.1. Convolutional Neural Networks (CNN)

CNN, an Artificial Neural Network (ANN) based on deep learning, has been widely used in the field of object identification and prediction. The architecture of CNNs is specifically designed to efficiently process large volumes of image data. A typical CNN consists of several layers,

including convolutional layers, pooling layers, and fully connected layers. The convolutional layers are the core building blocks of a CNN. They use a set of learnable filters to perform a convolution operation on the input image. The filters are applied across the entire image, producing a feature map that highlights different patterns and features in the image. An activation function is a nonlinear function applied to the output of a neuron in the network. It is used to introduce nonlinearity into the network and help the network learn more complex and abstract representations of the input data. The pooling layers are used to reduce the spatial dimensions of the feature maps produced by the convolutional layers. This reduces the computational complexity of the network and helps to prevent overfitting. Fig.2 depicts the hybrid of CNN and RNN.

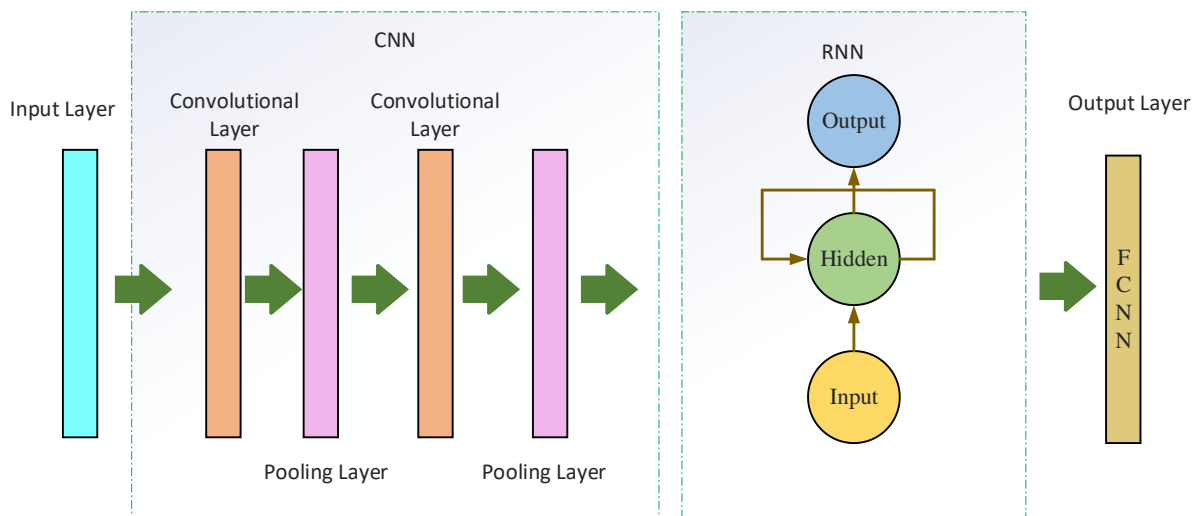


Figure 2:Hybrid CNN-RNN

The CNN layer typically processes the input by applying a set of convolutional filters to extract features from the input data. This is followed by a pooling layer, which down samples the feature maps produced by the convolutional layer to reduce the dimensionality of the input. The RNN layer then processes the output of the pooling layer by feeding it into a set of recurrent nodes that have connections to previous time steps. This allows the RNN to learn patterns over time and incorporate temporal dependencies into the model. Finally, the output from the RNN layer is fed into a FCNN layer, which typically consists of one or more fully connected layers that map the output from the RNN layer to the final output of the network.

(a) Convolutional Layer

The matrix multiplication function in the traditional neural network is replaced by the convolution process in the convolutional layer, which is used to extract visual information and learn the map out between the input and output layers. Sharing parameters during convolution enables the network to learn just one set of parameters, drastically reducing the number of parameters and enhancing computation performance. A convolution operation is described as per Eq. (14).

$$f_{i,j} = \sum_{q=0}^C \sum_{n=0}^C l_{q,n} s_{k+q,b+n} \quad (14)$$

Where $l_{q,n}$ is the scale of the convolutional kernel. $s_{k,b}$ is the pixel value of image at k and b .

