A Hybrid Fuzzy-Genetic Algorithm for Performance Optimization of Cyber Physical Wireless Body Area Networks

Amit Choudhary[1] · M. Nizamuddin[1] · Vibhav Kumar Sachan[2]

Abstract The use of fuzzy decision-making in datapath selection extends the sensor network lifetime with a uniform distribution of routing load among network nodes. Fuzzy-logic based routing protocols are mostly designed for general wireless sensor networks (WSN). However, such protocols are not compatible with a Wireless Body Area Network (WBAN) comprised of biosensor nodes. WBAN nodes carry inferior computational, communication and energy resources as compared to general WSN nodes. A WBAN routing protocol needs to be designed as per IEEE 802.15.6 WBAN standards to meet high-end QoS requirements of medical applications. This paper presents a fuzzy-logic-based clustering protocol for data routing in WBANs. Nodes are grouped into clusters and cluster head nodes are selected through a Fuzzy-Genetic Algorithm termed as EB-f_g-MADM. EB-f_g-MADM makes an assessment of dual attributes of each cluster node in terms of node residual energy and CH selection cost. CH selection cost of a node is the forecasted value of network energy consumption if the node acts as a cluster head. EB-f_g-MADM utilizes a fuzzy-TOPSIS function which makes a quantitative comparison of cluster nodes and selects the cluster head node possessing the aforementioned attributes closest to their ideally desired values. A Genetic Algorithm-based optimization process adapts the attribute weights for cluster head selection. EB-f_g-MADM provides enhanced network lifetime with a uniform distribution of routing load. Protocol performance is obtained in terms of network lifetime, throughput and latency. Results are compared with existing WBAN routing protocols and are found to be better.

Keywords Wireless Body Area Network · Fuzzy-TOPSIS · Genetic algorithm · Routing protocol · Clustering · Network lifetime · Throughput

1 Introduction

A Wireless Body Area Network (WBAN) is a cyber-physical system which integrates the sensing and computational capabilities of distributed biosensor nodes with wireless networking for real-time monitoring and control of physiological parameters of the human body [1]. A WBAN system consists of multiple wireless bio-sensor nodes. Bio-sensor nodes are designed to measure diverse human body physiological parameters such as blood pressure (BP), heart rate, body temperature, blood oxygen saturation, respiration rate etc. Nodes are attached to related body parts for physiological data sensing. Sensed data is transmitted to a central sink node using on-body wireless communication links [2]. Sink node processes the node data and uploads it to an internet cloud network for remote examination by a medical professional. WBANs find their potential use in telemedicine, sports, and military sectors [3, 4]. Figure 1 shows a pictorial representation of a WBAN system.

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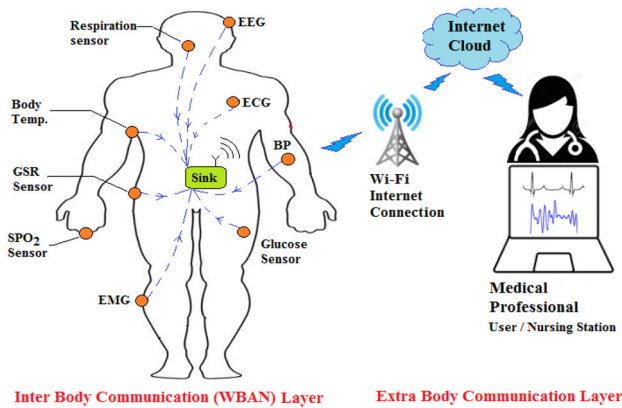
Fig. 1 WBAN system for telemedicine healthcare applications

As per IEEE 802.15.6 WBAN communication standards, a WBAN system needs to deliver high QoS performance to meet medical application norms. For example, successful data packet delivery rates (network throughput) should be more than 90%. An end to end delay (network latency) above 125 ms is unacceptable. WBAN communication links should deliver 1 Kbps to 10 Mbps data transmission rates. Maximum transmitted power from a WBAN node transceiver module is limited to − 10 dBm [5–11].

A wearable biosensor node needs to be compact for the better compatibility with the patient's body. The foremost constraint of a tiny biosensor node is its miniature power source [2, 5]. Sensor nodes consume a considerable amount of assigned node energy for transmitting data to other nodes [12]. The requirement of high QoS performance with the constraint of limited node power demands an energy-efficient data routing protocol for WBAN systems.

Figure 2 demonstrates three basic data routing schemes for WBAN: (i) single hop, (ii) Multihop and (iii) clustering-based data routing.

In a single hop transmission scheme, data loss rates remain high for distant boundary nodes (up to 80%) as low power signals get blocked by lossy transmission medium of the human body. Multihop routing protocols utilize
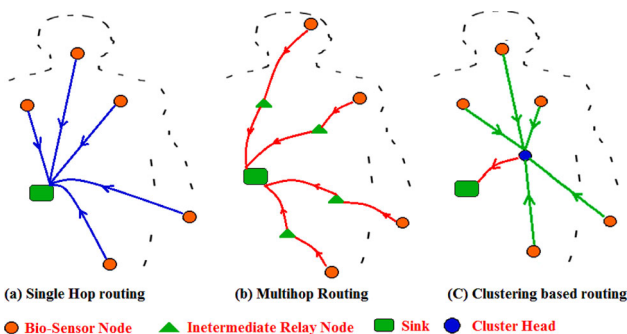

(a) Single Hop routing **(b) Multihop Routing** **(C) Clustering based routing**

● Bio-Sensor Node ▲ Intermediate Relay Node ■ Sink ● Cluster Head

Fig. 2 Different routing schemes for WBANs

intermediate nodes as relay nodes [13]. It helps in reducing packet loss rates of boundary nodes. At the same time, it results in larger network latency.

Clustering approach-based routing protocols are appropriate for WBAN systems. Based on a predefined grouping criterion, nodes are clubbed into different clusters. A suitable cluster member node is selected as a cluster head (CH node). Thus, the cluster member nodes are considered as candidates for the job of CH node. CH node collects data packets from the cluster node in a single hop manner, aggregates them into a single datum packet and transmits the datum to the sink node. Overall, two hop data transmission provides affordable data packet loss rates for boundary nodes with an acceptable end to end delay. Data aggregation compresses the transmitted data. It saves node transmission energy [14–17].

Due to additional responsibilities like data aggregation, CH node consumes more power as compared to child sensor nodes. Hence, the CH nodes are dynamically selected for every transmission round. Dynamic cluster head selection distributes the load of cluster head job among network nodes and equalizes the node energy consumption across the network. Equalized node energy consumption results in an enhanced network lifetime [18, 19].

Multi-Attribute Decision-Making (MADM) algorithms are widely used for dynamic cluster head selection [15, 17, 18]. MADM approach quantitatively compares the candidate cluster member nodes and ranks them for their appropriateness for cluster head selection. Node ranking is done on the basis of multiple node attributes such as node residual energy level, node distance from the sink etc. Node possessing the most desired attribute values gets selected as cluster head [20]. Section 2 discusses various MADM approaches.

Conventional MADM approaches require precise values of node attributes. Precise evaluation of each node attribute value is a tedious task in a real-time environment [18].

Fuzzy logic-based MADM techniques perform efficiently in case of insufficient, missing or vague attribute information [21]. Fuzzy MADM approach transforms the node attribute values into fuzzy linguistic grades such as *low*, *medium* or *high*. Fuzzy mapping rules are used to provide node rankings on the basis of desirability criteria of fuzzy attribute grades [22]. Fuzzy-MADM approaches offer a substantial increase in network lifetime with consistent distribution of routing load among network nodes as compared to conventional MADM techniques [23].

Existing fuzzy logic-based routing protocols are mostly designed for general wireless sensor networks [18, 24, 25]. However, such protocols cannot efficiently be applied to WBANs.

WBANs are different from common WSNs in terms of network architecture and node count. WBAN nodes possess inferior computation power, memory and energy as compared to a general WSN node [13].

Hence, a WBAN routing protocol should be designed using fuzzy logic and needs to be optimized for IEEE 802.15.6 WBAN communication standards to meet high-QoS requirements of medical applications [6].

Present research work proposes a Fuzzy Genetic Algorithm (FGA)-based clustering protocol for data routing in WBAN systems.

The Proposed protocol incorporates a hybrid Fuzzy-Genetic MADM algorithm for dynamic cluster head selection. It is called as "*Energy Budget-based Fuzzy-Genetic Multiple Attributes Decision-Making Algorithm (EB-f_g-MADM)*".

To select an appropriate cluster head node, EB-f_g-MADM assesses two attributes of every candidate cluster member node- (i) "*CH selection cost*" of the node & (ii) "*Current residual energy level*" of the node.

The first attribute, *CH selection cost* of a particular node is calculated by assuming the node as next cluster head and forecasting the value of network energy loss if it is used for executing the clustering-based data routing operation as cluster head. EB-f_g-MADM estimates the *CH selection cost* values of each candidate cluster member node using the first-order radio model for node transmission energy consumption [19]. Here, it is to be noted that the model-based estimations generally result into approximates values [18].

For an optimum cluster head node, its *CH selection cost* needs to be minimized while the value of *Residual energy* attribute is desired to be maximized.

After having an assessment of node attribute values, EB-f_g-MADM decides the relative importance of two node attributes for cluster head selection. A genetic algorithm (GA)-based iterative global search optimization process is used to decide the weights of two node attributes for each round of cluster head selection.

EB-f_g-MADM applies the node attribute values and attribute weights to a fuzzy logic-based TOPSIS function for cluster head selection. TOPSIS is an abbreviation for the Technique for Order Preference by Similarity to Ideal Solution.

Besides the advantage of fuzzy logic to adequately deal with the vagueness of selection process, fuzzy-TOPSIS provides a consistent assignment of node ratings through simple & rational mathematical operations [26, 27].

Fuzzy-TOPSIS function transforms the numerical node attribute values to fuzzy linguistic grades such as *Very low*, *Low*, *Medium*, *High* or *Very high*. Weighted fuzzy grades create a fuzzy Multi-Criteria Decision Matrix (MCDM). Fuzzy Positive and Negative ideal solutions (FPIS & FNIS) are identified involving the set of best and worst performance attribute values, respectively. Candidate node possessing attributes closest to positive ideal solution and farthest from negative ideal solution is selected as the optimum cluster head node.

EB-f_g-MADM distributes cluster head job among WBAN nodes in a uniform manner. It leads to elongated network lifetime.

