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RESEARCH ARTICLE

GFCO: A Genetic Fuzzy-Logic Channel Optimization Approach for LR-WPAN

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ABSTRACT The objective of IEEE 802.15.4 standard is to establish the foundation for a low-rate wireless personal area network that focuses on ubiquitous communication between devices while maintaining a reasonable data rate. Its popularity has increased significantly as a result of its implementation at low power and cheap cost, and the need to improve its performance has become a necessity. The most persistent issues are throughput, packet delivery ratio (PDR), packet loss ratio (PLR), and packet delay (PD). The advances in wireless technology place a strong emphasis on overcoming these problems. To accomplish stated goals, GFCO: A genetic fuzzy-logic approach to optimize channel of IEEE 802.15.4 LR-WPAN is proposed. It employs the *FuzzyLogicController* (FLC), and the *GeneticAlgorithm* (GA), by doing so, GA optimally modifies the FLC. For this, five algorithms are presented, Algorithm-1: GFCO for LR-WPAN, Algorithm-2: GA_1 for GFCO, Algorithm-3: FLC_1 for GFCO, Algorithm-4: GA_2 for GFCO, and Algorithm-5: FLC_2 for GFCO. The suggested GFCO approach is assessed for *RandomExponentialBackoff* (REB) algorithm, which was chosen as a fundamental algorithm, along with the *Survivability Aware Channel Allocation* (SACA) algorithm, taken as a benchmark study. Two scenarios are implemented in NS-3.20 in conjunction with fuzzylite in a hospital environment. First scenario is implemented in randomly deployed 10 sensors on a person's body ($2 \times 2\ m^2$ area), whereas second scenario is implemented in $20 \times 20\ m^2$ area of a ward in hospital having 10 to 50 persons. The simulated outcomes of both scenarios were recorded for REB, SACA, and GFCO. Simulated testing demonstrated that the proposed GFCO greatly enhanced performance of throughput 15.11%, SR 3.11%, PLR 3.11%, and PD 5.52% on average for scenario-I, whereas throughput 12.06%, SR 9.0%, PLR 9.0%, and PD 2.23% on average for scenario-II, as compared to SACA. Following that, these results are used to calculate the throughput, PDR, PLR, and PD and to draw a graphical representation. The proposed GFCO technique significantly improved efficiency, according to the results of the simulated testing.

INDEX TERMS REB, FLC, channel optimization, genetic-fuzzy, IEEE 802.15.4, LR-WPANs.

I. INTRODUCTION

The IEEE-802.15.4 LR-WPAN is a Low Rate Wireless Personal Area Network standard [1] which, offers the essential lower network layers with the emphases on low speed, low cost communication between ubiquitous devices. The key distinction with other standards, like WLAN is, the difference of acquiring more power and bandwidth, whereas, LR WPAN's key focus is on very low communication cost as well as very low power/ energy consumption of

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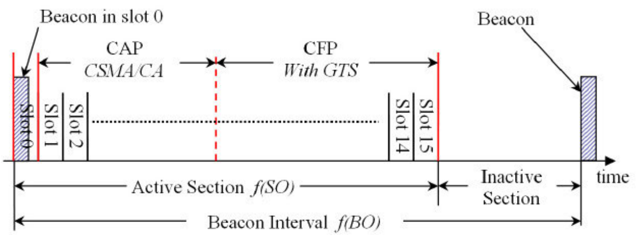


FIGURE 1. 802.15.4 LR-WPAN superframe structure [1].

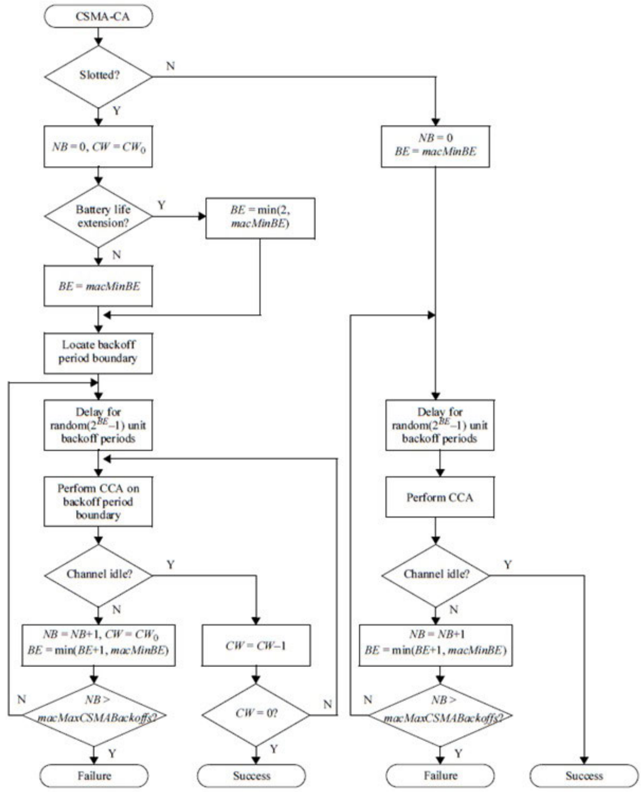


FIGURE 2. LR-WPAN CSMA/CA algorithm (REB) [1].

interacting devices/ nodes without essential infrastructure. The CSMA/CA protocol is used to get access to the physical medium of communication as depicted in the Fig.1.

The IEEE 802.15.4 MAC's operational method may be divided into two categories, namely beacon and non-beacon, according to *RandomExponentialBackoff* (REB). Both modes with and without beacon support employ the CSMA/CA mechanism. All of this article's attention will be on the Slotted CSMA/CA beacon-enabled mode. Such networks, which are not using beaconing mechanisms, employ the listening medium of an unslotted variation, whereas, in beaconing mechanisms, there are two mode 1st is CFP (Contention Free Period) which, works with GTS (Guaranteed Time Slots) and 2nd is CAP (Contention Access Period) which, works with slotted CSMA/CA leveraged by a REB algorithm. The slotted CSMA/CA performs the following roles during the CAP process. To begin transmitting, a number of variables must be set up, including CW_{size} (CW = 2 at startup and whenever the channel is determined to be busy), the number of backoff stages (NB = 0), and the backoff exponent (BE initialised to the standard parameter macMinBE). Node then waits until a random backoff time (BP) is picked from $[0, 2^{BE} - 1]$ before proceeding. Node launches first clear channel assessment (CCA1) after backoff timer expires, which determines the channel's state. It is possible that the channel isn't being used, in which case a second CCA (CCA2) is run. If the channel is idle for a second time, the node starts delivering data while it awaits an acknowledgement packet from the coordinator. There is always one unit added to BE and NB if one of the two CCA identifies an overloaded channel. The macMaxBE and macMaxCSMABackoffs levels for BE and NB can both be reached in the same period of time. While $[0, 2^{BE+1} - 1]$ will be assigned to BE if it meets or exceeds its value, NB will fail to transmit and packets will be refused, resulting in the network being disconnected. Complete working is shown in Fig.2. ZigBee is the most prominent example of the IEEE standard 802.15.4 being used with modifications [2], [3], [4], [5].

