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TSFIS-GWO: Metaheuristic-driven takagi-sugeno fuzzy system for adaptive real-time routing in WBANs

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HIGHLIGHTS

- Introducing a hybrid heuristic-metaheuristic routing protocol for WBANs.
- Presenting a heuristic Takagi-Sugeno FIS (TSFIS) for just-in-time routing.
- Applying a metaheuristic-driven GWO for optimizing the TSFIS model.
- Utilizing a tunable fitness function based on the application specifications.

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ABSTRACT

Wireless body area network (WBAN) is an internet-of-things technology that facilitates remote patient monitoring and enables medical staff to administer timely treatments. One of the main challenges in designing WBANs is the routing problem, which is complicated due to dynamic changes in network topology and the limited resources of nodes. Several heuristic and metaheuristic methods have been presented to solve the routing problem in WBANs. Although metaheuristics outperform heuristics by producing higher-quality solutions, they cannot respond to real-time requests. This paper introduces a reactive routing protocol for WBANs that combines a fuzzy heuristic with a metaheuristic learning model. It utilizes a Takagi-Sugeno Fuzzy Inference System in conjunction with the Grey Wolf Optimizer (named TSFIS-GWO). The objective is to simultaneously benefit from the advantages of both approaches, namely, the effectiveness of metaheuristics for offline hyperparameter tuning and the quickness of fuzzy heuristics for real-time routing. At every round, the tuned fuzzy system takes multiple parameters of the current state of the nodes and links to construct the multi-hop routing tree under IEEE 802.15.6. To optimize the performance of the protocol for each WBAN, the fuzzy rules of the TSFIS model are automatically adjusted through a learning method based on GWO. This is done in accordance with the specific requirements of the application, and the tuning process takes place once before the protocol is applied. Simulation results in three applications demonstrate that the proposed TSFIS-GWO model is capable of providing real-time solutions while outperforming the existing methods in terms of application-specific performance measures.

1. Introduction

Over the past two decades, the use of wireless sensor networks (WSNs) has become widespread for monitoring and controlling various environmental conditions such as temperature, humidity, wind, etc. [1]. A wireless body area network (WBAN) is a particular kind of WSN that is

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made up of a set of low-power bio-sensor nodes which are either implanted in or attached to the human body [2]. Each sensor node is able to communicate over short distances with other nodes and with the central processor unit through wireless links [3]. The utilization of WBANs has gained significant attention in recent years, due to their real-time and continuous monitoring capabilities in various medical and non-medical applications such as entertainment, sports, aerospace, telemedicine, and treatments [4]. In the WBAN health monitoring application, vital information from the body is continuously transmitted to medical servers, which allows medical personnel to remotely monitor and provide the appropriate treatments to patients [5].

The overall structure of a monitoring system based on WBANs is shown in Fig. 1, which consists of three main parts, including WBAN on the patient side, network connection side, and medical service side. In this figure, notations 'p' and 'm' mean data forwarding from the patient side and medical service side, respectively. A WBAN includes several bio-sensor nodes and a central control unit (i.e., sink) [6]. Each node is able to identify local data, encompassing both physiological and non-physiological information such as blood pressure, blood oxygen, electroencephalograph (EEG), electrocardiograph (ECG), and electromyograph (EMG) [7]. During each round, every node transmits its own data either directly or with the assistance of a relay node (cluster head) to the sink, and then, the sink forwards the gathered data to medical servers through wired/wireless communications, for further processing [3].

1.1. Routing problem in WBANs

While several challenges are common to both WBANs and WSNs, it is important to adequately recognize and address the functional differences between them when designing a routing protocol for a WBAN [8]. Bio-sensors must be harmless to the human body with less transmitted power. Unlike node-based mobility in WSNs, a WBAN has a group-based movement topology. WBANs belong to heterogeneous networks in which different nodes have different tasks. WBANs are typically in contact with medical data, requiring more reliability than WSNs [7]. Unlike free-space WSNs, routing in WBANs encounters more physical challenges, attenuation, and greater path loss [9].

In WSNs, the network lifetime is typically assessed using diverse metrics such as first node dies (FND), half nodes die (HND), and last node dies (LND) [10]. However, in the case of WBANs, the failure of even a single sensor node can have irreversible consequences, making the network lifetime primarily defined as FND [4]. More specifically, in WBANs, if one or more nodes fail, the remaining nodes can still sustain communication, and the network lifetime can be still measured using various metrics such as FND, HND, and LND. However, considering that many WBAN applications become impractical after the failure of the first node, most research places emphasis on FND as the primary measure of network lifetime.

Challenges associated with minimum energy consumption and maximum satisfaction of quality of service (QoS) metrics are among the essential goals when designing a routing protocol for WBANs. Furthermore, as bio-sensors in WBANs are connected to the human body, they typically have a smaller battery and antenna than WSNs [11]. Therefore, bio-sensors are highly resource-constrained with ultralow-power supplies, where replacing or recharging their batteries is difficult [12]. In this case, reliable energy-efficient routing is of utmost importance to improve the stability period until FND while taking QoS metrics into account.

1.2. Our motivation

Cluster-based protocols are commonly employed routing techniques for achieving energy efficiency in WBANs [13,14]. It should be noted that cluster-based routing in WBANs has been proven to be a non-deterministic polynomial-time hard (NP-hard) problem [15]. As a result, exact search techniques cannot solve it within polynomial time [12]. Although various heuristic [4], [7], [17–30] and metaheuristic [8], [31–38] algorithms have been proposed to solve this problem, the existing methods suffer from some drawbacks, which can be highlighted as:

- The controllable parameters of current heuristics are manually set and kept constant, which means that no retuning process is performed considering the specific requirements of the application.
- In WBANs, it is crucial to respond quickly to the online routing requests from the patient sensor nodes. So, the direct use of time-consuming metaheuristic algorithms as the routing protocol does not make practical sense in WBANs, as it may lead to irreparable damages in transmitting critical data packets.

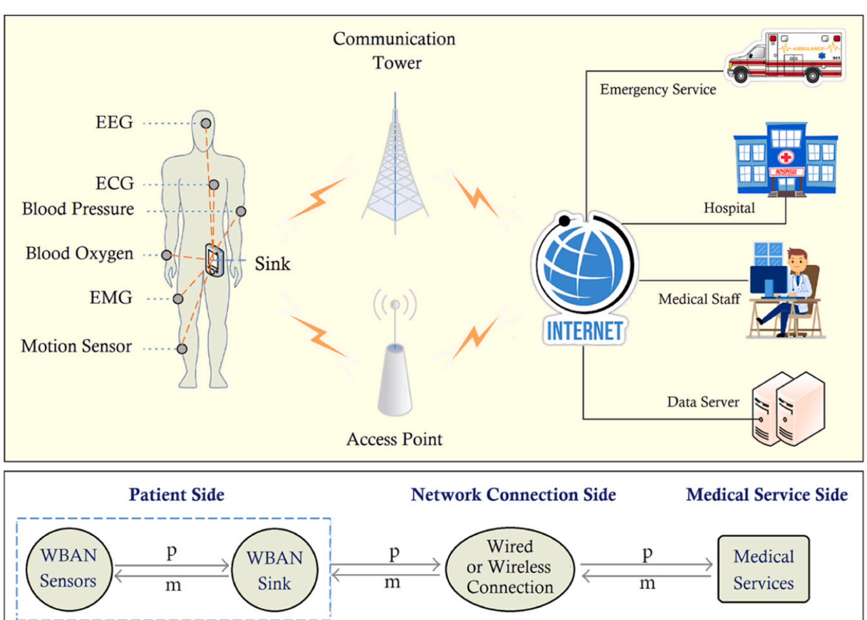

Fig. 1. General architecture of WBAN-based monitoring systems.

- In most existing methods, some important issues such as energy efficiency, reliability, path loss, and hotspot problems are not properly taken into account. Although these parameters may be reported as a performance measure in the final results, they have not been used within the routing algorithm to guide it to achieve a higher-quality solution.

Metaheuristic-based routing protocols in WBANs have acceptable results with high solution quality. However, they apply an iteratively-based optimization algorithm to construct the optimized paths, which boosts overhead and delay at the data transmission phase. On the other hand, heuristic-based algorithms can generate routing solutions very fast but suffer from low solution quality (e.g., low network lifetime). Our motivation is to alleviate the drawbacks of both heuristic and meta-heuristic techniques, while simultaneously benefitting from their advantages, i.e., high quality of the metaheuristic algorithms and the fast speed of the heuristic algorithms.

1.3. Our contributions

In this study, we present a tunable routing protocol for WBANs utilizing a multi-criteria Takagi-Sugeno fuzzy inference system (TSFIS) and a grey wolf optimizer (GWO). The TSFIS is used as the core of the routing protocol to generate real-time solutions, while the GWO is used offline for the hyperparameter tuning of the TSFIS, once before it performs for the online routing in WBANs. The proposed method can be seen as a hybrid technique based on a fuzzy heuristic (for online routing) and a metaheuristic (for offline tuning). We have considered the Takagi-Sugeno fuzzy system for the fuzzy heuristic part of the proposed method because of its simpler structure, smoother landscape, and ease of parameter optimization compared to other fuzzy inference systems like the Mamdani system [39]. Furthermore, we have chosen the GWO algorithm for the metaheuristic part, as it offers several advantages including fast convergence, a balanced method of exploration and exploitation, simplicity, flexibility, and robustness, which make it a promising approach for optimizing continuous hyperparameter tuning problems [40]. Overall, the main contributions of this paper can be highlighted as follows:

- Introducing a tunable hybrid heuristic-metaheuristic routing protocol for WBANs based on TSFIS and GWO (named TSFIS-GWO). It not only delivers high performance by automatically optimizing the TSFIS model using GWO based on the application-specific objectives but also functions as a real-time routing protocol that can quickly respond to online routing requests.
- As far as we know, this is the first study to introduce a Takagi-Sugeno fuzzy system for just-in-time (JIT) routing in WBANs. The majority of the existing fuzzy systems for WBANs have utilized Mamdani fuzzy systems, while this paper presents a tunable parameter-based Takagi-Sugeno fuzzy system.
- Presenting a multi-criteria TSFIS to select a proper forwarder node for each routing request based on various informative criteria of the communication links and sensor nodes such as the residual energy, distance, reliability, path loss, and estimated dissipated energy.
- Performing GWO in an offline scheme to optimize Takagi-Sugeno fuzzy rules of the TSFIS model using a weighted averaging fitness function, where its weights are determined according to the application-specific requirements in terms of the network lifetime, reliability, and path loss.

The organization of this study is as follows: Section 2 reviews the existing routing protocols in WBANs. The system model is presented in Section 3. Section 4 introduces the TSFIS-GWO routing protocol. Section 5 presents the simulation results of the TSFIS-GWO protocol and compares them with existing methods. Finally, concluding remarks with some directions for future works are provided in Section 6.

2. Review of literature

To achieve energy efficiency in WBANs, clustering is the most widely used routing protocol. These methods involve dividing various sensor nodes into distinct clusters, with each cluster containing a cluster head (CH), also called the forwarder or the relay node [41]. The CH nodes act as gateways between their member nodes and the base station (sink). Clustering techniques can be distinguished by how forwarder nodes would be selected [42]. Considering the NP-hardness of the clustering problem in WBANs, there are three alternatives to search for the optimal solution:

- *Exact methods*: Generally, there are 2^N-1 different clustering solutions for WBANs with N nodes [4], which means that the search space grows exponentially with the number of sensor nodes. Although exact methods such as branch-and-bound [43] and column generation [44] obtain the optimal solution, these techniques cannot be applied to real-size WBAN applications.
- *Heuristic methods*: Heuristics refer to problem-specific techniques that can produce near-optimal solutions within a reasonable time-frame [45,46]. In the context of routing techniques for WBANs, heuristic methods are extensively utilized and can be classified as either classical or fuzzy heuristics. Classical heuristics utilize a precise crisp function to determine the priority of nodes that will function as CH [10]. On the other hand, fuzzy heuristics calculate the priority of nodes using a fuzzy inference system (FIS) [47].
- *Metaheuristic methods*: As an extension to heuristics, metaheuristics are a class of problem-independent algorithms that are designed to improve the quality of solutions through iteratively refining intermediate solutions [45, 48, 49]. In WSNs and WBANs, metaheuristic-based clustering methods aim to partition active sensor nodes into distinct clusters to optimize one or more objective functions, such as extending the network's lifetime. Although metaheuristic algorithms generally take more running time than heuristics, they usually converge to a solution of higher quality [50].

Due to the NP-hardness of the clustering problem in WBANs, exact search techniques are not applicable, and thus, heuristics or meta-heuristics should be applied. In the following, existing classical (crisp) heuristic, fuzzy heuristic, and metaheuristic-based routing protocols for WBANs are described in detail.

2.1. Classical heuristics

Several routing protocols based on classical heuristics have been introduced for WBANs, including thermal-aware, clustering, delay-aware, and QoS-based techniques. Thermal-aware routing algorithm (TARA) [17] distributes the load over different nodes/links to avoid data transfer through hotspot zones. M-ATTEMPT is another thermal-aware routing protocol that was developed by Javaid et al. [18] to select the shortest path with the minimum number of hops among all possible routes. However, M-ATTEMPT does not consider the energy level of the nodes, and its procedure for the detection of hotspot zones boosts more complexity and causes more dissipated energy [51]. Moreover, these techniques do not take into account the reliability and network lifetime.

Clustering protocols distribute load among all sensor nodes. Anybody is a clustering protocol presented by Watteyne et al. [19], which utilizes a random self-election strategy, where each sensor decides whether or not its role is a CH. While this method ensures load balancing across all nodes, it fails to take into account factors such as node positions, reliability, path loss, and energy consumption. Nadeem et al. [20] presented a multi-hop protocol called SIMPLE, which chooses relay nodes with higher energy and less distance. It ensures that energy consumption is balanced among all nodes while achieving maximum throughput. However, SIMPLE does not consider mobility, path loss, or hotspot problems, which may result in a single node forwarding the data of all source nodes. Ullah et al. [7] introduced an energy-efficient and reliability-aware protocol, called ERRS, which focuses on improving the lifetime and reliability of WBANs. The protocol includes two strategies for CH selection and rotation, making it an adaptive static protocol. However, it does not consider path loss, load balancing, or hotspot problems.