Proposed protocol utilizes a Loss-less data compression-based intra-network data transmission scheme. Utilized transmission scheme removes redundant data from the transmission and saves node transmission energy.

Proposed protocol is simulated and the performance results are obtained in terms of network lifetime, packet success rate and end to end network latency. Results are compared with existing WBAN routing protocols and are found to be better. This protocol fulfills the technical requirements of an energy-efficient and high-QoS WBAN system.

The given paper is organized as follows: Section 2 presents a brief literature review of existing routing protocols along with research motivation and our contribution. Section 3 defines the various system model and assumptions. Section 4 describes the proposed protocol and the results are given in Sect. 5. Section 6 concludes the paper along with the future scope.

2 Literature Survey and Motivation

This section presents an introduction to different MADM techniques followed by a brief survey of related works from the literature. Section ends by highlighting the motivation, contribution and research impact of the present work.

2.1 MADM Approaches for Cluster Head Selection

A cluster head selection process completes in three steps: Alternative qualification, attribute formulation and node ranking for final selection. The first step determines the alternatives. Cluster nodes possessing the residual energy above a predefined threshold usually qualify as alternatives. The next step devises the required node attributes for the consideration in selection process. The consideration of suitable node attributes helps in achieving the desired objectives of selection process like energy-efficient data routing, improved network throughput and latency etc. The final step utilizes a Multi-Attribute Decision Making (MADM) algorithm for the final selection of optimum cluster head node [23, 26].

A MADM algorithm processes the attributes of candidate cluster member nodes and rates them for their suitability for being the cluster head. Node possessing the set

of most desired attribute values is selected as cluster head [20].

A decision matrix forms the foundation for an MADM approach-based cluster head selection process [20]. It is composed of alternatives as S_i; $i = 1, 2… N$, node attributes as A_j; $j = 1, 2… M$, attribute weights as W_j; $j = 1, 2… M$, and attribute values as m_{ij}; $i = 1, 2… N$, $j = 1, 2… M$. Table 1 shows a multi-attribute decision matrix.

The classical MADM approach like Simple Additive Weighting (SAW) assigns the node ratings in form of composite performance scores (Cost function) [28]. Composite performance score C_i of a particular candidate cluster member node-i is computed as follows:

$$C_i = \sum_{j=1}^{M} W_j * (m_{ij})_{\text{Normalized}}. \tag{1}$$

Here $(m_{ij})_{\text{Normalized}}$ denotes the normalized value of attribute-A_j of node-i. If A_j is a beneficial attribute that is desired to be high, then it is normalized as $m_{ij}/\max (A_j)$ where $\max (A_j)$ is the maximum of the set of the values of attribute-A_j of all alternatives. Normalization of a non-beneficial attribute is done as $\max (A_j)/m_{ij}$. Node obtaining the highest performance score is selected as cluster head.

WPM [29] and PDW [15, 17] methods assign composite performance scores according to Eqs. 2 and 3, respectively. Node obtaining the highest score becomes the cluster head.

$$C_i = \prod_{j=1}^{M} \{(m_{ij})_{\text{Normalized}}\}^{W_j} \tag{2}$$

$$C_i = \frac{\text{Product of beneficial attributes of node}-i}{\text{Product of non-beneficial attributes of node-}i} \tag{3}$$

Performance score-based MADM approaches provide the ease of computation. But such techniques show inconsistency in node ratings and the selected cluster heads do not always posses the attributes closest to their ideally desired values [27].

The classical TOPSIS approach identifies the cluster head node possessing the attributes closest to ideally desired values and farthest from ideally undesired values. TOPSIS multiplies the decision matrix to the attribute

weight matrix and creates the weighted multi-criteria decision matrix. Positive and Negative ideal solutions (PIS & NIS) are identified involving the set of best and worst performance attribute values, respectively. Candidate node possessing attributes closest to PIS and farthest from NIS is selected as the optimum cluster head node [26, 27, 30].

The TOPSIS fulfills the characteristics of an effective and efficient MADM approach. Following are the advantages of TOPSIS approach.

i. TOPSIS provides the flexibility to consider unlimited numbers of alternatives and attributes.
ii. Number of steps remains same regardless of the number alternatives and attributes.
iii. TOPSIS provides a consistent assignment of node ratings through simple & rational mathematical operations.
iv. TOPSIS offers a reliable & fast decision making.

The TOPSIS and other classical MADM need precise values of node attributes. Precise evaluation of attribute values is a tedious task in a real-time environment [18].

The fuzzy logic based MADM approaches adequately deals with the estimated or vague attribute information [23, 31, 32]. They transform the node attribute values into linguistic fuzzy grades like very low, low, medium, high or very high. The alternatives are qualitatively compared and ranked for the selection on the basis of the desirability criteria of fuzzy attribute grades. The node possessing the fuzzy attributes closest to ideally desired grades gets the CH job.

The literature reports several fuzzy-MADM approaches like Mamdani Fuzzy Controllers [23], Fuzzy Inference Relation [24], Fuzzy TOPSIS [26] and Fuzzy-AHP [32] etc.

Fuzzy-TOPSIS approach offers the advantages of classical TOPSIS technique along with its ability to deal with the vagueness of cluster head selection process [18, 26]. Fuzzy-TOPSIS MADM approach proceeds in following steps.

i. Transform the normalized node attribute values m_{ij}; $i = 1, 2… N$, $j = 1, 2… M$ and attribute weights as W_j; $j = 1, 2… M$ into fuzzy linguistic grades $\tilde{m}_{ij}$ and $\tilde{W}_j$ such as *Very low*, *Low*, *Medium*, *High* and *Very high*. As depicted by Table 6, a fuzzy linguistic grade is characterized by an associated triplet fuzzy number (TFN).
ii. Create a fuzzy decision matrix ($\tilde{D}$) and fuzzy weight matrix ($\tilde{W}$). Fuzzy decision matrix includes the fuzzy attribute grades ($\tilde{m}_{ij}$; $i = 1, 2… N$, $j = 1, 2… M$). Fuzzy weight matrix includes fuzzy weights ($\tilde{W}_j$; $j = 1, 2… M$) Eq. 4 and 5 show $\tilde{D}$ and $\tilde{W}$ matrices

Table 1 Decision matrix

Alternatives (cluster nodes)	Attributes			
	$A_1 (W_1)$	$A_2 (W_2)$	..	$A_M (W_M)$
S_1	m_{11}	m_{12}	..	m_{1M}
S_2	m_{21}	m_{22}	..	m_{2M}
:	:	:	:	:
S_N	m_{N1}	m_{N2}	..	m_{NM}

respectively.

$$\tilde{D} = \begin{bmatrix} \tilde{m}_{11} & \dots & \tilde{m}_{1M} \\ \vdots & \ddots & \vdots \\ \tilde{m}_{N1} & \dots & \tilde{m}_{NM} \end{bmatrix}_{N \times M} \tag{4}$$

$$\tilde{W} = \begin{bmatrix} \tilde{W}_1 & \tilde{W}_2 & \dots & \tilde{W}_M \end{bmatrix} \tag{5}$$

iii. Obtain the weighted fuzzy decision matrix ($\tilde{V}$) by multiplying the fuzzy decision matrix ($\tilde{D}$) by the fuzzy weight matrix ($\tilde{W}$). Equation 6 shows the $\tilde{V}$ matrix.

$$\tilde{V} = \begin{bmatrix} \tilde{m}_{11} * \tilde{W}_1 & \dots & \tilde{m}_{1M} * \tilde{W}_M \\ & \vdots & \ddots & \vdots \\ \tilde{m}_{N1} * \tilde{W}_1 & \dots & \tilde{m}_{NM} * \tilde{W}_M \end{bmatrix} = [\tilde{v}_{ij}]_{N \times M} \tag{6}$$

iv. Obtain fuzzy positive and negative ideal solutions (FPIS & FNIS), according to Eqs. 7 and 8 respectively. Where $\tilde{v}_j^+$ and $\tilde{v}_j^-$ are the best and worst performance attribute values of jth attribute, respectively.

$$\text{FPIS} = [\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_M^+] \tag{7}$$

$$\text{FNIS} = [\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_M^-] \tag{8}$$

v. Compute the separation indexes, $dist(i)^+$ and $dist(i)^-$ for each candidate cluster member node from $\tilde{v}_j^+$ and $\tilde{v}_j^-$ respectively. They are computed as follows.

$$\text{dist}(i)^+ = \sum_{j=1}^{M} D_f(\tilde{v}_{ij}, \tilde{v}_j^+) \tag{9}$$

$$\text{dist}(i)^- = \sum_{j=1}^{M} D_f(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{10}$$

Note: The term $D_f(\tilde{x}, \tilde{y})$ represents the Euclidean distance in between two triangular fuzzy numbers $\tilde{x}$ and $\tilde{y}$.

vi. Compute the TOPSIS ranks SC_i $i = 1, 2\dots N$ of each candidate cluster member node, according to the Eq. 11.

$$SC_i = \frac{\text{dist}(i)^-}{\text{dist}(i)^- + \text{dist}(i)^+} \tag{11}$$

vii. Select the candidate node obtaining the highest TOPSIS rank as the cluster head node. It possesses the attributes closest to FPIS and farthest from FNIS.

2.2 Related Works

This sub-section presents a review of existing multihop and clustering-based routing protocols. The reviewed protocols are classified into following categories on the basis of their MADM approach for route selection.

i. Classical MADM approaches
ii. Fuzzy MADM approaches
iii. Bio-inspired MADM approaches

Following is the category wise review of existing protocols.

i. Classical MADM approaches

Kaur et al. proposed a multihop data routing protocol for WBAN applications termed as Optimized Cost Effective and Energy-Efficient Routing (OCER) [13]. Protocol assigns a cost function value to each intermediate node which is a function of node residual energy, link reliability and link path loss. Node obtaining the minimum cost function value is selected as the forwarder node. Load distribution is fairly uniform across the high throughput network.

Nadeem et al. proposed iM-SIMPLE protocol for multihop data routing in WBANs [33]. Composite performance score based MADM technique is used for route selection in between source nodes and sink node. Each intermediate node gets a cost function value which is equal to the ratio of node residual energy to its proximity to sink. Highest cost function value node gets selected as the forwarder. The consideration of node energy and proximity to sink attributes in route selection leads to uniform load distribution and high network throughput. Protocol takes account of different body postures and body movements in route selection.