The REB algorithm has certain limitations like low throughput, low PDR, high PLR, and high PD. While the majority of the limitations have been mitigated over time [3], [5], [6], [7], [8], [9], advances in wireless technologies emphasize overcoming them, and one way to do so is to optimize channel access/ CW_{size}, every node and sensor complies with the channel's requirements whenever they own a channel or anticipate one opening up. Within the fundamental operations of the REB, several improved and substantially modified algorithms have been presented. The size of CW throughout the execution process must still be determined by a superior backoff computation, which must also determine how much the size of CW should be reduced. This kind of methodology is referred to as an adaptive strategy.

There are several obstacles and problems facing LR-WPANs, including channel sharing, the requirement for error-free communication lines, the absence of centralised coordination, and the lack of exact temporal synchronisation [4], [10], [11], [12], [18], [19]. Everyone involved in the MAC protocol strives to obtain the optimal medium consumption throughout the network design phase. This is particularly true for the deployment of a backoff interval, such as CW_{size}, using a accurate backoff mechanism during the network design process. The backoff algorithm choices could significantly improve message success ratio by lowering packet loss ratio and packet delay, as well as network efficiency, delay and latency.

It is evident that throughput, PDR, PLR, and PD are the most significant challenges, current research aims to address these issues to improve network performance. In order to improve REB outcomes, the GFCO technique is developed, with a focus on simplifying streamlining channel access/

CW_{size} for the 802.15.4 standard. These results illustrate the comparison of an existing Fuzzy method, as well as the REB, with a new mechanism called the GFCO approach. An analysis revealed that fine-tuning FLC using GA resulted in optimal and superior outcomes. The knowledge of FLC and GA has been incorporated into a mechanism that takes into account the best practises of current algorithms used for IEEE 802.15.4 LR-WPANs and uses a modified/new approach, namely the GFCO approach, in such a way that the challenges and problems faced by the community's challenges and problems are substantially reduced and results of the evaluation are superior to the existing approach [6]. Our proposed method not only addresses the difficulties, but it also provides a unique approach to the objective of performance enhancement through channel / CW_{size} optimization for 802.15.4 LR-WPANs, which is beneficial to the wider community. In the long term, we feel that this will be beneficial to the community.

The proposed GFCO approach is assessed for REB algorithm, which is taken as the de facto standard, and the SACA mechanism, which assumed as the foundation-based research and is implemented in NS-3.20 in conjunction with fuzzylite in two scenarios. First scenario is implemented in randomly deployed 10 sensors on a person's body ($2 \times 2\ m^2$ area), whereas second scenario is implemented in $20 \times 20\ m^2$ area of a ward in hospital having 10 to 50 persons. The simulated outcomes of both scenarios were recorded for REB, SACA, and GFCO. These results were then utilised to compute the throughput, PDR, PLR, and PD, as well as to generate a graphical representation. The results of the simulated testing indicated that the proposed GFCO approach considerably enhanced performance.

In this paper, we use the NS-3.20 environment in conjunction with fuzzylite to simulate and compare the performance of a standard algorithm, the REB, SACA and our proposed GFCO approach for the channel / CW_{size} optimization. The rest of the paper is organised as follows: GFCO is explained in Section IV; Section V provides information on its implementation and analysis; and Section II contains a literature study on the specified topic, in which several approaches/algorithms are presented. Research contributions are in Section III. After that, in section VI, the article comes to an end.

II. LITERATURE REVIEW

This section's main goal is to elaborate on the important contributions made by several scientists, particularly those who recommended improving and altering CW performance to improve the performance of 802.15.4 LR-WPANs. Even though there is a lot of development in the field of 802.15.4 LR-WPANs, there are still many issues and limitations in the present systems, including throughput, PDR, PLR, PD, and success probability. The following section highlights some of the most significant studies that diverse researchers have produced in this particular area:

Elappila et al. [6] to enhance 802.15.4 LR-WPAN performance, presented a concept-based method, namely the Survivability Aware Channel Allocation (SACA) procedure. Using the NS-2 simulator, the efficiency of this suggested approach is compared to the ACS, CLFB, D2MAC, NB-Step, and CSMA / CA mechanisms of 802.15.4 LR-WPAN. The results obtained have been produced to ensure that the suggested process efficiency is greater than those of comparative techniques.

Akbar et al. [3] suggested a method to improve the performance of the 802.15.4 protocol based on the clear idea of the Fuzzy Logic System (FLS). The suggested FLS was compared to REL, LABILE, and AODV, and the simulation results indicated that the proposed solution performed better than the competing solutions.

Pushpan et al. [7] proposed a low-level understanding technique, namely the Dynamic time slot (DTS) allocation procedure, which enhanced the PDR and decreased the end-to-end latency. The DTS technique is designed in an ambiguous manner, with the FL receiving three inputs: the power rating, the buffer rate, and the packet arrival rate. This method avoids time-consuming credit and unnecessary network delays, resulting in a greater degree of network dependability through increased channel utilisation. Using the NS-2 simulator, the proposed system's efficiency is assessed in terms of PDR, intermediate end-to-end delays, and central EC in comparison to the 802.15.4 standard and the telemedicine protocol (TMP). It is worth noting that the DTS was created without altering the superframe structure of the 802.15.4 MAC standard.

Masud et al. [8] proposed a high-level Traffic Class Prioritization technique that is built on CSMA/CA, i.e. (TCP-CSMA / CA) technologies. Using the NS-2 simulator, this proposed technique is compared to the PLA-MAC, the eMC-MAC, and the PG-MAC; the findings show that the efficiency of this proposed method is higher.

Henna and Sarwar [9] presented a novel method called RAI MAC, which stands for Retransmission Adaptive Intelligent MAC. This suggested approach makes advantage of adaptive Backoff process, experimental findings revealed that the suggested technique outperformed the 802.15.4 standard.