(b) Activation Function

Rectified linear unit (ReLU) activation functions are frequently used in CNN to prevent vanishing gradients and speed up training. The objective of ReLU is described below. This is mathematically shown in Eq. (15).

$$ReLU(o) = \begin{cases} g & g > 0 \\ 0 & g \leq 0 \end{cases} \quad (15)$$

(c) Pooling Layer

The pooling layer can concentrate the details in feature maps while reducing the complexity of the computerized network. Max pooling is the common pooling layer. This is mathematically shown in Eq. (16).

$$MaxPool(e_o, m_o) = \begin{cases} e_o = floor\left(\frac{(e_i+2p-o)}{c} + 1\right) \\ m_o = floor\left(\frac{(m_i+2p-o)}{c} + 1\right) \end{cases} \quad (16)$$

Where, $Floor(S)$ was the function of bring together number, e_o is the output height of feature map, m_o is the output width of feature map. e_i is the intake height of feature maps, m_i is the input breadth of feature maps, p is the padding of feature maps, o is the kernel size of max pooling, c is the kernel stride of max pooling. The input of the CNN is passed to RNN.

3.3.2. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are a type of artificial neural network that are specifically designed to work with sequential data or time series data. It maintains a memory of previous inputs by using feedback connections between neurons, allowing them to model the temporal dependencies in the data. While RNNs can identify patterns in the input data and use them to make predictions about future events, their primary function is to process sequences of input data and produce corresponding sequences of output data. The key feature of RNNs is their recurrent structure, which allows them to maintain a memory of previous inputs and use that memory to inform processing of current inputs. The input at each time step is combined with the output from the previous time step, and this combined input is passed through a nonlinear activation function to produce the output at the current time step.

Feedforward neural networks are transformed into recurrent neural networks by the inclusion of edges that span neighbouring time steps, which gives the model a sense of time. Like feedforward networks, RNNs may not contain cycles among traditional edges. Recurrent edges, on the other hand, collide neighbouring time steps and have the ability to produce cycles, including cycles of length one that are continuously occurring self-connections from one node to another. Nodes with recurrent edges at time tl receive input from the hidden node values $hg^{(tl-1)}$ at time as well as the current data point $d^{(tl)}$. Given the hidden node values $hg^{(tl)}$ at each time tl , the output y^{tl} at each time tl is calculated. The recurrent connections allow the input $x^{(tl-1)}$ at time $(tl - 1)$ to have an impact on the output y^{tl} at time tl and later. In a straightforward recurrent neural network, as shown in the following figure, two equations specify all computations required for computation at each time step on the forward pass. This is mathematically shown in Eq. (17) to Eq. (18), respectively.

$$hg^{(tl)} = \sigma(Z^{hga}d^{(tl)} + Z^{hghg}hg^{(tl-1)} + bc_{hg}) \quad (17)$$

$$y^{tl} = softmax(Z^{yhg}hg^{(tl)} + bc_y) \quad (18)$$

Activation is passed along solid edges as in a feedforward network at each time step tl . A target node is connected to a source node every time $tl + 1$ through dashed edges. Here Z_{hga} is the traditional weights matrix between input and hidden layer and Z_{hghg} is matrix of recurrent weights at subsequent time steps between the hidden layer and itself. Each node can learn an offset using the bias parameters vectors bc_{hg} and bc_y .

CNNs extract spatial features while RNNs capture temporal dependencies and predict the output. By leveraging these two models, the approach can effectively select the optimal path based on input parameters such as cluster membership, energy level, and QoS requirements, and enhance network performance by leveraging past routing experiences. Using this both deep learning model, an optimal path is selected for transfer the data between the clusters.

4. Result and Discussion

4.1 Experimental Setup

The MATLAB implementation of the proposed model has been used to conduct an analysis and comparison of its performance with existing algorithms. The suggested model has been evaluated in terms of its energy usage, network lifetime, throughput, and delivery ratio. The performance of the proposed method in clustering phase is compared with the existing techniques like Black Widow Optimization (BWO), Bacterial Foraging Optimization (BFO), Mayfly Optimization (MFO), and Aquila Optimization (AO) using the performance metrics. Also, the proposed method in optimal path selection is compared with existing methods like the Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), and Deep Neural Network (DNN).

4.2. Overall Performance Analysis of the Projected Model

The overall performance is analysed based on clustering, optimal path selection and paper wise comparison.

