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Hybrid FGWO Based FLCs Modeling for Performance Enhancement in Wireless Body Area Networks

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Abstract The progression over wireless technologies paves the way for the emergence of wireless body area networks (WBAN) towards several motivating applications. Specifically, in terms of health concern applications, both the performance and reliability is regarded as the essential elements of WBANs. Many of the soft computational methodologies employed the manual modeling of fuzzy logic controllers (FLCs) by evolutionary algorithms in WBAN. This existing model encodes the entire control parameters of "FLCs" membership functions. This leads to the degradation of network performance by maximizing the latency. In order to rectify this issue, here we propose a hybrid firefly grey wolf optimizer (hybrid FGWO) approach for the optimal modeling of "FLC". The major goal behind our proposed work relays on the optimal selection of control parameters from the "FLCs" with hybrid FGWO. The modeling of "FLCs" is carried out with CLFB (cross-layer fuzzy logic dependent back-off controller) mechanism to control the frequent access of channels. The efficiency of the "FLCs" model is enhanced by utilizing the coding technique known as unrestricted coding scheme. The performance of our hybrid FGWO approach is contrasted with three conventional "EAs". Two major modeling goals are established whereas, the initial goal aims for the modeling of "FLCs" on particular configuration of network and the second goal aims on the modeling of "FLCs" over multiple network configurations. The "FLCs" modeled by means of our proposed hybrid FGWO approach exhibits its performance in terms of throughput, latency and packet delivery ratio with some of the challenging algorithms.

Keywords Fuzzy logic controllers · CLFB · Wireless body area networks · Hybrid FGWO · Evolutionary algorithms · URCS

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1 Introduction

A wireless body area network (WBAN) specifically includes of the highly efficient as well as the sensor nodes with minimized power that can function closer to the human body in a wireless manner [1]. The WBANS can be placed on the human body or it can be implanted in order to detect the health status of human being's by means of distinctive signals. The examples of such bio signals are EEG (Electroencephalography), HR (Heart Rate), BP (Blood Pressure) etc. The basic function of WBAN is to make the patient relieved from the pressure just by eliminating the wires, which makes a great threat to the people. The function of WBAN begins by gathering the essential information from the sensor nodes and transmitting it to the exterior medicinal health framework by means of a particular node referred to as coordinator. The coordinator is termed as a highly significant gadget similar to the 'smart phone'.

The widely utilized standard over WBAN is IEEE 802.15.4 and this standard is particularly built towards the most significant devices. In order to ignore the collision occurrence in MAC (Medium Access Control) sub-layer it is being specified by the standard IEEE 802.15.4. The collision occurrence normally generates at the time the data packets are transmitted simultaneously by means of sensor nodes with the aid of channel assessment. The performances of IEEE 802.15.4 were determined by the previous authors and they stated that this standard faces the limitations of network reliability. Consequently, the reliability is estimated through P_{dr} (Packet delivery ratio) and the performance is estimated by means of throughput [2–4].

In order to deal with the above described drawbacks, more literal works [4–7] are being advanced prior for the enhancement of performance as well as reliability that corresponds to the standard IEEE 802.15.4. Moreover to the investigation, "FLCs" have been admitted to make use of the information about cross layer for the accurate channel scheduling approach. Consequently, "FLCs" efficient modeling turns to be important in the achievement of highly significant performance and reliability that corresponds to WBANs. Presently, the enhanced versions of WBANS performance completely depend on the man-made applications to model "FLCs" in error prone manner [3, 8, 9]. For this reason, we studied the benefits behind the automatic techniques to generate the organized modeling of "FLCs" against WBANs.

In addition to the above delineated drawbacks, our proposed hybrid FGWO have the benefits of translucent equilibrium, yet they possess the ability to function with distinctive sorts of fuzzy rules in the automatic modeling of "FLCs" [10]. Thus to generate effective "FLCs" model by hybrid FGWO, we make use of three technical issues. For the generation of efficient "FLCs" model, we, in turn, carried out the experimentation with the "URCS" coding technique utilizing multiple constraint degrees. Our experimental analysis ensures that the coding technique with minimized constraints can enhance the WBANs performance. The next subsequent issue aims for the modeling of fitness function in order to regulate the procedures of evolutionary computation in more convenient manner. The major concern behind our work is to enhance P_{dr} (Packet delivery ratio) it means reliability, latency and the throughput performance. Throughout this work, it is well known that the throughput can be attained just by the enhancement of P_{dr}. But by the enhancement of P_{dr} spontaneously it maximizes the latency in the transmission of packets. The main perspective is to follow the P_{dr} as the major concern and the latency as one of the restriction.

Related to our research, if it experiences latency in the transmission of packets based on the "FLCs" candidates, yet it is better as similar to the standard IEEE 802.15.4, then we focused on the enhancement of P_{dr} by the fitness function. Alternatively, if it experiences corrosion over the latency contrasted to the IEEE 802.15.4, here the penalization is carried out for the fitness function, thus to maintain better equilibrium among latency and P_{dr}. The third concern is to focus on distinctive modeling goals of "FLC" over WBAN. In this work, two basic modeling goals are defined. The initial goal is the optimal modeling of "FLCs" in order to maintain the performance and reliability in terms of particular network setting against WBAN. The next subsequent goal is the optimal modeling of "FLCs" in terms of various network configurations.

The short contributions behind this work are organized as follows:

- Here we present a hybrid FGWO approach for the optimal modeling of "FLC" with optimal control parameters selection.
- Fitness function influences are keenly investigated for the strong maintenance of equilibrium among performance and reliability of networks.
- The experimental validation is carried out with distinctive two goals, which aims for the optimal modeling of "FLC with specific and multiple configurations of network.
- The efficiency of the proposed hybrid FGWO approach utilizing "URCS" coding technique is evaluated with three conventional "Evolutionary Algorithms" namely (firefly, GWO and PSO). From the analysis it is inferred that our proposed hybrid FGWO algorithm shows better performance than the other three conventional "EAs".
- The performance analysis is also carried out with several challenging algorithms such as *IEEE 802.15.4,* D^2*MAC, ACS, and NB-Step* stated in [7] and from the experimental outcome it is possible to identify that our proposed hybrid FGWO approach exhibits better performance in terms throughput, collision, latency and P_{dr} (packet delivery ratio).

The residual part of this paper is structured as follows: Sect. 2 provides the review of the literal works. The zone 3 provides the background study of the algorithms. The advantageous behind "FLCs" modeling are portrayed in zone 4. Section 5 describes the proposed hybrid FGWO dependent "FLCs" modeling against WBANs. Results behind this work are analyzed in zone 6. This paper gets completed up with zone 7.

2 Review of Related Works

Various standards were proposed for the WBANs functions, the examples for such standards are IEEE 802.15.6 and standard IEEE 802.15.4. Several investigations have been carried out by the researches in order to improve the functionalities of IEEE 802.15.6 just by yielding the WBANs energy which is portrayed in [10–13]. Additionally, Ibarra et al. [14, 15] established the control technique by means of three modules in order to attain the efficient Qos services by making use of the optimized energy. The similar researches in [16] also introduced HEHMAC (Human Energy Harvesting MAC). The functionality of this methodology is to prioritize the sensor nodes depending upon their functions. Particularly, the sensor nodes which makes use of the polling applications is regarded as the highly prioritized data and it can access the data in contention-free manner.

Furthermore, the node that functions with normal prioritized data utilizes the contention dependent mechanisms. Consequently, the WBANs in turn access of the standard IEEE 802.15.4 than the standard IEEE 802.15.6 according to [1, 17]. Moreover, the standard IEEE 802.15.4 demands for the commonly known application referred to as CSMA/CA

(Carrier Sense Multiple Access with Collision Avoidance) in order to prioritize the parallel access of channel [18].

Establishment of arbitral (random) *BackoffDelay* prior to the access of channel by means of carrier sense approach obtains the ability to attain the CA (Collision Avoidance) application. Specifically, the assessment of channel is in a busy state and then *BackoffDelay* is maximized with an exponential velocity. Thus the present transmission eliminates of the channel criteria over the standard IEEE 802.15.4 which utilizes the "CSMA/CA" applications. Depending upon these present channel criteria it unknowingly initiates the entire *BackoffDelay* procedures as an alternative of balancing the *BackoffDelay*. Since the assessment of channel remains to a busy state, and then the rate of collision is maximized in an exceeding manner. The spontaneous increase in the rate of collision results in the reduction of throughput.

In order to resolve this problem, various adjustments were established thus for the updation of the tremendous amount of *BackoffDelay* through a more convenient approach [19]. For instance, the application namely ECR (Enhanced Collision Resolution) have been depicted clearly in [19]. This technique converts of the "CSMA/CA" application to be effectively utilized over the busy state of the channel, hence the networks performance is decreased in the condition if the criteria of channel disrupt continuously. Thus to balance this fluctuated latency or delay, a technique referred to as *ACS* (Additional Carrier Sensing) is proposed by Wong et al. [20]. They, in turn, utilize of the additional assessment of channel prior to the maximization of *BackoffDelay* in order to gather huge information based on the condition of the channel. Therefore *BackoffDelay* is not being able to be administered depending upon the particular requirements of application over every sensor nodes. In order to cope with these drawbacks, the new path is provided by the cross-layer throughput the entire investigation [20].

The cross-layering frameworks [2, 6, 7] that relate to the soft computing methodology makes use of the specific fuzzy logic applications. Previous studies translucently explain about the mechanism of fuzzy logic in the management of cross layer control over assessment of channel due to its simplicity and flexibility [2, 3, 6, 7, 9]. This application is appropriate in the management of non-linear frameworks considering of various inputs that belong to the typical nature as well as to associate these inputs and outputs it defines few specific rules. We, in turn, proposed the CLFB (cross-layer fuzzy logic based back-off controller) [4] to control the assessment of channel. The "CLFB" makes use of the data rate applications as well as the busy rate of the channel for the generation of *BackoffDelay*. Regardless to the automatic modeling of "FLC" our simulative investigations demonstrate the performance of the "CLFB" with few challenging algorithms.

Clearly, an intense modeling of "FLCs" is necessary to provide flexible communication among WBANs [2–4, 6, 7]. Anyway, the literature study reveals the basic modeling issues behind WBANs which is not being entirely reported. Commonly, the authors completely relates the "FLCs" automatic modeling that demands for a tremendous amount of man-made mechanisms, but it couldn't deliver any of the assurance for performance [2, 4, 6, 7]. In order to cope with these drawbacks, the WBANs entire modeling of "FLCs" has been investigated. Moreover to the comparison among these methods, our proposed hybrid FGWO based "EAs" have the benefits of translucent equilibrium, yet they possess the ability to function with distinctive sorts of fuzzy rules in the automatic modeling of "FLCs". This depends on distinctive sorts of MF_{ns} as well as to the rule base frameworks [11].

In addition to this "EAs" the "Gradient-Free Optimizer" method [21] can be extensively applied to the issues of multimodal as well as to the noisy environment. The advantage behind this is due to the effective functions of WBANs it possess the ability to operate well in the multimodal and noisy environment [22]. Depending on the review of literature study, we are in need to investigate the effective modeling of “FLCS” that depends to the “EAs” towards the perspective of WBANs. Various “EAs” includes the algorithms namely GA (genetic algorithm [8, 23], DE (differential evolutionary) [11, 12], firefly algorithm [24] and PSO (particle swarm optimization) [10, 25]. These “EAs” turns to be an effective application for the modeling of “FLCs”. Table 1 provides the summarization of few recent investigation works. For instance, Bingul et al. [10] modeled the Gaussian MF_{ns} by means of PSO. Pishkenari et al. [12] utilized the GA and DE in terms of effective modeling of trapezoidal MF_{ns}. Hachicha et al. [11] make use of the DE alone for the modeling of triangular MF_{ns}.Two well known “EAs” namely GA as well as PSO is proposed by Martinez et al. [26] for the efficient modeling of MF_{ns}. They, in turn, evaluate the benchmark issues and reported that the “EA” can outperform the GA. It should be noted that several authors focused only on the single objective to enhance the modeling of “FLCs” [10–12]. Moreover, Marinaki et al. [27] introduced various optimal tasks of PSO for the FLCs modeling to compute the issues of vibration management.