Nekooei et al. [10] Cross Layer Fuzzy logic Backoff (CLFB) was proposed in 802.15.4 as an evolutionary method for automating the construction of fuzzy logic for cross layer media access control. Two well-known evolutionary algorithms used to evaluate the proposed approach, one is particle swarm optimization (PSO), while the other one is differential evolution (DE). The suggested method's performance is compared to that of ACS, D^2MAC, NB Step, and the 802.15.4 LR-WPAN CSMA/CA mechanism using the OMNeT++ simulator. In simulations, the suggested fuzzy logic-based method outperformed the traditional comparison techniques.

Bouazzi et al. [11] presented a technique which uses fuzzy logic to apply a dynamic allocation of priority level for nodes that contest for the acquisition of the medium through tuning parameters in the CSMA/CA algorithm. The proposed algorithm integrates fuzzy rules in the CSMA/CA algorithm with added conditions for the priority of nodes who wish to access the medium. The priority level is calculated based on defuzzification stage of fuzzy controller. The proposed technique is evaluated under different scenarios by using NS-2 simulator. Simulation results showed various significant enhancement that, the network performance with the proposed technique is more reliable than 802.15.4 standard algorithm.

Henna et al. [12] A traffic adaptive priority-based superframe structure that may decrease congestion during the CAP period is suggested. The name of this new suggested MAC protocol is traffic adaptive priority based MAC (TAP-MAC). According to the authors, this new method gives low priority traffic a fair opportunity. When compared to the priority-based MAC protocol, the simulation results produced by NS-3 showed that the suggested method achieved high throughput, low energy consumption, and low latency (PA-MAC and 802.15.4 standard).

Al-Humairi et al. [13] proposed four (4) Alternate Backoff time Optimization algorithms to optimize the BT in Zigbee standard 802.15.4 protocol. Performance of the proposed algorithms are evaluated in four scenarios, with Zigbee, ACO, Tabu Search, and Counting Packets. Results revealed that the proposed algorithms are better than the comparing algorithms.

Vutukuri et al. [14] proposed an enhanced algorithm, which improved the performance of the backoff algorithm in 802.15.4. Evaluation of the proposed algorithm in NS-2 environment, confirmed that the proposed algorithm is better than the 802.15.4.

Dahham et al. [15] proposed an Efficient Backoff Algorithm (EBA 15.4MAC). Simulation results proved that proposed algorithm enhanced the performance of slotted CSMA/CA algorithm, through CW adjustment and managing the collision issue by using Temporary Backoff (TB) and Next Temporary Backoff (NTB).

Zhou et. al. [16] proposed a Fuzzy Control Medium Access (FCMA) mechanism. To evaluate the proposed model in first step, MATLAB environment is used to build the fuzzy control system, in second step Castalia simulator is used to compare the performance of FCMA with the 802.15.4. Obtained results through experiments validated the enhanced performance of FCMA.

A. FINDINGS OF THE LITERATURE

In compliance of a thorough literature review, we have decided to concentrate on these subjects since we are developing a cutting-edge technique in this research piece, which includes using a genetic fuzzy logic approach to optimise the channel / CW_{size} in LR-WPANs as well as a thorough examination of the REB algorithm. In the first step, preliminary and background information was gathered, but after a thorough search, we found a wealth of information and literature on the subject. However, we limit ourselves to only those information and literature pieces that contain channel / CW_{size} optimisation related material in the domain of LR-WPANs.

1) FINDINGS NO.1

The major issues (throughput, PDR, PLR, and PD) are faced by IEEE-802.15.4 LR-WPANs and scientists have made improvements to the channel / CW_{size} for LR-WPANs standard in order to handle these challenges.

2) FINDINGS NO.2

The recommended solutions are based on simulation and mathematics, as stated in the literature study section. To categorise them, all of them may be put into the following groups:

- Mechanisms which alter conventional algorithms
- Mechanisms that use FLC to accomplish goals
- Mechanisms for adjusting the parameters to a finer degree.

3) FINDING NO.3

Although it is not yet evident which approach or methodology will be most helpful, the application and effectiveness of any particular methodology depends on the type of data used, the setting, and the performance indicators employed. An extensive experimental study followed by a statistical analysis is required to ascertain which strategy or approach is the most successful.

III. RESEARCH CONTRIBUTIONS

Since we are interested in optimising channel / $CW size$ for 802.15.4 LR-WPANs, we've looked into all of the current methodologies and approaches, and we've compared them all. The results are given in the Table1. When conducting a comparative analysis, the following parameters are considered: reference and year of the paper, presented algorithm or scheme, the techniques that are being compared, and the performance metrics that are being used, such as PDR, PLR, CR, FI, EC, and Experimental Tool. A few items have come to our notice, and we've decided to proceed with the actions indicated below as a result of what we've discovered.

1) Comparative study of current channel / CW_{size} optimization methods utilised in LR-WPANs, as well as the development of new ones.
2) A key component of channel or CW_{size} optimisation is the choice of a CW_{size} following each collision or successful packet delivery. Choosing to do so via FIS is a wise decision, but it comes with two significant drawbacks.
    - Developing the most effective rules
    - fine-tuning the functions of membership
3) For the most difficult problems in any FIS, Genetic Algorithms are considered to be a viable option. The knowledge regarding FLC and GA has been integrated,

TABLE 1. Surveyed approaches/algorithms related to LR-WPAN comparison.

Ref:	Proposed Approaches/ Algorithms	Approaches compared with	Evaluation Metrics					Experimental Tool
			PDR	**PLR**	**CR**	**FI**	**EC**	
[6] 2020	SACA	REB, ACS, CLFB, D2MAC, NB-Step	Yes	Yes	No	No	No	NS-2
[3] 2019	FLS	REB, REL, LABILE, AODV	Yes	No	No	No	No	Castalia OMNeT++
[7] 2019	DTS	REB, TMP	Yes	Yes	No	No	Yes	NS-2
[8] 2019	TCP-CSMA/CA	PLA-MAC, eMAC-MAC,PG-MAC	Yes	Yes	No	No	Yes	NS-2
[9] 2018	RAI-MAC	REB	Yes	No	No	No	Yes	NS-2
[10] 2017	CLFB	REB, ACS, D2MAC, NB-Step	Yes	Yes	Yes	No	No	OMNeT++
[11] 2017	Fuzzy based proposed algorithm	REB	Yes	Yes	No	No	Yes	NS-2
[12] 2017	TAP-MAC	REB, PA-MAC	Yes	No	No	No	Yes	NS-3.20
[13] 2016	4 Alternate Backoff Time optimization algorithms	Zigbee, ACO, Tabu Search, Counting Packets	Yes	No	No	No	Yes	OPNET
[14] 2014	Enhanced Algorithm	REB	Yes	Yes	No	No	No	NS-2
[15] 2014	EBA-15.4MAC	REB	Yes	No	No	No	Yes	NS-2
[16] 2014	FCMA	REB	Yes	Yes	No	No	No	MATLAB Castalia

and we have created a way for GA to tune the FLC optimally, as well as a novel Genetic Fuzzy approach for channel / CW_{size} optimization that we propose.