Delay-aware approaches focus on finding low-delay paths from each node to the sink. Umer et al. [21] proposed a delay-aware protocol named HRRR to address the need for the fast delivery of critical data while conserving the energy of nodes. However, this protocol does not consider load balancing or packet overhead. Mehmood et al. [22] proposed an energy-efficient and cooperative fault-tolerant protocol (EECFTP) to enhance throughput, latency, and lifetime. Nevertheless, the concept of cooperative communications introduces some challenges in WBANs such as increased processing overhead and computational complexity.

QoS-based methods are composed of separate modules that address different QoS metrics, such as reliability, delay, and energy efficiency. Kumar et al. [23] presented a lightweight QoS routing protocol (LQRP), which adopts a modular technique considering two types of data packets, i.e., normal data and high-priority data. In this protocol, at first, the packets at the upper layer arrive at the data packet classification unit. Then, the packets with high priorities are transmitted in real-time, while normal packets need to wait for a proper transmission time. In [24], an energy-efficient sustainable WBAN using renewable energy systems (ESRES) has been presented that utilized an optimization method to enhance reliability, QoS, and network lifetime. Although QoS-based approaches provide low delay and high reliability, they also lead to increased computational complexity due to the management of different QoS modules. Additionally, there is no guarantee of a prolonged network lifetime in these techniques.

Although classical heuristic techniques are simple and robust methods with the capability of quickly responding to real-time routing requests, they often have poor performance especially when multiple criteria are taken into account. Furthermore, these methods are not adaptable to new network architectures and lack the ability to be tuned by decision-makers based on specific application requirements.

2.2. Fuzzy heuristics

Fuzzy inference systems have also been used for routing in WBANs. Chen and Peng [25] present a fuzzy technique for selecting the appropriate relay nodes (FSRN) in WBANs by calculating the cost of the different links to prolong the useful lifetime. The FIS considers the traffic load, the battery level, and the number of data packets that have been previously forwarded through the different links, to select the optimal link. Singh and Singh [26] developed the fuzzy adaptive routing protocol (FARP) based on clusters for WBANs, in which some nodes are selected as CHs based on FIS utilizing node priority, node density, battery level, and distance to the sink. In addition, some nodes can be selected as CHs based on the level of the battery, the criticality of their data packets, and proximity to the sink.

Aghbolagh and Pourmina [27] proposed a fuzzy clustering algorithm (FCA), in which the CHs are adaptively selected at every round based on the energy level, intra-cluster distances, and position shifting of the nodes due to the body movements. Chavva and Sangam [28] presented a fuzzy multi-hop protocol (FMHP) for health monitoring in WBANs, in which data collected by each sensor node is transferred to the sink through a parent node section using a Mamdani FIS, using the energy level of the nodes as the only fuzzy input parameter. Wang et al. [29] developed an energy-efficient protocol that establishes a fuzzy control (EEP-FC) that includes the residual energy of the sensor nodes and the quality of the different links to determine the best forwarder nodes.

SIMOF [4] is a multi-objective temperature-aware fuzzy routing protocol that utilizes multiple criteria including energy consumption, network lifetime, and temperature control, for the cluster head selection using a Mamdani FIS. In [30], a fuzzy relay node selection model to obtain energy-efficient reliable routes (FRNS-ER) has been suggested. In this method, the relay nodes are selected via a FIS according to the estimated distances based on the received RSSI, and the estimated directions based on the MUSIC algorithm. In general, fuzzy heuristics outperform classical heuristics in handling uncertainty and providing flexibility to manage multiple criteria. However, the main limitation of these techniques is the difficulty in adjusting numerous fuzzy rules by the expert when several criteria are utilized as fuzzy inputs. Additionally, these methods have similar limitations to classical heuristics in terms of the lack of adaptability to new WBANs and limited application-specific tunability.

2.3. Metaheuristics

Metaheuristic algorithms have also been utilized for routing in WBANs. Kaur and Singh [31] developed an energy-efficient routing protocol utilizing a genetic algorithm (GA), named EERP-GA. They formulated a multi-objective problem comprising energy level, reliability, and path loss, to choose optimal routes from the different sensor nodes to the sink. Xu and Wang [32] developed an energy-efficient protocol based on the combination of GA and ant colony optimization (ACO), to balance energy among all nodes and extend the lifetime. Esmaeili et al. [16] proposed a cluster-based protocol called EMRP that incorporates GA to obtain the best routes considering energy, path loss, distance, and energy consumption. In [33], a congestion control mechanism based on TARA has been presented that utilizes spider monkey optimization (SMO) to select relay nodes according to energy, temperature, and congestion. Dhanvijay and Patil [34] introduced a protocol named QoSEP that uses ACO to route critical data packets efficiently to their destination nodes. Bilandi et al. [35] proposed a particle swarm optimization (PSO) to identify the correct relay nodes using the energy level and distance to the sink. Sharma [36] developed a quantum-based PSO (QPSO) to find the shortest energy-efficient paths to the sink. Karunanithy and Velusamy [37] developed the MEVPS protocol utilizing ACO to tackle congestion issues in WBANs and decrease latency. Aryai et al. [52] proposed a metaheuristic-driven machine learning routing protocol (MDML-RP) to optimize the routing path of sensor nodes in the WBANs aiming to reduce network congestion and improve the overall performance of the system. Samal et al. [38] presented an adaptive cuckoo search algorithm (ACSA) for data routing and placement of relay nodes in WBANs. They have formulated a linear integer programming model to solve the routing/placement problem in WBANs. Metaheuristic-based routing protocols can provide high-quality solutions to complex routing problems, effectively handle multiple criteria and objectives, adapt to new WBANs, and be customized by the decision-maker to achieve specific objectives. However, these methods require significant computational resources, resulting in slower performance and reduced robustness against dynamic changes. It results in a prolonged response time for the routing protocol (i.e., the time duration between receiving the routing request and delivering the routing solution), which poses challenges particularly when urgent data transmission is necessary.

2.4. Our contributions against existing approaches

Fig. 2 categorizes the reviewed classical heuristic, fuzzy heuristic, and metaheuristic approaches, and provides the pros. and cons. of them. Generally, classical and fuzzy heuristic-based routing protocols are robust methods that have lower computational complexity, enabling them to be effective for real-time routing which is of utmost importance in WBANs. However, they do not guarantee solution quality since they do not incorporate an optimization process. Additionally, these methods are not adaptable to new WBANs and applications and cannot be automatically adjusted based on the needs specified by the decision-maker. In contrast, metaheuristic-based techniques provide higher-quality

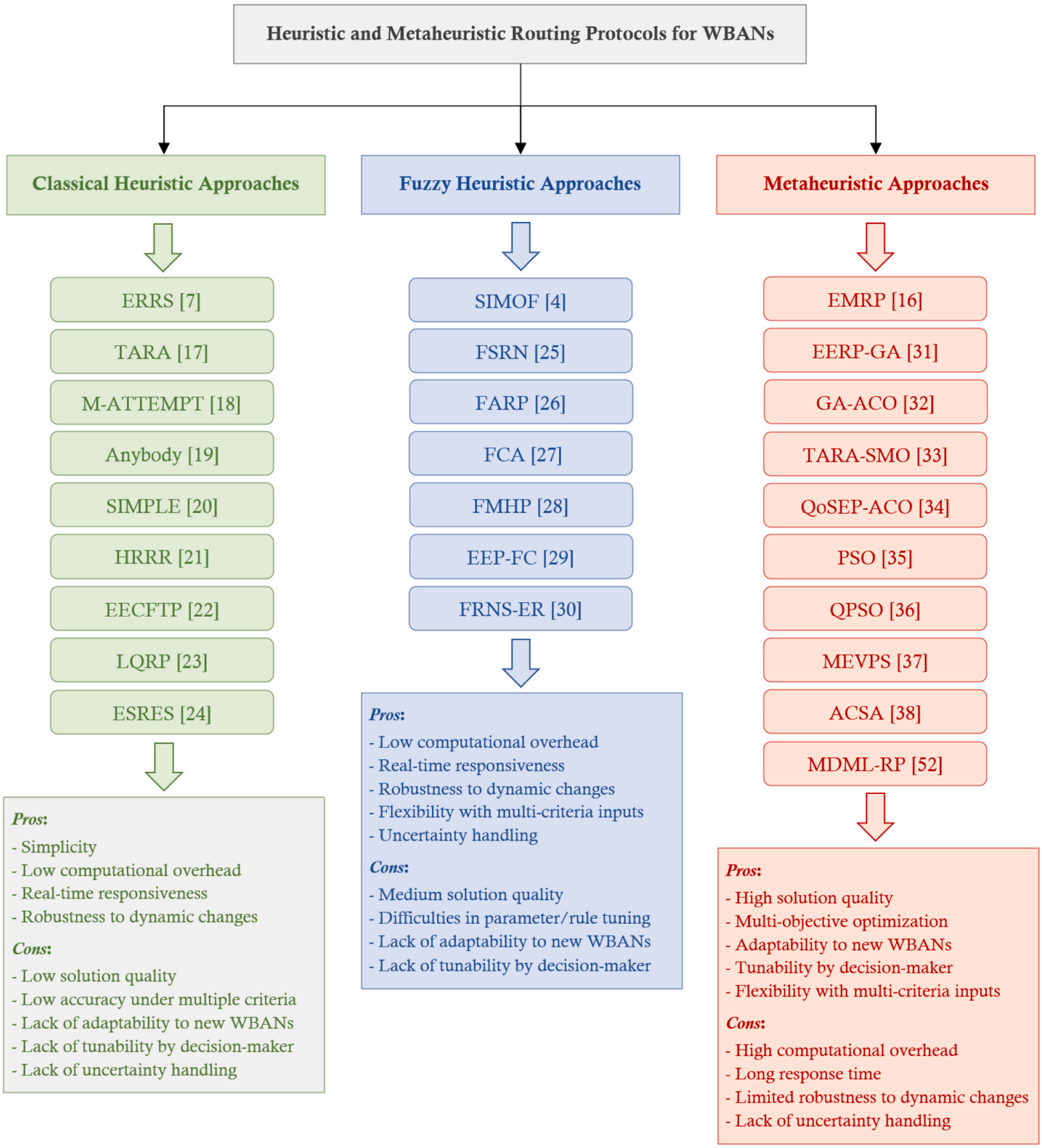

Fig. 2. Classification of the existing routing protocols for WBANs, based on the methodology.

solutions with the added benefits of adaptability and tunability. Nevertheless, since these methods mostly rely on applying a metaheuristic algorithm during each round to generate routes, there is an increase in computational complexity and data transmission overhead.

To address the limitations of the existing heuristics and metaheuristics while capitalizing on their respective strengths, the proposed metaheuristic-driven fuzzy heuristic protocol utilizes a fuzzy heuristic for online routing, capable of providing real-time routing solutions while minimizing computational overhead. To optimize the routing protocol and make it adaptable and tunable for specific application requirements, a metaheuristic algorithm based on GWO is employed as a preprocessing phase to adjust the hyperparameters of the routing protocol in an offline procedure. The proposed TSFIS-GWO protocol offers numerous benefits including low computational overhead in online routing, real-time responsiveness, high solution quality, uncertainty handling, and robustness to dynamic changes. The model is flexible with multi-criteria fuzzy inputs, metaheuristic-driven optimization, and adaptability to new WBANs. Moreover, it can be tuned by decision-makers according to specific requirements in each application.

3. System model

The functioning of the TSFIS-GWO routing protocol can be categorized into two phases, namely setup and steady-state. In the setup phase, all routes are designed at the beginning of every round in the sink node via a centralized fashion, and then, the sink notifies all nodes about their designed routes. Whenever all routes have been set, the steady-state phase can be started. In the steady-state phase, each node transmits the collected information to the sink, directly or through a relay node (CH or forwarder). According to the WBAN architecture in Fig. 3, there is a sink attached to the human body. All nodes are assumed to be aware of their real-time location, i.e., via GPS or any localization technique. All

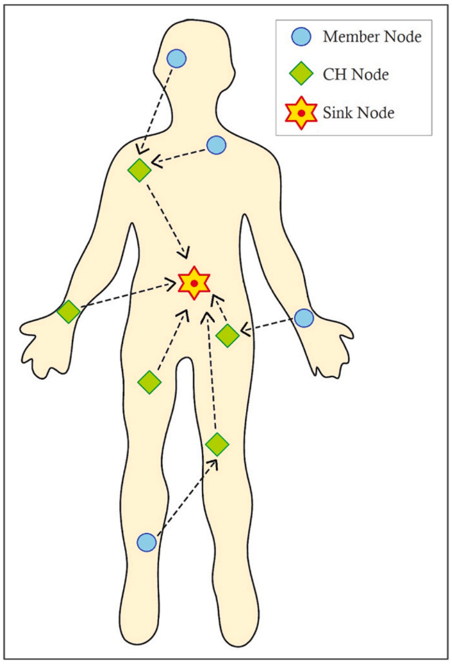

Fig. 3. Cluster-based routing in TSFIS.

communications are done through wireless links. As seen in Fig. 3, only single-hop and two-hop communications are allowed according to IEEE 802.15.6 standard, that is, two-hop for member (non-CH) nodes, and single-hop for forwarder (CH) nodes. Each member (non-CH) sensor node sends the gathered packet to the corresponding CH node, while a CH communicates directly with the sink by sending its sensed data as well as the gathered data from all its member nodes.

3.1. Model of energy

At every round, the energy level of all nodes is updated using the first-order radio communication model [53]. According to this model, the energy consumed during the transmission of a data packet of length l (bit) from node n to node m is expressed using the following equations:

$$E_T(n) = E_{elec}^T \times l + E_{amp} \times l \times d^{\eta} \tag{1}$$

$$E_R(m) = E_{elec}^R \times l \tag{2}$$

where d is the Euclidean distance from node n to node m (meters), E_{amp} is the consumed energy (joules per bit per meter by the power of η) of the amplifier in the transmitter node, and E_{elec}^T and E_{elec}^R are energy consumption parameters (joules per bit) of the electronic circuitry of the transmitter and receiver nodes, respectively. Furthermore, η expresses the path loss exponent of the communication link.