The LAEEBA protocol from Ahmed et al. computes the node cost function values as the ratio of the square root of node residual energy to its distance from sink [34].

Ahmed et al. proposed CO-LAEEBA protocol which is a modified version of LAEEBA protocol [35]. CO-LAEEBA utilizes cooperative routing. Single hop routing paths are used for emergency data. While the multihop paths are used for normal data. The desired criteria for path selection include minimum hop count and the highest

energy intermediate forwarder nodes. CO-LAEEBA shows improved energy efficiency and network throughput.

Javaid et al. presented M-ATTEMPT, a multihop routing scheme for WBAN [36]. Minimum hop routing paths are elected and dynamically changed whenever the temperature of intermediate forwarder nodes rises beyond the threshold level. Node residual energies are not considered for path selection. It results in non-uniform load distribution.

Javaid et al. proposed a relay-based routing strategy for the WBANs incorporating in-body sensors [37]. The minimum required transmission range is used for in-body sensors. Relay nodes are placed on the body. Relay selection criteria is the minimum distance from the transmitting in-body sensor. Proposed scheme minimizes the energy consumption of in-body sensors with an acceptable end to end delay.

The Tripe-EEC protocol of Ullah et al. adapts its multihop route selection criteria based on the type of the data [38]. A data path for normal data includes the minimum number of relay nodes with minimum rise in temperature. Critical or on-demand data is routed through priority-based minimum delay paths.

In the case of hotspot discovery, multihop routing protocols change the current path to a usually longer new routing path [36]. It results in a larger end to end delay. Clustering-based routing protocols offer the benefits of both single hop and multihop type of communication [15].

Ali et al. proposed the EERP Protocol for the clustering based data routing in WBANs. It uses product and division weighting (PDW) method for dynamic CH node selection [15]. A cost function is assigned to each candidate cluster member node as a ratio of node residual energy to its distance from the sink. Node obtaining the maximum cost function value gets selected as the cluster head.

Similarly, the SIMPLE protocol from Nadeem et al. selects the CH node having the highest residual energy and closest proximity to sink [16]. Cluster head distribution is fairly uniform across the network.

The DSCB protocol from Zahid et al. uses a dual sink approach for clustering-based routing in WBANs [17]. Protocol calculates a cost function for each node. Cost function of a particular node is equal to the ratio of node residual energy to the product of sink distance and the minimum node transmission power. The node possessing the highest cost function value becomes the CH. Dual sink approach handles the single sink failure condition. However, dual sink increases the cost overhead.

Fouad et al. proposed an adaptive multihop routing protocol (AMRP) for wireless sensor networks with multiple constraints [39]. Analytic Hierarchy Process (AHP) is used to adapt the node weights and the classical TOPSIS approach is used for forwarder node selection. The desired criteria for relay selection include minimum hop count, maximum node centrality and bridging centrality. *TOPSIS* provides the flexibility to consider unlimited numbers of alternatives and attributes.

ii. Fuzzy logic based MADM approaches

The fuzzy logic based MADM approaches transform the attribute values into fuzzy linguistic grades and adequately deals with the vagueness of cluster head selection process [21].

For example, Lee et al. proposed LEACH-ERE protocol which uses a Fuzzy Inference Relation-based cluster head selection mechanism [24]. The protocol makes an assessment of two node attributes (node residual energy and expected node residual energy) of each candidate node. Expected node residual energy is the remaining energy of the node if it acts as the cluster head. Attribute values are transformed to fuzzy linguistic grades as *High*, *Medium* and *Low*. Fuzzy mapping rule sets the highest CH selection priority for node possessing the both attributes as "*High*". LEACH-ERE provides consistent distribution of routing load among network nodes and achieves elongated network lifetime. LEACH-ERE is designed for general WSNs only.

Ayati et al. proposed SCHFTL protocol which utilizes three levels of Mamdani fuzzy inference based MADM approach [23]. The first level MADM performs alternative qualification. The second level MADM selects the cluster heads. The third level MADM selects a super cluster head of cluster heads. The provision of super cluster head reduces the packet loss rate. Thus, the packet retransmissions are less required and result is the elongated lifetime. SCHFTL is designed for general WSNs.

Pawan et al. proposed the FBECS protocol for clustering-based data routing in general WSNs [25]. A fuzzy inference system considers the node residual energy, node distance to sink and neighbor node density attributes of each alternative. Fuzzy mapping rules set the highest CH selection priority for node possessing the three attributes residual energy as *High*, distance *as Far* and neighbour density as *Dense*. FBECS provides improved node lifetime with a balanced load distribution.

Balaji et al. demonstrated the use of fuzzy inference control using type-1 fuzzy sets for CH selection [22]. Selection criteria included high trust factor and minimum distance to sink. Proposed technique achieves lifetime maximization and network overhead reduction.

Sonam et al. proposed a fuzzy logic-based hybrid WSN routing protocol (FHRP) for precision agriculture application [31]. Critical nodes directly transmit their data to sink. Normal nodes report through a cluster-based data routing network. A fuzzy inference MADM approach is used for CH node selection. Node transmissions occur only when the data exceeds a predefined threshold. The reduced

number of data transmissions leads to an elongated network lifetime.

The FEEC-IIR protocol from Preeth et al. performs the cluster head selection using a hybrid fuzzy-AHP and TOPSIS MADM approach [32]. The considered attributes are node energy, QoS impact and node location. Protocol achieves an improved QoS performance along with an extended network lifetime.

A Fuzzy-TOPSIS approach is used for cluster head selection by Puneet et al. [18]. Selection criteria include node residual energy, number of immediate neighbors, and the sink distance.

Fuzzy-TOPSIS approach provides the flexibility to consider unlimited numbers of alternatives and attributes. Bilal et al. considered five node attributes (node energy, node energy expenditure rate, neighbor density, average distance from neighbor nodes, and sink distance) for the fuzzy-TOPSIS-based CH node selection [40].

iii. Bio-inspired MADM approaches

Recently published works show the use of Genetic Algorithm (GA), Particle Swarm Optimization (PSO) & Ant Colony Optimization (ACO)-based routing mechanisms.

For example, Elhoseny et al. proposed GAHN protocol which uses a GA-based clustering method for heterogeneous WSNs [41].Chromosomes of the initial population are the random sets of nodes (0 for Child and 1 for CH). In the iterative steps of fitness evaluation, selection, crossover, & mutation, GA applies the minor changes to the population and minimizes the objective function of total communication distance. Over successive iterations, the population evolves towards optimized cluster formation. GAHN achieves a significant increase in network lifetime.

Lin et al. proposed particle swarm optimization-based relay selection (PSO-LSMR) for low-SAR multihop routing for WBAN [8]. Selection criteria include relay SAR value and relay transmission power. PSO performs the particle initialization (possible relay position) and the iterations of particle fitness evaluation, local & global best updates and particle position & velocity updates. After certain number of iterations, PSO finds the optimum relay node with the minimized objective function of relay SAR and transmission power. The major drawback with a static relay node is that it consumes its limited power soon due to heavy relaying load.

Xie et al. proposed CRT2FLACO protocol which utilized Ant colony optimization in conjunction with type-2 Mamdani fuzzy inference-based MADM approach for CH node selection [42]. Selection criteria include node energy, neighbor node density and sink distance. Protocol uniformly balances the load and enhances the network lifetime.

Fuzzy-MADM and bio-inspired approaches offer a uniform load distribution and a substantial increase in network lifetime as compared to classical approaches. Table 2 shows the details of the surveyed protocols.

2.3 Motivation and Contribution

The proposed EB-f_g-MADM algorithm performs model-based estimation of node *CH selection cost* attribute value. Model-based estimation generally result in approximate values [18].

The fuzzy logic-based MADM approaches perform efficiently in case of estimated or imprecise attribute information [26]. Moreover, the fuzzy-MADM-based cluster head selection mechanisms offer a uniform distribution of cluster head load among network nodes resulting in a substantial increase in network lifetime as compared to conventional MADM approaches [23].

Existing fuzzy-based routing protocols are mostly designed for general wireless sensor networks [18, 24, 25]. However, such protocols cannot efficiently be applied to WBANs. WBANs are unlike to common WSNs in terms of network-architecture and node count. WBAN nodes possess inferior computation power, memory and energy as compared to a general WSN node [6, 13].

Hence, a WBAN routing protocol should be designed using fuzzy logic and needs to be optimized for IEEE 802.15.6 WBAN communication standards to meet high-QoS requirements of medical applications.

In the present work, we propose a new hybrid Fuzzy-Genetic Algorithm (EB-f_g-MADM)-based clustering protocol for data routing in WBANs.

Following are the contributions of the present research work.

a. Fuzzy-TOPSIS approach based dynamic cluster head selection.
b. Optimization of node attributes weights through an iterative process of Genetic Algorithm (GA).
c. Utilization of a Loss-less data compression technique for redundancy removal.

Fuzzy-TOPSIS approach is suitable for WBAN applications. It provides a consistent assignment of node ratings through simple & rational mathematical operations [27].

The proposed protocol meets the technical requirements of an energy-efficient and high-QoS WBAN system. An efficient and wearable WBAN system constantly monitors the patient's health status, while he or she may remain at home [3]. This is a great help for elderly patients because frequent visits to a doctor's clinic or hospital can be painful for them.

Table 2 Details of different protocols

CH selection criteria	Composite performance score based MADM				TOPSIS	Fuzzy logic based MADM						Bioinspired
Protocol name	iMSIMPLE [33]	OCER [13]	EERP [15]	DSCB [17]	AMRP [39]	FBECS [25]	LEACH-ERE [24]	Fuzzy-TOPSIS [18]	FEECIIR [32]	SCHFT L [23]	FHRP [31]	GAHN [41]
Node Residual Energy	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
Node Distance to sink			✓	✓		✓		✓	✓	✓	✓	
Hop count in between node and sink	✓				✓							
Link reliability		✓								✓		
Path loss in between node and sink		✓										
Node transmission power				✓								
Neighbor node density						✓		✓			✓	
Expected node residual energy							✓					
Centrality					✓					✓		
QoS impact									✓			
DoS attacks and total delay										✓		

3 WBAN System Model

For the proposed research work, the WBAN system consists of eight bio-sensor nodes and a single sink. Figure 3 shows the target WBAN system. Table 3 contains details of bio-sensor nodes.

3.1 Heterogeneous WBAN Topology

Target WBAN adopts heterogeneous network topology. Source bio-sensor nodes have limited energy resource. Sink node is designed to have more power supply and processing potential as compared to source nodes. Sink performs energy-consuming tasks and coordinates cluster head selection process.