Looking into this strategy the similar authors established a novel multi-modeling technique referred to as DE [28]. The comparison is carried out with these similar approaches to evaluate its performance. In this work, we are in demand to increase the performance of EA dependent modeling. Towards this existing work, this research work focused on the modeling of single “FLC”. In because of this, it moves on to distinctive approaches. The proposed work aims for the significant P_{dr} (Packet delivery ratio) and minimized latency in the deliverance of packets as a major concern, the disruption in this constraint is ought to be fined (penalized) over the fitness function. Thus to resolve the

Table 1 Modeling of FLCs with EAs-related works

Authors	“EAs”	MF_{ns}	Tuned parameters
Bingul et al. [10]	PSO	Gaussian	Deviation ± center
Hachicha et al. [11]	DE	Triangular	3 control parameters of MF_{ns}
Kim et al. [8].	GA	Triangular	3 control parameters of MF_{ns}
Pishkenari et al. [12]	GA ± DE	Trapezoidal	4 control parameters of MF_{ns}
Liu et al. [13]	GA	Triangular	Linguistically hedging
Nasser et al. [25]	PSO	Triangular	Width ± centre
Casillas et al. [23]	GA	Triangular	3 control parameters ± linguistically hedging
Marinaki et al. [28]	MOPSO ± MODE	Trapezoidal ± Triangular	MF_n break points, Rule weights and logical operations
Martinez et al. [26]	GA ± PSO	Gaussian + Triangular	3 control parameter, deviation ± center
Marinaki et al. [27]	MOPSO	Triangular ± Trapezoidal	MF_n break points, rule weights and logical operations
Chang et al. [29]	PSO	Triangular	Centre measure

difficulty in the modeling procedures, Nasseer et al. [25] introduced the triangular MF_{ns} in the reduction of search space by two optimal control parameters namely the width and center. More probably, Chang et al. [29] utilized the triangular MF_{ns} of the symmetric form for the search space reduction. Liu et al. [13] verified the basic issues as well as reported the investigation of linguistic modifiers group corresponding to the stable fuzzy rules in the "FLCs" effective modeling. By the condition, both the control parameters as well as the linguistic modifiers related to MF_{ns} are regarded and the complete pattern for the modeling of "FLCs" is introduced in [23]. Casillas et al. [23] conducted the experiments on linguistic modifiers and reported that it doesn't violate the framework of "FLCs" thus it has the ability to regularize the interpretation.

Throughout the investigations, we take into account the odds of utilizing the linguistic modifiers during the modeling of "FLCs" over WBANs. Thus for the reduction of difficulties in the modeling procedures we just focused on the optimal determination of control parameters over MF_{ns} using hybrid FGWO. Thus the literal works [10–12, 23] aimed at the determination of other coding techniques. As a result, this suffers from the limitation over efficiency and reliability by the comparison of distinctive coding techniques. To recover this we move towards the investigation of "URCS" coding technique amended with multiple degrees of constraints. From the experimental outcome, it is inferred that the coding techniques with limited constraints exhibit good performance over WBANs. The acronyms utilized throughout this work are delineated in Table 2.

3 Background Informations of GWO and Firefly

3.1 Grey Wolf Optimization (GWO)

The GWO is termed as a geographically motivated optimization algorithm. The GWO algorithm [30], in turn, exhibits the hunting (chasing) characteristic that depends on the

Table 2 List of acronyms

Acronyms	Meaning
ACS	Additional carrier sensing
FLC	Fuzzy logic controller
ANOVA	Analysis of variance
MAC	Medium access control
CLFB	Cross-layer fuzzy logic dependent back-off
CSMA/CA	Carrier sense multiple access with collision avoidance
OCF	Overlapping control factors
DE	Differential evolutionary
PSO	Particle swarm optimization
ECR	Enhanced collision resolution
ECG	Electro Cardio gram
URCS	Un-restricted coding scheme
EMO	Evolutionary multi-objective
WBAN	Wireless body area network
D^2MAC	Dynamic delayed MAC
NB-Step	Number of back-offs step

family of the grey wolf. Basically, the preference of grey wolves tends to be situated over the pack. The size of pack related to the grey wolves ranges to the limit of 5–12. They, in turn, dominate the social hierarchy in 4 degrees. Based on the levels of hierarchy, the finest (best) candidate of the grey wolf is known as α-*alpha* it is termed as the top most leader of the pack of wolves. The next finest candidate referred to as β-*beta* is known as the second leader among the pack. If the topmost leader α is absent, then the second leader β dominant the pack. The least ranked wolves are defined by means of ω-*omega*. The function of ω wolves is to permit other wolves to eat first and this stays at last. The wolves that are not being recognized as β-*beta* or ω-omega wolf are declared as δ-*delta*. The function of δ wolves is to suggest α, β wolves but in turn, it possesses the leadership against ω wolves situated over the pack [30]. The order of hierarchical leadership is presented below in Fig. 1.

The numerical pattern of GWO algorithm includes the stages tracing, prey encircles and prey attack [30]. The initial stage of chasing is prey encircling. The numerical evaluation for prey encircling is expressed below:

$$\vec{G} = \left|\vec{H} \cdot \vec{Y}_p(t) - \vec{Y}(t)\right| \tag{1}$$

$$\vec{Y}(t+1) = \vec{Y}_p(t) - \vec{F} \cdot \vec{G} \tag{2}$$

whereas the present iteration is denoted by $\vec{G}$, and the coefficient vectors are termed as $\vec{F}$ and $\vec{H}$ the prey's position vector is represented by $\vec{Y}_p$, yet the grey wolf's position vector is $\vec{Y}$. The vectors $\vec{F}$ and $\vec{H}$ is expressed below

$$\vec{F} = 2\vec{k} \cdot \vec{R}_1 - \vec{k} \tag{3}$$

$$\vec{H} = 2 \cdot \vec{R}_2 \tag{4}$$

Hence $\vec{k}$ is termed as variable, on the way of iteration it is decremented linearly from (2 to 0). The random vectors are expressed as $\vec{R}_1$ and $\vec{R}_2$. Depending on the random vectors $\vec{R}_1$ and $\vec{R}_2$ the position updation can be carried out randomly (arbitrarily) over the search domain [30, 31]. The hunting operation is normally done by means of the leader α, preceded by β and δ. The grey wolves chasing (hunting) characteristics can be stated numerically as:

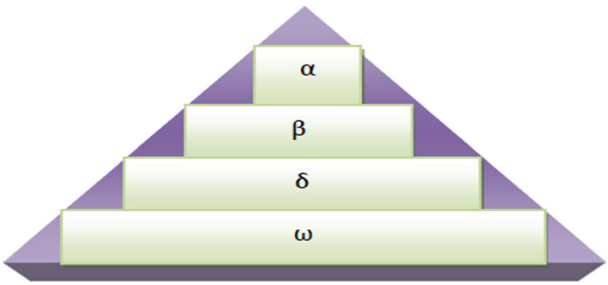

Fig. 1 Grey wolves social hierarchy

$$\vec{G}_\alpha = \left|\vec{H}_1 \cdot \vec{Y}_\alpha - \vec{Y}\right|, \vec{G}_\beta = \left|\vec{H}_2 \cdot \vec{Y}_\beta - \vec{Y}\right|, \vec{G}_\delta = \left|\vec{H}_3 \cdot \vec{Y}_\delta - \vec{Y}\right| \tag{5}$$

$$\vec{Y}_1 = \vec{Y}_\alpha - \vec{F}_1 \cdot (\vec{G}_\alpha), \vec{Y}_2 = \vec{Y}_\beta - \vec{F}_2 \cdot (\vec{G}_\beta), \vec{Y}_3 = \vec{Y}_\delta - \vec{G}_3 \cdot (\vec{G}_\delta) \tag{6}$$

$$\vec{G}(t+1) = \frac{\vec{Y}_1 + \overrightarrow{Y_2} + \overleftarrow{Y_3}}{3} \tag{7}$$

whereas the initial three finest (best) solutions are being taken into account and the residual solutions are eliminated, hereby the average measure of 3 finest (best) solutions is provided by $\vec{Y}$.The hunting process gets terminated only after prey attack, and prey should pause its movement. By the condition if $|F| < 1$ the attacking process of prey is done by grey wolf, yet if $|F| > 1$ after this they take a diversion from the prey and moves towards the finest (best) prey which is fitter one. Hereby, $\vec{k}$ is denoted as linear variable and random vectors $\vec{R}_1$ and $\vec{R}_2$ are being chosen arbitrarily (randomly).

3.2 Firefly Algorithm

The establishment of firefly algorithm was carried out by Yang [32] thus it completely depends on the potential flashing behaviors of fireflies. The flashing behavior of fireflies can be defined by 3 conditions, they are as follows:

- The entire fireflies are focused as unisex; therefore a single firefly gets attracted by another firefly without considering the gender.
- Attractiveness is generally related to the brightness, in because of the characteristics of the fireflies that diminished brighter follows the highly brighter fireflies. Attractiveness is highly related to brightness, thus the following fireflies reduce their brightness in terms of increased distance. By chance, if any of the Fireflies doesn't possess the brightness, then the Firefly begins to relocate in a random manner.
- The firefly's intensity or brightness is being gradually damaged or being identified by means of objective functions background that is ought to be evaluated (optimized).

More conveniently, the intensity of light is termed as $L(z)$ that may change accordingly with the distance z in exponent form and is expressed as

$$L = L_0 e^{-\alpha z} \tag{8}$$

The actual intensity of light is L_0 and the coefficient of light absorption is α. The attractiveness of fireflies is largely related to the intensity of light obtained from the nearby fireflies, the firefly's attractiveness can be defined as,

$$\gamma = \gamma_0 e^{-\alpha z^2} \tag{9}$$

whereas γ_0 is referred to as attractiveness over $z = 0$. The significant point to be noted is that towards the function αz^2 the exponent is possible to be replaced with the exponent αz^k if $k > 0$.The measure of distance against two fireflies noted as g and h, the "Cartesian Distance" is being determined to utilize Eq. (10)

$$r_{gh} = \left\|Y_g - Y_h\right\| = \sqrt{\sum_{e=1}^{n} \left(Y_{g,e} - Y_{h,e}\right)^2} \tag{10}$$

whereas $Y_{g,e}$ is referred to as the eth element related to the spatial coordinate of gth Firefly. The relocation of Firefly g towards the far brighter (more attractive) Firefly h is evaluated based on the Eq. (11):

$$Y_g = Y_g + \gamma_0 e^{-\alpha z^2}(Y_g - Y_h) + \beta_1(r_{and} - 0.5) \tag{11}$$

The attraction of fireflies is defined in the second term and the randomization is defined in the third term, whereas the parameter of randomization is shown by the notation β_1, the 'random number generator' is noted by the notation r_{and} which is being uniformly distributed over the limit [0–1].

4 System Model

4.1 Functions of FLC ("fuzzy logic controller") on WBAN's

The WBAN includes of various distinctive quick, well-enhanced sensor nodes with minimized consumption of power. Example for such type of minimized power consumed sensor nodes are 'heart rate', 'glucose degree', and 'blood pressure' sensors and these sensors, in turn, are administered to various positions of the human body. The WBAN includes of one of the particular node referred to as the coordinator [1], is well delineated into Fig. 2. This dominant coordinator node holds of the similar functions of a highly enhanced device known as PDA (personal digital assistant). The main function of the coordinator node is to receive the sensors information and to redirect this received information towards an exterior medicinal health framework.

Various studies demonstrate about the wireless channels eminence that the channels closer to the human body show low quality as well as it experiences link loss in an extreme manner [22]. The WBANs with low-quality channels may suffer from the transmission drops as well as it faces the reduced performance and reliability, which are regarded as chief elements in the applications of healthcare domain [4]. In order to tackle the uncertainty of the channels, the FLC is commonly employed over WBANs by considering a number of factors such as the requirements of application and condition of the channel. The next subpart 4.2 provides the *IEEE 802.15.4* MAC layers overview. Under the Sect. 4.3 it explains about the introduction of CLFB (cross-layer fuzzy logic dependent back-off controller) [4] over the access of control channel. The observations recognized from this segment promote us to develop a hybrid FGWO based FLC model is planned to be projected under the Sect. 5.