In accordance with Eq. (1), it is evident that the distance and the path loss exponent play a pivotal role, exerting a substantial exponential impact (d^{η}) on the dissipation of energy within transmitter nodes [54]. This effect amplifies notably when the transmitting node serves as a CH, tasked with transmitting larger data packets [55]. The path loss exponent is affected by the communication link passing through the human body, typically hovering between 3 and 7 depending on the line of sight (LOS) or non-line of sight (NLOS) communication scenarios [9, 16, 52]. Therefore, an energy-efficient routing protocol necessitates not only a keen consideration of inter-node distance but also careful attention to the communication link's path loss exponent for optimal operation.

3.2. Model of path loss

Path loss of a communication link is described as the amount of attenuation in the power density of an electromagnetic wave, when it propagates through space, and is measured in dB (decibels) [20], as follows:

$$PL_{n,m} = 20\log\left(\frac{4\pi d_0 f}{c}\right) + 10\eta\log\left(\frac{d_{n,m}}{d_0}\right) + X_{\sigma} \tag{3}$$

where c is light speed, d_0 is the reference distance, f is the frequency, and $d_{n,m}$ is the distance between nodes n and m. Moreover, X_{σ} is a shadowing factor representing the movement of the human body and is considered a Gaussian random number whose mean and standard deviation are established as 0 and σ.

3.3. Model of reliability

The link reliability between nodes n and m can be expressed as the packets received at node m divided by the packets sent by node n [56]. Based on Eq. (4), the reliability of a path from node n to the sink can be calculated by multiplying the reliability of all the links within the path,

$$R_n = \begin{cases} R_{n,sink} & if\ n\ \text{isaCHnode} \\ R_{n,f_n} \times R_{f_n,sink} & if\ n\ \text{isanon}-\text{CHnode} \end{cases} \tag{4}$$

where f_n is the forwarder node of the member node n.

4. Proposed TSFIS-GWO routing protocol

The proposed TSFIS-GWO model is an application-specific routing protocol utilizing online routing (via TSFIS) and offline tuning (via GWO), as seen in Fig. 4. It should be emphasized that the online TSFIS model is embedded in the processor unit located at the sink and is capable of responding to real-time routing requests from sensor nodes at every round. However, the TSFIS model should be fine-tuned using GWO based on the specific network details and application requirements, once before programming the tuned TSFIS model on the processor unit located at the sink for any new WBAN scenario. Since the optimization procedure using GWO is done in an offline scheme, it can be performed in any software in a PC. In this paper, we have utilized the MATLAB software for this purpose.

4.1. Online routing using TSFIS

The overall operation of TSFIS at every round can be divided into two phases: setup and steady-state. In the setup phase, the sink gathers information on the current status of all nodes. Then, for every root node n, the sink calculates the fuzzy priority (FP) of all other candidate nodes using the TSFIS model, and accordingly, identifies the node with the highest FP as CH of node n. Once all routes are designed, the sink creates a time division multiple access (TDMA) schedule specifying when each CH can communicate with the sink. Then, a message is broadcasted to all nodes to inform them of their current routing role, parents/children, and the TDMA schedule. During the steady-state phase, each CH establishes its own intra-cluster TDMA to notify its members when they should transmit their sensed data packets to the chosen CH node. After receiving all the data packets from the member nodes, the CH forwards the collected data as a unified packet with its own data to the sink within its designated time window.

At every round, after gathering the information on the current state of all nodes by the sink, the crisp value of the input parameters of the TSFIS model is calculated for all root nodes (Subsection 4.1.1). Then, the FP of the candidate CHs is computed using three main parts: fuzzification (Subsection 4.1.2), fuzzy inference engine (Subsection 4.1.3), and defuzzification (Subsection 4.1.4). Once the FP of all candidate nodes is calculated, the best route for the root node is selected via a single-hop or

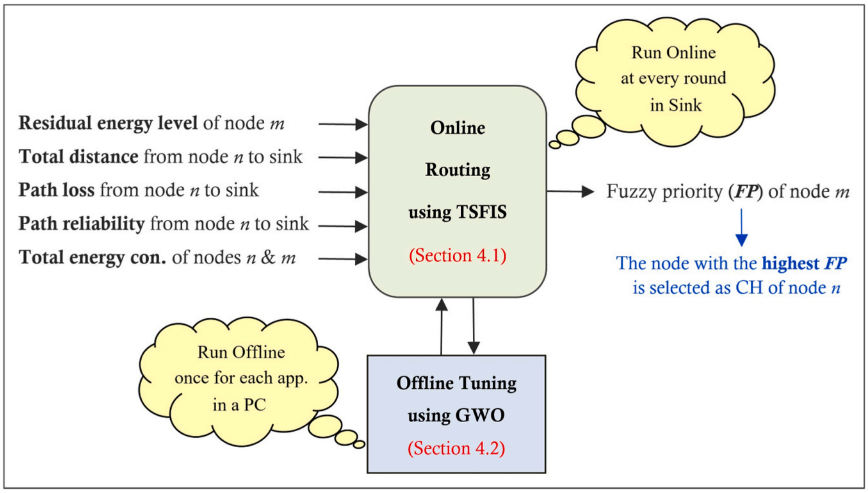

Fig. 4. Overall structure of online routing (using TSFIS) and offline tuning (using GWO).

two-hop communication (Subsection 4.1.5). This procedure is repeated for all root nodes until designing the routing solution for all nodes.

4.1.1. Input parameters

For calculating the priority of each candidate node m, $FP(m)$, to be selected as the CH of the root node n, the TSFIS model takes five inputs of the candidate node. As highlighted in Subsection 3.1, both distance and the path loss exponent have substantial influences over energy dissipation. This oversight becomes particularly pronounced when a transmitting node undertakes the role of a CH transmitting larger data packets. Therefore, in addition to energy, path loss, and reliability, which have direct effects on the determined objectives, we also consider the total distance and estimated energy consumption as fuzzy inputs of the TSFIS model. This augmentation enables the TSFIS model to holistically estimate the combined effect of distance and path loss exponent on energy consumption and path loss of the communication links.

The input criteria of the TSFIS protocol for each candidate node m consist of the energy level of node m (E_m), the total distance from node n to the sink ($d_{n,m}$+$d_{m,sink}$), the total path loss of communication links between node n and the sink ($PL_{n,m}$+$PL_{m,sink}$), the total reliability of the communication link from node n to the sink (R_m), and the total estimated dissipated energy from the node n and its relay node m ($EC_{n,m}$+$EC_{m,sink}$). These parameters are normalized within [0,1], as stated below:

$$x_1(m) = \frac{E_m}{\max_{i=1:N}(E_i)}; \qquad \forall m = 1,2,.,N \tag{5}$$

$$x_2(m) = \frac{d_{n,m} + d_{m,sink}}{\max_{i=1:N}\left(d_{n,i} + d_{i,sink}\right)}; \qquad \forall m = 1,2,.,N \tag{6}$$

$$x_3(m) = \frac{PL_{n,m} + PL_{m,sink}}{\max_{i=1:N}\left(PL_{n,i} + PL_{i,sink}\right)}; \qquad \forall m = 1,2,.,N \tag{7}$$

$$x_4(m) = \frac{R_m}{\max_{i=1:N}(R_i)}; \qquad \forall m = 1,2,.,N \tag{8}$$

$$x_5(m) = \frac{EC_{n,m} + EC_{m,sink}}{\max_{i=1:N}\left(EC_{n,i} + EC_{i,sink}\right)}; \qquad \forall m = 1,2,.,N \tag{9}$$

4.1.2. Fuzzification

After calculation of the normalized crisp value of the input parameters for each candidate node using Eqs. (5)-(9), they should be transformed into linguistic fuzzy variables. The fuzzification process for each input parameter utilizes three fuzzy membership functions, namely Low, Medium, and High, as depicted in Fig. 5. As all input parameters have been normalized to the same range of [0,1], we consider the same membership functions for the fuzzification of the different inputs.

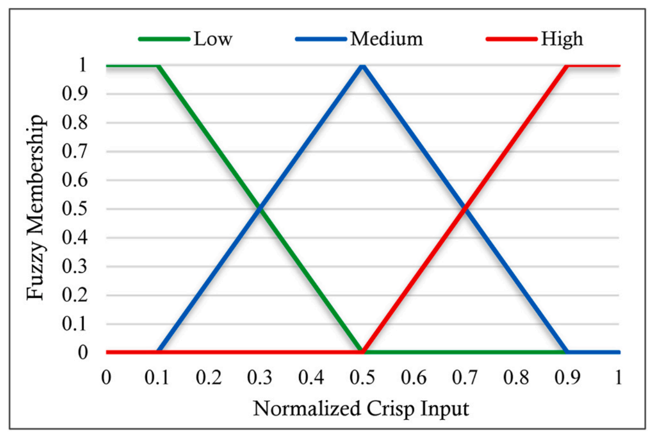

Fig. 5. Fuzzy membership functions of the normalized crisp input criteria.

4.1.3. Fuzzy inference engine

There are different fuzzy inference systems. Among them, Mamdani [57] and Takagi-Sugeno [58] are the most widely used techniques to model the fuzzy inference system. Both models have their specific advantages and limitations. Although the Mamdani model is more interpretable for being manually tuned by an expert [59], the Takagi-Sugeno model has some advantages like simpler structure, smoother landscape, and more importantly, parameter-based output structure, making it more amenable to automatic tuning using optimization algorithms [39, 60]. Since we apply a metaheuristic-driven optimization procedure for the tuning of the fuzzy system, we have chosen the Takagi-Sugeno fuzzy model. Generally, a Takagi-Sugeno fuzzy rule k can be expressed as follows:

$$\text{If } antecedence_k, \text{ then } consequence_k\,; \quad \forall k = 1,2,.,K \tag{10}$$

where K is the number of fuzzy rules stored within the fuzzy rule base table. The precedence part is the same for all fuzzy types, which typically utilizes AND-based rules, each of which represents a combination of the different fuzzy inputs. However, the consequence part differs for each fuzzy type.

Considering five inputs $x_1(m)$ to $x_5(m)$ and one output $FP(m)$ for each candidate node m, a typical Takagi-Sugeno fuzzy rule in the TSFIS can be expressed as follows:

$$\text{If } x_1(m) = a_1^k \ \& \ x_2(m) = a_2^k \ \& \ x_3(m) = a_3^k \ \& \ x_4(m) = a_4^k \ \& \ x_5(m) = a_5^k, \ \text{then } y_k(m) = f(x_1, x_2, x_3, x_4, x_5) \ ; \quad \forall k = 1, 2, ., K, \ \ m = 1, 2, ., N \tag{11}$$

where $a_i^k \in$ {Low, Medium, High} is the k-th membership function that has been fired for the i-th fuzzy input, and $y_k(m)$ is a crisp function which is formulated as a polynomial function of the crisp values of the five inputs as follows:

$$y_k(m) = P_k x_1(m) + Q_k x_2(m) + R_k x_3(m) + S_k x_4(m) + T_k x_5(m) + U_k \ ; \quad \forall k = 1, 2, ., K, \ \ m = 1, 2, ., N \tag{12}$$

where P_k, Q_k, R_k, S_k, and T_k, are the relative weights of the five inputs x_1, x_2, x_3, x_4, and x_5 in rule k, respectively, and also U_k is a bias number used to balance the output of rule k.

4.1.4. Defuzzification

The defuzzifier is used to aggregate the fired fuzzy outputs achieved from the different rules and combine them into a single crisp output. The TSFIS utilizes all AND-based combinations from the five inputs in Eq. (11). For each candidate node m, some of the rules may be fired if all existing input memberships have been activated. Consequently, the final crisp output of node m can be obtained using the weighted average method [13], as follows:

$$FP(m) \ = \ \frac{\sum_{k=1}^{K} (\mu_k \times y_k)}{\sum_{k=1}^{K} \mu_k} \tag{13}$$

where μ_k is the multiple (or minimum) of the activated values of the five fuzzified inputs, associated with the fired membership functions within the rule k.

4.1.5. Design of routing solutions

After calculating $FP(m)$ of all candidate nodes for each root node n, the candidate node with the highest FP value is identified as the forwarder node (CH) of node n, f_n. Based on the IEEE 802.15.6 standard, which is used in the TSFIS model, each node may use single-hop or two-hop transmission to send its sensed data packet to the sink [61]. If the selected forwarder node is any node other than node n (i.e., $f_n \neq n$), node n is considered a non-CH node and submits its data to the sink using a two-hop communication with the help of the selected forwarder node. Otherwise, in the case of $f_n = n$, node n is considered a CH node and sends its data as well as the data from its member nodes (as existed) directly to the sink (single-hop communication).

	P	Q	R	S	T	U
Rule 1	P_1	Q_1	R_1	S_1	T_1	U_1
Rule 2	P_2	Q_2	R_2	S_2	T_2	U_2
Rule 3	P_3	Q_3	R_3	S_3	T_3	U_3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Rule K	P_K	Q_K	R_K	S_K	T_K	U_K

Fig. 6. Representation of a feasible solution.

4.2. Offline tuning using GWO

In this section, we present an offline tunning process based on the GWO algorithm to optimize the TSFIS model once before applying it for online routing. Given the mentioned advantages of GWO in addressing continuous-space hyperparameter tuning problems, it has been chosen to optimize the continuous Takagi-Sugeno fuzzy parameters within the TSFIS protocol.

4.2.1. Optimization problem

As mentioned above, the proposed TSFIS model employs all AND-based Takagi-Sugeno fuzzy rules. With five fuzzy inputs (i.e., I=5) within Eq. (11), each processed through three fuzzy membership functions, the TSFIS model encompasses a total of K=3^5=243 fuzzy rules. As per Eq. (12), each Takagi-Sugeno fuzzy rule comprises I+1 parameters including P_k, Q_k, R_k, S_k, T_k, and U_k (k=1,2,…,K). As seen in Fig. 6, a feasible solution can be represented as a matrix with K=243 rows and I+1=6 columns, where each row k represents the six parameters of the fuzzy rule k. As a result, the TSFIS model entails a total of $K \times (I+1)$= 1458 controllable parameters that should be fine-tuned according to the specific application measures.