Sensor nodes S_4 and S_5 (heart rate and body temperature) perform data sampling at low-sampling rates (< 50 Hz). These sensor nodes are allowed to transmit their data packets directly to the sink using a single-hop LOS communication channel.

Nodes S_1, S_2, S_3, S_6, S_7, and S_8 perform at higher sampling rates. They are designed to work in a cluster and send their data packets to the selected cluster head. Figure 4 shows the target WBAN topology.

Biological sensor nodes require 10 to 72 Kbps bit rates for output data transfer [10]. Bluetooth wireless RF communication module is suitable for target WBAN sensor nodes as it provides data transfer rate up to 1 Mbps.

3.2 Energy Model

Proposed work adopts first-order radio model for the estimation of node energy expended by a node in data transmission [19, 35].
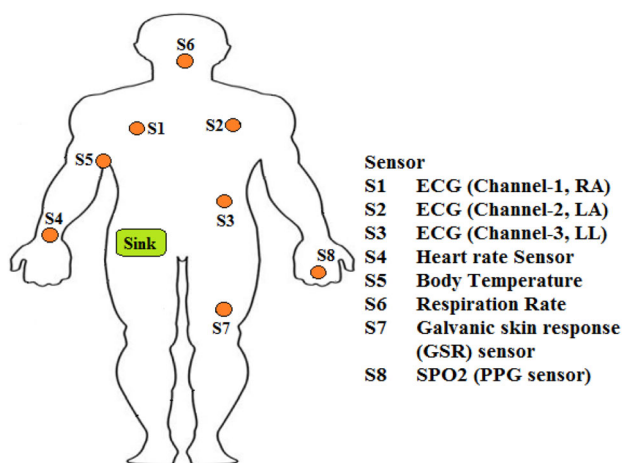

Fig. 3 Biosensor positions on the patient body

According to first-order radio model, node transmission energy consumption for relaying a data packet (W number of bits) to a distance 'D' can be estimated as follows:

$$E_{\text{Tx}}(W, D) = E_{\text{TX-elect}} \times W + E_{\text{Amp}} \times \eta \times D^\eta \times W \quad (12)$$

The same model also accounts for node energy consumption in receiving a data packet of 'W' bits as follows:

$$E_{\text{RX}}(W) = E_{\text{RX-elect}} \times W \quad (13)$$

Using the same model, node energy consumed in aggregating 'W' number of bits can be accounted as follows:

$$E_{\text{DA}}(W) = E_{\text{DA}} \times W. \quad (14)$$

Here, $E_{\text{Tx-elect}}$, $E_{\text{Rx-elect}}$, and E_{Amp} denote per bit node energy consumption in running node transmitter, receiver, and amplifier circuits, respectively. E_{DA} denotes per bit data aggregation energy consumption. The path loss index η is used to represent additional path loss presented on body communication channels.

In the proposed technique, node processing energy losses are ignored as they are negligible as compared to data transmission [12].

3.3 Propagation Path Loss Model

Present work assumes Line of Sight (LoS) on-body wireless transmission channels along with 2.4 GHz frequency of operation in ISM narrow band range. As per IEEE 802.15.6 standards, Industrial, Scientific and Medical (ISM) open-frequency band is quite useful for WBAN system. It supports higher data rates at lower transmission power. Furthermore, it offers reasonably stable channel gain, less body attenuation and insignificant ISI [8]. Simulation of the proposed technique has been carried out using an on-body communication path loss model as follows [13]:

$$\text{PL}(D, F) \text{ in dB} = 10 \cdot \log(4\pi D_o f / c) + 10\eta \log\left(\frac{D}{D_o}\right) + \chi_\sigma. \quad (15)$$

Here, PL, F and D denote for propagation path loss (dB), channel frequency (MHz) and the node distance (m), respectively. Reference distance is denoted by D_o. Additionally, the Gaussian random parameter χ_σ carries zero mean and σ standard deviation. It accounts for the shadowing factor in dB. Table 4 summarizes different notations used in the current paper.

Table 3 Biological sensor details

| Node no.	Health parameter	Sampling rate [11] (Hz)	Output data rate [5, 7, 10] (Kbps)	Range
S1	ECG (RA)	1024	72	P and T wave (0.5–10 Hz)
S2	ECG (LA)			QRS complex (4–20 Hz)
S3	ECG (LL)			
S4	Heart rate	50	10	60–80 BPM
S5	Body Temp.	50	10	97–100.4 °F
S6	Respiration rate	512	10	12–20 BPM
S7	Blood oxygen saturation sensor	128	32	95–100%
S8	GSR Galvanic skin response sensor	128	10	Skin conductance—2–20 μS (according to stress level)
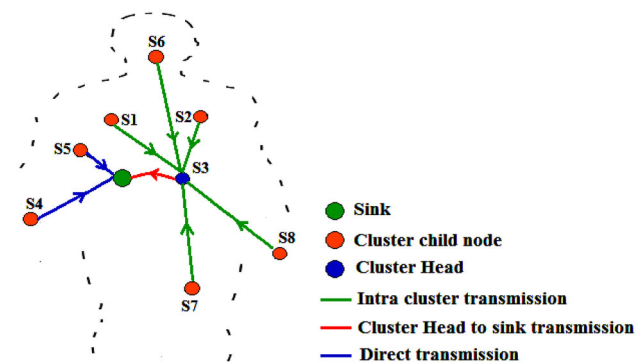
Fig. 4 Target WBAN topology

3.4 Inherent Redundancy in Sensed Data

A general WBAN encounters the problem of unnecessary node transmission power consumption due to redundant data. Table 5 shows various physiological data samples extracted from previous research. These data samples are experimentally measured using different biological sensors in a real-time WBAN environment [5, 11]. It is evident from green data fields, that the biosensors may measure correlated similar values of physiological parameters in consecutive data sensing cycles.

A node can save a considerable amount of energy if it does not send consecutively sensed correlated packets to sink. The sink can reuse such data packets from its own memory.

Proposed protocol utilizes a loss-less data compression based intra-network data transmission scheme. This scheme removes consecutively sensed redundant data from the node transmission and saves node energy.

4 Proposed WBAN Routing Protocol

For each transmission round, proposed algorithm performs the following operations.

Table 4 Notations

Notation	Meaning	Notation	Meaning
MADM	Multi-attribute decision making	D_o	Reference distance
CH	Cluster HEAD	χ_σ	Gaussian variable
GA	Genetic Algorithm	σ	Standard deviation
TOPSIS	Technique for order preference by similarity to ideal solution	P_{rsens}	Receiver sensitivity
FPIS/FNIS	Fuzzy positive/negative ideal solution	P_{tk}	Min. required transmission power
$E_{Tx\text{-}elect}$	Transmitter per bit energy consumption	$P_{rec.}/P_{trans}$	Tx/Rx signal power
E_{Amp}	Amplifier per bit energy consumption	E_L/E_R	Node attributes
$R_{x\text{-}elect}$	Receiver per bit energy consumption	E_{Rn}/E_{Ln}	Normalized node attributes
E_{DA}	Per bit aggregation energy	E_{Rf}/E_{Lf}	Fuzzy node attributes
η	Path loss index	E_{Rw}/E_{Lw}	Weighted fuzzy attributes
D	Node distance	W_L/W_R	Node attribute weights
PL	Path loss	SC	TOPSIS rank
F	Channel frequency	CW	Composite weight

Table 5 Biological parameter data samples

Sample No.	Sensor Type					
	ECG CH-1 (S1)	ECG CH-2 (S2)	ECG CH-3 (S3)	Heart Rate (S4)	Body Temp (S5)	GSR (S8)
	mV	mV	mV	BPM	ºF	kΩ
1	-0.065	-0.564	-1.499	69	96.2	1257.46
2	-0.065	-0.563	-1.502	70	96.6	1257.46
3	-0.064	-0.557	-1.491	73	96.8	1258.18
4	-0.065	-0.563	-1.499	79	96.9	1257.46
5	-0.066	-0.565	-1.492	72	97.0	1258.18
6	-0.068	-0.563	-1.492	74	97.0	1257.46
7	-0.069	-0.552	-1.492	81	97.0	1258.18
8	-0.074	-0.556	-1.492	63	97.1	1258.17
⋮	⋮	⋮	⋮	⋮	⋮	⋮
100	-0.067	-0.534	-1.467	83	98.3	1259.62

4.1 Localization

At the starting of each transmission phase, each bio-sensor node measures its proximity to sink and other nodes. Distance data is estimated using the RSSI-based localization method.

Each node including sink transmits a "*HELLO*" packet with transmitting node ID. Each "*HELLO*" message carries the same transmitted power P_{trans}.

Assuming that node-i receives "*HELLO*" packet of node-j with $P_{\text{rec}}.(i, j)$ as received power. The propagation path loss in the received signal can be calculated as follows:

$$\text{PL(dB)} = P_{\text{trans.}}(\text{dBm}) - P_{\text{rec}}(i, j)(\text{dBm}) \qquad (16)$$

The distance between node-i and node-j, represented by $D(i, j)$; $i, j \,\forall\, i, j \in U$, can be computed by putting the value of estimated path loss in Eq. 15. Here, U represents the set of network nodes including sink.

In this manner, each node estimates its distance from sink as well as other nodes and saves the estimated distance values to its local onboard memory.

4.2 Cluster Head Selection

Nodes S_1, S_2, S_3, S_6, S_7, and S_8 create a cluster. A suitable cluster node becomes the cluster head (CH). Cluster member nodes possessing the residual energy more than a predefined energy threshold ($E_R > E_{\text{thr}}$) are considered as the candidate nodes for CH selection.

A novel EB-f_g-MADM algorithm is proposed to perform dynamic CH node selection. To select an appropriate CH node, EB-f_g-MADM assesses following attributes of each candidate cluster member node:

i. *CH selection cost* of the node, $E_L(i)$; $\forall\, i \in N$.
ii. *Residual energy level* of the node, $E_R(i)$; $\forall\, i \in N$.

Here, N denotes the set of candidate cluster member nodes.

The proposed algorithm works in the following steps.

Step-1: Estimation of CH selection cost of each node

Each candidate cluster member node estimates its *CH selection cost* attribute value.