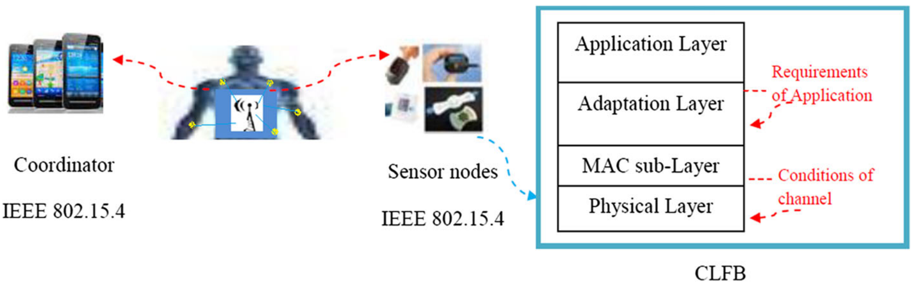

Fig. 2 Example of WBAN utilizing IEEE 802.15.4 adapted with CLFB

4.2 Description of IEEE 802.15.4

This segment provides the complete illustration of *IEEE 802.15.4* slots of MAC [33]. The CSMA/CA which is being slotted turns to be the main concern in the WBANs mode of communication as well as it functions on the "Back-off Period" (B_P) unit time. Based on this mode of communication, each of the nodes is in demand to evaluate the channel prior to the occurrence of every transmission; it means to pay attention before the initiation of communication [22, 34–36]. In case, the transmission doesn't begins at the time of channels idle state, the transmission is ought to be delayed in terms of the arbitral (random) interval known as "Back-off Delay". Figure 3 delineates the flow description of both the CSMA/CA slots as well as the CLFB (for more reference took a glance over Sect. 4.3). The CLFB is allotted for the identification of "Back-off delay", at the condition "FUZZYENABLE = True", yet at the condition, "FUZZYENABLE = False" the CSMA/CA which is being slotted over IEEE 802.15.4 are administered.

The MAC (medium access control) is described with 3 specific variables over the slotted "CSMA/CA":

- *Back-off exponent* B_{e_x}: B_{e_x} captures the amount of Back-off periods (B_{ps}) in which a node should wait prior to each of channel estimation. The initial stage of "CSMA/CA" begins by initializing B_{e_x} to $Mac_{\min}B_{e_x}(=3)$. During the transmission process over the node, if a packet is in the ready state, then the "CSMA/CA" approach pushes of the node to eliminate the collision by permitting the node towards the Back-off meant for the arbitrary (random) delay. The arbitral (random) delay are being preferred in a uniform manner arbitrarily (randomly) at a limit of $[0, 2^{B_{ex}} - 1]$ is expressed underneath:

$$Backofftime = r_{and}(0, 2^{B_{ex}} - 1) \times B_p \quad (12)$$

  Subsequent to the condition after the completion of *Backofftime*, yet the channel remains in the busy state then B_{e_x} should be added with one, till it attains $Mac_{\max}B_{e_x}$(the measure in default is setup to 5 towards the valid limit of [2, 3…8]). After this, the measure that relates to B_{e_x} is capped next to $Mac_{\max}B_{e_x}$.
- *Contention window Cw*: *Cw* represents the count of *Backoffperiods* demanded by the channel for the clarity prior to the initiation of each and every process of transmission. The term *Cw* should be initiated by means of $Cw_0(=2)$. Then this initialized measure is ought to be retuned to Cw_0, at the criteria if the channel is recognized at the busy state. In case, if it is recognized as clear, then *Cw* should be decreased with one. This process is continued till *Cw* attains the level zero, only after this process the transmission of data begins.
- *Count of Back-offs CB*: *CB* estimates the amount of *Backoff* trials practiced in terms of the present transmission trials. The term *Count of Backoffs* should be initiated to zero $CB = 0$, in terms of any occurrence of novel transmission. By chance if any of the channels is reviewed in the busy state then *CB* should be added with one. At this criteria the algorithm discourage the permission of *CB* to go beyond the limit of $Mac_{\max}B_{e_x}$(= 4). If the algorithm courage's *CB* to go beyond the limit $CB = Mac_{\max}B_{e_x}$ then the failure in transmission is identified, else the procedure *Backoff* trials are continued.

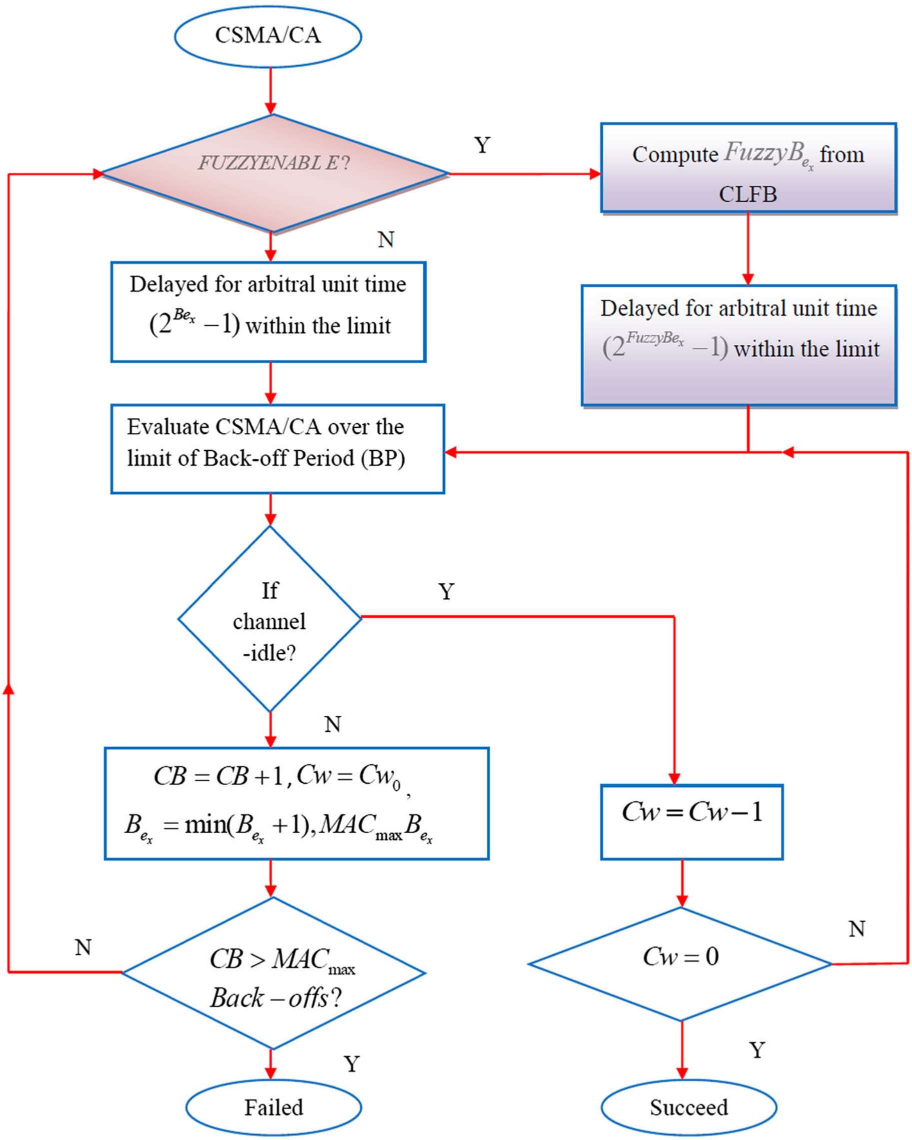

Fig. 3 Flow chart of "CSMA/CA" and "CLFB" algorithms, in which it highlights the distinction between the "CSMA/CA" and the "CLFB" (cross-layer fuzzy logic back-off)

4.3 Mechanisms of CLFB (Cross Layer Back-Off) Utilizing Fuzzy Logic

At the time of *BackoffDelay* adjustment the IEEE 802.15.4 has no ability to take into account the particular requirements of application; example for this is channel access frequencies. Hence, IEEE 802.15.4 increments B_{e_x} potentially if the accessed channel is in busy state. The procedures are well delineated in Fig. 3. Figure 3 illustrates that each node rebuilds the entire process of *Backoff* by means of every novel transmission, apart from the particular requirements of application and present condition of the channel. As a result, nodes faces complexity in the adjustment of *BackoffDelay* rapidly, this leads to the momentous increase in the rate of the collision over WBANs [9, 37]. Consequently, the utility, as well as the reliability of channels, are influenced negatively. Thus to overcome this problem, we just established "CLFB" [4] in order to accomplish the *BackoffDelay* by balancing B_{e_x}, which in turn relates to distinctive conditions of channel and requirements of the application. The FLC (fuzzy logic controller) is utilized by CLFB in order to tune B_{e_x} that relates to the present conditions of the network and to the application requirements. Thus to differentiate the term B_{e_x} identified by means of "FLC" mechanism administered in CLFB and also B_{e_x} over IEEE 802.15.4, the previous one is referred to as $FuzzyB_{e_x}$ throughout this work. Accordingly, prior to the channel assessment in CLFB the arbitrary (random) *BackoffDelay* pursued along every node is expressed as follows:

$$Backofftime = r_{and}(0, 2^{FuzzyB_{e_x}} - 1) \times B_p, FuzzyB_{e_x} \in \{2, 3, 4, \ldots, 8\} \tag{13}$$

Taking a glimpse over Fig. 4 the "FLC" mechanism administered to "CLFB" takes off two input variables known as CB_{Rt} (*count of backoffs rate*) and D_{Rt} (*data rate*), which is well illustrated in under beneath section.

4.3.1 Input and Output Variables of FLC

The initial input variable assigned to "FLC" over "CLFB" is termed as CB_{Rt}. The term CB_{Rt} should be evaluated by means of the *CB* average measure relocating with a certain period (time).

$$CB_{Rt}(t+1) = \begin{cases} \gamma \times CB + (1-\gamma) \times CB_{Rt}(t), & if\ CB \leq MAC_{\max} Backoffs \\ \gamma \times CB_{fine} + (1-\gamma) \times CB_{Rt}(t), & if\ CB > MAC_{\max} Backoffs \end{cases} \tag{14}$$

whereas γ, $0 \leq \gamma \leq 1$, is referred to as the factor of discount and CB_{fine} denotes the fine (penalty) allotted for the failure of each transmission. It is to be noted that the measure of γ must is assigned with a larger measure similar to 0.86 in order to obtain better performance [4]. By the condition, CB_{fine} is ought to be rigorously larger than $Mac_{\max}$ *Backoffs* based on our trials the penalty of *CB* is administered as $CB_{fine} = 6$. Moreover, *CB* behaves as a straight forward indicator for the condition of channel over years, but if the condition of the channel is depreciated, then CB_{Rt} begins to grow spontaneously. Likewise, it gets

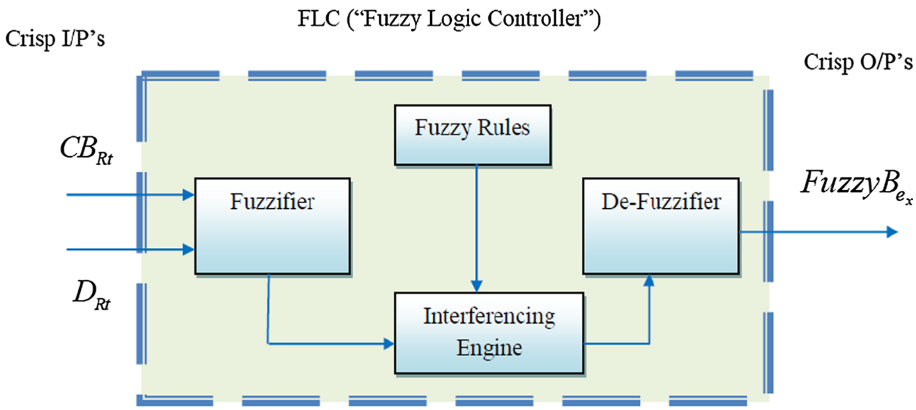

Fig. 4 'FLC' design meant for 'CLFB'

decreased by further improvement in the channel conditions. Subsequently related to our prior research, four fuzzy degrees are fuzzified for CB_{Rt} they are Very low, moderate, high and very high [4].

Data rate D_{Rt} is noted as "FLC" 2nd inputted variable, which is shown in Fig. 4. As described in [4], in order to identify the appropriate *BackoffDelay* it is necessary to consider each sensor nodes D_{Rt}. For the occasion, a node that possesses larger D_{Rt} leads to frequent access of channel, yet it must be assigned with corresponding larger delay thus to withstand the major collisions. The D_{Rt} within WBAN has the ability to change considerably over distinctive kinds of nodes. Thus to deal with distinctive settings of network, the normalization of D_{Rt} against "CLFB" is administered in the scope of about [1, 2, 3…. 100] [4]. The partitioning is carried out for normalized D_{Rt} into 4 distinctive degrees of fuzzy namely, very low, moderate, high and very high. The term $FuzzyB_{e_x}$ is considered as the output for "FLC". Thus to increase the accuracy level, the term $FuzzyB_{e_x}$ is being partitioned up into 4 distinctive fuzzy degrees, denoted as E_1, E_2, E_3 and E_4.