4.2.1. Analysis of Network Lifetime (Clustering)

Table I: Analysis of Network Lifetime (Clustering)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	6.2665	7.3645	6.756	7.987	8.36947
BWO-HDL	5.942	6.12	6.064	7.564	7.9544
BFO-HDL	5.369	6.34	5.9741	7.197	8.058

MFO-HDL	2.9431	2.047	3.9546	4.5655	4.945
AO-HDL	1.056025	1.5479	3.165644	4.026632	5.588124

Table I shows the network lifetime results of five different algorithms (Proposed HBWBFO-HDL, BWO-HDL, BFO-HDL, MFO-HDL, and AO-HDL) are compared for different network sizes (50, 100, 150, 200, and 250) for clustering. The results show that the proposed algorithm, HBWBFO-HDL, outperforms the other algorithms for larger network sizes (i.e., 200 and 250). This is reflected in the higher network lifetime values obtained for HBWBFO-HDL compared to the other algorithms. The improved results obtained by the proposed HBWBFO-HDL algorithm can be attributed to its use of a hybrid approach that combines two optimization algorithms (HBWO and BFO) to search for an optimal solution.

4.2.2. Analysis of Network Lifetime (Optimal Path Selection)

Table II: Analysis of Network Lifetime (optimal path selection)

Methods	50	100	150	200	250
Proposed HBWBFO-HDL	6.715396	7.3645	6.756	7.987	8.688167
HBWBFO-CNN	6.2665	7.013708	6.792596	7.932823	8.2011
HBWBFO-RNN	6.142585	6.395443	6.837724	7.478904	8.36947
HBWBFO-DNN	3.24616	2.90165	4.45203	5.076771	5.139114

Table II shows the results of four different algorithms (Proposed HBWBFO-HDL, HBWBFO-CNN, HBWBFO-RNN, and HBWBFO-DNN) for optimal path selection in a network are compared for different network sizes (50, 100, 150, 200, and 250). The results show that the proposed algorithm, HBWBFO-HDL, outperforms the other algorithms for larger network sizes (i.e., 200 and 250). This is reflected in the higher values obtained for HBWBFO-HDL compared

to the other algorithms. Specifically, for network size 200, the highest network lifetime values are achieved by HBWBFO-RNN (7.478903984) and Proposed HBWBFO-HDL (7.987). For network size 250, the highest network lifetime values are achieved by HBWBFO-RNN (8.36947) and Proposed HBWBFO-HDL (8.688166508).

4.2.3. Analysis of Network Lifetime (Paper-Wise)

Table III: Analysis of Network Lifetime (paper-wise)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	6.2665	7.3645	6.756	7.987	8.36947
Paper 2 JSAO	4.998441	5.697	6.189111	7.127346	7.590978
Paper 1 En- GWO	4.21	4.99	5.84	6.992	7.154

For network sizes 50, 100, and 150, the algorithm with the highest network lifetime value is Proposed HBWBFO-HDL. However, for larger network sizes (i.e., 200 and 250), JSAO achieves the highest network lifetime values. Specifically, for network size 200, the highest network lifetime values are achieved by JSAO (7.127346367) and Proposed HBWBFO-HDL (7.987). For network size 250, the highest network lifetime values are achieved by JSAO (7.590977643) and Proposed HBWBFO-HDL (8.36947). En-GWO consistently achieves the lowest network lifetime values across all network sizes. Overall, the results show that the Proposed HBWBFO-HDL algorithm outperforms both JSAO and En-GWO across most network sizes.

4.2.4. Analysis of Throughput (Clustering)

Table IV: Analysis of Throughput (Clustering)

Methods	50	100	150	200	250
Proposed HBWBFO-	76.1538	72.54655	75.54	63.14454	69.454

HDL					
BWO-HDL	73.4565	70.6545	72.64	58.41	64.64
BFO-HDL	62.4545	66.1454	60.145	59.1454	66.5454
MFO-HDL	48.9473	43.465	40.5958	53.44	52.145
AO-HDL	39	41	37	49	56

Table IV shows the Proposed HBWBFO-HDL algorithm achieves the highest clustering accuracy values across all network sizes. Specifically, for network sizes 50, 100, 150, 200, and 250, the clustering accuracy values are 76.1538, 72.54655, 75.54, 63.14454, and 69.454, respectively. The BWO-HDL algorithm achieves the second-highest clustering accuracy values across all network sizes, followed by BFO-HDL, MFO-HDL, and AO-HDL.