For *CH selection cost* estimation, a candidate cluster node assumes itself as the cluster head. Then, it makes a model-based prediction of network energy loss if it carries out the data routing operation as a cluster head. This predicted value of network energy loss is the *CH selection cost* of the node. Node *CH selection cost* attribute values are calculated as follows:

i. Node-i; $\forall\, i \in N$ visualizes itself as the next CH node.
ii. Using First-order radio model, node-i forecasts the energy losses of other cluster nodes in sending their data packet to node-i. Denoting these losses as $E_{\text{Loss\_Child}}$, Eq. 17 models $E_{\text{Loss\_Child}}$.

$$E_{\text{Loss\_Child}}(i) = \sum_{\forall j \in N: j \neq i} \left[E_{\text{Tx-elec}}\, E_{\text{Rx-elec}}\, E_{\text{DA}}\, E_{\text{Amp}} \right]$$
$$\times \begin{bmatrix} 1 \\ 0 \\ 0 \\ \eta D(i,j)^{\eta} \end{bmatrix} \times W; \quad \forall i \in N$$
$$(17)$$

iii. Now node-i forecasts its own energy loss in performing the tasks of CH node like reception of data packets from child nodes, data aggregation and transmission of aggregated datum to sink. Denoting such loss as $E_{\text{Loss\_CH}}$, Eq. 18 models $E_{\text{Loss\_CH}}$.

$$E_{\text{Loss\_CH}}(i) = \left[E_{\text{Tx-elec}}\, E_{\text{Rx-elec}}\, E_{\text{DA}}\, E_{\text{Amp}} \right]$$
$$\times \begin{bmatrix} 1 \\ (N-1) \\ 1 \\ \eta D(i, \text{Sink})^{\eta} \end{bmatrix} \times W; \quad \forall i \in N$$
$$(18)$$

Here, $D(i, j)$ represents the distance between node-i and node-j. Other abbreviations are the same as used in the first-order radio model of Eqs. 12 to 14.

iv. CH selection cost for node-i is denoted by $E_L(i)$, which is given by Eq. 19.

$$E_{\mathrm{L}}(i) = E_{\mathrm{Loss\_Child}}(i) + E_{\mathrm{Loss\_CH}}(i) \quad (19)$$
$$; \forall i \in N$$

Step 2: Energy packet transmissions to sink node

Cluster member nodes send an "*ENERGY*" packet to sink. "*ENERGY*" Packet contains the current level of node residual energy E_{R}, node *CH selection cost* value E_{L} and the node ID.

Thus, sink gets the node attribute values ($E_{\mathrm{R}}(i)$ and $E_{\mathrm{L}}(i) \; \forall \; i \in N$) from each candidate cluster member node. Now sink determines the relative importance of node attributes for cluster head selection.

Step 3: Genetic Algorithm (GA) based weight optimization

In this step, the sink decides the relative importance of three node attributes for cluster head selection by assigning certain weights to them such as W_{L} for E_{L} attribute and W_{CH} for E_{R} attribute. More the weight of a node attribute, higher is the importance given to that attribute for cluster head selection.

In a conventional MADM approach, node attribute weights are decided on the basis of certain experiments and past experiences of the target optimization problem. In the present work, the sink uses an iterative optimization process of Genetic Algorithm (GA) for determining the node attribute weights.

Genetic Algorithm optimizes the two node attribute weights in such a manner so that the selected cluster head needs minimum transmission power for communicating its data to sink. The Genetic Algorithm functions as follows:

i. Initialization

Initially, a certain number δ of random solutions are assigned to two weight variables W_{L} & W_{R}. This set of initial random solutions create an initial population $W_{\mathrm{L}i}$ & $W_{\mathrm{R}i}$; $i = 1, 2\ldots\delta$. A solution in the population is termed as a chromosome. For example, $W_{\mathrm{L}i}$ & $W_{\mathrm{R}i}$ represent the chromosome-i. Individual weight values of a chromosome are called genes. The constraint for initialization is that the summation of $W_{\mathrm{L}i}$ and $W_{\mathrm{R}i}$ equals unity. Figure 5 shows the initial population of Genetic Algorithm.

After initialization, GA works with iterative steps. Each iteration carries out following function-*fitness evaluations* for each chromosome of the current population, *selection* of parent chromosomes for crossover, *crossover* of parent chromosomes to generate new chromosomes (offspring) and *mutation* of genes of new chromosomes.

ii. Fitness evaluation

For each chromosome value of current population, a fitness function is calculated. Fitness of the first chromosome $W_{\mathrm{L}1}$ & $W_{\mathrm{R}1}$ is calculated as follows:

Fig. 5 Initial population

Sink calculates the composite indexes $\mathrm{CW}_{1,j}; \; \forall \; j \in N$, for each candidate cluster member node-j; $\forall \; j \in N$ (see Eq. 20).

$$\mathrm{CW}_{1,j} = W_{\mathrm{L}1} \times \left| \frac{E_{\mathrm{L\,max}} - E_{\mathrm{L}}(j)}{E_{\mathrm{L\,max}}} \right|$$
$$+ W_{\mathrm{R}1} \times \left| \frac{E_{\mathrm{R\,max}}}{E_{\mathrm{R\,max}} - E_{\mathrm{R}}(j)} \right|; \quad \forall j \in N \quad (20)$$

Here, $E_{\mathrm{L}}(j)$ and $E_{\mathrm{R}}(j)$ represent the node attributes of candidate cluster member node-j. $E_{\mathrm{L\,max}}$ and $E_{\mathrm{R\,max}}$ are maximum attribute values of the current node attribute set of cluster member nodes.

Now GA finds the candidate cluster member node obtaining the maximum composite weight index for the first chromosome. Assuming that the kth candidate cluster member node (node-k) obtains the maximum composite weight index that is max ($\mathrm{CW}_{1,j}; \; \forall \; j \in N$).

Now, the GA estimates the minimum transmission power (P_{tk}) as required by node-k for communicating its data to sink. Following equation is used for power calculation.

$$P_{\mathrm{tk}} \text{ in dBm} = \mathrm{PL}_{k,\mathrm{sink}} \text{ in dB} + P_{\mathrm{rsens}} \text{ in dBm} \quad (21)$$

Here, $\mathrm{PL}_{k,\,\mathrm{sink}}$ represents the signal path loss from node-k to sink. P_{rsens} is the receiver sensitivity.

Now fitness value of the first chromosome of the initial population is computed as follows:

$$\mathrm{Fitness}_1 = \frac{1}{1 + P_{\mathrm{tk}}} \quad (22)$$

Similarly, fitness values of remaining chromosomes of the initial population are obtained. Figure 6 demonstrates fitness evaluation steps.

iii. Parent selection

Now, the parent chromosome couples are selected for crossover. The chromosomes with higher fitness function (i.e. lower values of minimum transmit power) have a higher probability of becoming a parent. Roulette Wheel process is used for the selection. A predefined crossover rate (ρ_{c}) decides the number of parent couples for crossover.
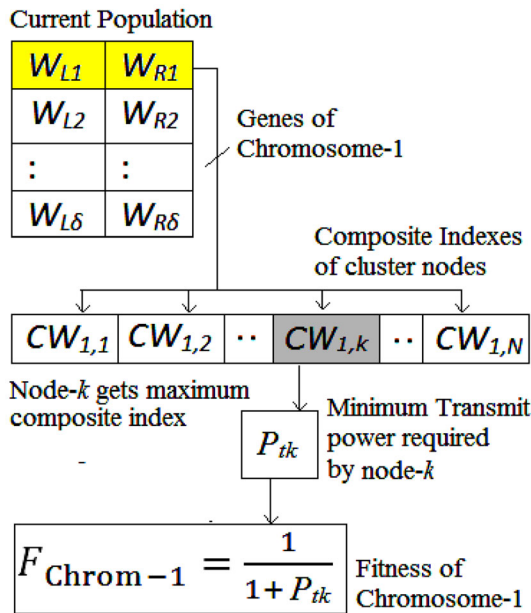
Fig. 6 Fitness evaluation

iv. Crossover

Each selected couple of parent chromosomes carries out crossover and generates a new chromosome called as offspring. The first gene of an offspring (W_L) is the first gene of the first parent and the second gene of an offspring chromosome (W_R) is the second gene of the second parent.

Each newly borne offspring replaces its first parent chromosome from the current population and a new population is formed. Figure 7 demonstrates the crossover step.

v. Mutation

Now, GA carries out the mutation function. In a mutation process, the first or second gene of a randomly selected chromosome of the new population is replaced with a random value. A predefined mutation rate (ρ_m) decides the number of mutations to be carried out in the iteration. Figure 8 demonstrates the mutation step.

After the mutation step, the fitness function is calculated for each chromosome of the mutated population. Then, the GA repeats the steps-ii to step-v.

Thus, the GA in each of its iteration applies minor changes to chromosomes of the current population to
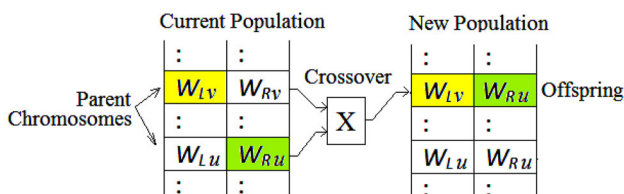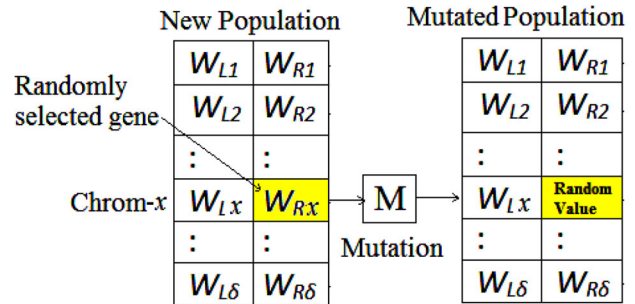

Fig. 7 Crossover step

Fig. 8 Mutation step

maximize objective fitness function. Over successive iterations, the population evolves towards an optimized weight value solution.

Step 4: Fuzzy-TOPSIS based quantitative comparison of candidate nodes

Now, EB-f_g-MADM lets the sink node to apply fuzzy logic-based TOPSIS process on node attribute data and node attribute weigths. TOPSIS ranks each candidate node for their appropriateness for CH job.

At first, the numerical attribute values of each cluster member node are transformed into fuzzy grades such as *Very low, Low, Medium, High, and Very high*. Then a multi-criteria decision matrix (MCDM) is created comprising of weighted fuzzy node attributes of each candidate cluster member node. Fuzzy positive and negative ideal solutions (FPIS & FNIS) are identified involving the set of best performance attribute (highest E_R & lowest E_L) and worst performance attribute values, respectively.