According to Eq. (12), each Takagi-Sugeno fuzzy rule utilizes a weight for each input plus a bias parameter. The selection of CH is influenced positively by the residual energy (x_1) and reliability (x_4) of nodes, where higher energy or path reliability increases the likelihood of a node for being selected as a CH. On the other hand, the distance (x_2), path loss (x_3), and energy consumption (x_5) have negative impacts on the selection, decreasing the priority of the node to be chosen as the CH. Accordingly, the range of parameters is defined as $P_k \in$[0,1], $Q_k \in$[-1,0], $R_k \in$[-1,0], $S_k \in$[0,1], $T_k \in$[-1,0]. Furthermore, as the role of the bias parameter is to balance the outputs, its range is considered as $U_k \in$[-1,1]. These ranges are used to limit the range of parameters (lower and upper bounds of GWO) in the random generating initial population as well as updating the entire population at every iteration.

To measure the quality of a feasible solution g (i.e., a grey wolf), the corresponding Takagi-Sugeno fuzzy rule base table is extracted by decoding the solution using Eqs. (11) and (12), and then, the WBAN is simulated considering the fuzzy rules provided by the solution. When the network simulation has been completed, the fitness of the solution can be calculated based on an application-specific fitness function. To achieve this purpose, each solution g can be evaluated by a normalized weighted averaging fitness function to maximize the FND network lifetime, minimize the average path loss (APL), and maximize the average path reliability (APR), as follows:

$$maximize : \left\{ Fitness_g = w_{FND} \times \left(\frac{FND_g}{R_{\max}}\right) + w_{APL} \times \left(\frac{APL_g}{PL_0}\right)^{-1} + w_{APR} \times \left(APR_g\right) \right\} \tag{14}$$

subject to

$$FND_g < R_{\max} \quad \forall g, \tag{15}$$

$$APL_g \geq PL_0 \quad \forall g, \tag{16}$$

$$APR_g \leq 1 \quad \forall g, \tag{17}$$

$$APR_g = \frac{1}{LND_g} \sum_{r=1}^{LND_g} \left(\frac{1}{A_{r,g}} \sum_{n=1}^{A_{r,g}} R_n(r,g) \right) \quad \forall g, \tag{18}$$

$$APL_g = \frac{1}{LND_g} \sum_{r=1}^{LND_g} \left(\frac{1}{A_{r,g}} \sum_{n=1}^{A_{r,g}} PL_{n,sink}(r,g) \right) \quad \forall g, \tag{19}$$

$$LND_g \le R_{\max} \quad \forall g, \tag{20}$$

$$PL_0 = 20 \log \left(\frac{4\pi d_0 f}{c} \right), \tag{21}$$

$$PL_{n,sink}(r,g) \ge PL_0 \quad \forall g, r, \tag{22}$$

$$w_{FND} + w_{APL} + w_{APR} = 1. \tag{23}$$

In Eq. (14), $Fitness_g$ measures the fitness value of the solution g (i.e., grey wolf g), wherein FND_g, APL_g, and APR_g, are the FND, APL, and APR obtained by simulation of the WBAN using the corresponding TSFIS model decoded from the solution g. Eqs. (15)-(17) express the boundaries of FND_g, APL_g, and APR_g, which causes all three objective terms as well as the total fitness function to be between zero and one. Eqs. (18) and (19) measure the average reliability and path loss of all communications from alive nodes to the sink during the whole network simulation, where $A_{r,g}$ is the number of alive nodes in the simulation round r for the solution g, and notations $R_n(r,g)$ and $PL_{n,sink}(r,g)$ are respectively the reliability and path loss of data transmission from node n to the sink at round r for the solution g. Eq. (20) expresses that the maximum rounds considered for the network simulation ($R_{\max}$) must be larger than the LND of any solution g. Eq. (21) calculates the path loss at the reference distance d_0, and Eq. (22) emphasizes that the path loss of any communications is higher or equal to PL_0. Furthermore, Eq. (23) expresses that the summation of the weights of different objectives (w_{FND}, w_{APL}, and w_{APR}) is equal to 1. The w_{FND}, w_{APL}, and w_{APR} are constant parameters within [0,1], which adjust the relative effects of FND, APL, and APR, within the fitness function, respectively.

4.2.2. Optimization algorithm

GWO is a swarm intelligence algorithm with balanced exploration-exploitation ability, which was first proposed in 2014 by Mirjalili et al. [40]. It was inspired by the hunting behavior of grey wolves. As seen in Fig. 7, the search begins by randomly initializing a population of grey wolves consisting of *PopSize* solutions. During each iteration, the quality of the current population is assessed using a fitness function tailored to the specific application. Then, the entire population is modified using the attacking prey (exploitation) and the search for prey (exploration). These processes are carried out in successive steps until the stop criterion is satisfied. A pre-specified number of iterations (i.e., *MaxIter*) is defined as the termination condition of the GWO algorithm. Pseudo-code of the hyperparameter tuning process for the TSFIS protocol with GWO is provided in Algorithm 1.

Algorithm 1. . Tuning of TSFIS using GWO.

Inputs:
WBAN model parameters
Application-specific fitness function
GWO parameters: *PopSize*, *MaxIter*, …
Output:
Application-specific tuned TSFIS
GWO Algorithm:
i = 0 (initial population)
Initialization of a random population of grey wolves
Evaluation of the fitness function for all grey wolves using Eq. (14)
S_α: best solution (alpha)
S_β: second best solution (beta)
S_δ: third best solution (delta)
while (i < *MaxIter*)
  Update a
  for g = 1 : *PopSize*
    Update r_1, r_2, A and C for alpha, beta, and delta wolves
    if ($|A|$ < 1)
      Apply the *attacking prey* operator for updating the grey wolf g
    else if
      Apply the *search for prey* operator for updating the grey wolf g
    end if
  end for
  Amend any solution that goes beyond the defined searching space
  Evaluation of the fitness function for all grey wolves using Eq. (14)
  Update S_α, S_β, and S_δ
  i = i+1
end while
Return S_α as the application-specific tuned TSFIS protocol

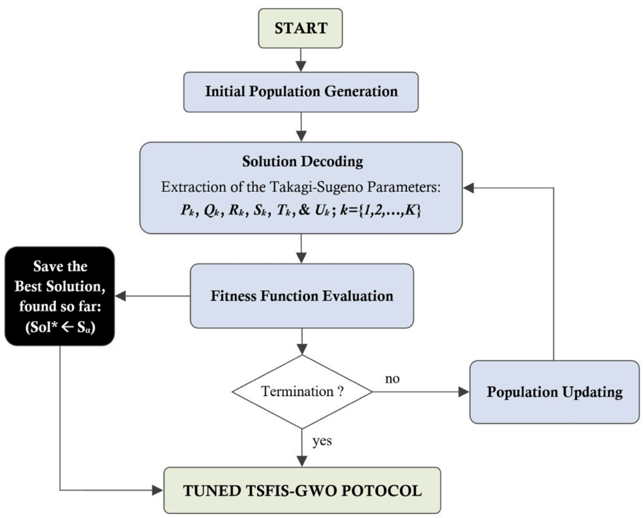

Fig. 7. Flowchart of GWO for the fuzzy rule tuning of the TSFIS.

4.2.3. Fitness function evaluation

Whenever a solution has been updated via the GWO operators, its feasibility must be checked. If all the parameters are within the allowable ranges, the solution is feasible. Otherwise, if any parameter goes beyond the search space, it is amended by limiting the violated parameters in the corresponding boundaries. To measure the quality of each wolf, the corresponding Takagi-Sugeno fuzzy rule base table is extracted, and then the WBAN is simulated considering the fuzzy rules provided by that wolf. When the simulation has been completed, the fitness of the wolf is calculated based on the application-specific objective(s). It should be noted that the fitness function presented in Eq. (14) is a hypothetical fitness function, which is used as an example to provide the simulation results in this paper. However, depending on the application specifications, it is possible to define the fitness function using alternative formulas.

4.2.4. Population updating

Gray wolves possess a social structure that consists of hierarchy levels, namely alpha, beta, delta, and omega [62]. The alpha is the leader whose instructions must be obeyed by all other grey wolves. The beta serves as an advisor to the alpha, reinforcing the alpha's orders and providing feedback to the alpha. The delta must submit to the alpha and beta but dominates the rest of the pack (omegas). During each iteration of the algorithm, the fitness function is used to evaluate the quality of all gray wolves, which are then sorted based on their fitness value from best to worst. The top three solutions are designated as alpha (S_α), beta (S_β), and delta (S_δ), respectively. At each iteration t, the position of each gray wolf g is updated as follows:

$$S_g\left(t+1\right) = \frac{1}{3}\left(X_g^\alpha + X_g^\beta + X_g^\delta\right) \tag{24}$$

where X_g^α, X_g^β, and X_g^δ, are respectively the factors of the encircling prey based on the alpha, beta, and delta, which are expressed as follows:

$$X_g^\alpha = S_\alpha - A_g^\alpha.\ \left|C_g^\alpha.\ S_\alpha - S_g(t)\right| \tag{25}$$

$$X_g^\beta = S_\beta - A_g^\beta.\ \left|C_g^\beta.\ S_\beta - S_g(t)\right| \tag{26}$$

$$X_g^\delta = S_\delta - A_g^\delta.\ \left|C_g^\delta.\ S_\delta - S_g(t)\right| \tag{27}$$

where A and C are random vectors that are generated respectively as Eqs. (28) and (29), where r_1 and r_2 are uniform random vectors with arrays in [0,1], and a is a parameter that is decreased from 2 to 0.

$$A = 2a.\ r_1 - a \tag{28}$$

$$C = 2.\ r_2 \tag{29}$$

Based on the values of the arrays within A, *attacking prey* or *search for prey* is performed. More specifically, each wolf may converge toward the prey if $|A|<1$ (attacking prey) or diverge from it if $|A|>1$ (search for prey). According to Eq. (28), the value of the arrays of A is within [-a,a]. As a is a linearly decreasing parameter over the course of iterations, the chance of the exploitation (attacking prey) gradually increases, while the probability of the exploration (search for prey) decreases.

4.3. Computational complexity analysis

In the following, the computational complexity of the proposed TSFIS-GWO model in the online routing phase using TSFIS and the offline tuning phase using GWO is analyzed. The TSFIS model has a computational complexity of $O(M^I)$ for constructing the route of a single node at every round, where I is the number of fuzzy input parameters and M is the number of memberships considered for the fuzzification of each input parameter. As a result, the computational complexity of the TSFIS model at every round in the online routing phase over a WBAN comprising N sensor nodes can be expressed as $O(N\times M^I)$. Furthermore, the offline tuning phase using GWO has a computational complexity of $O(MaxIter\times PopSize\times CC_{Fitness})$, where *PopSize* is the population size of GWO, *MaxIter* is the maximum number of iterations of GWO, and $CC_{Fitness}$ is the computational complexity of evaluating the fitness of a grey wolf at a single iteration. To calculate the fitness of a grey wolf, the WBAN must be completely simulated using the corresponding TSFIS for R_{max} rounds. So, the fitness function evaluation has a computational complexity of $O(N\times M^I\times R_{max})$. As a result, the computational complexity of the offline tuning phase using GWO can be expressed as $O(MaxIter\times PopSize\times N\times M^I\times R_{max})$.

It should be emphasized that the high computational complexity of the GWO algorithm is solely present in the offline tuning phase and does not impose any overhead during the online routing phase, where the model is actually used for routing. Therefore, while the offline tuning phase may be computationally intensive, it does not impact the real-time responsiveness of the proposed model during the online routing phase. This guarantees that the routing process remains efficient and streamlined, while also allowing for the essential application-specific adjustments and optimization to be implemented beforehand.

Table 1
WBAN parameters.

Parameter	Value
MAC	IEEE 802.15.6
Size of workspace	1.8 m × 0.8 m × 0.3 m
Height of body	1.8 m
Width of body	0.8 m
Thickness of body	0.3 m
Position of sink	(1 m, 0.4 m, 0.3 m)
No. nodes	20
Size of data packets	100 bit
Size of control packets	16 bit
Link reliabilities	[0.8,1]
Initial energy of nodes	0.5 J
E_{amp}	1.97 nJ/bit/m$^\eta$
E_{elec}^T	16.7 nJ/bit
E_{elec}^R	36.1 nJ/bit
d_0	0.1 m
f	2.4 GHz
c	3×10^8 m/s
η	[3,6]

Table 2
Controllable parameters of the TSFIS-GWO protocol.

Phase	Parameter	Definition/Value	Fixed/Variable
TSFIS	No. input parameters	5	Fixed
	Range of input parameters	Linear normalization within [0,1]	Fixed
	No. input fuzzy membership functions	3 (Low, Medium, High)	Fixed
	No. parameters within TSFIS model	1458	Fixed
	Value of parameters within TSFIS model	[-1,1]	Variable (Tuned by GWO)
	Defuzzification	Weighted average method	Fixed
GWO	Population size (*PopSize*)	50	Fixed
	Maximum number of iterations (*MaxIter*)	1000	Fixed
	Fitness function weights (w_{FND}, w_{APL}, w_{APR})	[0,1]	Variable (Defined by user)

Table 3
Application-specific weights within the proposed fitness function.

Scenario	FND		APL		APR	
	weight (w_{FND})	impact	weight (w_{APL})	impact	weight (w_{APR})	impact
App. 1 (High Stable Lifetime)	0.8	Very high	0.1	Low	0.1	Low
App. 2 (Low Path Loss)	0.5	High	0.5	High	0	Zero
App. 3 (High Path Reliable)	0.5	High	0	Zero	0.5	High

5. Simulation results

The TSFIS-GWO approach was successfully implemented on a computer with MATLAB R2020b, utilizing a 2.6 GHz i7 CPU and 16 GB RAM. For the metaheuristic-driven offline tuning phase, we have used MATLAB source codes of the original GWO algorithm, accessible at http://www.alimirjalili.com/SourceCodes/GWO.zip.