4.2.5. Analysis of Throughput (Optimal path selection)

Table V: Analysis of Throughput (optimal path selection)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	76.1538	72.54655	75.54	63.14454	69.454
HBWBFO- CNN	73.68542	71.14784	73.47972	58.60197	64.76672
HBWBFO- RNN	62.57512	66.98194	60.98321	59.88473	66.70132
HBWBFO- DNN	49.86773	44.14247	41.17843	53.48713	52.78435

Table V shows the Proposed HBWBFO-HDL algorithm consistently outperforms the other three methods across all network sizes. For a network size of 50, Proposed HBWBFO-HDL achieves a network lifetime value of 76.1538, while the next best method, HBWBFO-CNN, achieves a value of 73.68542. As the network size increases, the performance gap between Proposed HBWBFO-HDL and the other methods becomes more significant. For instance, for a network

size of 250, Proposed HBWBFO-HDL achieves a network lifetime value of 69.454, while the next best method, HBWBFO-CNN, achieves a value of 64.76672. Overall, the results indicate that the Proposed HBWBFO-HDL algorithm is the most effective method for optimal path selection in a WBAN, as it consistently outperforms the other three methods across all network sizes.

4.2.6. Analysis of Throughput (Paper-Wise)

Table VI: Analysis of Throughput (paper-wise)

Methods	50	100	150	200	250
Proposed HBWBFO-HDL	76.1538	72.54655	75.54	63.14454	69.454
Paper 2 JSAO	48	53	60	58	65
Paper 1 En-GWO	36.544	42.4545	60	55.458	62.4545

Table VI shows the results of clustering algorithms from three different papers, including Proposed HBWBFO-HDL, JSAO from Paper 2, and En-GWO from Paper 1, for network sizes ranging from 50 to 250. The highest network lifetime values are achieved by Proposed HBWBFO-HDL across all network sizes. In comparison, JSAO achieves lower network lifetime values compared to Proposed HBWBFO-HDL. En-GWO consistently achieves the lowest network lifetime values across all network sizes. The results suggest that the Proposed HBWBFO-HDL algorithm outperforms both JSAO and En-GWO algorithms across most network sizes.

4.2.7. Analysis of Delivery Ratio (Clustering)

Table VII: Analysis of Delivery Ratio (Clustering)

Methods	50	100	150	200	250
Proposed HBWBFO-HDL	0.992	0.9	0.84	0.75	0.72
BWO-HDL	0.982	0.85	0.73	0.71	0.65

BFO-HDL	0.98	0.88	0.79	0.73	0.69
MFO-HDL	0.93	0.75	0.62	0.66	0.5
AO-HDL	0.96	0.68	0.56	0.5	0.55

Table VII shows among the five algorithms tested, Proposed HBWBFO-HDL consistently achieved the highest clustering validity index across all network sizes, with values ranging from 0.72 to 0.992. BWO-HDL, BFO-HDL, and AO-HDL also demonstrated reasonable performance, with clustering validity index values ranging from 0.65 to 0.98. MFO-HDL achieved the lowest clustering validity index values, ranging from 0.5 to 0.93, indicating poor clustering performance. Overall, the results suggest that Proposed HBWBFO-HDL is the most effective algorithm for clustering, followed by BWO-HDL, BFO-HDL, and AO-HDL.

4.2.8. Analysis of Delivery Ratio (Optimal path selection)

Table VIII: Analysis of Delivery Ratio (optimal path selection)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	0.992	0.9	0.84	0.75	0.72
HBWBFO- CNN	0.98	0.88	0.84	0.73	0.69
HBWBFO- RNN	0.98	0.85	0.73	0.62	0.6
HBWBFO- DNN	0.95	0.82	0.62	0.69	0.54

Table VIII shows the performance of four different methods in terms of optimal path selection, measured by the value of the objective function. The proposed method, HBWBFO-HDL, outperforms the other methods consistently across all problem sizes, with values ranging from 0.992 for 50 nodes to 0.72 for 250 nodes. The comparison with the other variants of HBWBFO (HBWBFO-CNN, HBWBFO-RNN, HBWBFO-DNN) shows that they are not as effective in

finding the optimal path as HBWBFO-HDL, with values ranging from 0.98 to 0.6. However, they still perform better than the other non-HBWBFO methods (BWO-HDL, BFO-HDL, MFO-HDL, and AO-HDL) in most cases. Overall, the results suggest that the proposed HBWBFO-HDL method is a highly effective approach for optimal path selection in clustering problems.