4) Proposed five algorithms, Algorithm-1: GFCO for LR-WPAN, Algorithm-2: GA_1 for GFCO, Algorithm-3: FLC_1 for GFCO, Algorithm-4: GA_2 for GFCO, and Algorithm-5: FLC_2 for GFCO.
5) We simulated the suggested Genetic Fuzzy method using NS-3.20 and the fuzzylite environment and compared it to the current REB and SACA. According on the outcomes of the simulated tests, the recommended Genetic Fuzzy approach greatly increased performance.

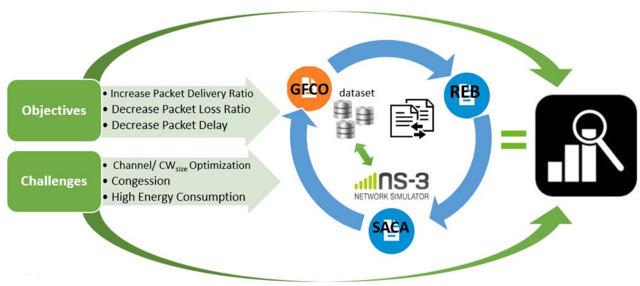


FIGURE 3. The GFCO approach: A proposed conceptual model.

IV. PROPOSED GFCO: A GENETIC FUZZY-LOGIC CHANNEL OPTIMIZATION APPROACH FOR LR-WPAN

The GFCO technique is described in detail in this section. It is intended to study and simulate the performance enhancement of the REB method, with a focus on channel / CW_{size} adjustment for 802.15.4 LR-WPANs, with the aim of increasing transmission and channel access throughput. GFCO method is developed with this goal in mind and after evaluating the current schemes presented by many studies, which improved the throughput, PDR and decreased the PLR, PD. The conceptual model shown below is recommended to more accurately convey how the GFCO technique, as seen in Fig.3, operates. Below is further information on its application:

We began by defining our research goals and challenges using the conceptual model, which we had to accomplish by carrying out the advised study design. For this study, a clear set of objectives has been established: raising throughput and PDR while lowering PLR and PD. Since we have addressed the difficulties, namely channel optimization / CW_{size} optimization, congestion, and excessive energy consumption, we have concentrated on channel optimization / CW_{size} optimization. We integrated the FLC and GA in this

Algorithm 1 GFCO for LR-WPANs

Input:

α_1 : CSI β_1 : PSR
α_2 : LQI β_2 : ADR
α_3 : DPL β_3 : PSF

Output:

γ_1 : Backoff Exponent value
γ_2 : Probability to get Channel Access/ CW_{size}
Result: Optimized Backoff delay for Channel Access/ Optimized CW_{size}

1: $nPkt$: The total No. of packets that will be sent
2: Pkt : Packets to be send
3: NB : Number of Backoff stages
4: CAP : Status of Contention Access Period
5: Ch : Channel to be used for transmission
6: BL : Battery Life
7: ε_1 : Tuned value of α_3
8: ε_2 : Tuned value of β_3
9: **while** ($nPkt > 0$) and (CAP is Yes) **do**
10: **if** (BL is Yes) **then**
11: $\gamma_1 :\leftarrow$ min(2,macMaxBE)
12: **else**
13: $\gamma_1 :\leftarrow$ macMinBE)
14: **end if**
15: Determine backoff boundary
16: Delay Random (2^{γ_1}-1) Unit Backoff periods
17: Conduct a CCA on the backoff period's border.
18: **if** (Ch Not Busy) **then**
19: CW = CW-1
20: **if** (CW = 0) and (Pkt is Successful) **then**
21: $\gamma_1 :\leftarrow$ Call $FLC_1(\alpha_1,\alpha_2,\alpha_3)$ Ref:Algo-3
22: $\alpha_3 :\leftarrow$ Update
23: $\gamma_2 :\leftarrow$ Call $FLC_2(\beta_1,\beta_2,\beta_3)$ Ref:Algo-5
24: $\beta_3 :\leftarrow$ Update
25: $nPkt = nPkt$ - 1
26: **else**
27: *Goto* :← Line 16
28: **end if**
29: **else**
30: NB = NB + 1
31: $CW = CW_0$
32: γ_1 = min(γ_1+1,macMinBE)
33: **if** ($NB > macMaxCSMABackoffs$) **then**
34: $\varepsilon_1 :\leftarrow$ Call $GA_1(\alpha_3)$ Ref:Algo-2
35: $\gamma_1 :\leftarrow$ Call $FLC_1(\alpha_1,\alpha_2,\varepsilon_1)$ Ref:Algo-3
36: $\varepsilon_2 :\leftarrow$ Call $GA_2(\beta_3)$ Ref:Algo-4
37: $\gamma_2 :\leftarrow$ Call $FLC_2(\beta_1,\beta_2,\varepsilon_2)$ Ref:Algo-5
38: **else**
39: *Goto* :← Line 16
40: **end if**
41: **end if**
42: $\gamma :\leftarrow ((100-\gamma_2)\text{x}(2^{\gamma_1}-1))/100$
43: WaitToRetry(γ)
44: **end while**

model, and GA adjusted the FLC ideally as a result. Five algorithms have been proposed for this purpose: Algorithm-1: GFCO for LR-WPAN, Algorithm-2: GA_1 for GFCO, Algorithm-3: FLC_1 for GFCO, Algorithm-4: GA_2 for GFCO, and Algorithm-5: FLC_1 for GFCO. The SACA technique was picked from a referenced work [6], and the chosen parameter values were repeatedly applied for each every algorithm as mentioned in the proposed model in Fig.3, and the results were recorded for two scenarios in separate files for REB, SACA, and GFCO. First scenario is implemented in randomly deployed 1 - 9 sensors on a person's body (2 × 2 m^2 area) and 1 coordinator placed at the center whereas, the second scenario is implemented in 20 × 20 m^2 area with increasing number having 10 to 50 persons. These files were then used to compute metrics like as throughput, success ratio/packet delivery ratio, packet loss ratio, and packet delay. The findings established that the GFCO outperforms the REB and SACA.