5.1. Settings

The network parameters are summarized in Table 1. The experiments were conducted in a workspace modeled as a 3D human body with dimensions of 1.8 m × 0.8 m × 0.3 m. The sink is positioned at coordinates (1 m, 0.4 m, 0.3 m). There are 20 sensor nodes attached to or implanted in the body, where each node is furnished with a power source that possesses an initial energy of 0.5 Joule.

The parameters of the TSFIS-GWO protocol are summarized in Table 2. In the online routing phase, we have designed a typical Takagi-Sugeno fuzzy system with AND-based rules. As described in Subsection 4.1, the parameters related to the number of inputs, normalization of inputs, fuzzification, and defuzzification, have been set with fixed values. However, the parameters within the fuzzy rule base table of TSFIS are automatically tuned using GWO. In the offline tuning phase using GWO, *PopSize* and *MaxIter* have been set as 50 and 1000, respectively. Furthermore, the weights of the fitness function of Eq. (14), i.e., w_{FND}, w_{APL}, and w_{APR}, are variable parameters that can be determined by the user based on the desired impacts of the FND, APL, and APR in the application.

Table 3 showcases three WBAN applications (scenarios), each tailored with specific emphasis on different objectives within the fitness function of Eq. 14. Since WBANs are networks that consist of heterogeneous nodes, the network's validity significantly diminishes after reaching FND. Therefore, it is deemed the most critical metric in all applications considering an FND's weigh at least equal to 0.5, i.e., $w_{FND} \geq 0.5$. By prioritizing varying aspects of FND, APL, and APR, three applications are considered for simulations, which can be described as follows:

App. 1 (High Stable Lifetime): By focusing on a prolonged and highly stable network lifetime until FND, the weightage within the fitness function is adjusted to prioritize FND significantly. Accordingly, the weight assignments are set as w_{FND}=0.8, w_{APL}=0.1, and w_{APR}=0.1, ensuring a robust extension of network stability until FND while also considering slight impacts for the APL and APR.

App. 2 (Low Path Loss): This application aims at minimizing path loss while still taking into account the importance of FND. Here, the fitness function is balanced between the three objectives with weights set as w_{FND}=0.5, w_{APL}=0.5, and w_{APR}=0, ensuring both reduced path loss and sustained network longevity.

App. 3 (High Path Reliable). In this application, the primary focus lies on enhancing the link reliability while maintaining a reasonable FND. Consequently, the weights of the fitness function are assigned as w_{FND}=0.5, w_{APL}=0, and w_{APR}=0.5, thereby emphasizing link reliability alongside network sustainability while ignoring the path losses of the communications.

It is important to highlight that the proposed application-specific fitness function (formulated in Eq. 14) serves as a hypothetical function that leverages the FND, APL, and APR objectives to describe the given scenarios of App. 1, App. 2, and App. 3. Nevertheless, it can be customized by the decision maker to include additional QoS metrics and objectives such as HND, LND, bandwidth, and so forth, within the fitness function to address new applications and other types of scenarios.

5.2. Results of offline tuning

As mentioned above, the proposed TSFIS-GWO protocol should be tuned using GWO once before applying it to any new WBANs (applications). Generally, the higher the value of *PopSize* and *MaxIter* in a metaheuristic algorithm, the more chance to achieve a better solution by accepting more computational complexity [63]. To evaluate the effects of *MaxIter* and *PopSize* on the fitness value and running time, the GWO has been performed to optimize the TSFIS model considering different iterations of 100, 500, 1000, and 2000, and different populations of 10, 25, 50, 100. The obtained fitness value and running time for App. 1 are provided in Tables 4 and 5, respectively. Furthermore, the results are graphically illustrated as surface plots in Fig. 8. The results show that increasing both *MaxIter* and *PopSize* leads to enhancing the fitness value while increasing the running time, due to generating and evaluating more solutions.

Table 4
Average fitness value of GWO over 10 successive runs in App. 1.

Iterations	**Population**			
	10	20	50	100
100	0.416	0.440	0.499	0.510
500	0.455	0.487	0.524	0.526
1000	0.473	0.502	0.533	0.534
2000	0.486	0.512	0.535	0.537

Table 5
Average running time [h] of GWO over 10 successive runs in App. 1.

Iterations	**Population**			
	10	20	50	100
100	0.07	0.17	0.46	1
500	0.50	1.1	3.1	6.8
1000	1.1	2.7	6.7	14.4
2000	2.4	5.8	14.2	29.3

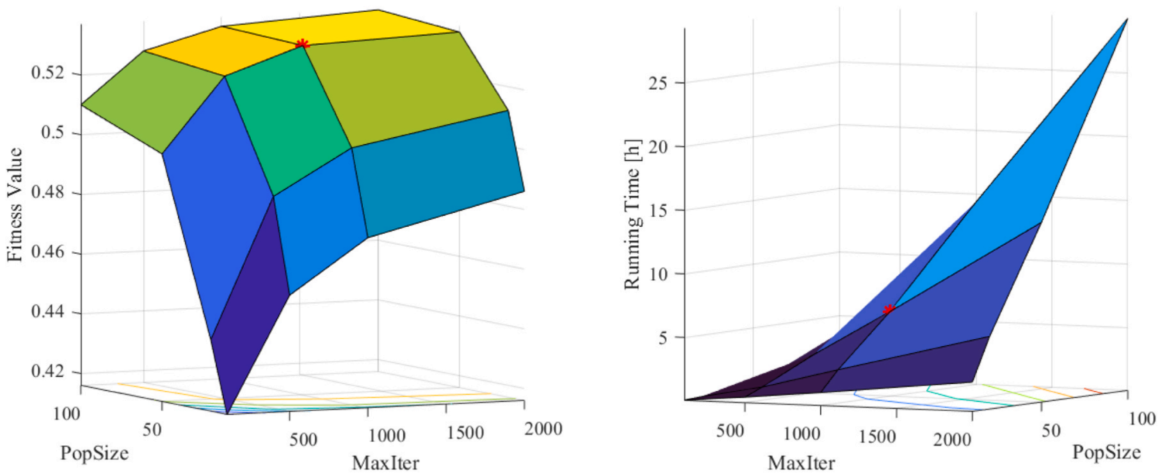

Fig. 8. Effects of *MaxIter* and *PopSize* on the fitness value (left) and running time (right) of the GWO.

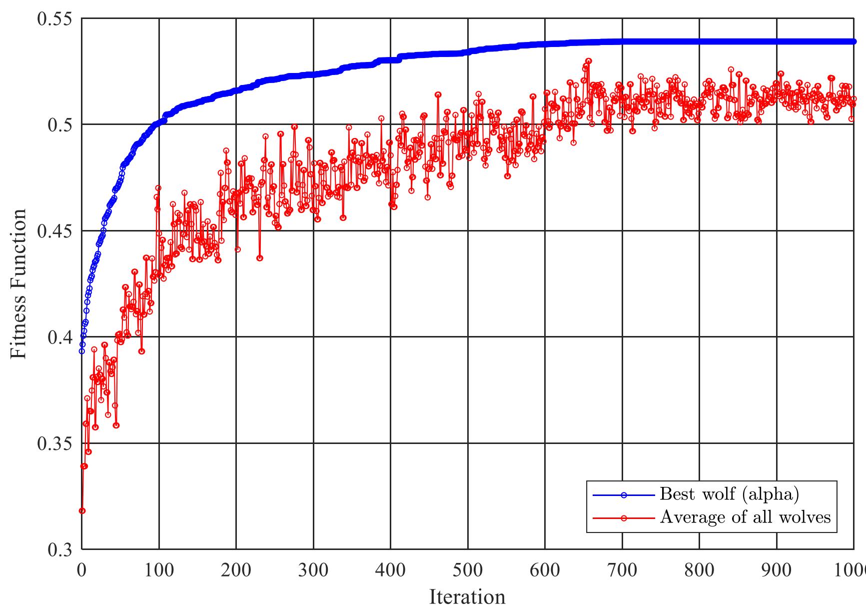

Fig. 9. Convergence of GWO for the TSFIS tuning in App. 1.

According to Table 4 and the left-side plot in Fig. 8, for any *PopSize*, the convergence speed is gradually decreased during the execution of the algorithm and finally fed into saturation. By comparing the runs with the same number of fitness evaluations (NFE), i.e., *MaxIter*×*PopSize*, we can find different results in small and large numbers of populations. The results show that with a small population size of 10 or 20, more iterations with the same NFE cannot lead to a better solution. For example, the GWO with *MaxIter*=1000 and *PopSize*=20 outperforms the GWO with *MaxIter*=2000 and *PopSize*=10. In contrast, in the case of higher population sizes, the higher number of iterations works a little bit better than a higher population size. It can be seen by comparing the GWO with *MaxIter*=1000 and *PopSize*=50 with that of with *MaxIter*=500 and *PopSize*=100.

From the time analysis in Table 5 and the right-side plot in Fig. 8, it can be seen that the number of iterations significantly extended the computation time, even more than a linear relationship. The main reason is that at the early iterations, the algorithm encounters random solutions leading to a small lifetime obtained by the TSFIS model. As mentioned above, to evaluate the fitness of each feasible solution (i.e., a grey wolf), the WBAN must be completely simulated using the corresponding TSFIS for $R_{\max}$ network simulation rounds. Therefore, the higher the quality of a solution, the more time is required for the fitness evaluation with a higher value of average alive nodes within $R_{\max}$. For a *PopSize* of 50, the time increases 31 folds with an increase in the number of iterations from 100 to 2000, which is 1.55 times higher than the increasing amount in the NFE. The situation is similar with other population sizes.

According to the obtained results, in many situations when *PopSize* was 50 or 100 with 1000 or 2000 iterations, the final fitness values are very close and almost similar. Even considering a *PopSize* of 50 with 500 iterations has a little bit smaller fitness. However, to ensure achieving the best fitness while the running time is also under consideration, we have set *PopSize* and *MaxIter* of GWO as 50 and 1000, respectively. These values are used for the remainder of the simulations in this paper. Although a JIT solution is of utmost importance for the online routing phase, we can accept more time for the offline tuning phase. It should be emphasized that the GWO-based tuning procedure with a huge running time of 6.7 h is performed as a training phase only once before applying the tuned TSFIS for a new WBAN application, and thus, it doesn't boost any delay during the online data transmission phase.

To capture the convergence of GWO, Fig. 9 provides the best and average fitness among all individuals versus iterations for App. 1. The

Table 6
Comparison of the different metaheuristic algorithms in terms of the fitness value (best, worst, mean, and STD%) and running time [h] for 10 successive runs in App. 1.

# Run	GA	PSO	ACO	AO	GWO
1	0.515	0.515	0.515	0.517	0.533
2	0.523	0.507	0.521	0.504	0.532
3	0.517	0.519	0.520	0.527	0.539
4	0.511	0.496	0.510	0.524	0.532
5	0.522	0.499	0.526	0.516	0.533
6	0.519	0.528	0.516	0.520	0.532
7	0.523	0.518	0.519	0.517	0.529
8	0.504	0.497	0.510	0.510	0.530
9	0.517	0.512	0.524	0.514	0.530
10	0.515	0.504	0.518	0.508	0.532
Best Fitness Value	0.523	0.528	0.526	0.527	0.539
Worst Fitness Value	0.504	0.496	0.510	0.504	0.529
Average Fitness Value	0.517	0.510	0.518	0.516	0.532
STD% of Fitness Values	1.13	2.11	1.04	1.41	0.51
Average Running Time [h]	6.8	6.6	7.1	6.8	6.7

blue points, depicting the global best solution, showcase an impressive initial surge in convergence through more emphasis on exploration within the first 100 iterations. As the algorithm progresses, a gradual shift in the convergence speed can be observed by transitioning from rapid optimization to more exploitation of the refined solutions. After around 500–600 iterations, a slowdown in convergence speed marks a pivotal moment, signifying the algorithm's maturation in search of the most optimal solution. Furthermore, the red points, representing average fitness, portray a gradual descent towards higher fitness values, revealing the collective performance of the algorithm.

To verify the effectiveness of the GWO algorithm in the fuzzy rule tuning of the TSFIS model, it is compared with GA (as the most common evolutionary algorithm), PSO (as a popular metaheuristic with continuous search space), ACO (as a popular metaheuristic with discrete search space), and Aquila Optimizer (OA) [64] (as a recent metaheuristic). Each algorithm was applied separately to tune the TSFIS protocol with the same circumstances. To ensure an equitable comparative analysis across diverse metaheuristic algorithms, all approaches underwent simulation with identical parameters to GWO (i.e., $PopSize$=50 and $MaxIter$=1000), maintaining uniformity in the NFE. However, due to variations in parameterization among different algorithms (GA, PSO, ACO, and AO), fine-tuning was achieved through iterative experimentation guided by the original papers. For GA, specific probabilities were refined, setting recombination, uniform crossover, and swap mutation at 10%, 60%, and 30%, respectively. For PSO, the inertia weight has been set to be decreased from 0.9 to 0.1 during the execution of the algorithm, while the attraction coefficients have been set as c_1=c_2=2. ACO has been set up by initial pheromones at 0.5 bounded within the [0,1] range for pheromone trials, while the evaporation and deposition factors stood at 5% and 0.2, respectively. Finally, as suggested in [64], the exploitation adjustment parameters of AO have been fixed to α=δ=0.1.

Due to the random nature of metaheuristics, each algorithm was applied to tune the TSFIS protocol in 10 runs. The results obtained by the different methods on 10 runs in App. 1 can be seen in Table 6, which shows that GWO outperforms the GA, PSO, ACO, and AO, by obtaining higher fitness (on average). Another point is that the GWO algorithm obtains less STD% over 10 runs, which demonstrates that it is more trustable than the other metaheuristics for every run. Moreover, the comparative analysis of the algorithms reveals strikingly similar running times, albeit with nuanced differences arising from the distinct operators employed within each algorithm. This uniformity mainly stems from the intrinsic time-intensive nature of the fitness evaluation part, eclipsing the unique operators within each algorithm. The convergence of the different algorithms under the same NFE exposure to the identical fitness function underscores their nearly running times.

Table 7
Obtained FND, HND, and LND in various applications.

Lifetime Definition	App.1	App.2	App.3
FND	2663	1855	1581
HND	3163	3253	3387
LND	3382	3999	4771

Table 8
The number of functioning nodes as the rounds progressed in various applications.