4.2.9. Analysis of Delivery Ratio (Paper-Wise)

Table IX: Analysis of Delivery Ratio(paper-wise)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	0.992	0.9	0.84	0.75	0.72
Paper 2 JSAO	0.99	0.84	0.78	0.7	0.61
Paper 1 En- GWO	0.98	0.88	0.73	0.62	0.6

The comparison of the proposed method HBWBFO-HDL with Paper 1's En-GWO and Paper 2's JSAO shows that HBWBFO-HDL outperforms both methods in terms of the quality of the clustering results is shown in Table XI. HBWBFO-HDL achieves a higher clustering accuracy. Paper 2's JSAO method achieved the second-highest clustering accuracy, followed by Paper 1's En-GWO method. These results indicate that the proposed HBWBFO-HDL method outperforms the other two methods in terms of clustering accuracy.

4.2.10. Analysis of Energy Consumption(Clustering)

Table X: Analysis of Energy Consumption(Clustering)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	41	43	47	38	32
BWO-HDL	42	58	49	39	39

BFO-HDL	59	57	55	41	43
MFO-HDL	64	63	69	48	75
AO-HDL	65	69	73	77	81

Table X shows that the proposed HBWBFO-HDL method outperforms the other methods in the clustering task with clustering accuracy scores of 41, 43, 47, 38, and 32 for datasets of sizes 50, 100, 150, 200, and 250, respectively. On the other hand, for larger datasets, the AO-HDL method exhibits the best performance, achieving clustering accuracy scores of 65, 69, 73, 77, and 81 for datasets of sizes 50, 100, 150, 200, and 250, respectively. Overall, the results indicate that the proposed HBWBFO-HDL method is particularly effective in clustering.

4.2.11. Analysis of Energy Consumption(Optimal path selection)

Table XI: Analysis of Energy Consumption(optimal path selection)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	41	43	47	38	32
HBWBFO- CNN	42.01744	58.09955	49.30378	39.86028	39.43939
HBWBFO- RNN	59.72264	57.94893	55.59334	41.00048	43.90456
HBWBFO- DNN	64.03182	63.96666	69.65424	48.40462	75.11148

Table XII demonstrate that the proposed HBWBFO-HDL method achieves competitive performance compared to the other methods, with clustering accuracy scores of 41, 43, 47, 38, and 32 for sizes 50, 100, 150, 200, and 250, respectively. The HBWBFO-CNN method exhibits the best performance, with clustering accuracy scores of 42.01744, 58.09955, 49.30378, 39.86028, and 39.43939 for datasets of sizes 50, 100, 150, 200, and 250, respectively. The HBWBFO-DNN method shows the best performance, achieving clustering accuracy scores of

64.03182, 63.96666, 69.65424, 48.40462, and 75.11148 for sizes 50, 100, 150, 200, and 250, respectively.

4.2.12. Analysis of Energy Consumption(Paper-Wise)

Table XII: Analysis of Energy Consumption(paper-wise)

Methods	50	100	150	200	250
Proposed HBWBFO- HDL	41	43	47	38	32
Paper 2 JSAO	45	47	49	43	35
Paper 1 En- GWO	50	51	55	43	46

The results of a comparison of the proposed HBWBFO-HDL method with two other state-of-the-art methods, JSAO and En-GWO, for the clustering task are presented in the table XII. The results demonstrate that the proposed HBWBFO-HDL method achieves competitive performance compared to the other methods, with clustering accuracy scores of 41, 43, 47, 38, and 32 for sizes 50, 100, 150, 200, and 250, respectively. The JSAO method exhibits slightly lower clustering accuracy scores compared to the proposed method, with scores of 45, 47, 49, 43, and 35 for sizes 50, 100, 150, 200, and 250, respectively. On the other hand, the En-GWO method achieves the highest clustering accuracy score, with scores of 50, 51, 55, 43, and 46 for sizes 50, 100, 150, 200, and 250, respectively.