Towards "FLC" the 'Centre of Gravity' is utilized for the de-fuzzification of $FuzzyB_{e_x}$ to generate the crisp measure in Eq. (13). On behalf of efficiency and simplicity for the entire input and output variables of "FLC", we make use of the membership function in triangular shape [6, 7]. Figure 5 delineates the example for such type of membership function. Throughout this entire work, the membership functions control parameters denoted as p, q and r are designed automatically by means of our proposed hybrid FGWO algorithm. By the proper implementation of this membership functions, it turns easy to control "FLCs" *BackoffDelay* (for more convenience see Sect. 4.3) as well as it attains better steadiness over performance and reliability of WBANs (go through the Sect. 5).

4.3.2 Rules of Fuzzy Logic

Here in this work, it includes 16 distinctive conditions (antecedents). The 16 distinctive antecedents are meant by 4 degrees of fuzzy $CB_{Rt} \times$ 4 degrees of fuzzy D_{Rt}. Subsequently, about 16 distinctive rules are being comprised in function of "FLC" administered over "CLFB". Each rule of fuzzy pursue the general structure, which is delineated below:

$$RL(n): \begin{array}{rcl} IF\ CB_{Rt(n)} & is & p_1^t \\ and\ D_{Rt(n)} & is & q_2^i \\ THEN\ FuzzyB_{ex(n)} & is & r^1 \end{array} \tag{15}$$

The "CLFB" fuzzy rules summarizations are described in Table 3. The table shows that if CB_{Rt} is termed as Very Low then it demonstrates that busy state is not being experienced by the channel, to avoid the longer delays our "FLC" sets $FuzzyB_{e_x}$ to E_1, for instance, the rules of fuzzy $RL^{(1)}, RL^{(2)}, and\ RL^{(3)}$ illustrated in Table 3. Moreover, the node that contributes large D_{Rt} aims to take into account the larger delays thus to shield it against from the blockage of Very Low D_{Rt} nodes, an example for this is $RL^{(4)}$. In terms of the highly congested channel, it means that CB_{Rt} is at Moderate degree, at this stage our "FLC" generates reasonably higher $FuzzyB_{e_x}$, an example for this is $RL^{(5)}, RL^{(6)}, and\ RL^{(7)}$. Anyway, the nodes that experience very high D_{Rt} tends to achieve the longer delays, an example for this is $RL^{(8)}$. This is due to the fact, nodes that experience larger D_{Rt} generate tremendous amount of packets as well as it achieves the channel in more frequent form. The occurrence of collisions in the packet can be diminished by accepting the longer delays. In addition to the criteria, that the channel turns to be highly congested (High) in order to diminish the collision occurrence the *BackoffDelay* established the rules of fuzzy,

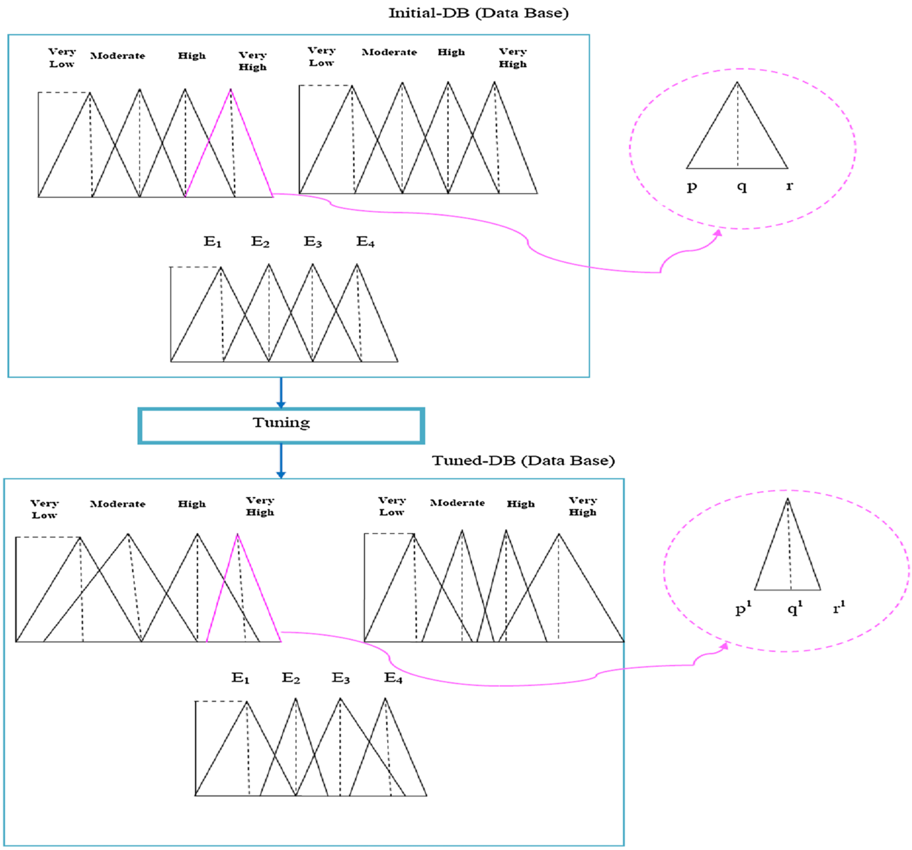

Fig. 5 Modeling procedures of "CLFB" in which the hybrid FGWO balances the rule base acquired from the initial DB as well as from the expert DB

it means $RL^{(9)}, RL^{(10)}, and\ RL^{(11)}$ turns to E_3. However the node that experiences very high D_{Rt} tends to achieve the longer delays, it means E_4. At last, if the utility of channel is very high then "FLC" in turn generates a longer delay E_4, with respect to the input D_{Rt}. One of the exceptional nodes that still attains the shorter delay, it means E_3 by the node that experiences very low D_{Rt}. Consequently, to describe the rules of fuzzy, we just go through two very low D_{Rt} sensor nodes over the network; the idle state of the channel is identified for the more frequent period. Related to $RL^{(1)}$, $FuzzyB_{e_x}$ tends to be shorter and each sensor node shows only minimized delay. Based on rules, $RL^{(12)}$ and $RL^{(16)}$ the $FuzzyB_{e_x}$ remains Very High thus to eliminate the unimportant occurrence of collisions in terms of entire WBANs reliability.

5 Optimal Modeling of FLCs in WBANs by Proposed Hybrid FGWO

In this segment, we propose a hybrid Firefly and Grey Wolf Optimization (FGWO) algorithm to model the "FLCs" optimally in CLFB in order to acquire the enviable equilibrium between performance and reliability of WBANs. The extensive report

Table 3 Rules of fuzzy logic in CLFB

Rule no	Antecedent or condition (input)		Consequent or actions (output)
	CB_{Rt}	D_{Rt}	$FuzzyB_{e_x}$
1	Very low	Very low	E_1
2	Very low	Moderate	E_1
3	Very low	High	E_1
4	Very low	Very high	E_2
5	Moderate	Very low	E_2
6	Moderate	Moderate	E_2
7	Moderate	High	E_2
8	Moderate	Very high	E_3
9	High	Very low	E_3
10	High	Moderate	E_3
11	High	High	E_3
12	High	Very high	E_4
13	Very high	Very low	E_3
14	Very high	Moderate	E_4
15	Very high	High	E_4
16	Very high	Very high	E_4

maintained in the past research [11, 18–21], most of the Evolutionary Algorithm [EAs] were administered for the automatic modeling of "FLCs" by distinctive aspects. As delineated in Fig. 5, the main goal of this work is to optimize the control parameters of "FLCs" entire Membership Functions MF_{ns}.

Specifically, based on the perspective of WBANs, we recognized some of the methodological issues related to the "FLC" modeling. The issues are being categorized into three forms namely, (a) encoding method (b) fitness derivation and (c) estimation technique. These issues are well described correspondingly to the upcoming sections. For the progression of our work, we preferred hybrid FGWO for the optimal modeling procedures of "FLC" due of their worthiness stated in [7, 10, 11, 25, 27, 29]. The preference for hybrid Firefly based Grey wolf Optimization (hybrid FGWO) is carried out owing to their familiarity, yet they do not override the odds of utilizing other 'Evolutionary Algorithms'.

5.1 Encoding Method

Several "EAs" works mainly over the population of candidate solutions. Each and every specific 'candidate solution' presents an individual model of "FLC" and it works by following a particular coding technique. Thus the coding technique encodes each and every MF_{ns} (Membership Functions) entire control parameters by means of numbers in the form of real or by floating point vectors. Moving towards this vector, the control parameters separate groups are formed with dimensions of 3 successive numbers. For instance, take a glance over Fig. 6 in which the parameters initial group that in turn controlling initial MF_n is tinted in pink color. In because of the triangular MF_{ns} utilization, it follows the criteria

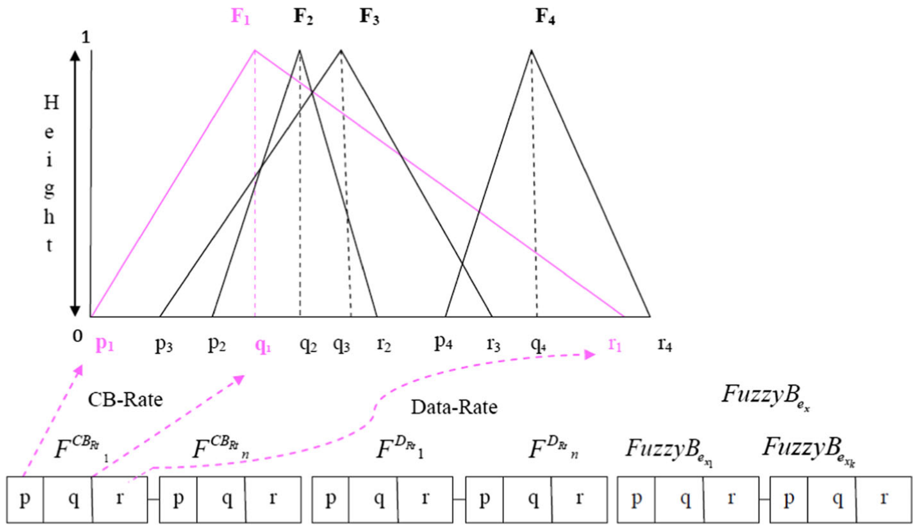

Fig. 6 URCS ("un-restricted coding scheme"), where F denotes linguistic related to each MF_n (membership function)

that in any specific group (p, q, r) the initial control parameter should be lesser than the parameter located in the intermediate position $(p < q)$. Similarly the intermediate control parameter should be lesser than the parameter located at the third position $(q < r)$. For the sake of clarity, the above-mentioned encoding method can be referred to as URCS (Un-restricted Coding Scheme). As delineated in Fig. 6 if "URCS" is being utilized the MF_{ns} domain has the ability to cover other MF_{ns} domain. It can be explained by means of Fig. 6, the membership function F_1 domain tinted in pink color encompasses the other membership functions F_2 and F_3 domains entirely. The "URCS" coding technique is utilized by our proposed hybrid FGWO approach due its simplicity and is well suited for control parametric selection.