A. ALGORITHM1: GFCO FOR LR-WPANs

This is the primary algorithm of the GFCO method that is being suggested and it is responsible for the proper operation of the entire machine. Two FIS $FuzzyRuleBase_1$ and $FuzzyRuleBase_2$ used in this proposed approach with six input parameters, α_1, α_2, α_3, β_1, β_2, and β_3, which respectively reflect the Channel Strength Indicator (CSI), Link Quality Indicator (LQI), Path Loss distance between nodes/ sensors (DPL), Packet Service Rate (PSR), Application Data Rate (ADR), and Path Survivability Factor (PSF), are used to generate γ_1, Backoff exponent value; and γ_2, probability to get channel access/ CW_{size}. At the end by using these two outputs the optimized channel / CW_{size} is calculated. A fitness function is used in the first phase of GA_1 (Algorithm-2) to fine-tune α_3; the entire method of GA_1 is described in Section IV-B. In the second step, a FLC_1 (Algorithm-3) is invoked to get the optimal value of γ_1 through α_1, α_2, and α_3; the entire procedure is also detailed in Section IV-C. In the third phase, GA_2 (Algorithm-4) is called to adjust the β_3 using a fitness function; the full procedure of GA_2 is explained in Section IV-D; in the fourth and final phase, FLC_2 (Algorithm-5) is called to get the optimal value of γ_2 using β_1, β_2, and β_3. Section IV-E provides a detailed description of the entire procedure.

The GFCO algorithm is executed until the packet limit is reached and the CAP option is activated. In the first instance, where the channel is not busy, the CW value is 0, and The packet was despatched successfully, FLC_1 and FLC_2 are called without colliding and update α_3, β_3, and nPkt. When there is a collision, the collision bit is set to true, and only FLC is implemented. When the channel is not idle, it is the crucial circumstance. Given this, GA_1 is applied to α_3 in order to get the customised value of α_3, which is ε_1, and GA_2 is applied to β_3 to obtain the finger degree value of β_3, which is ε_2, and then these fine grained values are passed to FLC_1 and

FLC_2 to obtain the appropriate values of γ_1 and γ_2. Finally these γ_1 and γ_2 values used to get optimized backoff delay for channel access/ optimized CW_{size}. The complete Algorithm is as under.

B. ALGORITHM2: GA_1 FOR GFCO

The operation of the GA_1 for the GFCO algorithm is described in this section. When the value of α_3 is tuned using the provided Fn_1, which is the fitness function for GA_1, the algorithm continues to work until a sufficient value of ε_1 is obtained that is fit enough, or until a specified amount of time has elapsed First, the function Fn_1 is calculated for the value of α_3, and then a random pick is made, and the value that has been calculated is evaluated in order to estimate the function ε_1. Once this estimate has been validated, the returned value is determined by how well it fits in. The entire Algorithm is as under.

Algorithm 2 GA_1 for GFCO

Input:
α_3 : DPL
Pop_1 : Population Size for GA_1
Fn_1 : Fitness Function for GA_1
Output:
ε_1 : Fine grained value of α_3
while (ε_1 is reasonably fit) OR (There has been sufficient time) **do**
  x :← Random-Pick(Pop_1,Fn_1)
  ε_1 :← Evaluation(x)
end while
Return(ε_1)

C. ALGORITHM3: FLC_1 FOR GFCO

The FLC is utilised by the GFCO algorithm, as illustrated in Algorithm 3. With the help of α_1, α_2, and α_3, in order to get the best value for γ_1, a FLC_1 is employed. By Combining the three separate value of α_1, α_2, and α_3, twenty-seven (27) potential combinations are built as mentioned in Table 4. These twenty-seven (27) values (1 - 27) are essentially the inputs kept in the $\mu_R[R_1]$ and outputs kept in the $\mu_A[G_1]$ that define the possible value for γ_1 by using this FLC_1 algorithm. The entire Algorithm is shown in the next part.

D. ALGORITHM4: GA_2 FOR GFCO

This section explains how the GA_2 for the GFCO algorithm works. This method adjusts the value of β_3 by utilising the provided Fn_2, i.e. fitness function for GA_2, and does its job until it obtains a reasonable value of ε_2 that is fit enough or until the specified time elapses. 1st, Fn_2 is calculated for the value of β_3; following that, a random pick is made, and the value that has been calculated is evaluated in order to estimate the function ε_2. Finally, if the projected value is near enough to the actual value, the actual value is returned. The whole Algorithm is shown in the diagram below.

Algorithm 3 FLC_1 for GFCO

Input:
$F_1 = 3$: No of Fuzzy Input Variables
$N_1 = 3$: No of Membership Functions per Variable
$R_1 = 27$: No of Fuzzy Rules ($R = N_1^{F_1}$)
$G_1 = 256$: No of divisions used for centroid calculation
$X_1[F_1] = [\alpha_1, \alpha_2, \alpha_3]$: Array of Fuzzy Input Variables values
$\mu[R_1][1..F_1]$: each membership function's matrix of input values
$\mu_o[R_1][G_1]$: each membership function's matrix of output values
Variables:
$\mu_R[R_1]$: Each rule's membership values array
$\mu_A[G_1]$: All rule's activation values array
r : integer
Output:
γ_1 : Backoff Exponent value
for ($r := 1$ step 1 until R_1) **do**
  $\mu_R[r]$:← min($\mu_R[1]$, $\mu_R[2]$,..$\mu_R[F_1]$)
end for
for ($r := 1$ step 1 until G_1) **do**
  $\mu_A[r]$:← max[min($\mu_R[1]$, $\mu_o[1][r]$), min($\mu_R[2]$, $\mu_o[2][r]$),.. min($\mu_R[R_1]$, $\mu_o[R_1][r]$)]
end for
γ_1 :← $[\Sigma_{i=1}^{G_1}((256/G_1).\mu_A(i))]/\Sigma_{i=1}^{G_1}\mu_A(i)$
Return(γ_1)

Algorithm 4 GA_2 for GFCO

Input:
β_3 : sf
Pop_2 : Population Size for GA_2
Fn_2 : Fitness Function for GA_2
Output:
ε_2 : Fine grained value of β_3 :
while (ε_2 is reasonably fit) OR (There has been sufficient time) **do**
  y :← Random-Pick(Pop_2,Fn_2)
  ε_2 :← Evaluation(y)
end while
Return(ε_2)

E. ALGORITHM5: FLC_2 FOR GFCO

The GFCO method employs the Fuzzy Logic Controller (FLC), as illustrated in Algorithm 5. With the help of β_1, β_2, and β_3, The optimally tune value for γ_2 may be obtained using a FLC_2. By combining the three separate value of β_1, β_2, and β_3, twenty-seven (27) potential combinations are built as mentioned in Table 5. These twenty-seven (27) values (1 - 27) are essentially the inputs kept in the $\mu_R[R_2]$ and outputs kept in the $\mu_A[G_2]$ that define the possible value for γ_2 by using this FLC_2 algorithm. The entire Algorithm is shown in the next part.