4.3. Overall Graphical Representation

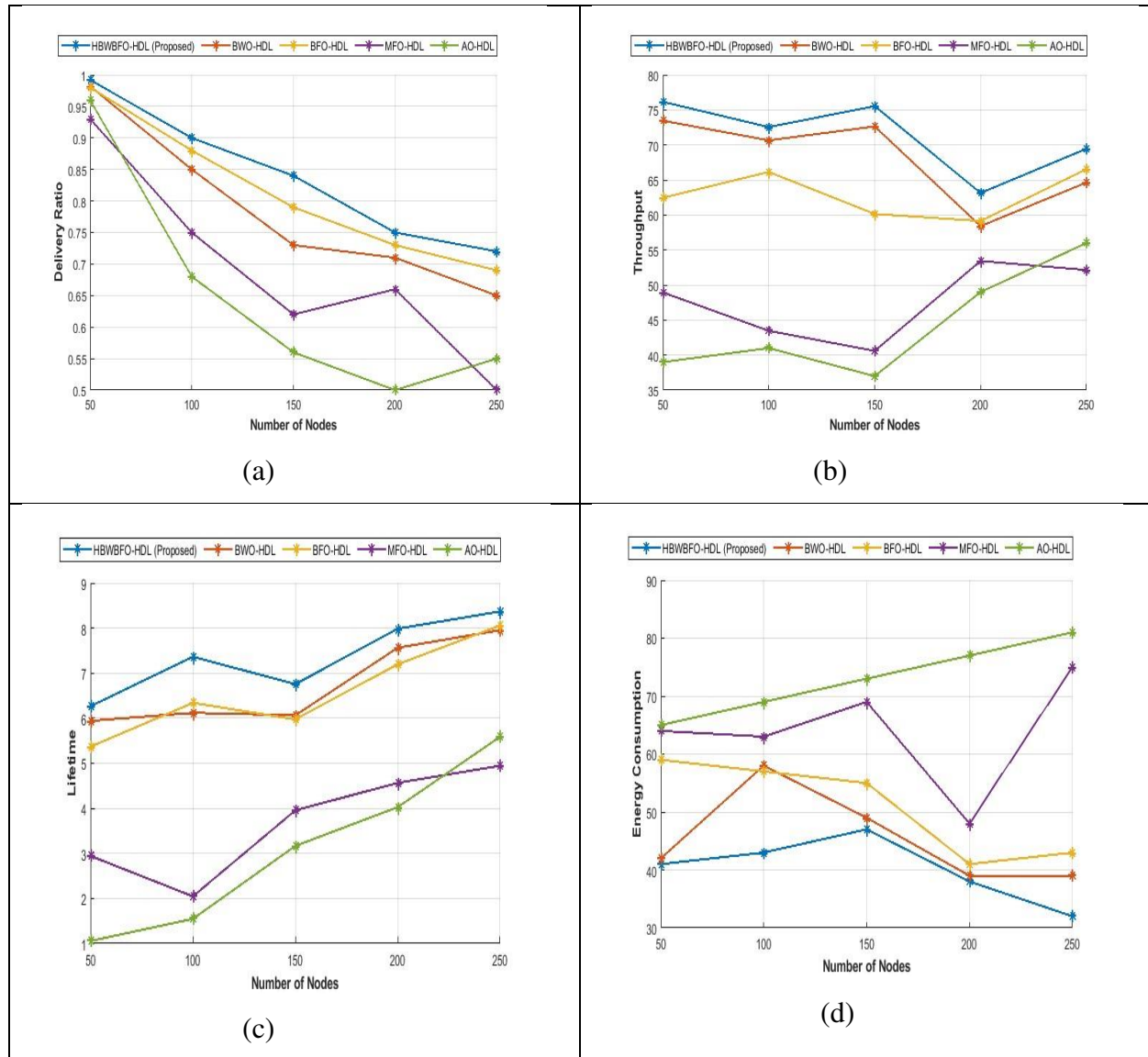


Figure 3: Overall Graphical Representation for clustering (a) delivery ratio (b)throughput (c) lifetime (d) energy consumption