5.2 Fitness Derivation

The evaluation of fitness measure is to be carried out, thus for the maintenance of equilibrium among performance and reliability over WBANs. The term P_{dr} (Packet delivery ratio) is utilized for the estimation of reliability according to [5], which is derived entirely throughout the work. The term P_{dr} is defined as the proportion between the successful deliverance of packets towards coordinator to the amount of packets transmitted by entire sensor nodes which in turn related to the WBAN, the condition is provided underneath transparently:

$$P_{dr} = \frac{Amount\ of\ packets\ achieved\ by\ the\ coordinator}{Total\ amount\ of\ packets\ transmitted\ by\ entire\ sensor\ nodes} \tag{16}$$

Moreover, in the sense, if P_{dr} is in very high rate, then the critical data copes with reduced collision at the time of WBANs data transmission. In order to accomplish this collision reduction goal, the term P_{dr} is denoted as ∇P_{dr}.

$$\nabla P_{dr} = P_{dr_{CLFB}} - P_{dr_{STD}} \tag{17}$$

whereas $P_{dr_{CLFB}}$ and $P_{dr_{STD}}$ denotes the "Packet delivery ratios" acquired by means of the utilization of both *CLFB* as well as *IEEE 802.15.4* standard, correspondingly. In case, $\nabla P_{dr} > 0$ then *CLFB's* reliability is regarded as the better one than the reliability attained by *IEEE 802.15.4*. Beyond reliability, this turns to be largely enviable in the enhancement of WBAN's performance. The assessment of performance is carried out by means two sorts of metrics, they are delay and throughput. Furthermore, the throughput enhancement is comprehended by the improvement of P_{dr}. Hence, throughout this work, throughput is considered in an implicit manner. Accordingly, the major aim of this work depends on reduction of 'packet latency'. The packet delay is denoted as $\nabla_{latency}$ and it is expressed as,

$$\nabla_{latency} = \begin{cases} latency_{STD} - latency_{CLFB}, & if\ latency_{CLFB} > latency_{STD} \\ 0, & if\ latency_{CLFB} \leq latency_{STD} \end{cases} \tag{18}$$

The measure of $\nabla_{latency}$ is maintained at 0. Moreover with Eq. (18), $\nabla_{latency}$ shows the behavior in the constraint manner. If the delay experienced is in minimized form, the major goal of our implementation procedure mainly depends on the P_{dr} maximization. Based on the above-explained terms, ∇P_{dr} represented in Eq. (17) is considered as the main term for the optimization as well as $\nabla_{latency}$ represented in Eq. (18) functions as the constraint form in order to balance the delay attained through "FLC" over CLFB with challenge to *IEEE 802.15.4*. Accordingly, the fitness measure is computed as,

$$Fitness = \nabla P_{dr} + \eta \times \nabla_{latency} \tag{19}$$

whereas η is considered as coefficient. For illustration, if $P_{dr_{CLFB}} = 0.55$ and $P_{dr_{STD}} = 0.80$, hereby by computation $\nabla P_{dr} = 0.55 - 0.80 = -0.25$. At this condition, if $\nabla_{latency} = 0$ the measure of the fitness in Eq. (19) turns to be -0.25. From this it can be noted that the latency reduction attained by means of "FLC" is regarded as the better one similar to the standard *IEEE 802.15.4* and P_{dr} is possible to be enhanced by not including any of the fine (penalty). This work mainly focused on the determination of appropriate coefficient thus to acquire the enviable trade-off among delay (latency) and P_{dr}.

5.3 Estimation Technique

In this work, the estimation of fitness related to each of the candidate solutions are being coordinated by means of two distinctive design goals. The initial design goal G_1 is applied for the modeling of "FLCs" that operates efficiently towards the particular network configuration. Example for this is the application that relates to healthcare examination, that means a old person after a long interval sent back to home subsequently from the recovery of cardiac surgery, followed by the per-fixed settings of WBAN with the inclusion of 'ECG' (Electrocardiogram) with 3 leads, namely the Blood Pressure (BP), Heart Rate (HR) sensors are in demand [38]. Consequently, we aimed for the enhancement of performance and reliability towards this specific configuration. The second goal G_2 aims to operate frequently throughout various configurations (settings) of network. The goal G_2 aims for the enrichment of "FLCs" general applications. Thus for the differentiation of modeling goals, each results related to the utilization of "CLFB" depending to the goals G_1 and G_2 are referred to as $CLFBG_1$ and $CLFBG_2$, correspondingly. Related to these design goals, two distinctive estimation techniques are considered. The initial technique estimates the candidate solution depending on the WBAN's pre-defined individual measure. The next subsequent estimation technique makes use of various prefixed settings of WBAN just for the mutual computation of similar candidate solution. Comparatively on the second technique, the measured ∇P_{dr} and $\nabla_{latency}$ against various settings of network is used for the determination of candidate solutions fitness measure based on the Eqs. (17), (18) and (19). Each and every settings of network is ought to be verified for about 5 non-dependent executions in terms of both estimation techniques. For sake of clarity, please take a quick look on Sect. 4.

5.4 Optimal Control Parameters Selection by Hybrid-FGWO

The main goal behind our proposed approach relays on the optimal selection of control parameters related to entire MF_{ns} of the "FLC" model. Here in this work we just passed over hybrid FGWO (hybrid firefly grey wolf optimization) algorithm, in because of GWO constraint, which means the optimal position is being controlled by two selected constant variables. In order to overcome this drawback, we propose hybrid FGWO instead of conventional GWO. Based on the hybrid method, the GWO executes the optimal position of prey and at the same moment, optimal controlling parameters $\vec{R}_1$ and $\vec{R}_2$ are being selected by firefly operator. The basic inspiration behind proposed hybrid FGWO algorithm is to merge the benefits of firefly with the conventional GWO in order to withstand the GWO's static issues. Hereby, the conventional GWO includes of the arbitral (random) control parameters selection namely the parameters $\vec{R}_1$ and $\vec{R}_2$, the local minimal issue emerges out due to these static control parameters. At this point, firefly is utilized to pick out the optimal control parameters in favor of GWO. The steps behind the control parameters selection by proposed hybrid FGWO algorithm is described below:

- At the chasing (hunting) operation, prey encircling is carried out by grey wolves and the grey wolfs, in turn, confirms about the movement of prey (i.e. none of the prey is in moving condition). The prey encirclement operation can be performed by utilizing the Eqs. (1) and (2), here the firefly picks out the control parameters $\vec{R}_1$ and $\vec{R}_2$. When moving towards the conventional 'firefly algorithm' it is observed that the optimization methods are enacted by means of the attractiveness and intensity variations.
- In proposed hybrid FGWO algorithm (Table 4) the entire MF_{ns} optimal control parameters selection is done by the subsequent strides: (i) Depending upon the fitness measure sorting and ranking of entire fireflies is carried out (ii) Finest (better) fitness value is being selected in terms of present generation or iteration and this selected fitness measure is ought to be replaced, only if it is inferred that the currently estimated fitness measure is better than the fitness measure acquired over previous generation (iteration), else maintain the previously generated fitness measure alone. The measure of intensity that corresponds to the Firefly acquired at the final cycle (trials) is considered as the optimal solution. The resultant output generated by means of firefly includes the optimal control measures. (iii) The intensity value of the firefly obtained at the end of the trials is the optimum best solution for the optimization problem. Here the output of Firefly algorithm consists of optimum control parameters. Figure 7 illustrates a flow chart of proposed hybrid FGWO approach.

Table 4 Algorithm for proposed hybrid FGWO

Input: n control parameters
Output: optimal control parameters selection
1: begin
2: Initialize the population of grey wolves $Y_i(1,2,3\ldots n)$
3: Initialize the parameters $k, F, H, Y_\alpha, Y_\beta, Y_\delta$
4: Evaluate the search agents fitness utilizing Eq. (19)
Y_α =the initial finest search agent
Y_β =the 2nd finest search agent
Y_δ =the 3rd finest search agent
5: if $(t_i < \max cycle_i)$
6: then
7: for each of the search agents
8: Update the position of the present search agent utilizing Eq. (6)
9: End for
10: Update the position of $\vec{R}_1$ and $\vec{R}_2$ utilizing the firefly operator
11: Evaluate the intensities and position of all the fireflies based on Eqs. (8-11)
12: Sorting and ranking of firefly intensities and position based on fitness utilizing Eq. (19)
13: Selection of $n/2$ worst agents and combine the new agents obtained from the firefly to the GWO finest (best) agents
14: else
15: Update $k, F, H, Y_\alpha, Y_\beta, Y_\delta$
16: $t_i = t_i + 1$
17: if $(t_2 > \max cycle_j)$
18: then
19: Repeat the steps from 10 to 13
20: else
21: Return best solutions
22: if $(t_2 = t_2 \max {}_j)$
23: End of iteration, if maximum cycles are attained
24: Else go to step 16
25: end

6 Results and Discussion

This section describes about the WBANs simulation settings under Sect. 6.1, the parameters setting of proposed hybrid FGWO are described under Sect. 6.2. Finally, the results obtained by simulation are delineated in Sects. 6.4 and 6.5. The outcomes obtained from modeling of "FLCs" to attain the goal G_1(it means particular network management (settings) in FLCs) are described under Sect. 6.4. The simulation outcomes obtained by means of "FLCs" modeling over goal G_2(it means various network management (settings) in FLCs) is analyzed under

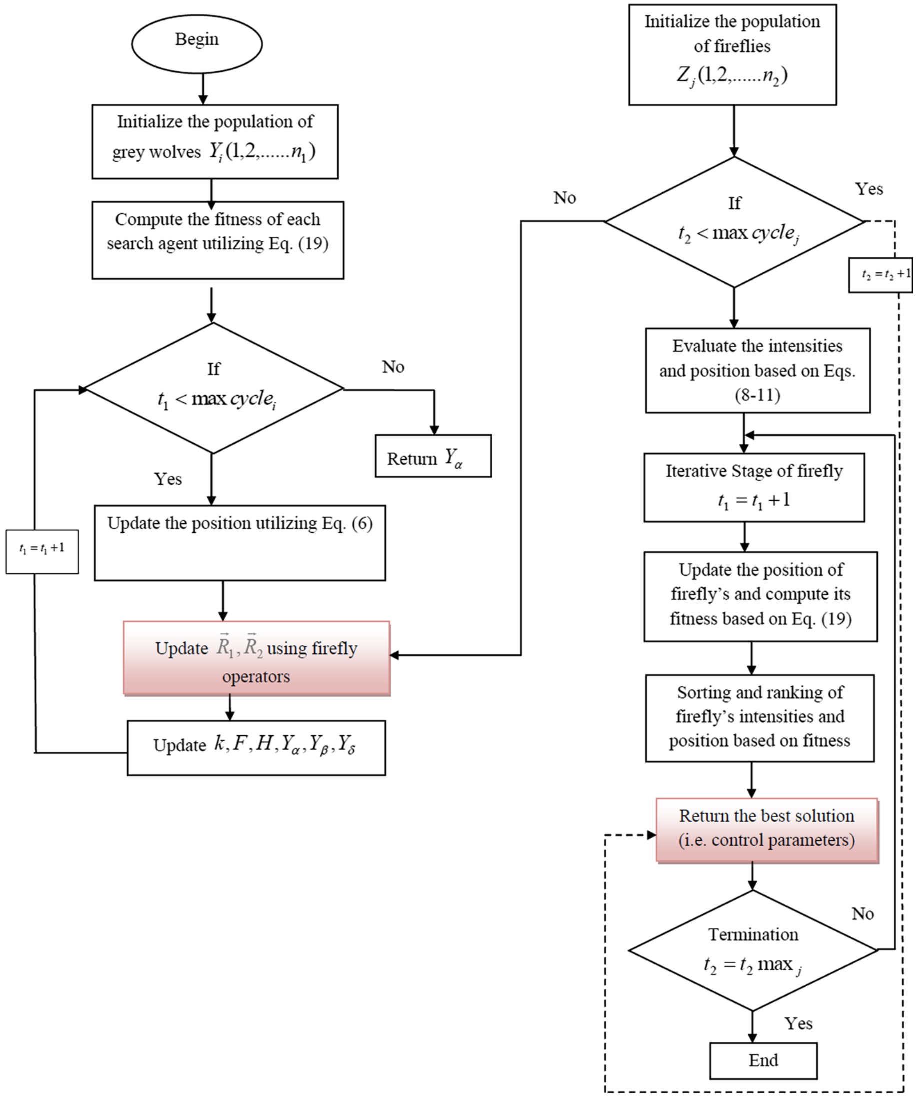

Fig. 7 Flow chart of proposed hybrid FGWO

Sect. 6.5. Initially under Sect. 6.4, to identify fitness functions appropriate coefficients in Eq. (19), we conducted experiments on 11 distinctive coefficients. After this evaluation, we move towards the specific investigations on “FLCs” efficiency by our proposed hybrid FGWO approach utilizing “URCS” coding technique with three conventional “evolutionary algorithms” (firefly, GWO and PSO), these conventional algorithms are used for comparison with our proposed hybrid approach due to its simplicity and efficiency in terms of effective modeling of “FLCs”. Based on the investigation, we inferred that our proposed hybrid FGWO approach outperforms other three conventional “EAs” in terms of significant P_{dr} and minimized latency. At last, from the wide-ranging simulation experiments, we finalized that our proposed hybrid FGWO in modeling of “FLC” also obtains the ability to override more of the challenging algorithms such as, *IEEE 802.15.4*, D^2MAC, *ACS*, and *NB-Step* stated in [7]. Initially, under Sect. 6.5, we just illustrated various scenarios for modeling of "FLCs" automatically based on the goal G_2.