Algorithm 5 *FLC_2* for GFCO

Input:

$F_2 = 3$: No of Fuzzy Input Variables
$N_2 = 3$: No of Membership Functions per Variable
$R_2 = 27$: No of Fuzzy Rules ($R = N_2^{F_2}$)
$G_2 = 100$: No of divisions used for centroid calculation
$X_2[F_2] = [\beta_1, \beta_2, \beta_3]$: Array of Fuzzy Input Variables values
$\mu[R_2][1..F_2]$: each membership function's matrix of input values
$\mu_o[R_2][G_2]$: each membership function's matrix of output values

Variables:

$\mu_R[R_2]$: Each rule's membership values array
$\mu_A[G_2]$: All rule's activation values array
s : integer

Output:

γ_2 : Probability to get Channel Access/ CW_{size}

for ($s := 1$ step 1 until R_2) **do**
  $\mu_R[s] :\leftarrow \min(\mu_R[1], \mu_R[2], .. \mu_R[F_2])$
end for
for ($s := 1$ step 1 until G_2) **do**
  $\mu_A[s] :\leftarrow \max[\min(\mu_R[1], \mu_o[1][s]), \min(\mu_R[2], \mu_o[2][s]), .. \min(\mu_R[R_2], \mu_o[R_2][s])]$
end for
$\gamma_2 :\leftarrow [\Sigma_{i=1}^{G_2}((100/G_2).\mu_A(i))]/\Sigma_{i=1}^{G_2}\mu_A(i)$
Return(γ_2)

F. COMPUTATIONAL COMPLEXITY OF GFCO

The computational complexity of the REB has been the subject of various research initiatives [3], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]. After extensive simulation of the methods, we developed simpler techniques that not only reduced the computational complexity to a practical level of O(n^2) but also produced a 0.95 confidence interval.

1) TIME COMPLEXITY OF GFCO

The Best, Worst, and Average case scenario illustrates how the proposed GFCO technique functions in the following manner.:-

a: BEST-CASE SCENARIO

There is evidence that the suggested algorithms can be processed in linear time, i.e. Ω(n), which implies that if n packets to be transmitted are sent over a channel that is not busy and are delivered successfully, the algorithm will run n times and its time complexity is Ω(n).

b: WORST-CASE SCENARIO

In the worst-case situation, the total processing time needed by the suggested methods is O(n^2), or polynomial time. Hence the contention node/sensor must wait for at most n constant times before trying to transmit another packet, and this may happen up to NxN times in total if there are n packets available for transmission.So the technique runs n x n times, and each time it fails because the channel is busy, yielding a total time complexity of O(n^2).

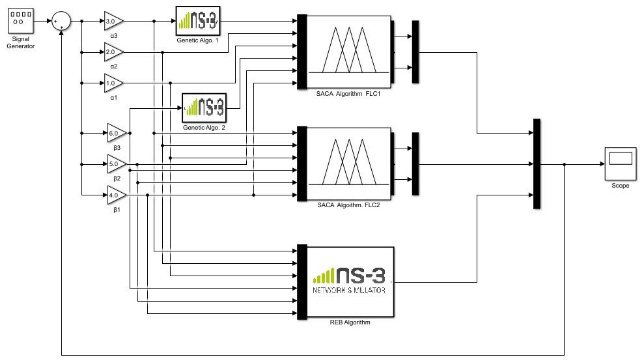


FIGURE 4. Simulation model of proposed GFCO approach.

c: AVERAGE-CASE SCENARIO

The average case for the suggested approach is also polynomial-time, Θ(n^2), since sometimes n packets to be transmitted are sent over a channel that is not busy and are delivered successfully and other times n packets to be transmitted are sent over a channel that is occupied. This means that if you run the method n times, it can occur between 1xn and nxn times in all of the algorithms, resulting in a total time complexity of 1xn or nxn ≈ Θ(n^2).

Fig.12 to Fig.19 exhibit simulation results that demonstrate that the suggested GFCO approach has a less computational difficulty than the other two comparing techniques, namely REB and SACA.

V. SIMULATION AND ANALYSIS

There is extensive discussion of the GFCO approach in this section, which utilises and combines the FLC and GA to optimise the FLC, and its simulation has been performed in NS-3.20 environment in conjunction with fuzzylite in two scenarios, according to the Simulation Model given in Fig.4. Each scenario is evaluated using various parameters as mentioned in the Table 2 and Table 3, in order to determine throughput, "PDR," "PLR," and "PD.". First scenario is implemented in randomly deployed 10 sensors on a person's body ($2 \times 2\ m^2$ area), whereas second scenario is implemented in $20 \times 20\ m^2$ area of a ward in hospital having 10 to 50 persons. The simulated outcomes of both scenarios were recorded for REB, SACA, and GFCO. Following that, a graphical representation was created using these results. The outcomes of the simulated testing demonstrated that the suggested GFCO technique significantly improved performance and had a substantial influence on enhancing the overall effectiveness.

A. SIMULATION SCENARIOS

The effectiveness of the suggested GFCO method is examined in two distinct situations, as shown in the selected

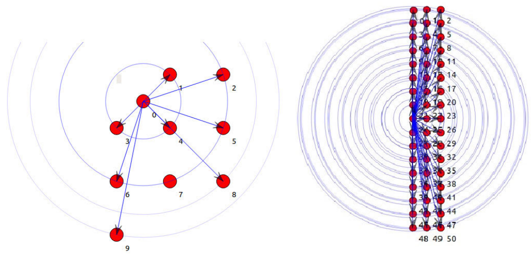


FIGURE 5. Scenario-I and Scenario-II of GFCO approach.

TABLE 2. Nodes/ sensors used with data rates.