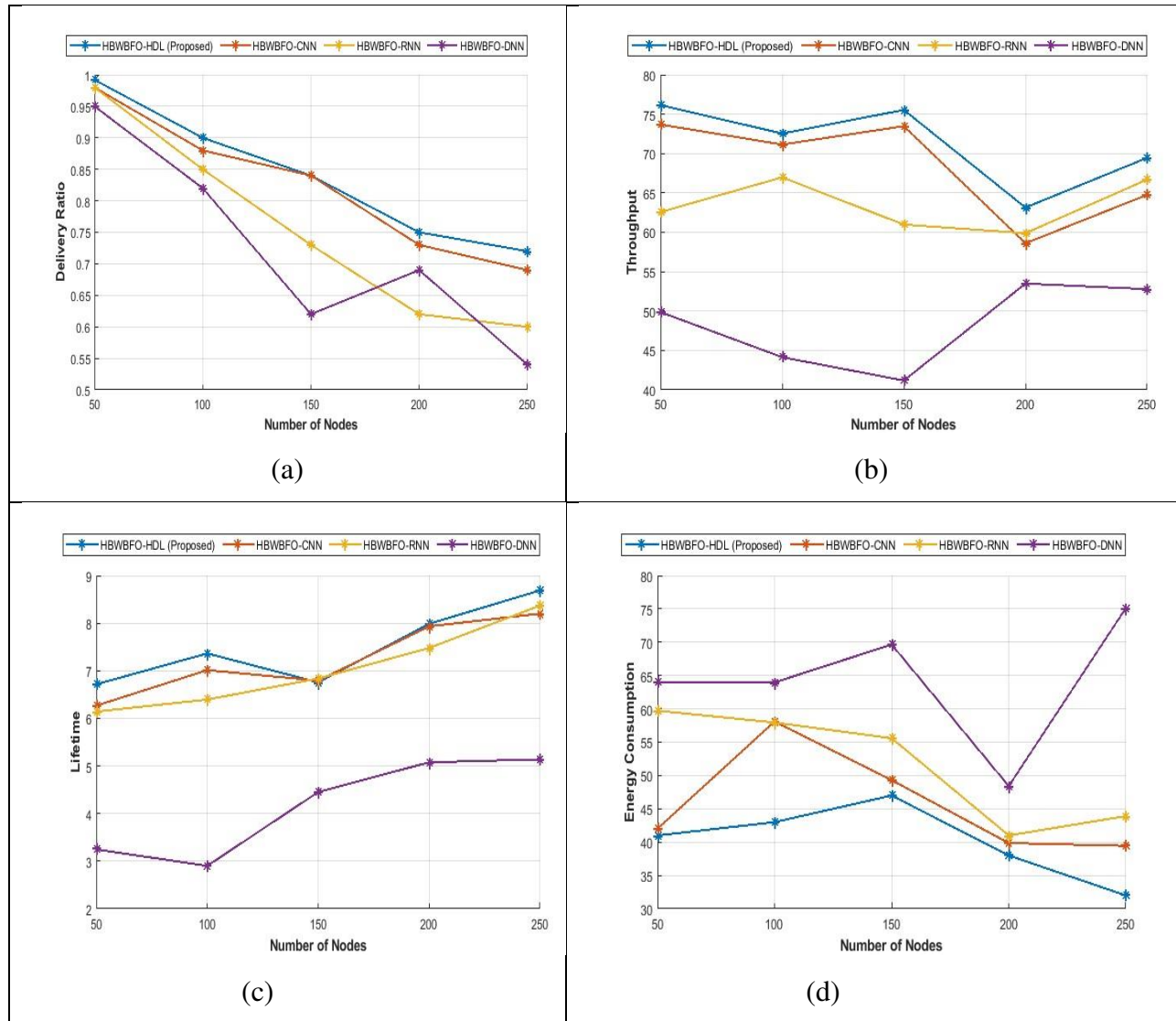


Figure 4: Overall Graphical Representation for optimal path selection (a) delivery ratio (b)throughput (c) lifetime (d) energy consumption