6.1 WBANs Experimental Environment

For the simulation of WBAN, we, in turn, make use of the networking simulator "NS2" [39]. Subsequently, classical setup over the research [5] D_{Rt} is maximized about a rate of 250 kb/s along with 2.5 GHZ frequency. Based on our simulation, the deployment of entire sensor nodes is carried out in a random manner within the search space of $3 \times 3m^2$ amended along with the individual coordinator of WBAN utilizing 'star topology'. Correspondingly, the simulation time of network related to our experiment is about 500 s (simulation time should not be in higher form to vary our main identification). Here, we just utilized the model of 'log-normal shadow' the same as the channel design form. When contrasted to the modernized distributions of both "Rayleigh and Ricean" fading of about small scale are generated to WBANs conveniently by means of "log-normal shadowing" [35].

6.2 Parameter Settings of Hybrid FGWO

The main scope of our research is to demonstrate that our proposed hybrid FGWO algorithm works effectively on the "FLC" modeling approach. As a result, two familiar Conventional "EAs" namely "Firefly and Grey Wolf Optimizer" aided with standardized functions are used for the effective implementation of "FLC" modeling. For both the conventional Firefly and GWO approach, the size of the population is administered to 50, whereas, the maximum number of iterations or generations is employed to 100. Based on this setup, it is inferred that the hybrid FGWO is near to the convergence subsequent to 100 iterations, the same as shown in Fig. 8. Table 5 delineates the parameter settings of proposed hybrid FGWO.

In order to obtain the consistent outcomes, our proposed hybrid FGWO based on the same administrations is continually repeated for about 30 epochs considering distinctive initial seeds. Thus to gather reliable information about the distinctive differences in reliability and performance the "ANOVA" (Analysis of Variance) test is performed. Also, to determine the flexible distinction over reliability and performance two different analyses are executed namely the "*t* test" and "Tukey's post hoc" experiment. From the analysis, it is inferred that our proposed FGWO exceeds the performance of the conventional Firefly and GWO algorithms.

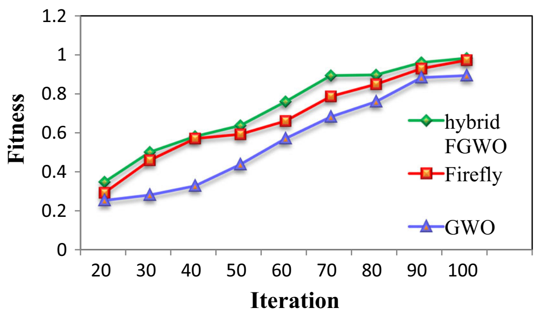

Fig. 8 Hybrid FGWO dependent procedure for the modeling of "FLC" convergence subsequent to 100 iterations. The outcomes for the illustrated "URCS" coding method are acquired by means of 30 non-independent trials

Table 5 Parameter settings

Parameters	Firefly	GWO	Hybrid FGWO
Size of population	50	50	50
No. of. generations (iterations)	100	100	100
Control parameters	Dynamic	R_1, R_2	R_1, R_2
Intensity of light (initial) L_0	0	–	0
Attractiveness (initial) γ	0.5	0.5	0.5
Light absorption α	1.25	–	1.25
Parameter of randomization β_1	0.25	–	0.25

6.3 Validation Metrics

The WBANs performance and reliability are compared quantitatively by means of four validation metrics, they are as follows:

- *Packet delivery ratio* (P_{dr}) Proportion between the successful deliverance of packets towards coordinator to the amount of packets transmitted by entire sensor nodes as presented in Eq. (16).
- *The rate of collision* The average collision occurrence of data packets towards the WBANs interaction (communication) channel.
- *Latency* It is measured by means of the data packets arrival time to the coordinator. The latency in the arrival of data packets begins as soon as the frames of data come closer to the "MAC sub-layer".
- *The throughput of MAC* The successful deliverance of data frames to the "MAC sub-layer" transmitted by means of a communication channel.

Thus in terms of flexible judgment with few challenging algorithms, each of the challenging algorithms is ought to be executed for about 30 runs individually at the simulative environment. The results acquired for the performance and reliability are again utilized to distinguish the "FLCs" modeling intended by means of our proposed hybrid FGWO.

6.4 Modeling of FLCs with Goal G_1

The simulative environment of WBAN with a goal G_1 is established in this sub-segment. After this, the flexibility of multiple coding techniques aided with hybrid FGWO for the modeling of "FLC" is examined. Subsequently, the wide-ranging coefficient influence namely η is investigated over the fitness measure in Eq. (19). At last, the "CLFBs" performance and reliability attained by means of "FLCs" modeling against this work are contrasted with few challenging algorithms.

6.4.1 Simulation Setup of Network with Goal G_1

The initial design goal G_1 is applied for the modeling of "FLCs" that operates efficiently towards the particular network management. For instance, we just include the application that relates to healthcare examination, that means a old person after a long interval sent back to home subsequently from the recovery followed by certain procedures, such as per-fixed settings of WBAN by the inclusion of 'ECG' ("Electrocardiogram") with 3 leads, namely the blood pressure (BP), heart rate (HR) sensors, EEG ("Electroencephalogram"), motion sensors, Rate of respiratory and a coordinator of 'Smart-Phone'. The sensor nodes certain interactive (communication) features are discussed in the underneath Table 6.

6.4.2 Comparing Hybrid FGWO with the Conventional "Evolutionary Algorithms"

Utilizing the scenarios of WBAN we just portrayed the outcomes of hybrid FGWO obtained by means of "URCS" coding technique as well as with distinctive coefficients (i.e.η) are delineated in Table 7. Based on the outcomes, it is inferred that our proposed hybrid FGWO algorithm utilizing "URCS" coding technique shows better performance than the "EAs" namely Firefly, GWO and PSO in terms of both the P_{dr} and packet latency strategies. These two strategies are evidenced by well known test referred to as "One-Way ANOVA" and "Turkey's post hoc". For instance, if the measure of the coefficient $\eta = 2$ as shown in Table 7, it is observed that the coding technique "URCS" utilized by our proposed hybrid FGWO maintains the highly reliable P_{dr} and appropriately diminished latency when contrasted it with the conventional "Evolutionary Algorithms". Let us consider another instance $\eta = 2.5$, the "URCS" coding technique with our proposed hybrid FGWO exhibits highly reliable P_{dr}(p measures < 0.0001) as well as diminished latency when contrasted to the other three "EAs" (Firefly, GWO and PSO)

The "FLCs" modeling examples of hybrid FGWO utilizing "URCS" coding technique are depicted in Fig. 9 correspondingly. The depiction in Fig. 9 shows that the domain related to individual MF_n of "URCS" has the ability to encompass entirely by means of other MF_{ns} domains. For instance, the MF_{ns} domain in terms of E_2 contradicted in Fig. 9c is entirely encompassed with E_3 domain related to the MF_n. As a result, the "URCS" MF_{ns} in hybrid FGWO approach is possible to be classified in terms of both performance and reliability. Encompassing the Fuzzy partition [62] is another interpretation characteristic for "FLCs". As tinted in Fig. 9b the MF_{ns} molded by means of "URCS" may ignore some of the essential data points. Expect the issues in interpretability; the outcomes demonstrated in Table 7 shows that the hybrid FGWO approach utilizing "URCS" performance turns to be good when contrasted to the performance of the conventional "EAs" (Firefly, GWO and PSO). Moreover, traditionally the performance is provided with higher priority also the interpretation necessity is also investigated. Practically, the hybrid FGWO approach with "URCS" can maintain the reliable pathway among the performance and reliability; this is well delineated in our simulative result. Besides, the implemented rules possess some of the recent WBANs information. The rules administered in Table 3 $RL^{(1)}, RL^{(2)}, andRL^{(3)}$ expresses that prior to the transmission of packets the sensor node is not in a constraint to wait as much as the channel returns to an idle state (i.e. not in a busy state.

Thus for the better providence of performance and reliability equilibrium over the network, it is in demand for the identification of fitness functions Eq. (19) appropriate coefficients. As a result, the $\nabla_{latency}$ different coefficients namely, η are being analyzed. From the description provided in Table 7, we obtain some of the identifications that the coefficient η with higher measure (i.e. $\eta > 2.5$) promotes higher concentration on our proposed hybrid FGWO for the reduction of packet latency to highly minimized level (this is not considered as an essential term). By the fact, P_{dr} appears to be more influenced if the measure of η turns to be small (example for this is $\eta < 2.0$). Moreover, we in turn, presented analysis by means of detached "One-Way ANOVA" against entire coefficients in terms of each and every illustrated coding technique. From the result it is verified that over

Table 6 Sensor nodes communicative features utilized over the simulation [5, 38]

Sensor node	"ECG"	"Motion sensors"	HR-"heart rate"	"Respiratory rate"	"Blood pressure (BP)"	"Imaging by endoscope"	"EEG"	"Temperature"
Distribution generation traffic	Stable	Poisson	Stable	Stable	Stable	Poisson	Stable	Stable
D_{Rt}	158.45 Bps	16 Bps	68 Bps	25 Bps	516 Bps	1637.65 Bps	32.4 Bps	14.6 Bps

Table 7 Results obtained for hybrid FGWO with conventional "EAs"

η	Terms	Hybrid FGWO	Firefly	GWO	PSO
001.5	P_{dr}	0.908 ± 0.007	0.905 ± 0.003	0.872 ± 0.003	0.765 ± 0.002
	Latency	0.751 ± 0.006	0.770 ± 0.002	0.753 ± 0.002	0.790 ± 0.004
002.0	P_{dr}	0.868 ± 0.006	0.860 ± 0.010	0.856 ± 0.011	0.800 ± 0.003
	Latency	0.737 ± 0.004	0.752 ± 0.006	0.758 ± 0.006	0.890 ± 0.008
002.5	P_{dr}	0.848 ± 0.006	0.807 ± 0.002	0.811 ± 0.003	0.901 ± 0.005
	Latency	0.719 ± 0.002	0.721 ± 0.001	0.721 ± 0.001	0.713 ± 0.009
003.5	P_{dr}	0.833 ± 0.003	0.801 ± 0.001	0.800 ± 0.001	0.798 ± 0.008
	Latency	$0.723 \pm 4.6 \times 10^{-4}$	$0.726 \pm 6.0 \times 10^{-4}$	0.725 ± 0.001	$0.856 \pm 6.0 \times 10^{-4}$
004.5	P_{dr}	0.833 ± 0.003	0.801 ± 0.001	0.798 ± 0.001	$0.654 \pm 6.0 \times 10^{-4}$
	Latency	$0.725 \pm 4.6 \times 10^{-4}$	0.725 ± 0.001	0.726 ± 0.001	0.898 ± 0.005
005.5	P_{dr}	0.820 ± 0.005	0.801 ± 0.002	$0.808 \pm 4.5 \times 10^{-4}$	0.656 ± 0.008
	Latency	0.725 ± 0.001	0.725 ± 0.003	0.723 ± 0.001	0.987 ± 0.007
006.5	P_{dr}	0.820 ± 0.002	$0.801 \pm 0.3 \times 10^{-4}$	0.811 ± 0.001	0.765 ± 0.003
	Latency	$0.726 \pm 3.7 \times 10^{-4}$	0.723 ± 0.001	0.726 ± 0.002	0.856 ± 0.008
007.5	P_{dr}	0.822 ± 0.01	$0.810 \pm 3.3 \times 10^{-4}$	$0.815 \pm 4.8 \times 10^{-4}$	0.755 ± 0.009
	Latency	$0.724 \pm 3.5 \times 10^{-4}$	0.723 ± 0.003	0.724 ± 0.001	0.854 ± 0.006
008.5	P_{dr}	0.833 ± 0.003	0.801 ± 0.001	0.798 ± 0.001	0.675 ± 0.003
	Latency	$0.725 \pm 4.6 \times 10^{-4}$	0.725 ± 0.001	0.726 ± 0.001	0.825 ± 0.004
009.5	P_{dr}	0.820 ± 0.005	0.801 ± 0.002	$0.808 \pm 4.5 \times 10^{-4}$	0.701 ± 0.009
	Latency	0.725 ± 0.001	0.725 ± 0.003	0.723 ± 0.001	0.876 ± 0.001
100.0	P_{dr}	0.820 ± 0.002	$0.801 \pm 0.3 \times 10^{-4}$	0.811 ± 0.001	0.654 ± 0.003
	Latency	$0.726 \pm 3.7 \times 10^{-4}$	0.723 ± 0.001	0.726 ± 0.002	0.876 ± 0.002