Candidate node possessing the attributes closest to FPIS and farthest from FNIS is selected as the optimum cluster head node. The steps involved in fuzzy-TOPSIS process are as follows:

i. Normalization of node attribute values

Node attribute values ($E_R(i)$ and $E_L(i)$; $\forall$ $i \in N$) are normalized to a range of [0, 1]. Equations 23 & 24 fulfill this purpose.

$$E_{Rn}(i) = \frac{E_R(i) - \min(E_R)}{\max(E_R) - \min(E_R)} \tag{23}$$

$$E_{Ln}(i) = \frac{E_L(i) - \min(E_L)}{\max(E_L) - \min(E_L)} \tag{24}$$

Here, $E_{Rn}(i)$ and $E_{Ln}(i)$ represent attributes of node-i, normalized to a range of [0, 1].

ii. Fuzzy transformation of numerical node attributes

Normalized node attributes are transformed into appropriate fuzzy grades such as *Very low, Low, Medium, High* and *Very high*.

Table 6 Fuzzy transformation table

Fuzzy grade	Associated triplet fuzzy number $\{E_{f\,min}, E_{f\,mode}, E_{f\,max}\}$
Very low (VL)	{0, 0.1, 0.25}
Low (L)	{0.15, 0.3, 0.45}
Medium (M)	{0.35, 0.5, 0.65}
High (H)	{0.55, 0.7, 0.85}
Very high (VH)	{0.75, 0.9, 1}

As depicted by Table 6, each of the five fuzzy grades are characterized by an associated triplet fuzzy number E_{f} = {$E_{f\,min}$, $E_{f\,mode}$, $E_{f\,max}$}. Triplet fuzzy numbers are overlapping in nature with a spread of 0.25 or 0.3. Such characteristics of triplet numbers replicate the fuzziness of transformed attribute data.

A normalized attribute value, E_{Rn}/E_{Ln} is mapped to a corresponding fuzzy grade E_{Rf}/E_{Lf} with the help of fuzzy membership function, $\mu_{E_{Rf}}(E_{Rn})/\mu_{E_{Lf}}(E_{Ln})$.

In general, Eq. 25 is used to evaluate fuzzy membership function, $\mu_{E_f}(E_n)$ of a particular fuzzy grade, E_f = {$E_{f\,min}$, $E_{f\,mode}$, $E_{f\,max}$} extracted from the input attribute value, E_n.

$$\mu_{E_f}(E_n) = \begin{cases} \dfrac{E_n - E_{f\,min}}{E_{f\,mode} - E_{f\,min}} & \text{if } E_{f\,min} \leq E_n \leq E_{f\,mode} \\ \dfrac{E_{f\,max} - E_n}{E_{f\,max} - E_{f\,mode}} & \text{if } E_{f\,mode} \leq E_n \leq E_{f\,max} \\ & \text{else } 0 \end{cases}$$ (25)

For the given normalized attribute value $E_{Rn}(i)/E_{Ln}(i)$ fuzzy membership function values of each of five fuzzy grades are obtained. Fuzzy grade obtaining maximum membership value for a given attribute value is assigned to that attribute value and is termed as $E_{Rf}(i)/E_{Lf}(i)$.

Transformed fuzzy grades of node attributes, $E_{Rn}(i)/E_{Ln}(i)$; $\forall$ $i \in N$, create the fuzzy sets, $E_{Rf}(i)/E_{Lf}(i)$; $\forall$ $i \in N$.

Table 7 depicts the transformed triplet fuzzy attribute grades of six cluster member nodes. This data is obtained from the simulation of proposed algorithm for 100th transmission round.

iii. **Multi-criteria decision matrix (MCDM)**

Optimized node attribute weight values (W_R & W_L) are also transformed into triplet fuzzy numbers; {$W_{R\,min}$, $W_{R\,mode}$, $W_{R\,max}$} & {$W_{L\,min}$, $W_{L\,mode}$, $W_{L\,max}$}, respectively.

During protocol simulations, for 100th transmission round, the optimized node attribute weights (W_R & W_L) were found to be High {0.55, 0.7, 0.85} & Low {0.15, 0.3, 0.45} respectively.

Transformed node attribute fuzzy grades, $E_{Rf}(i)$ and $E_{Lf}(i)$; $\forall$ $i \in N$ are multiplied to their respective fuzzy weights to get weighted node attribute fuzzy grades, $E_{Rw}(i)$ and $E_{Lw}(i)$; $\forall$ $i \in N$. Multiplication takes place as per Eq. 26.

$$\begin{aligned} E_{Rw}(i) &= E_{Rf}(i) \times W_R \\ &= \{E_{Rfmin}(i), E_{Rfmode}(i), E_{Rfmax}(i)\} \\ &\quad \times \{W_{Rmin}, W_{Rmode}, W_{Rmax}\} \\ &= \{E_{Rfmin}(i) \times W_{Rmin}, E_{Rfmode}(i), \times W_{Rmode}, E_{Rfmax}(i), \times W_{Rmax}\} \\ &= \{E_{Rwmin}(i), E_{Rwmode}(i), E_{Rwmax}(i)\} \end{aligned}$$ (26)

Weighted node attribute fuzzy grades, $E_{Rw}(i)$ and $E_{Lw}(i)$; $\forall$ $i \in N$, form an $N \times 2$ Multi-Criteria Decision Matrix (MCDM) which is expressed as follows:

$$MCDM = \begin{bmatrix} E_{Rw}(1) & E_{Lw}(1) \\ E_{Rw}(2) & E_{Lw}(2) \\ \vdots & \vdots \\ E_{Rw}(N) & E_{Lw}(N) \end{bmatrix}_{N \times 2}$$ (27)

MCDM given below is obtained from the fuzzy grade data of Table 7.

$$MCDM_{\substack{@100 \\ \text{Transmission} \\ \text{Round}}} = \begin{bmatrix} \{0, 0.0700, 0.2125\} & \{0.1125, 0.2700, 0.4500\} \\ \{0, 0.0700, 0.2125\} & \{0.0225, 0.0900, 0.2025\} \\ \{0.4125, 0.6300, 0.8500\} & \{0, 0.0300, 0.1125\} \\ \{0.4125, 0.6300, 0.8500\} & \{0, 0.0300, 0.1125\} \\ \{0.1925, 0.3500, 0.5525\} & \{0.0525, 0.1500, 0.2925\} \\ \{0.0825, 0.2100, 0.3825\} & \{0.0525, 0.1500, 0.2925\} \end{bmatrix}_{(N=6) \times 2}$$ (28)

iv. **Fuzzy ideal solutions (FPIS & FNIS)**

Now sink analyses *MCDM* and identifies Fuzzy Positive and Negative ideal solutions (FPIS & FNIS). FPIS and FNIS involve the set of best and worst performance attribute values, respectively (see Eq. 29 & 30).

$$\begin{aligned} FPIS &= [E_R^+, E_L^+] \\ &= \left[\max_i\{E_{Rw}(i); \forall i \in N\}, \min_i\{E_{Lw}(i); \forall i \in N\} \right] \\ &= [\{E_{R\,min}^+, E_{R\,mode}^+, E_{R\,max}^+\}, \\ &\quad \{E_{L\,min}^+, E_{L\,mode}^+, E_{L\,max}^+\}] \end{aligned}$$ (29)

$$\begin{aligned} FNIS &= [E_R^-, E_L^-] \\ &= \left[\min_i\{E_{Rw}(i); \forall i \in N\}, \max_i\{E_{Lw}(i); \forall i \in N\} \right] \\ &= [\{E_{R\,min}^-, E_{R\,mode}^-, E_{R\,max}^-\}, \{E_{L\,min}^-, E_{L\,mode}^-, E_{L\,max}^-\}] \end{aligned}$$ (30)

Table 7 Transformed Fuzzy Grades @ 100th transmission round

Node attribute-1 (Node residual energy E_R)			
Node-i	$E_R(i)$ (J)	$E_{Rn}(i)$	Fuzzy grade $E_{Rf}(i)$ {$E_{Rf\ min}(i)$, $E_{Rf\ mode}(i)$, $E_{Rf\ max}(i)$}
Node-1	0.4910	0	*Very low*; {0, 0.1, 0.25}
Node-2	0.4910	0.0814	*Very low*; {0, 0.1, 0.25}
Node-3	0.4912	1	*Very high*; {0.75, 0.9, 1}
Node-4	0.4912	0.9787	*Very high*; {0.75, 0.9, 1}
Node-5	0.4911	0.5236	*Medium*; {0.35, 0.5, 0.65}
Node-6	0.4911	0.3423	*Low*; {0.15, 0.3, 0.45}
Node attribute-2 (CH selection cost E_L)			
Node-i	$E_L(i)$ (μJ)	$E_{Ln}(i)$	Fuzzy grade $E_{Lf}(i)$ {$E_{Lf\ min}(i)$, $E_{Lf\ mode}(i)$, $E_{Lf\ max}(i)$}
Node-1	1.1881	1	*Very high*; {0.75, 0.9, 1}
Node-2	1.1629	0.3436	*Low*; {0.15, 0.3, 0.45}
Node-3	1.1498	0	*Very low*; {0, 0.1, 0.25}
Node-4	1.1511	0.0342	*Very low*; {0, 0.1, 0.25}
Node-5	1.1688	0.4958	*Medium*; {0.35, 0.5, 0.65}
Node-6	1.1655	0.4092	*Medium*; {0.35, 0.5, 0.65}

v.   Separation Index

Sink computes the two separation indexes, $dist(i)^+$ and $dist(i)^-$ for each cluster member node. These indexes, $dist(i)^+$ and $dist(i)^-$ are the measure of closeness of node-i's attributes to ideal solutions FPIS & FNIS, respectively. They are computed as follows:

$$dist(i)^+ = D_f\left(E_{Rw}(i), E_R^+\right) + D_f\left(E_{Lw}(i), E_L^+\right) \quad (31)$$

$$dist(i)^- = D_f\left(E_{Rw}(i), E_R^-\right) + D_f\left(E_{Lw}(i), E_L^-\right) \quad (32)$$

The term $D_f(E_{Rw}(i), E_R^+)$ of Eq. 20 represents the fuzzy distance in between two fuzzy numbers: $E_{Rw}(i) = \{E_{Rw\ min}(i), E_{Rw\ mode}(i), E_{Rw\ max}(i)\}$ and $E_R^+ = \{E_{R\ min}^+, E_{R\ mode}^+, E_{R\ max}^+\}$. It is given by Eq. 33.

$$D_f\left(E_{Rw}(i), E_R^+\right) = \sqrt{\begin{bmatrix} \left(E_{Rwmin}(i) - E_{R\ min}^+\right)^2 + \left(E_{Rwmode}(i) - E_{R\ mode}^+\right)^2 \\ + \left(E_{Rwmax}(i) - E_{R\ max}^+\right)^2 \end{bmatrix}} \quad (33)$$

Similarly, other fuzzy distances of Eq. 31 and 32 can also be calculated.

vi.   TOPSIS Rank

Now, using Eq. 34, sink computes TOPSIS ranks $SC(i)$; $\forall$ $i \in N$ of each candidate cluster member node for their suitability for cluster head job.

$$SC(i) = \frac{dist(i)^-}{dist(i)^- + dist(i)^+}); \forall i \in N \quad (34)$$

Step-5 Selection of optimum cluster head

The candidate cluster member node with highest TOPSIS rank, $SC(i)$, is chosen as the cluster head. Thus, a cluster member node possessing the attributes closest to positive ideal solution and farthest from negative ideal solution is selected.