Sr.	Node/Sensor Name	No. of Nodes/ Sensor	Data rates (bits/s)
1	ECG	2	1322
2	Blood Pressure	1	4096
3	Body Temperature	1	100
4	Motion Sensor	1	512
5	EEG	1	250
6	Heart Rate	1	160
7	Respiratory Rate	1	120
8	Endoscope Imaging	1	12307.68

base article [6]. The suggested GFCO method is put to the test using two sets of simulations. Simulation is explained in Scenario-I in a single transmission-range radius with a varying No. of transmissions happening simultaneously. Furthermore, by varying the packet generation intervals of the transmitters, the testing may be extended to cover a wider range of traffic conditions (from high to low). Scenario-II depicts a hospitalisation and monitoring situation in which individuals are hospitalised and observed. Several sensor nodes and a coordinator node are linked to an 802.15.4 personal area network, which is used to connect these patients. Regularly, the coordinator will transmit the data collected to a nearby processing and storage facility for further processing and storage (base station). Changes to the wearer's sensor count and the number of patients placed in the deployment region allow for LR-WPAN simulations, which is $20 \times 20\, m^2$ in size. Fig.5 illustrates simulation in the setting of scenario-I and scenario-II from the benchmark manuscript, even if each node or sensor utilised in the simulation has a datarate that is mentioned in Table 2.

These nodes or sensors have ready-to-transmit packets at all times, and their datarates range from 100 to 12307.68 bits/s. The position of the receiver, the underlying network, and other variables that have a big influence on the operation of the network all affect the SINR between interacting nodes or sensors. Using the additive interference model, constant bit rate application payload of 100 bytes is used, and at or above the threshold, a sufficient circumstance for packet receipt is preserved. Table 2 shows the placement of all participating nodes or sensors of scenario-I inside the $2 \times 2\ m^2$ space. The log-normal shadowing model is the data transmission propagation model. The overall simulation

TABLE 3. Simulation parameters used.

Parameters	Values
Overall Simulation Time	60s
Simulation Area (scenario-I)	2 x 2 m^2
Simulation Area (scenario-II)	20 x 20 m^2
Number of Nodes/ Sensors (I)	10
Number of Nodes/ Sensors (II)	50
Nodes/ Sensors Generating Traffic	1 to 9
Constant bit rate	100 bytes
Data rate	variable
MAC type	802.15.4 LR-WPAN
Propagation model	log-normal shadowing
Interference model	Additive
Number of Iterations	30

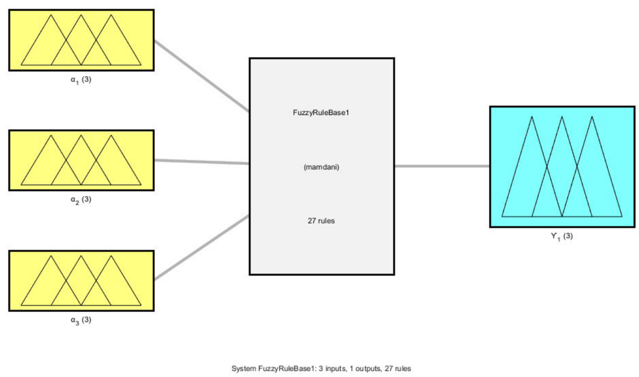


FIGURE 6. FIS used in Scenario-I for GFCO approach.

time was 60 seconds for each iteration. Table 3 gives a brief description of the simulation's parameters.

1) SCENARIO-I DETAILS

In the simulation phase-1, Fuzzy Logic *FuzzyRuleBase*1 uses three inputs parameters α_1, α_2 and α_3 (α_3 is optimized by GA_1), as illustrated in Fig.6, to get the value of backoff exponent i.e. γ_1. The 27 inference rules presented in Fig.6, are understood in Equation-1 as the following linguistic statements:-

$$\alpha_1, \alpha_2, \alpha_3 \quad and \quad \gamma_1 \,\epsilon \begin{cases} L & \text{Low} \\ M & \text{Medium} \\ H & \text{High} \end{cases} \tag{1}$$

However, as a mathematical representation the fuzzy members of each α_1, α_2, α_3 and γ_1 characterized by membership function are defined in Equation-2 and Equation-3 respectively.

$$\mu_A(G_1) \;=\; \begin{cases} 0 & \text{if } G_1 \leqslant \text{L} \\ \dfrac{G_1 - L}{M - L} & \text{if L} < G_1 < \text{M} \\ \dfrac{G_1 - M}{H - M} & \text{if M} < G_1 < \text{H} \\ 256 & \text{if H} \leqslant G_1 \end{cases} \tag{2}$$

TABLE 4. ***FuzzyRuleBase1*** **27 inference rules.**

α_1 \ α_2	***L***	***M***	***H***
L	LL	LM	LH
M	ML	MM	MH
H	HL	HM	HH

$\alpha_1\alpha_2$ \ α_3	***H***	***M***	***L***
LL	L	L	M
LM	L	L	M
LH	L	M	M
ML	L	M	M
MM	L	M	H
MH	M	M	H
HL	M	M	H
HM	M	H	H
HH	M	H	H

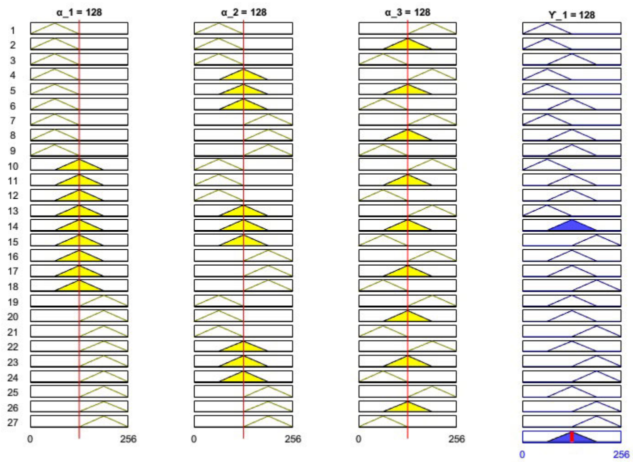


FIGURE 7. **Fuzzy logic rule viewer (FuzzyRuleBase1).**

$\mu_A(G_1)$ is called membership degree of G_1 in α_1,α_2,α_3.

$$\mu_o(G_1) = \begin{cases} 0 & \text{if } G_1 \leqslant \text{L} \\ \dfrac{G_1 - L}{M - L} & \text{if L} < G_1 < \text{M} \\ \dfrac{G_1 - M}{H - M} & \text{if M} < G_1 < \text{H} \\ 256 & \text{if H} \leqslant G_1 \end{cases} \tag{3}$$

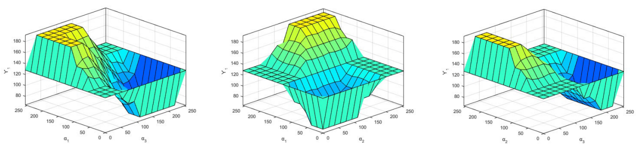
$\mu_o(G_1)$ is called membership degree of G_1 in γ_1.