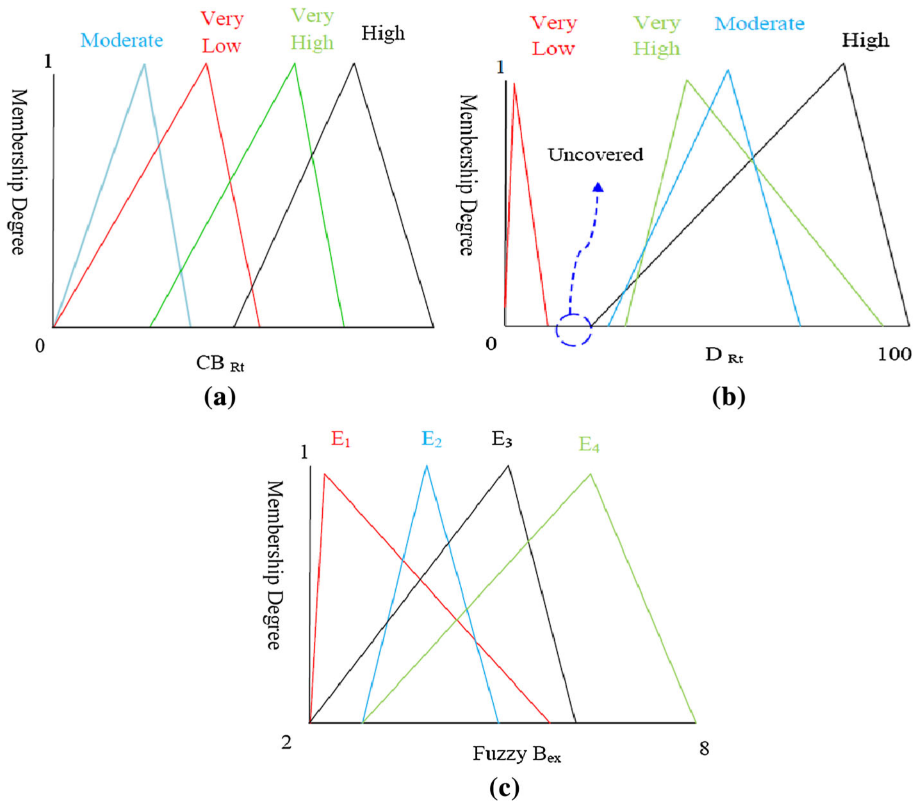

Fig. 9 Examples of "FLC" modeling with hybrid FGWO utilizing "URCS"

the criteria $\eta < 2.0$, $CLFB_{G_1}$ shows gradual variation in latency. Notably, as delineated in Table 7, if the measure of coefficient η varies by means of 2.0–1.5, the latency gets increased with 0.038 scs. Conversely, if in turn, $\eta > 2.0$ the latency variation is constantly lesser than 0.015 scs. As a result, two coefficients are chosen it means $\eta = 2.0$ as well as $\eta = 2.5$ all the way throughout the investigation. Thus, these two coefficients for convenience are demonstrated in bolded form over the Table 7, this, in turn, afforded a probable equilibrium over P_{dr} and latency.

6.4.3 Comparison Among Hybrid FGWO Dependent FLC Modeling (Goal G_1) and the Challenging Algorithms

Thus to determine the efficiency of "FLCs" automatic modeling, we distinguished it with some of the well known challenging algorithms namely, *IEEE 802.15.4*, *D^2MAC*, *ACS*, and *NB-Step*. Table 8 demonstrated that the $CLFB_{G_1}$ overrides some of the challenging algorithms *IEEE 802.15.4*, *D^2MAC*, *ACS*, and *NB-Step* by means of P_{dr} and latency. The analysis technique namely "One-Way ANOVAs" provides considerable variations among them p measures < 0.0001. Thus the subsequent "Tukey's post hoc" test also ensures our statement. Particularly, P_{dr} attained for $CLFB_{G_1}$ is appreciably larger than the challenging algorithms *IEEE 802.15.4*, *D^2MAC*, *ACS*, and *NB-Step*, not including any of the influence on latency. As illustrated in Sect. 6.4.2, another modeling goal is to enhance the throughput and this can be achieved with the improvement of P_{dr}. Moreover, Table 8 also suggested the throughput of WBAN utilizing each of the challenging algorithms. The statistical test also ensures that the $CLFB_{G_1}$ greatly attains larger throughput over the challenging algorithms. Hence, the rate of collision can be significantly diminished in $CLFB_{G_1}$ by carrying out entire challenging algorithms comparison.

6.4.4 Summary

Related to this sub-segment, we in turn, achieved the efficient modeling of "FLCs" depending to the hybrid FGWO with goal G_1. We further determined the efficiency of "FLCs" model with the "URCS" coding technique. From the analysis, we finalized that "URCS" coding technique utilized by our proposed FGWO approach in the modeling of "FLCs" outperforms other "Evolutionary Algorithms" performance (Firefly, GWO and PSO). Moreover, for the satisfaction of WBANs requirements of performance and reliability, it is necessary to employ the measure $\eta = 2.5$ for the fitness evaluation. At last, we proved the $CLFB_{G_1}$ efficiency in a statistical manner thus by distinguishing it with various challenging algorithms. From the statistical result, it is analyzed that the $CLFB_{G_1}$ utilizing the sensor nodes maintains significant performance as well as reliability in contradiction with the challenging algorithms namely, *'IEEE 802.15.4*, *D^2MAC*, *ACS*, and *NB-Step*. Anyway, once the modeling of $CLFB_{G_1}$ is done, then it is possible to employ within each of the sensor nodes and it can be utilized towards distinctive applications of WBAN.

6.5 Modeling of FLCs Automatically with Goal G_2

Moving to this sub-segment it first explains about the simulative environment of WBAN in goal G_2.Consequently, the proposed hybrid FGWO algorithms efficiency has been studied statistically with distinctive scenarios. At last, the $CLFB_{G_2}$ performance and reliability is contrasted with distinctive challenging algorithms.

6.5.1 Simulative Environment of Network with Goal G_2

Modeling of "FLC" with a goal G_2 couldn't generate the proficient equilibrium by means of performance and reliability towards the extensive setting settings of WBAN. As a result delineated under Sect. 4.3, we in turn aimed for the modeling of "FLCs" depending on the goal G_2, it means improving the reliability and performance towards various (multiple) settings of WBAN. Due to this fact, we constructed distinctive training as well as testing

Table 8 Results obtained with challenging algorithms

Challenging algorithms	P_{dr} (packet delivery ratio)	Latency	Rate of collision	Throughput
ACS	0.688 ± 0.002	0.719 ± 0.003	0.510 ± 0.002	1773.321 ± 10.977
IEEE 802.15.4	0.756 ± 0.003	0.720 ± 0.003	0.368 ± 0.003	1919.568 ± 11.510
D^2MAC	0.823 ± 0.003	0.759 ± 0.002	0.320 ± 0.002	2099.918 ± 12.387
NB-step	0.821 ± 0.003	0.759 ± 0.002	0.320 ± 0.002	2065.756 ± 12.108
$CLFB_{G_1}$ (ours)	0.845 ± 0.004	0.717 ± 0.002	0.256 ± 0.003	2206.875 ± 14.856

states. Specifically, training in a sense is put forward by means of five distinctive settings of the network, which is illustrated in Table 10. All over again each and every sensor nodes interaction features are recognized under Table 10. Moreover, Table 11 comprises entire testing states administered to this work. Subsequently, the “FLCs” models enhancement is tested by means of 8 distinctive sensors. The efficiency of each and every sensor is determined clearly on distinctive studies [5, 38]. Thus, for the determination of WBAN under high congestion (traffic load), about two sensors of ECG are employed over the testing condition 9 provided in Table 11.

6.5.2 Modeling of FLC Based on Hybrid FGWO

In the view of the fact, the Sect. 6.4 ensures that our proposed hybrid FGWO is highly significant in the effective modeling of “FLCs”. Consequently, the hybrid FGWO training and testing outcomes acquired in terms of “URCS” coding technique are illustrated in the Tables 9 and 10. Based on the results obtained, it is inferred that distinguishing the efficiency of proposed algorithm with distinctive scenarios in statistical form turns to be a tedious approach. Conversely, the training conditions with seven as well as eight, hybrid FGWO utilizing the coding technique “URCS” provides better performance, it means it delivers the enhanced P_{dr} amended with reduced latency. It is more essential to point out that the “FLCs” modeling computational time tends to be completely sensible; hence the “FLCs” design is possible to be utilized frequently on various applications of WBAN, as well as the networks efficiency is enhanced in a significant manner.

6.5.3 Comparison Among Hybrid FGWO Dependent FLC Modeling (Goal G_2) and the Challenging Algorithms

The $CLFB_{G_2}$ on differentiating it against the challenging algorithms comprising of $CLFB_{G_1}$ over testing the outcomes (refer to the Tables 11, 12, 13 and 14), we observed that $CLFB_{G_2}$ has the ability to override the performance of *IEEE 802.15.4* in terms of P_{dr} and latency. It can be explained in another form that the throughput and highly significant P_{dr} can be attained only by means of the algorithm $CLFB_{G_2}$ than the altered algorithm *IEEE 802.15.4*. This is not only efficient in terms of *IEEE 802.15.4* but also it overrides the other challenging algorithms in the way it promotes a highest significant level of reliability. The P_{dr} achieved is about 100% in the case if the network includes of the coordinator together with two nodes alone. The level of P_{dr} begins to reduce, if the congestion (traffic load) gets

Table 9 Configurations of WBAN in the modeling of FLCs with goal G_2

Conditions	Number of sensors	Settings of WBAN
1	3	ECG, respiratory rate, temperature
2	4	ECG, respiratory rate, temperature and HR
3	6	ECG, respiratory rate, temperature, HR, EEG and BP
4	7	Motion, ECG, respiratory rate, temperature, HR, EEG and BP
5	8	Imaging with endoscope, motion, ECG, respiratory rate, temperature, HR, EEG and BP

Table 10 Configurations of WBAN in terms of testing the modeled FLCs with Goal G_2

Conditions	Number of sensors	Settings of WBAN
1	1	ECG
2	2	ECG, respiratory rate
3	3	ECG, respiratory rate, temperature
4	4	Motion, ECG, respiratory rate, temperature
5	5	Imaging with endoscope, motion, ECG, respiratory rate, temperature
6	6	ECG, respiratory rate, temperature, HR, EEG and BP
7	7	Motion, ECG, respiratory rate, temperature, HR, EEG and BP
8	8	Imaging with endoscope, motion, ECG, respiratory rate, temperature, HR, EEG and BP
9	9	Imaging with endoscope, motion, ECG, respiratory rate, temperature, HR, EEG, BP and EEG

increased by the tremendous addition of sensor nodes. Table 11 illustrates that $CLFB_{G_1}$, NB-Step and D^2MAC attains larger P_{dr} than $CLFB_{G_2}$ based on few conditions (example for this is conditions 3, 4 and 5). By prompting the larger back-offs, higher P_{dr} can be attained. Alternatively, from the outcome it is observed that $CLFB_{G_2}$ turns to be highly flexible than the *ACS* and *IEEE 802.15.4* not including any of the higher back-offs over the sensor nodes.

More probably, by maximizing the amount of nodes, the level of P_{dr} gets diminished over entire algorithms. The reduction in the level of P_{dr} is due to the maximized occurrence of collision in the network, which is delineated in Table 12. Furthermore, $CLFB_{G_2}$ on contrasting with $CLFB_{G_1}$, NB-Step and D2MAC,$CLFB_{G_2}$ shows lesser rate of collision. They in turn admit more pressure on the sensor nodes just for maximizing the *Back-offDelay* in order to eliminate the occurrence of collisions. Hereby, without forfeiting any of the interaction (communication) latency, the $CLFB_{G_2}$ exhibits better performance than *ACS* and *IEEE 802.15.4* towards the rate of collision occurrence. Prior to the explanation, the throughput of the "MAC-sub layer" illustrated in Table 13 is enhanced just by maximizing the P_{dr} related to the WBANs. Hence $CLFB_{F_1}$, *NB-Step* and *D2MAC* attains larger P_{dr} than $CLFB_{G_2}$ based on few conditions related to throughput (example for this is conditions 3, 4 and 5). Alternatively, from the outcome, it is observed that $CLFB_{G_2}$ turns to be highly flexible than *ACS* and *IEEE 802.15.4* if the network includes in excess of two sensor nodes. Consequently, the outcomes of $CLFB_{G_1}$, *NB-Step* and *D2MAC* may attain the larger throughput and P_{dr} against $CLFB_{G_2}$, yet it permits the tremendous amount of packet latency, due to this function it turns to be less flexible in the applications of WBAN (i.e. for delay responsive). For instance, over the condition 7,$CLFB_{G_1}$, *NB-Step* and *D2MAC* establishes larger latency than *IEEE 802.15.4*. Contrasting to the challenging algorithms in Table 14, $CLFB_{G_2}$ obtains the ability to maintain its packet latency nearer to the IEEE 802.15.4 levels. Specifically, the analysis techniques namely, "ANOVA" and "Tukey's post hoc" demonstrates that the latency attained by means of $CLFB_{G_2}$ is complex to distinguish from *ACS* and *IEEE 802.15.4*. For the moment,$CLFB_{G_2}$ has the ability to handle the consequently diminished latency than *D^2MAC*, $CLFB_{G_1}$ and *NB-Step*.