Sink node announces the selection by broadcasting a *"CH_ANNOUNCE"* message containing node ID of the selected cluster head. Remaining cluster nodes act as the subordinate child node of the selected cluster head.

4.3 Data Sensing Phase

Biosensor nodes sense the intended body parameter and produce equivalent digital *"DATA"* packets using onboard analog to digital converters. Each *"DATA"* packet carries node IDs of sender node, receiver node and the sensed data.

4.4 Intra Cluster Data Transmission Phase

Subordinate cluster nodes communicate *"DATA"* packets to the CH node. They report in TDMA based time slots. This phase is carried out in the following two steps.

Step-1: Loss-less data compression technique for redundancy removal

Proposed technique adopts a loss-less data compression technique to remove consecutively sensed similar redundant data of a node from the transmission. It works as follows:

i.   Nodes store current and previously sensed data packets in memory.

ii. A sensor node transmits its current "*DATA*" packet if it detects a "sense and transmit event". Such event is detected when the currently sensed "*DATA*" packet is not similar to the last "*DATA*" packet sent by the node or the sensed parameter value goes beyond the threshold. The probability of the detection of a "Sense and Transmit event" is denoted by α.

iii. A sensor node stops the transmission of a "*DATA*" packet if the packet is found to have a close correlation to its previously transmitted "*DATA*" packet. Instead, it broadcasts an "*EMPTY*" message carrying its node ID.

iv. If sink receives the "*EMPTY*" message from a node, then it reuses the last packet it got from the same node.

v. In this manner, node energy is not consumed in transmitting redundant data.

Step-2: Link aware cooperative data transmission

Cluster child nodes cooperate with the cluster head to reduce its transmission burden. Link aware cooperative intra-cluster data transmission is performed as follows:

i. If the sink node is found to be nearer to a child node as compared to CH node, then the child node sends its "*DATA*" packet to the sink node directly. Furthermore, it broadcasts a "*BYPASS*" message carrying its node ID. In Fig. 9, node-S_1, instead of transmitting its "*DATA*" packet to CH node, sends it to sink directly. Selection of shorter path saves node transmission energy.
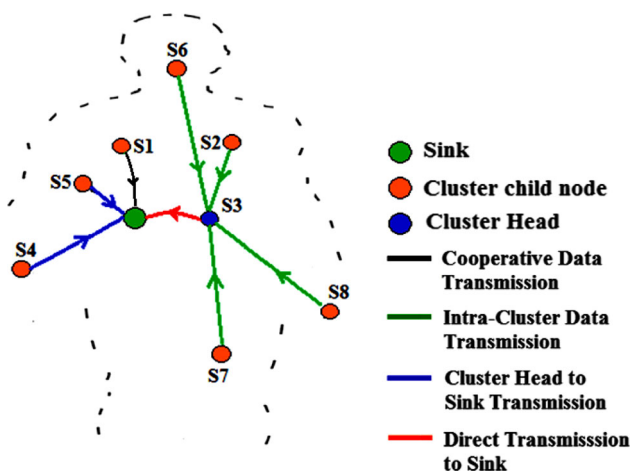
ii. Else child nodes send their packets to the CH node.

Fig. 9 Link aware cooperative data transmission

4.5 Data Aggregation Phase

After receiving "*DATA*" packets from child nodes, CH node piles them into a single datum packet. CH node ignores the child nodes from which it receives either "*EMPTY*" or "*BYPASS*" messages.

4.6 Data Reporting to Sink Node

CH node communicates its datum packet to sink. Then the node S_4 and S_5 send their packets to sink one by one.

4.7 Complexity of EB-*fg*-MADM Algorithm

The time-complexity assessment of the proposed EB-f_g-MADM algorithm is based on the number of arithmetic operations required to execute the algorithm.

After receiving the node attribute values, sink performs Fuzzy-TOPSIS based cluster head selection process and Genetic Algorithm based attribute weight optimization process.

Let the number of candidate cluster member node be n and the number of node attribute be m. Fuzzy-Topsis approach performs $3nm$ operations for attribute normalization, $15(n+1)m$ operations for the fuzzy transformation of node attribute & attribute weights, $3nm$ operations to compute multi-criteria decision matrix (MCDM), $14nm$ operations to compute separation indexes $\text{dist}(i)^+$ & $\text{dist}(i)^-$ and $2n$ operations to compute TOPSIS ranks of candidate cluster member nodes. Thus, the computational complexity of fuzzy-TOPSIS-based cluster head selection stage is given by Eq. 35.

$$\begin{aligned} T_{\text{fuzzy-TOPSIS}} &= 3nm + 15(n+1)m + 3nm + 14nm + 2n \\ &= 35nm + 15m + 2n \end{aligned}$$

(35)

The time complexity of fuzzy-TOPSIS-based cluster head selection stage is $O(nm)$.

The sink performs the attribute weight optimization through an iterative optimization process of Genetic Algorithm (GA). GA is a stochastic process. The time complexity of a GA is a function of GA parameters such as population size, chromosome gene count and number of iterations. GA complexity also depends on the methods used for fitness evaluation, parent selection, crossover and mutation. For Roulette Wheel selection of parents, one point crossover and point mutation, GA complexity becomes $O(pqr)$ where p denotes population size; q denotes the gene count and r denote the number of iterations.

5 Simulation and Analysis of Proposed Protocol

Simulated biosensor node data samples are generated with "Sense and Transmit event" detection probability of $\alpha = 0.6$. These data samples are used for protocol simulation. In this study, MATLAB tool is used for protocol simulation.

Figure 10 shows the initial positions of WBAN biosensor nodes in a 1.8 m $\times$ 1 m network area. Table 8 contains different simulation parameters.

5.1 Network Lifetime and Stability Period

Network lifetime is defined as the total number of transmission rounds until last network node dies out.

Network stability period can be defined as the time period in which all network nodes remains fully functional with all capabilities of data sensing, data processing and data communication. The following section presents a derived model for network stability period.

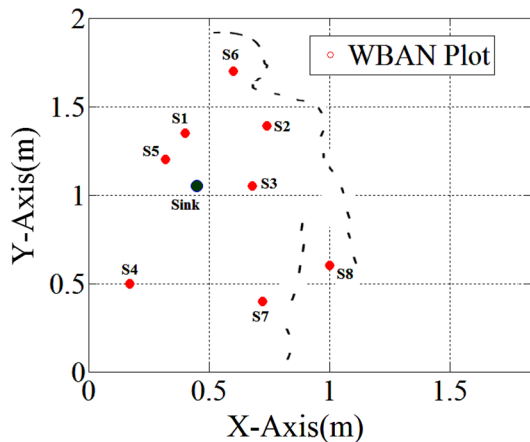Suppose node-i of a WBAN dies first after N_s rounds. Thus, N_s becomes the stability period of the network. Let

Fig. 10 WBAN biosensor nodes positions

E_o be the initial energy of node-i, m be the total number of nodes in the parent cluster of node-i.

Assuming uniform cluster head distribution, node-i remains a cluster head once in each m-transmission rounds. Thus, in N_s transmission rounds, node-i remains N_s/m times as cluster head and $N_s (1 - 1/m)$ times as child node.

Average energy consumed by node-i as a cluster head in a single round is given by Eq. 36 (derived using first-order radio model [19]).

$$E_{\text{Loss\_CH}} = \left[E_{\text{Tx-elec}} \; E_{\text{Rx-elec}} \; E_{\text{DA}} \; E_{\text{Amp}} \right] \times \begin{bmatrix} 1 \\ (m-1)\alpha \\ (m-1)\alpha \\ \eta D_{\text{toSink}}^{\eta} \end{bmatrix} \times W \tag{36}$$

Here, D_{toSink} represents the average distance between the cluster head and the sink. W is the bit length of data packets sent from sensor nodes to cluster head and aggregated datum created by cluster head and sent to sink.

Average energy consumed by node-i as a child node in a single round is given as Eq. 37 (derived using first-order radio model [19]).

$$E_{\text{Loss\_Child}} = \left[E_{\text{Tx-elec}} \; E_{\text{Rx-elec}} \; E_{\text{DA}} \; E_{\text{Amp}} \right] \times \begin{bmatrix} 1 \\ 0 \\ 0 \\ \eta D_{\text{toCH}}^{\eta} \end{bmatrix} \times \alpha w \tag{37}$$

Here D_{toCH} is the average distance between a child node and its cluster head.