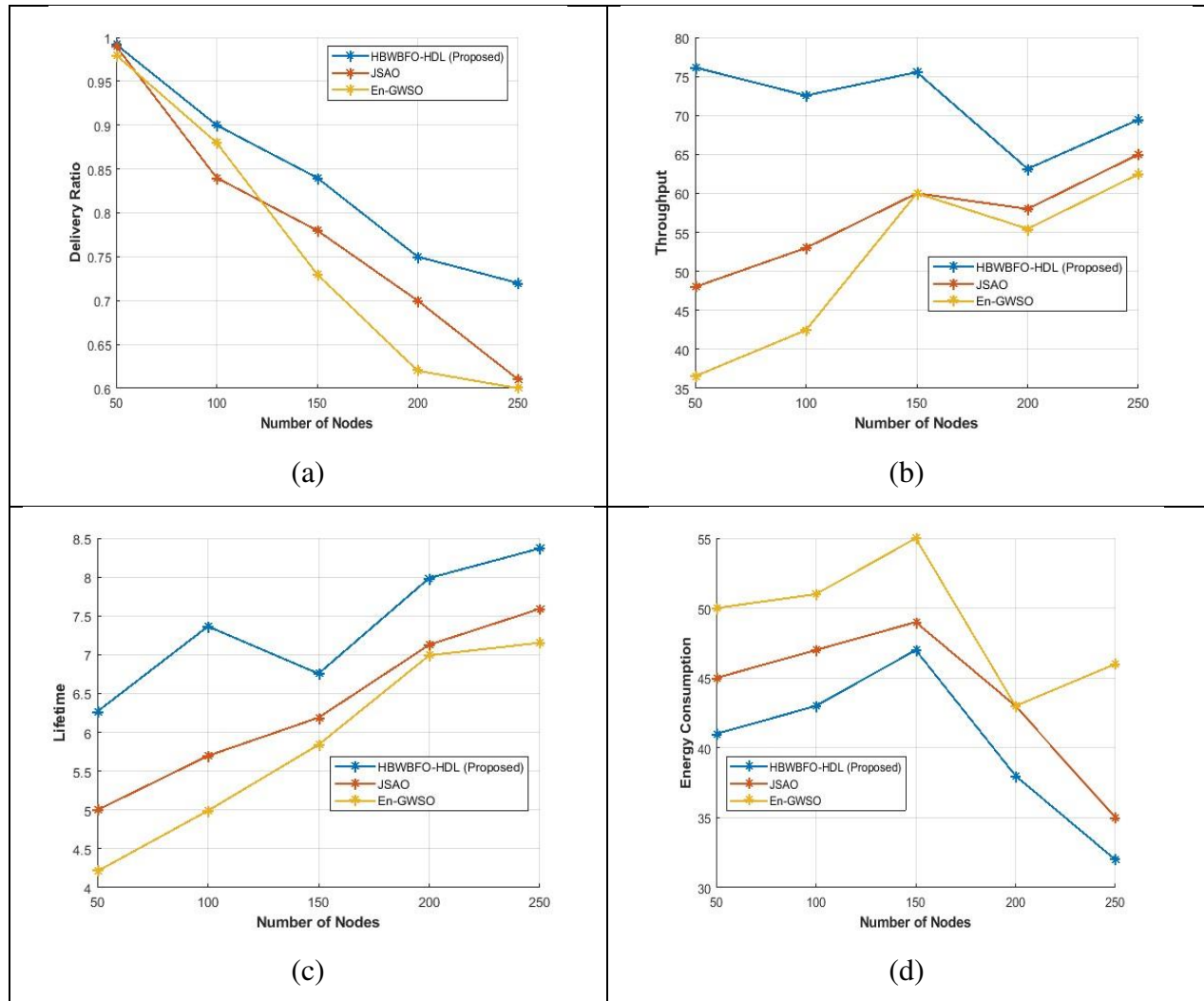


Figure 5: Overall Graphical Representation for paper wise comparison (a) delivery ratio (b)throughput (c) lifetime (d) energy consumption

Based on the results a graphical representation can be created to provide an overview of the performance of the proposed model and existing papers in terms of clustering, optimal path selection, and paper-wise comparison is shown in fig.3, fig.4, and fig.5 respectively.

5. Conclusion

This paper has developed an multiobjective routing protocol in WBAN. WBAN have become a practical technology for monitoring patients' health conditions in real-time. Nodes were positioned inside, on, or around the human body in WBANs in order to collect different

physiological data, including body temperature, heart rate, and blood pressure. Due to the dynamic nature of the body, however, data packet routing in WBANs encountered a number of difficulties, including limiting power, interference, and movement. In this research, a multiobjective routing protocol architecture was used to address these problems. This design was divided into two phases: clustering and optimal path selection. Using an optimised Fuzzy C-means clustering method, the suggested multiobjective routing protocol design in WBAN grouped nodes according to several criteria, including energy consumption, transmission delay, and network lifetime. A unique hybrid optimization model called HBWBF, which combines the Black Widow Optimization (BWO) and the Bacterial Foraging Optimization Algorithm, was used to calculate the membership function in fuzzy C-means clustering (BFOA). In addition, a hybrid deep learning strategy combining convolutional neural networks (CNNs) and recurrent neural networks was employed to find the best path between clusters (RNNs). MATLAB was used to implement the suggested model. To validate the efficiency of the proposed model, a comparative evaluation was performed.

Declaration statements

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Conflicts of interest/Competing interests -All authors have no conflict of interest to report.

Availability of data and material - The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Code Availability- Yes

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