Round #	App.1	App.2	App.3
0	20	20	20
500	20	20	20
1000	20	20	20
1500	20	20	20
2000	20	19	19
2500	20	18	17
3000	18	16	15
3500	0	6	9
4000	0	0	2
4500	0	0	1
5000	0	0	0

Table 9
The number of delivered data packets as the rounds progressed in various applications.

Round #	App. 1	App. 2	App. 3
0	0	0	0
500	10,000	10,000	10,000
1000	20,000	20,000	20,000
1500	30,000	30,000	30,000
2000	40,000	39,854	39,580
2500	50,000	49,273	48,586
3000	59,621	57,543	56,759
3500	62,843	62,514	62,680
4000	62,843	64,104	65,519
4500	62,843	64,104	66,468
5000	62,843	64,104	66,738

Table 10
Obtained fitness functions in various applications.

Measure	App. 1	App. 2	App. 3
FND	**2663**	1855	1581
APL (dB)	61.5	**53.07**	70.44
APR (%)	80.45	78.81	**82.74**
Total fitness	0.539	0.374	0.572

5.3. Results of online routing

Once the Takagi-Sugeno fuzzy rules of TSFIS have been optimized for a new application using GWO, it can be utilized as a real-time routing protocol in that specific application. Table 7 provides the network lifetimes obtained by the TSFIS-GWO protocol for three WBAN applications in terms of different definitions of FND, HND, and LND. The round histories of alive nodes and the number of delivered data packets are summarized in Tables 8–9, respectively. Moreover, sub-fitness functions (FND, APL, and APR) and the total fitness function (Eq. 14) were obtained as provided in Table 10, where the best results among the different applications are shown in bold. The results in Table 10 demonstrated that the best FND, APL, and APR were achieved in applications 1, 2, and 3, respectively, highlighting the flexibility of the proposed approach in adapting to changes in the fitness function based on the application-specific requirements.

To acquire a better understanding of the results achieved across various applications as simulation rounds progressed, Figs. 10–13

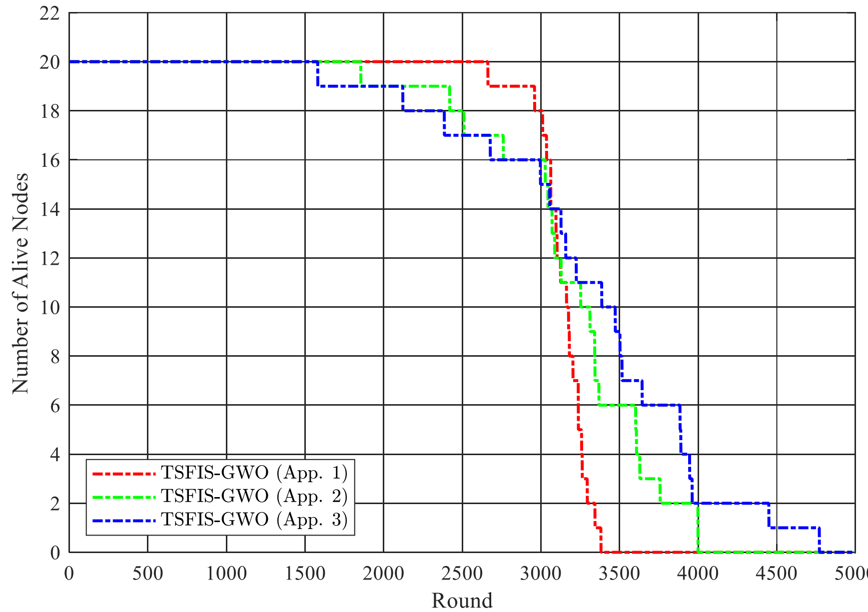

Fig. 10. The number of functioning sensor nodes in various applications.

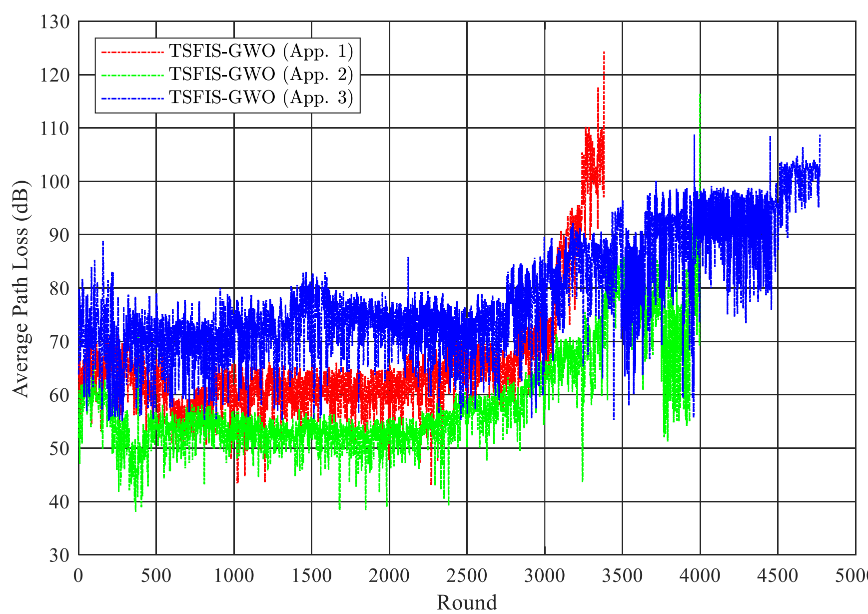

Fig. 11. The average path loss (dB) in various applications.

illustrate the history of the number of alive nodes, APL, APR, and hot-spot temperature, respectively. As mentioned above, the highest weight for the FND has been set in App. 1 with w_{FND}=0.8. As seen in Fig. 10, the highest FND has been obtained in App. 1, and then App. 2 obtains a little bit more FND against App.3. In terms of APL minimization, the three applications can be ordered from the least APL to the most APL as App. 2, App. 1, and App. 3 (see Fig. 11), considering the weight of APL as w_{APL}=0.5, w_{APL}=0.1, and w_{APL}=0, respectively. Moreover, as seen in Fig. 12, they can be ordered from the best to the worst as in App. 3, App. 1, and App. 2, in terms of the APR. The results show that the same orders as the impact weights have been achieved for each performance measure.

Based on the results obtained, it can be inferred that in App. 1, a prolonged stability period is achieved as the first node experiences delayed death, and the subsequent node deaths occur at a nearly constant rate until the last node's demise. Due to the superior performance of TSFIS-GWO in achieving FND in App. 1 relative to other applications, the amount of data received at the sink keeps increasing until FND is attained, but then it decreases sharply. Extending the FND in App. 1 results in more nodes being able to transmit their data to the sink over a greater number of rounds compared to the other applications. However, if a better trade-off between the network lifetime and APL/APR is required, more weight should be given to APL/APR, which is achieved in Apps. 2 or 3.

5.4. Evaluating against existing methods

To demonstrate the effectiveness of the TSFIS-GWO protocol, it was pitted against three other routing protocols in WBANs: a classical heuristic method (ERRS) [7], a fuzzy heuristic method (FRNS-ER) [30] and a metaheuristic-based protocol (ACSA) [38]. The network lifetimes of FND, HND, and LND, obtained by different routing protocols are

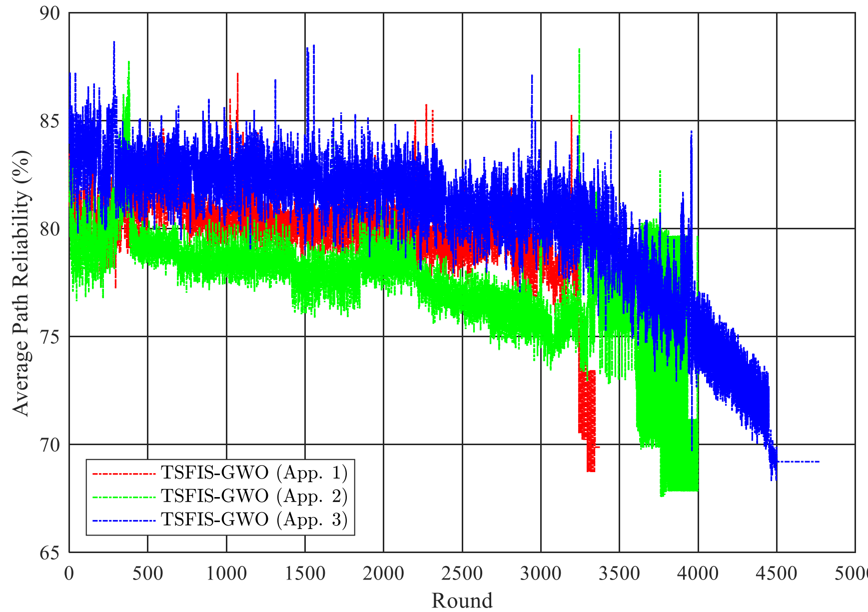

Fig. 12. The average path reliability (%) in various applications.

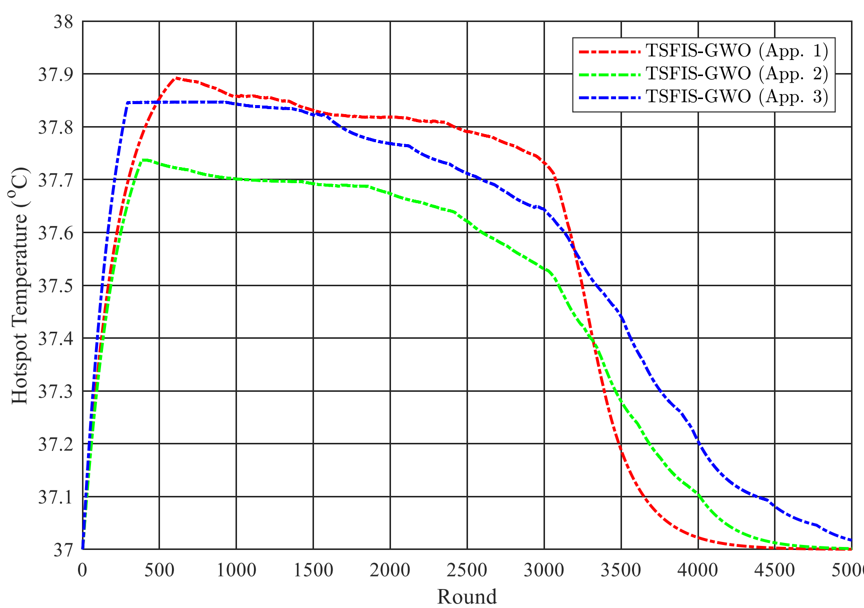

Fig. 13. The hotspot temperature in various applications.

Table 11
Obtained FND, HND, and LND by the different routing protocols.

Lifetime	ERRS [7]	FRNS-ER [30]	ACSA [38]	TSFIS-GWO		
				App.1	App.2	App.3
FND	528	1139	1658	2663	1855	1581
HND	2610	2384	3197	3163	3253	3387
LND	3199	3323	4335	3382	3999	4771

summarized in Table 11. Based on the results for App. 1, the TSFIS-GWO protocol demonstrated significantly better FND performance compared to three other routing protocols. By considering FND as the most significant factor within the fitness function of the GWO to tune the TSFIS model for App. 1, the TSFIS-GWO protocol obtains more stability period as the first node dies later than App. 2, App. 3, and other techniques. Specifically, the gain of TSFIS-GWO in FND is 404% higher than ERRS, 133% higher than FRNS-ER, and 60.6% higher than ACSA. Consider less weight for FND in TSFIS-GWO for Apps. 2 and 3, this gain for App. 2 has been reduced to 251%, 62.8%, and 11.9%, and for App. 3–199%, 38.8% and −4.6%, compared to ERRS, FRNS-ER, and ACSA, respectively. To illustrate the flexibility of the TSFIS-GWO protocol, Figs. 14–16 statistically qualify the different methods in terms of the number of alive nodes, APL and APR, respectively. These statistics indicate that the

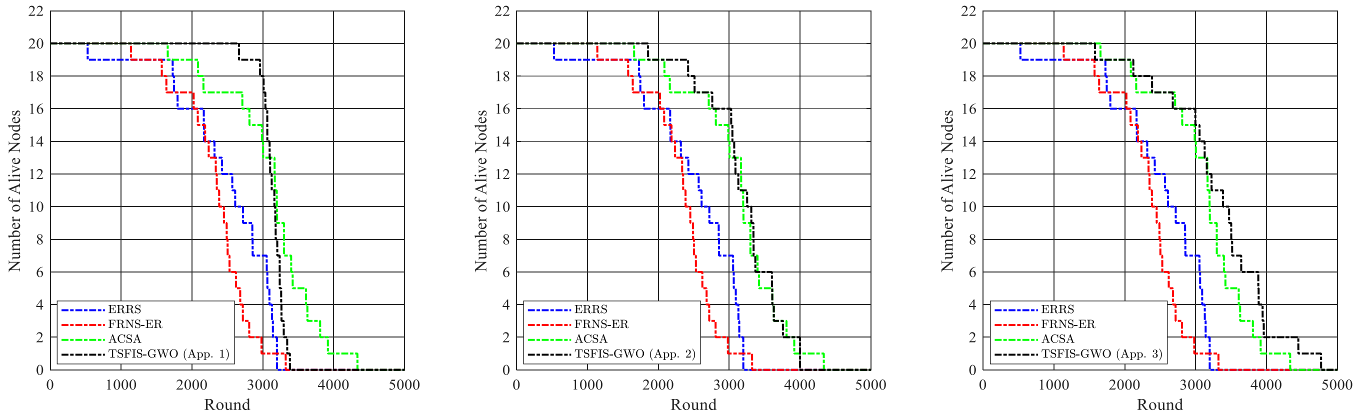

Fig. 14. Comparison of the number of functioning nodes obtained by different routing protocols.