Table 11 Results obtained for P_{dr}("packet delivery ratio") through challenging algorithms (IEEE 802.15.4, D^2MAC, ACS, and NB-step)

Algorithms	1	2	3	4	5	6	7	8	9
IEEE 802.15.4	1.000 ± 0.000	$0.987 \pm 3.9 \times 10^{-4}$	0.829 ± 0.001	0.850 ± 0.001	0.462 ± 0.001	0.475 ± 0.001	0.472 ± 0.001	0.459 ± 0.001	0.432 ± 0.001
ACS	1.000 ± 0.000	0.987 ± 0.001	$0.835 \pm 1.1 \times 10^{-4}$	0.843 ± 0.001	0.479 ± 0.001	0.476 ± 0.001	0.473 ± 0.001	0.446 ± 0.001	0.443 ± 0.001
D^2MAC	1.000 ± 0.000	0.998 ± 0.001	$0.891 \pm 1.1 \times 10^{-4}$	0.878 ± 0.001	0.510 ± 0.001	0.515 ± 0.001	0.482 ± 0.001	0.456 ± 0.001	0.452 ± 0.001
NB-Step	1.000 ± 0.000	0.998 ± 0.001	0.890 ± 0.001	0.883 ± 0.001	0.511 ± 0.001	0.508 ± 0.001	0.471 ± 0.001	0.605 ± 0.001	0.462 ± 0.001
$CLFB_{G_1}$	1.000 ± 0.000	0.987 ± 0.001	0.862 ± 0.001	0.890 ± 0.001	0.543 ± 0.001	0.552 ± 0.001	0.523 ± 0.001	0.500 ± 0.001	0.501 ± 0.001
$CLFB_{G_2}$	1.000 ± 0.000	0.983 ± 0.001	0.840 ± 0.001	0.864 ± 0.002	0.500 ± 0.001	0.510 ± 0.001	0.501 ± 0.001	0.492 ± 0.001	0.482 ± 0.001

Table 12 Results obtained for collision rate through challenging algorithms (IEEE 802.15.4, D^2MAC, ACS, and NB-step)

Algorithms	1	2	3	4	5	6	7	8	9
IEEE 802.15.4	0.000 ± 0.000	0.023 ± 0.001	0.142 ± 0.001	0.153 ± 0.001	$0.503 \pm 3.9 \times 10^{-4}$	0.510 ± 0.001	0.523 ± 0.001	0.535 ± 0.001	0.563 ± 0.001
ACS	0.000 ± 0.000	0.023 ± 0.001	0.142 ± 0.001	0.153 ± 0.001	$0.491 \pm 3.9 \times 10^{-4}$	0.493 ± 0.001	0.500 ± 0.001	0.512 ± 0.001	0.542 ± 0.001
D^2MAC	0.000 ± 0.000	0.012 ± 0.001	0.132 ± 0.001	0.143 ± 0.001	0.534 ± 0.001	0.540 ± 0.001	0.553 ± 0.001	0.573 ± 0.001	0.587 ± 0.001
NB-Step	0.000 ± 0.000	0.019 ± 0.001	0.140 ± 0.001	0.149 ± 0.001	0.549 ± 0.001	0.559 ± 0.001	0.572 ± 0.001	0.592 ± 0.001	0.593 ± 0.001
$CLFB_{G_1}$	0.000 ± 0.000	0.0307 ± 0.001	0.123 ± 0.001	0.132 ± 0.001	0.452 ± 0.001	0.478 ± 0.001	0.473 ± 0.001	0.520 ± 0.001	0.519 ± 0.001
$CLFB_{G_2}$	0.000 ± 0.000	0.024 ± 0.001	0.146 ± 0.001	0.152 ± 0.001	0.503 ± 0.001	0.519 ± 0.001	0.534 ± 0.001	0.534 ± 0.001	0.553 ± 0.001

Table 13 Results obtained for throughput through challenging algorithms (IEEE 802.15.4, D^2MAC, ACS, and NB-step)

Algorithms	1	2	3	4	5
IEEE 802.15.4	00200.564 ± 00000.202	01710.999 ± 00000.956	07678.056 ± 00005.234	07945.456 ± 00005.765	11,344.768 ± 00023.567
ACS	00200.564 ± 00000.202	01710.145 ± 00000.887	07891.890 ± 00003.202	07456.009 ± 00008.867	11,678.900 ± 00045.117
D^2MAC	00200.534 ± 00000.202	01715.234 ± 00000.702	08123.786 ± 00010.567	08123.897 ± 00014.009	13,446.987 ± 00032.679
NB-Step	00200.543 ± 00000.202	01715.345 ± 00000.734	08134.899 ± 00011.234	08278.789 ± 00013.890	13,234.890 ± 00023.343
$CLFB_{G_1}$	00200.567 ± 00000.202	01710.765 ± 00000.602	07898.043 ± 00013.678	08305.623 ± 00016.564	14,567.890 ± 00032.112
$CLFB_{G_2}$	00200.789 ± 00000.202	01710.087 ± 00001.002	07686.004 ± 00015.890	08145.567 ± 00034.90	12678.009 ± 00012.678

Algorithms	6	7	8	9
IEEE 802.15.4	11,943.234 ± 00043.009	11,789.034 ± 00012.009	11,765.678 ± 00024.145	11,678.005 ± 00034.567
ACS	11,768.900 ± 00036.567	12,789.902 ± 00013.765	12,890.456 ± 00045.567	12,079.009 ± 00021.678
D^2MAC	13,456.567 ± 00045.212	12,456.789 ± 00043.434	11,987.934 ± 00034.009	11,567.008 ± 00002.567
NB-Step	13,013.789 ± 00032.004	12,344.800 ± 00034.009	11,567.009 ± 00014.678	11,607.700 ± 00030.456
$CLFB_{G_1}$	13,467.890 ± 00023.123	12,456.678 ± 00023.789	13,456.879 ± 00004.112	12,934.908 ± 00023.134
$CLFB_{G_2}$	12,657.435 ± 00043.009	13,789.007 ± 00023.450	1334.890 ± 00012.678	12,987.876 ± 00043.009

Table 14 Results acquired for latency (time delay) through challenging algorithms (IEEE 802.15.4, D^2MAC, ACS, and NB-step)

Algorithms	1	2	3	4	5
IEEE 802.15.4	00.243 ± 00.001	00.254 ± 00.001	00.276 ± 00.001	00.245 ± 00.002	00.287 ± 00.005
ACS	00.234 ± 00.001	00.278 ± 00.001	00.265 ± 00.001	00.234 ± 00.003	00.234 ± 00.001
D^2MAC	00.245 ± 00.001	00.254 ± 00.002	00.323 ± 00.004	00.456 ± 00.001	54.003 ± 00.001
NB-Step	00.267 ± 00.001	00.265 ± 00.001	00.345 ± 00.001	00.356 ± 00.001	45.678 ± 00.125
$CLFB_{G_1}$	00.234 ± 00.001	00.267 ± 00.001	00.234 ± 00.001	00.345 ± 00.001	34.678 ± 00.012
$CLFB_{G_2}$	00.234 ± 00.001	00.250 ± 00.001	00.245 ± 00.001	00.234 ± 00.001	00.461 ± 00.001

Algorithms	6	7	8	9
IEEE 802.15.4	00.312 ± 00.001	00.389 ± 00.003	00.674 ± 00.001	00.876 ± 00.001
ACS	00.234 ± 00.001	00.231 ± 00.002	00.506 ± 00.001	00.323 ± 00.001
D^2MAC	45.878 ± 00.003	45.789 ± 00.001	34.787 ± 00.002	23.908 ± 00.001
NB-Step	24.789 ± 00.001	46.890 ± 00.006	00.789 ± 00.003	23.897 ± 00.002
$CLFB_{G_1}$	2.4564 ± 00.0145	30.156 ± 00.0234	24.678 ± 00.220	23.789 ± 00.212
$CLFB_{G_2}$	0.1235 ± 00.001	00.888 ± 00.001	00.456 ± 00.003	00.334 ± 00.004

6.5.4 Summary

Related to this sub-segment, we, in turn, achieved the efficient modeling of "FLCs" depending on the goal G_2 and based on our proposed hybrid FGWO. The basic strength of $CLFB_{G_2}$ is revealed in our simulation outcomes, it means its efficiency. From the outcome, it is inferred that $CLFB_{G_2}$ is regarded as the significant approach that can override the performance of IEEE 802.15.4 taking into account both the performance and reliability. In addition to its efficiency and its flexibility, $CLFB_{G_2}$ also promotes basic applications. The basic applications here it means is the practical usage, the patients, in turn, can remove or fix the sensor nodes to his/her body, but the network stays to be stable and effectual.

7 Conclusion

In this paper, we proposed the hybrid FGWO algorithm for optimal modeling of "FLCs" over WBANs. The proposed work relays on the optimal selection of control parameters from the "FLCs" with hybrid FGWO. The modeling of FLC is done by utilizing the CLFB ("Cross-Layer Fuzzy logic dependent Back-off controller") mechanism to control the frequent access of channels. By the optimal selection of control parameters the reliability and the performance can be achieved by minimizing the latency in the network. Thus "FLCs" are modeled optimally by means of our hybrid FGWO approach. The experimental analysis is carried out with three conventional "Evolutionary Algorithms" namely, Firefly, GWO and PSO, in order to derive the effectiveness of our proposed approach utilizing "URCS" coding technique. These three "EAs" are considered because of its simplicity and efficiency stated in [10, 27, 30]. From the evaluation we identified that our proposed hybrid FGWO utilizing "URCS' coding technique promotes better P_{dr} (Packet delivery ratio) with minimized latency than the other conventional "EAs". Moving towards the effectiveness of "FLCs", two major modeling goals are established. The initial goal G_1 aims for effective modeling of "FLCs", it means $CLFB_{G_1}$ attempts to promote better performance and reliability towards the particular configuration of WBAN. Meanwhile, the next subsequent goal G_2 intends for the optimal modeling of "FLCs", it means $CLFB_{F_2}$ to function on multiple configurations of WBAN. In addition to this, we just proved that $CLFB_{G_1}$ acquires the ability to attain significant performance and reliability than other challenging algorithms D^2MAC, IEEE 802.15.4, ACS and NB-Step. Through experimentation, we ensured that the $CLFB_{G_2}$ exhibits higher performance than IEEE 802.15.4in regards of packet latency as well as P_{dr} towards the extensive scope of interactive (communication) conditions. It is important to be noted that over the entire modeling procedures, we, in turn, established neither the probable variations nor the specific applications against IEEE 802.15.4. We have selected the fuzzy rules throughout this work for the modeling of "FLCs" because of its simplicity and easy computational techniques. After modeling of "FLCs" in CLFB by means of our proposed hybrid FGWO algorithm, it can be penetrated towards the sensor nodes if and only if they are in well-matched form against IEEE 802.15.4 not including any of the key variations. Our future scope is to attain the better interpretability by means of multi objective algorithm. In order to withstand our modeling issues, the advantages of EMO (Evolutionary Multi-Objective) algorithms can be applied. However, our work focused mainly on the CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance) employed over IEEE 802.15.4. The WBANs reliability and performance, can be attained in highly effective manner just by interlinking the TDMA

(Time Division Multiple Access) to the CSMA/CA approach. Therefore, to interlink both these approaches, we require the "FLCs" hierarchical modeling. In favor of this function, we aim to generate the novel modeling technique referred to as "co-operative co-evolution" technique in order to enhance the WBANs functionalities in practice.

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