Total energy consumed by node-i in N_s stability period is E_o (as it gets died in N_s period). Now E_o can be approximated as follows.

$$E_o = \left(\frac{N_S}{m} \right) E_{\text{Loss\_CH}} + N_S \left(1 - \frac{1}{m} \right) E_{\text{Loss\_Child}} \tag{38}$$

Table 8 Simulation parameters

Parameter	Value	Parameter	Value
$E_{\text{TX-elect}}$	16.7 nJ/bit	Initial node energy E_o	0.6 J
$E_{\text{RX-elect}}$	36.1 nJ/bit	Threshold energy E_{Thr}	0.1 J
E_{Amp}	1.97 nJ/bit	D_o	0.1 m
Data message	4000 bits	α	0.6
Broad. message	200 bits	Rx sensitivity in dBm	92 dBm
Energy message	20 bits	Transmitted power P_t	− 10 dBm
η	3.38 (LoS)	Node wakeup time	1 ms
f (ISM band)	2.4 GHz	Sleep to active transition	0.245 ms
Network area	1.5 $\times$ 0.5 m^2	Active to sleep transition	0.25 ms
Node count	8		

Using Eq. 36, 37 and 38, network stability period (N_s) gets formulated as follows.

$$N_S = \frac{E_o/W}{\left[E_{Tx-elec}\ E_{Rx-elec}\ E_{DA}\ E_{Amp}\right] \times \begin{bmatrix} \frac{1}{m} + \left(1 - \frac{1}{m}\right)\alpha \\ (1-1/m)\alpha \\ (1-1/m)\alpha \\ \frac{\eta D_{toSink}^{\eta}}{m} + \eta D_{toCH}^{\eta}\left(1 - \frac{1}{m}\right)\alpha \end{bmatrix}}$$

(39)

Figure 11 demonstrates network stability period and network lifetime in terms of the dead node count verses transmission round count.

Performance statistics for the network lifetime and stability period are shown in Table 9.

Simulated performance suggests a network stability period of 8420 rounds for the proposed protocol (EB-f_g-MADM) while for DSCB, EERP, and M-ATTEMPT protocols stability periods are 7938, 5315 and 2551, respectively. Similarly, proposed protocol offers an elongated network lifetime around 14,410 transmission rounds as compared to existing protocols.

Figure 12 depicts network residual energy plot verses transmission rounds. It clearly indicates that the network residual energy of EB-f_g-MADM protocol becomes zero after 14,410 transmission rounds.

The proposed protocol offers elongated network stability lifetime periods as compared to existing protocols. It proves that the proposed protocol uniformly distributes the CH load across network nodes. All sensor nodes work for a longer period with their full capacity. Hence, it results in a longer network lifetime.
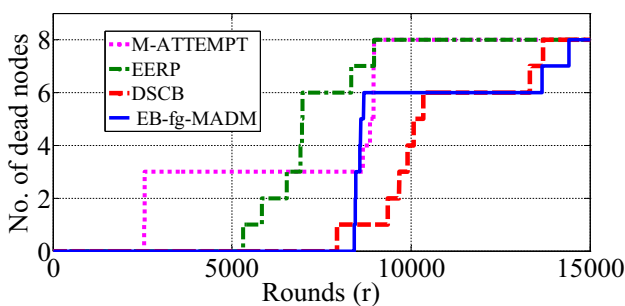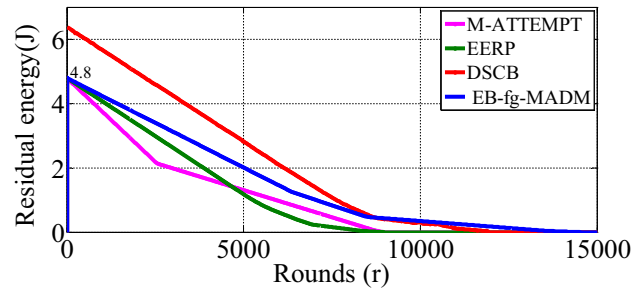

Fig. 12 Residual energy

Proposed protocol (EB-f_g-MADM) also adopts loss-less data compression technique which removes node redundant data from transmission. The omission of redundant data from transmission saves a considerable amount of node transmission energy. Figure 13 shows that omission of redundant data from node data transmission process saves 0.8 J of network energy in the first 5000 rounds. The result is the enhanced network lifetime of 14,410 rounds for proposed protocol.

5.2 Throughput (Data Packet Success Rate)

Network throughput can be measured by the number of effectively delivered data packets to the sink node. Figure 14 depicts the number of successfully delivered data packets to sink for various protocols.

EB-f_g-MADM protocol successfully delivers a sum of 5.6×10^4 packets from source to sink node in 15,000 transmission rounds. Proposed protocol provides better packet success rate as compared to other protocols.
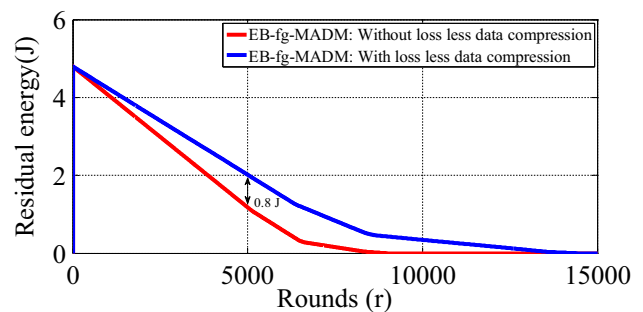

Fig. 11 Number of dead nodes per round

Fig. 13 Residual energy saving by loss-less data compression

Table 9 Network lifetime statistics	No. of dead nodes	Proposed	DSCB [17]	EERP [15]	M-ATTEMPT [36]
Stability period	1	8420	7938	5315	2551
Network lifetime	8	14,410	13,690	8987	8968

Fig. 14 Data packet delivered to sink

Fig. 16 Detailed view of network latency results
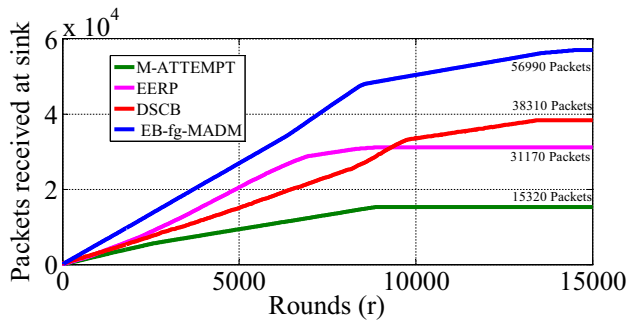
Better network throughput of the proposed protocol is due to the implementation of the loss-less redundant data compression scheme. In this scheme, a node does not transmit its currently sensed data packet if it is same as the previously sensed data packet. In this case, sink reuses the previous data packet from the same node and the data packet is virtually transmitted to sink without facing the noisy communication channel. It results in reduced data packet loss rates and better network throughput.

5.3 End to End Delay (Network Latency)

Network latency result is shown by Fig. 15. The proposed protocol offers a maximum network latency of 23.7 ms which is far below the IEEE 802.15.6 threshold level of 125 ms.

Figure 16 demonstrates a detailed view of network latency for the first second of the network operation. Network completes 59 transmission rounds in the first second of its operation.

Table 10 summarizes the performance results of the proposed and the existing routing protocols.
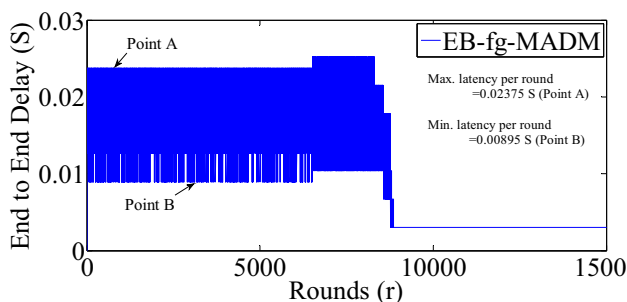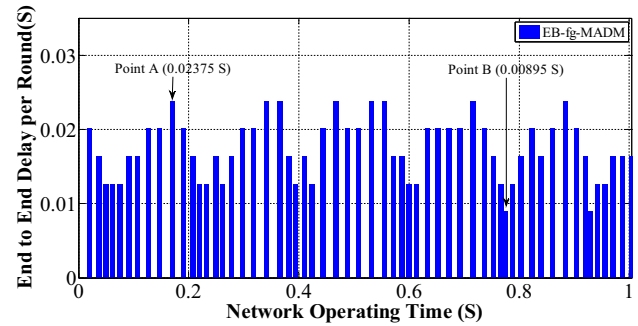
6 Conclusions and Future Work

An energy efficient data routing protocol is of paramount importance for WBAN because bio-sensor nodes consume a considerable amount of assigned node energy for transmitting data to other nodes. A clustering-based protocol provides an energy-efficient data routing scheme with affordable data loss rates and network latency. This paper proposed a novel clustering protocol for WBANs that utilizes a hybrid Fuzzy-Genetic MADM algorithm (EB-f_g-MADM) for dynamic cluster head selection.

Simulation results verified that the EB-f_g-MADM protocol offers an elongated network lifetime and stability period of 14,410 and 8420 transmission rounds, respectively, as compared to existing classical MADM-based routing protocols. The proposed protocol offers a consistent distribution of routing load among network nodes which results in elongated stability period and network lifetime.

EB-f_g-MADM protocol utilizes a loss-less data compression technique for intra-cluster data communication which removes the node redundant data from the transmission. According to the loss-less data compression technique, a sensor node does not transmit a data packet if it is similar to its previously transmitted data packet. In this case, sink reuses the packet from its memory. Thus, the packet is virtually transmitted to sink without facing the noisy communication channel. It results in an increased network throughput. The omission of redundant data from transmission saves around 0.8 J of network energy in the first 5000 transmission rounds. The proposed protocol offers an end to end delay of 23.7 ms. Proposed protocol provides an energy efficient & high QoS WBAN system to meet medical application norms.

The current work assumes that there is a single isolated WBAN system and the transmissions within the WBAN do not face any radio frequency cross-channel interference from other WBAN using similar spectrum. But in a multiple WBAN environment, there is a possibility of cross-channel interference which leads to degraded QoS

Fig. 15 End to end delay (latency)

Table 10 Comparative evaluation of protocols

Performance parameter	Network lifetime (rounds)	Stability period (rounds)	Throughput (packets received at Sink)
EB-f_g-MADM (proposed)	14,410	8420	5.6×10^4
DSCB [17]	13,690	7938	3.8×10^4
EERP [15]	8987	5315	3.1×10^4
m-ATTEMPT [36]	8968	2551	1.5×10^4
iM-SIMPLE [33]	7325	5300	2.9×10^4
SIMPLE [16]	7469	4438	2.8×10^4
LAEEBA [34]	7468	2767	2.7×10^4

performance & reduced network reliability. The current research work may be expanded to incorporate diverse WBANs working in closer proximity with the objective of mitigating cross-channel interference with higher reliability and network stability.

Our future research directions are focused on designing the WBAN routing protocol which overcomes the problem of cross-channel interference and provides the desired QoS performance in a multiple WBAN scenario.

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