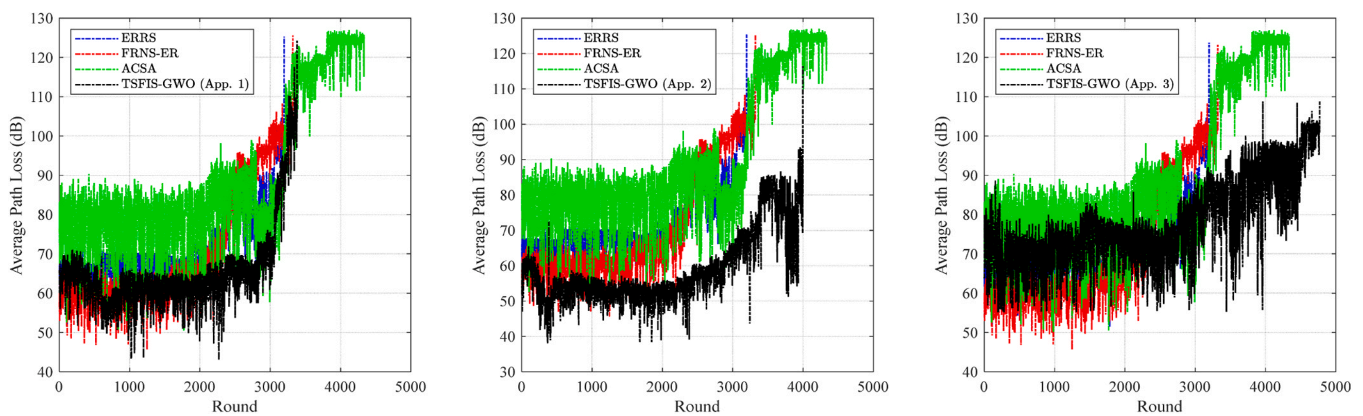

Fig. 15. Comparison of average path loss (dB) obtained by different routing protocols.

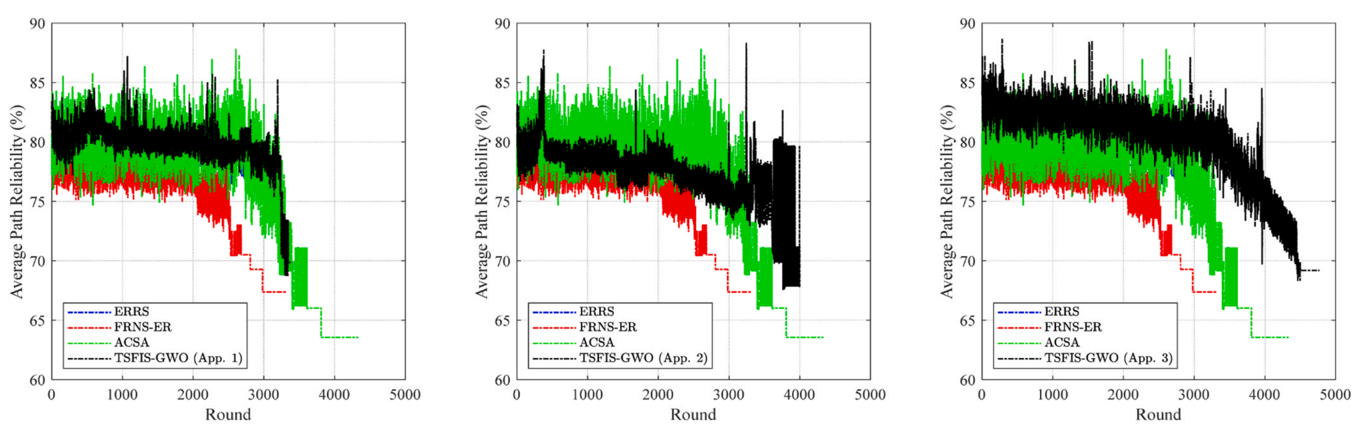

Fig. 16. Comparison of average path reliability (%) obtained by different routing protocols.

TSFIS protocol outperforms the other compared protocols on average for all three applications, as it has achieved the best overall results.

A comparison of the different objective measures can be seen in Table 12. The results demonstrated that the maximum gain of TSFIS-GWO in FND, APL, and APR, is in Apps. 1, 2, and 3, respectively. Although in some cases, TSFIS-GWO has worse FND, APL, or APR than the compared methods, it outperforms all existing methods in all applications in terms of the total fitness. For example, ACSA has better FND and worse reliability than TSFIS-GWO in App. 3, which results that the total fitness of TSFIS-GWO being a little bit more than that of ACSA. It clearly demonstrates the adaptability of TSFIS-GWO with the desired measures in each WBAN application, which can be re-tuned based on the specific requirements of the application.

To aggregate the obtained results, the total fitness obtained by the different techniques in different applications can be summarized in Table 13. Furthermore, the improvement rate of the total fitness value obtained by TSFIS-GWO in each application compared to other protocols is given. As we have reported in Table 12, the compared methods have obtained better results in some cases (e.g., APL of FRNS-ER in App. 1, APR of ACSA in App. 2, and FND of ACSA in App. 3). Obviously, there is a trade-off between the different objectives, i.e., FND, APL, and APR. However, the TSFIS-GWO protocol outperforms all existing methods in all applications in terms of the total application-specific fitness value. Based on the improvement rates in Table 13, the gain of TSFIS-GWO in

Table 12
Comparison of performance measures obtained by different routing protocols.

Application	Measure	ERRS [7]	FRNS-ER [30]	ACSA [38]	TSFIS-GWO
App. 1	FND	528	1139	1658	2663
	APL (dB)	64.4	59.43	76.82	61.5
	APR (%)	78.3	77.56	80.16	80.45
	Total Fitness	0.193	0.294	0.372	0.539
App. 2	FND	528	1139	1658	1855
	APL (dB)	64.4	59.43	76.82	53.07
	APR (%)	78.3	77.56	80.16	78.81
	Total Fitness	0.208	0.283	0.296	0.374
App. 3	FND	528	1139	1658	1581
	APL (dB)	64.4	59.43	76.82	70.45
	APR (%)	78.3	77.56	80.16	82.74
	Total Fitness	0.444	0.502	0.567	0.572

the total fitness value (on average for all applications) is 67.3%, 32.6%, and 20.3%, as compared to ERRS, FRNS-ER, and ACSA, respectively. It clearly illustrates the tunability of the TSFIS-GWO protocol with the specific objectives in each application.

5.5. Discussion

In Section 5, we have justified the effectiveness of the proposed TSFIS-GWO protocol against the existing techniques in terms of the different performance metrics. To compare the different techniques from the time analysis point of view, the total time required for the offline tuning and online routing phases is provided in Table 14. The online routing time (response time) of each routing protocol has been computed as the mean duration from the moment routing requests are received to the generation of the routing solution by the routing protocol. It should be emphasized that the existing classical/fuzzy heuristic and metaheuristic approaches don't have any tuning step, and consequently, they do have not an offline tuning time. Although the proposed metaheuristic-driven TSFIS protocol consumes an extra time of around 7 hours to tune the TSFIS model, this phase is done in an offline step once before applying the tuned TSFIS model for a new WBAN. Therefore, the time-consuming offline procedure not only does not boost any delay during the data transmission phase but also enables the TSFIS protocol with tunability and adaptability with the application-specific objectives. Besides, the results show that the online routing time of the proposed protocol is within the range of other classical/fuzzy heuristics (ERRS and FRNS-ER), which guarantees to provide JIT solutions in real-time applications. Although ACSA has obtained better results in some sub-objectives (such as the best APR in App. 2 and the best FND in App. 3), it is not tunable, and more importantly, suffers from the need for applying a time-consuming metaheuristic directly during the online routing phase.

As previously mentioned, ERRS is a classical heuristic that employs two methods for CH selection and rotation to prolong the network lifetime and enhance communication reliability. On the other hand, FRNS-ER is a fuzzy heuristic that selects relay nodes using a FIS to establish energy-efficient and reliable routes. Additionally, ACSA is a metaheuristic-based routing protocol that determines data routing and relay node placement in WBANs. Since FRNS-ER utilizes a FIS for route construction instead of a crisp function like ERRS, it has outperformed ERRS in almost all scenarios, except for slightly inferior performance in terms of reliability. Furthermore, as demonstrated by the simulation results, the metaheuristic-based ACSA protocol exhibits superior performance in terms of FND and APR compared to the two heuristic-based techniques. However, due to the absence of a path loss-related strategy, the APL of ACSA is inferior to all other techniques. The outcomes demonstrate that the proposed TSFIS-GWO protocol outperforms all compared techniques in terms of achieving superior performance based on the application-specific metrics. Specifically, it possesses the advantages of adaptability and flexibility in dealing with new scenarios and changing circumstances.

In summary, the proposed TSFIS-GWO model offers several advantages that stem from the combination of fuzzy heuristics and metaheuristics, which are outlined below:

- Real-time responsiveness (low response time) of the routing protocol, due to applying a heuristic-based model (i.e., TSFIS) for online routing.
- High solution quality, due to optimizing the routing protocol using the GWO metaheuristic algorithm.
- Flexibility with multi-criteria fuzzy inputs.
- Uncertainty handling and robustness to dynamic changes, which allows the model to adapt to changes in the network environment and continue to provide rapid routing solutions.
- Multi-objective optimization by converting the multiple objectives into a weighted averaging formula, which enables the system to simultaneously optimize different objectives.
- Adaptability to the application-specific requirements, as the TSFIS protocol can be re-optimized using GWO to suit the characteristics of a new WBAN.
- Tunability with new scenarios, as an application-specific fitness function can be determined by the decision maker to meet specific requirements of the application.

However, the proposed model encounters high complexity during the offline phase, which needs substantial computational resources and time for fine-tuning the routing protocol prior to its deployment in a new WBAN. As previously mentioned, the proposed routing protocol based

Table 13
Comparison of the total fitness and improvement rate (%) of TSFIS-GWO against the existing methods.

Application	Total Fitness Value				Improvement % of TSFIS-GWO against:		
	ERRS [7]	FRNS-ER [30]	ACSA [38]	TSFIS-GWO	ERRS [7]	FRNS-ER [30]	ACSA [38]
App. 1	0.193	0.294	0.372	0.539	179	83.3	44.9
App. 2	0.208	0.283	0.293	0.374	79.8	32.2	27.6
App. 3	0.444	0.502	0.567	0.572	28.8	13.9	0.9

Table 14
Comparison of the running time for offline tuning [h] and online routing [s], on average in different applications.

Phase	Classical Heuristic	Fuzzy Heuristic	Metaheuristic	Metaheuristic-Driven TSFIS (Proposed)				
	ERRS [7]	FRNS-ER [30]	ACSA [38]	GA	PSO	ACO	AO	GWO
Offline Tuning [h]	N/A	N/A	N/A	7.1	6.7	7.3	7	6.9
Online Routing [s]	0.13	0.21	34	0.18	0.18	0.18	0.18	0.18

on the TSFIS model requires an offline optimization procedure, conducted once before programming into the processor unit of the sink node for a new WBAN scenario. Consequently, a limitation of the proposed methodology arises when confronted with real-world applications wherein network structures may undergo alterations after several rounds of network operation. In such scenarios, the TSFIS model cannot be re-fined during its ongoing operation within the same network. Although the tuned TSFIS model demonstrates adaptability to minor changes (e.g., node failures or deaths), significant alterations can diminish the performance of the pre-tuned model.Top of Form

6. Conclusion

This study has presented a learning model utilizing Takagi-Sugeno fuzzy inference system and grey wolf optimizer, namely TSFIS-GWO, as an adaptive real-time routing protocol for WBANs. The TSFIS-GWO protocol is a hybrid technique based on a heuristic-based online routing and a metaheuristic-based offline tuning. The simulations over three WBANs have shown that the TSFIS-GWO protocol outperforms the existing heuristics and metaheuristics in terms of stability period, reliability, and path loss. Although the tuning procedure requires extra running time to perform GWO, it is performed in an offline scheme once before the protocol is applied for online applications, and thus, it does not boost any computational complexity and overhead within the online routing. Overall, the proposed method has the advantages of real-time responsiveness, high performance, flexibility, uncertainty handling, and adaptability with the application-specific measures defined by the decision-maker.

Despite the advantages of the proposed method, it still possesses certain limitations that could be addressed and enhanced in future research endeavors. As a future research direction, some missing criteria such as temperature and other QoS measures can be added as extra inputs to the fuzzy model. The proposed approach has been presented for data routing within a single WBAN (intra-WBAN routing), typically comprising only a few nodes. An intriguing avenue for future research lies in extending the proposed approach to larger-scale networks that encompass multiple WBANs, thereby incorporating both intra- and inter-WBAN routing problems. As another future work, newer metaheuristics such as Red Fox Optimization (RFO) [65], Artificial Hummingbird Algorithm (AHA) [66], Prairie Dog Optimization (PDO) [67], and Fire Hawk Optimizer (FHO) [68], could be applied and evaluated to optimize the TSFIS model. Another limitation of the proposed routing protocol is its reliance on an offline tuning phase when introduced to new WBAN scenarios, rendering it unable to autonomously adjust to changes in the network structure during the online phase. An appealing solution to overcome this limitation is to integrate reinforcement learning, which can enable the routing protocol with adaptability and real-time responsiveness, while eliminating the need for time-consuming offline tuning phase for new scenarios.

CRediT authorship contribution statement

Mohammad Shokouhifar: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Pouya Aryai:** Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Navid Behmanesh-Fard:** Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Saeideh Memarian:** Writing – original draft, Software, Methodology, Investigation, Conceptualization. **MCarmen Romero-Ternero:** Writing – review & editing, Validation, Supervision, Project administration. **Seyedali Mirjalili:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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References

[1] K.P. Rani, P. Sreedevi, E. Poornima, T.S. Sri, FTOR-Mod PSO: A fault tolerance and an optimal relay node selection algorithm for wireless sensor networks using modified PSO, Knowl. -Based Syst. (2023) 110583.
[2] S. Esmaeili, R. Shamsi, A lightweight and secure sensing model for body area networks in the Internet of Things in biological warfare applications, Internet Things 22 (2023) 100717.
[3] M. Cicioğlu, A. Çalhan, Energy-efficient and SDN-enabled routing algorithm for wireless body area networks, Comput. Commun. 160 (2020) 228–239.
[4] P. Aryai, A. Khademzadeh, S. Jafarali Jassbi, M. Hosseinzadeh, SIMOF: swarm intelligence multi-objective fuzzy thermal-aware routing protocol for WBANs, J. Supercomput. (2023) 1–36.
[5] S.R. Chavva, R.S. Sangam, An energy-efficient multi-hop routing protocol for health monitoring in wireless body area networks, Netw. Model. Anal. Health Inform. Bioinforma. 8 (1) (2019) 1–10.
[6] K. Hasan, M.J.M. Chowdhury, K. Biswas, K. Ahmed, M.S. Islam, M. Usman, A blockchain-based secure data-sharing framework for Software Defined Wireless Body Area Networks, Comput. Netw. 211 (2022) 109004.
[7] F. Ullah, M.Z. Khan, M. Faisal, H.U. Rehman, S. Abbas, F.S. Mubarek, An energy efficient and reliable routing scheme to enhance the stability period in wireless body area networks, Comput. Commun. 165 (2021) 20–32.
[8] T. Hai, J. Zhou, M. Masdari, H.A. Marhoon, A hybrid marine predator algorithm for thermal-aware routing scheme in wireless body area networks, J. Bionic Eng. *20* (1) (2023) 81–104.
[9] I. Ha, Even energy consumption and backside routing: an improved routing protocol for effective data transmission in wireless body area networks, Int. J. Distrib. Sens. Netw. 12 (7) (2016), 1550147716657932.
[10] M. Shokouhifar, A. Jalali, A new evolutionary based application specific routing protocol for clustered wireless sensor networks, AEU-Int. J. Electron. Commun. 69 (1) (2015) 432–441.
[11] D. Lu, S. Li, Q. Yang, H.M. Arafa, Y. Xu, Y. Yan, J.A. Rogers, Implantable, wireless, self-fixing thermal sensors for continuous measurements of microvascular blood flow in flaps and organ grafts, Biosens. Bioelectron. 206 (2022) 114145.
[12] V.M. Birari, J.B. Helonde, V.M. Wadhai, Algorithmic approach for reliable communication in wireless body area network for patient monitoring system, Int. J. Eng. Econ. Manag. 2 (3) (2014) 5.
[13] M. Shokouhifar, A. Jalali, Optimized sugeno fuzzy clustering algorithm for wireless sensor networks, Eng. Appl. Artif. Intell. 60 (2017) 16–25.
[14] P. Bedi, S. Das, S.B. Goyal, P.K. Shukla, S. Mirjalili, M. Kumar, A novel routing protocol based on grey wolf optimization and Q learning for wireless body area network, Expert Syst. Appl. 210 (2022) 118477.
[15] F. Saleem, M.N. Majeed, J. Iqbal, A. Waheed, A. Rauf, M. Zareei, E.M. Mohamed, Ant lion optimizer based clustering algorithm for wireless body area networks in livestock industry, IEEE Access 9 (2021) 114495–114513.
[16] H. Esmaeili, B.M. Bidgoli, EMRP: Evolutionary-based multi-hop routing protocol for wireless body area networks, AEU-Int. J. Electron. Commun. 93 (2018) 63–74.
[17] Q. Tang, N. Tummala, S.K. Gupta, L. Schwiebert, Communication scheduling to minimize thermal effects of implanted biosensor networks in homogeneous tissue, IEEE Trans. Biomed. Eng. 52 (7) (2005) 1285–1294.
[18] N. Javaid, Z. Abbas, M.S. Fareed, Z.A. Khan, N. Alrajeh, M-ATTEMPT: A new energy-efficient routing protocol for wireless body area sensor networks, Procedia Comput. Sci. 19 (2013) 224–231.
[19] Watteyne, T., Augé-Blum, I., Dohler, M., & Barthel, D. (2007, June). AnyBody: a self-organization protocol for body area networks. In BODYNETS (p. 6).
[20] Q. Nadeem, N. Javaid, S.N. Mohammad, M.Y. Khan, S. Sarfraz, M. Gull, Simple: Stable increased-throughput multi-hop protocol for link efficiency in wireless body area networks (October). 2013 eighth international conference on broadband and wireless computing, communication and applications, IEEE, 2013, pp. 221–226 (October).
[21] Umer, T., Amjad, M., Afzal, M.K., & Aslam, M. (2016, July). Hybrid rapid response routing approach for delay-sensitive data in hospital body area sensor network. In

Proceedings of the 7th international conference on computing communication and networking technologies (pp. 1-7).
[22] G. Mehmood, M.Z. Khan, S. Abbas, M. Faisal, H.U. Rahman, An energy-efficient and cooperative fault-tolerant communication approach for wireless body area network, IEEE Access 8 (2020) 69134–69147.
[23] M.A. Kumar, C.V. Raj, On designing lightweight qos routing protocol for delay-sensitive wireless body area networks (September), ICACCI (2017) 740–744.
[24] M.M. Kamruzzaman, O. Alruwaili, Energy efficient sustainable Wireless Body Area Network design using network optimization with Smart Grid and Renewable Energy Systems, Energy Rep. 8 (2022) 3780–3788.
[25] Y.M. Chen, Y. Peng, Energy efficient fuzzy routing protocol in wireless body area networks, Int. J. Eng. 4 (1) (2013) 8269.
[26] K. Singh, R.K. Singh, An energy efficient fuzzy based adaptive routing protocol for wireless body area network (December). 2015 IEEE UP Section Conference on Electrical Computer and Electronics (UPCON), IEEE, 2015, pp. 1–6 (December).
[27] M. Abdollahzadeh Aghbolagh, M.A. Pourmina, Fuzzy clustering based routing in wireless body area networks to increase the life of sensor nodes, J. Adv. Comput. Eng. Technol. 4 (3) (2018) 155–166.
[28] S.R. Chavva, R.S. Sangam, An energy-efficient multi-hop routing protocol for health monitoring in wireless body area networks, Netw. Model. Anal. Health Inform. Bioinforma. 8 (1) (2019) 1–10.
[29] X. Wang, G. Zheng, H. Ma, W. Bai, H. Wu, B. Ji, Fuzzy control-based energy-aware routing protocol for wireless body area networks, J. Sens. (2021) 2021.
[30] B. Shunmugapriya, B. Paramasivan, Fuzzy based relay node selection for achieving efficient energy and reliability in wireless body area network, Wirel. Pers. Commun. 122 (3) (2022) 2723–2743.
[31] N. Kaur, S. Singh, Optimized cost effective and energy efficient routing protocol for wireless body area networks, Ad Hoc Netw. 61 (2017) 65–84.
[32] G. Xu, M. Wang, An energy-efficient routing mechanism based on genetic ant colony algorithm for wireless body area networks, J. Netw. 9 (12) (2014) 3366.
[33] O. Ahmed, F. Ren, A. Hawbani, Y. Al-Sharabi, Energy optimized congestion control-based temperature aware routing algorithm for software defined wireless body area networks, IEEE Access 8 (2020) 41085–41099.
[34] M.M. Dhanvijay, S.C. Patil, Energy aware MAC protocol with mobility management in wireless body area network, Peer-to-Peer Netw. Appl. (2021) 1–18.
[35] N. Bilandi, H.K. Verma, R. Dhir, PSOBAN: a novel particle swarm optimization based protocol for wireless body area networks, SN Appl. Sci. 1 (11) (2019) 1–14.
[36] S. Sharma, QRP: QPSO Based Routing Protocol for Energy Efficiency in Wireless Body Area Networks. International Conference on Computing Science, Communication and Security, Springer, Cham, 2021, February, pp. 205–221.
[37] K. Karunanithy, B. Velusamy, Edge device based efficient data collection in smart health monitoring system using wireless body area network, Biomed. Signal Process. Control 72 (2022) 103280.
[38] T.K. Samal, S.C. Patra, M.R. Kabat, An adaptive cuckoo search based algorithm for placement of relay nodes in wireless body area networks, J. King Saud. Univ. -Comput. Inf. Sci. 34 (5) (2022) 1845–1856.
[39] V.C. Madanda, F. Sengani, F. Mulenga, Applications of Fuzzy Theory-Based Approaches in Tunnelling Geomechanics: a State-of-the-Art Review, Min., Metall. Explor. (2023) 1–19.
[40] S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey wolf optimizer, Adv. Eng. Softw. 69 (2014) 46–61.
[41] M.M. Sandhu, N. Javaid, M. Akbar, F. Najeeb, U. Qasim, Z.A. Khan, FEEL: Forwarding data energy efficiently with load balancing in wireless body area networks (May). 2014 IEEE 28th international conference on advanced information networking and applications, IEEE, 2014, pp. 783–789 (May).
[42] B. Jan, H. Farman, H. Javed, B. Montrucchio, M. Khan, S. Ali, Energy efficient hierarchical clustering approaches in wireless sensor networks: A survey, Wirel. Commun. Mob. Comput. (2017) 2017.
[43] M. Żotkiewicz, M. Pióro, Exact approach to reliability of wireless mesh networks with directional antennas, Telecommun. Syst. *56* (1) (2014) 201–211.
[44] R. Cerulli, R. De Donato, A. Raiconi, Exact and heuristic methods to maximize network lifetime in wireless sensor networks with adjustable sensing ranges, Eur. J. Oper. Res. *220* (1) (2012) 58–66.
[45] M. Sohrabi, M. Zandieh, M. Shokouhifar, Sustainable inventory management in blood banks considering health equity using a combined metaheuristic-based robust fuzzy stochastic programming, Socio-Econ. Plan. Sci. 86 (2023) 101462.
[46] X. Chen, H.F. Yan, Y.J. Zheng, M. Karatas, Integration of machine learning prediction and heuristic optimization for mask delivery in COVID-19, Swarm Evolut. Comput. *76* (2023) 101208.
[47] H. Esmaeili, V. Hakami, B.M. Bidgoli, M. Shokouhifar, Application-specific clustering in wireless sensor networks using combined fuzzy firefly algorithm and random forest, Expert Syst. Appl. 210 (2022) 118365.
[48] U. Kilic, E.S. Essiz, M.K. Keles, Binary anarchic society optimization for feature selection, Sci. Technol. *26* (3-4) (2023) 351–364.
[49] A. Shokouhifar, M. Shokouhifar, M. Sabbaghian, H. Soltanian-Zadeh, Swarm intelligence empowered three-stage ensemble deep learning for arm volume measurement in patients with lymphedema, Biomed. Signal Process. Control *85* (2023) 105027.
[50] M. Shokouhifar, FH-ACO: Fuzzy heuristic-based ant colony optimization for joint virtual network function placement and routing, Appl. Soft Comput. 107 (2021) 107401.
[51] W. Jiang, Z. Wang, M. Feng, T. Miao, A survey of thermal-aware routing protocols in wireless body area networks (July), in: 2017 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC), Vol. 2, IEEE, 2017, pp. 17–21 (July).
[52] P. Aryai, A. Khademzadeh, S.J. Jassbi, M. Hosseinzadeh, O. Hashemzadeh, M. Shokouhifar, Real-time health monitoring in WBANs using hybrid Metaheuristic-Driven Machine Learning Routing Protocol (MDML-RP), AEU-Int. J. Electron. Commun. *168* (2023) 154723.
[53] W.B. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Trans. Wirel. Commun. (2002) 660–670.
[54] D.K. Rout, D. Das, S. Das, Channel models for inter-body communication in ultra wideband-based body area networks, Wirel. Pers. Commun. *125* (3) (2022) 2819–2832.
[55] Zhang, Y., Shao, Y., Luo, R., Xiong, L., & Zhang, J. (2023). Multiple Human Activities Classification Based on Dynamic On-Body Propagation Characteristics Using Transfer Learning. *IEEE Internet of Things Journal.*
[56] M.A. Raayatpanah, A.A. Abyaneh, J. Elias, A. Trotta, Optimal reliable design of energy-efficient Wireless Body Area Networks, Internet Things 22 (2023) 100727.
[57] E.H. Mamdani, S. Assilian, An experiment in linguistic synthesis with a fuzzy logic controller, Int. J. Man-Mach. Stud. 7 (1) (1975) 1–13.
[58] T. Takagi, M. Sugeno, Fuzzy identification of systems and its applications to modeling and control, IEEE Trans. Syst., Man, Cybern. 1 (1985) 116–132.
[59] H. Ouifak, A. Idri, On the performance and interpretability of Mamdani and Takagi-Sugeno-Kang based neuro-fuzzy systems for medical diagnosis, Sci. Afr. *20* (2023) e01610.
[60] C.A. Bojan-Dragos, R.E. Precup, S. Preitl, R.C. Roman, E.L. Hedrea, A.I. Szedlak-Stinean, GWO-based optimal tuning of type-1 and type-2 fuzzy controllers for electromagnetic actuated clutch systems, IFAC-Pap. *54* (4) (2021) 189–194.
[61] D.R. Chen, A real-time streaming control for quality-of-service coexisting wireless body area networks, Appl. Soft Comput. *68* (2018) 719–732.
[62] M.H. Nasir, S.A. Khan, M.M. Khan, M. Fatima, Swarm intelligence inspired intrusion detection systems-a systematic literature review, Comput. Netw. 205 (14) (2022) 108708.
[63] D. Połap, Neuro-heuristic analysis of surveillance video in a centralized IoT system, ISA Trans. *140* (2023) 402–411.
[64] L. Abualigah, D. Yousri, M. Abd Elaziz, A.A. Ewees, M.A. Al-Qaness, A.H. Gandomi, Aquila optimizer: a novel meta-heuristic optimization algorithm, Comput. Ind. Eng. *157* (2021) 107250.
[65] D. Połap, M. Woźniak, Red fox optimization algorithm, Expert Syst. Appl. *166* (2021) 114107.
[66] W. Zhao, L. Wang, S. Mirjalili, Artificial hummingbird algorithm: A new bio-inspired optimizer with its engineering applications, Comput. Methods Appl. Mech. Eng. *388* (2022) 114194.
[67] A.E. Ezugwu, J.O. Agushaka, L. Abualigah, S. Mirjalili, A.H. Gandomi, Prairie dog optimization algorithm, Neural Comput. Appl. *34* (22) (2022) 20017–20065.
[68] M. Azizi, S. Talatahari, A.H. Gandomi, Fire Hawk Optimizer: A novel metaheuristic algorithm, Artif. Intell. Rev. *56* (1) (2023) 287–363.