The inference rules provided in Table 4 are based on fuzzy inputs and outputs of Equation-1 are also mathematically represented in Equation-4 and Equation-5 as linguistic statements.

$$f(\alpha_1, \alpha_2, \alpha_3) : [0 \quad 256] \rightarrow R1 \quad and \quad f(\gamma_1) : [0 \quad 256] \rightarrow R2 \tag{4}$$

$$(G_1 \in R1) = \mu_{R1}(G_1) \; and \; (G_1 \in R2) = \mu_{R2}(G_1) \tag{5}$$

The inference rules provided in Table 4 are based on fuzzy inputs, and the union of these rules generates final outcome, which can be written in mathematical form as under



(a) $\alpha_1\alpha_3$ effect (b) $\alpha_1\alpha_2$ effect (c) $\alpha_2\alpha_3$ effect

FIGURE 8. **Complete input-output surface (Scenario-I).**

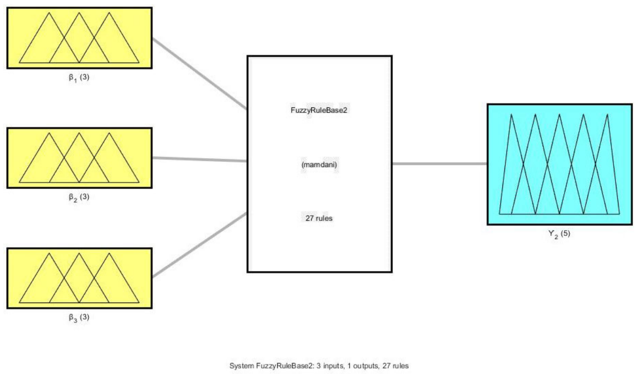


FIGURE 9. **FIS used in Scenario-II for GFCO approach.**

in Equation-6:-

$$R_1 \cup R_2 \cup R_3 \ldots\ldots \cup R_{27} = \bigcup_{i=1}^{27} R_i \tag{6}$$

where R_i is the result obtained after applying the ith rule, which is among the one of the twenty-seven rules as elaborated in Table 4. Furthermore, the Rule Review mode Fig.7 shows a particular single scenario, while the Fig.8 illustrates the complete input-output surface of FuzzyRuleBase1.

2) SCENARIO-II DETAILS

In the simulation phase-2, Fuzzy Logic *FuzzyRuleBase*2 also uses three inputs parameters β_1, β_2 and β_3 (β_3 is optimized by GA_2), as illustrated in Fig.9, to get the value of probability to get channel access/ CW_{size} i.e. γ_2. The 27 inference rules given in Fig.9, are interpreted in Equation-7 as the language assertions presented in the following statements:-

$$\beta_1, \beta_2, \beta_3 \; \epsilon \begin{cases} L & \text{Low} \\ M & \text{Medium} \\ H & \text{High} \end{cases} \qquad \gamma_2 \; \epsilon \begin{cases} VH & \text{Very High} \\ H & \text{High} \\ M & \text{Medium} \\ L & \text{Low} \\ VL & \text{Very Low} \end{cases} \tag{7}$$

However, as a mathematical representation the fuzzy members of each β_1, β_2, β_3 and γ_2 characterized by membership function are defined in Equation-8 and Equation-9

TABLE 5. ***FuzzyRuleBase2* 27 inference rules.**

		β_2		
		L	***M***	***H***
β_1	***H***	HL	HM	HH
	M	ML	MM	MH
	L	LL	LM	LH

		β_3		
		H	***M***	***L***
$\beta_1\beta_2$	***HL***	VL	VL	VL
	HM	H	M	L
	HH	VH	VH	M
	ML	L	L	VL
	MM	H	M	L
	MH	VH	H	L
	LL	H	M	L
	LM	H	M	M
	LH	VH	H	M

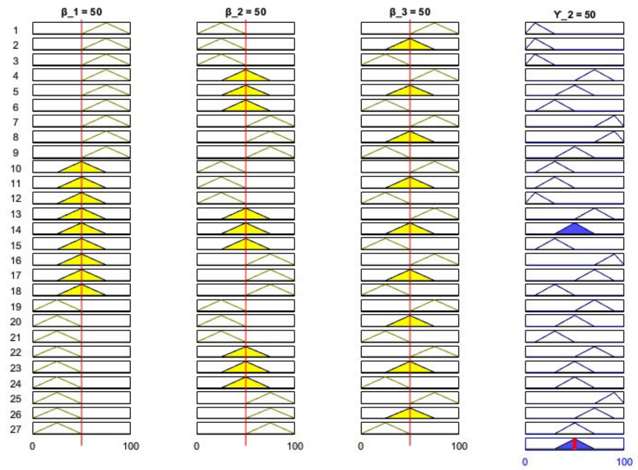
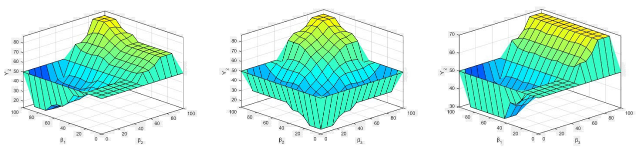


FIGURE 10. **Fuzzy logic rule viewer (FuzzyRuleBase2).**



(a) $\beta_1\beta_2$ effect (b) $\beta_2\beta_3$ effect (c) $\beta_1\beta_3$ effect

FIGURE 11. **Complete input-output surface (Scenario-II).**

respectively.

$$\mu_A(G_2) = \begin{cases} 0 & \text{if } G_2 \leqslant \mathrm{L} \\ \dfrac{G_2 - L}{M - L} & \text{if } \mathrm{L} < G_2 < \mathrm{M} \\ \dfrac{G_2 - M}{H - M} & \text{if } \mathrm{M} < G_2 < \mathrm{H} \\ 100 & \text{if } \mathrm{H} \leqslant G_2 \end{cases} \tag{8}$$

$\mu_A(G_2)$ is called membership degree of G_2 in β_1, β_2, β_3.

$$\mu_o(G_2) = \begin{cases} 0 & \text{if } G_2 \leqslant \mathrm{VH} \\ \dfrac{G_2 - VH}{H - VH} & \text{if } \mathrm{VH} < G_2 \leqslant \mathrm{H} \\ \dfrac{G_2 - H}{M - H} & \text{if } \mathrm{H} < G_2 \leqslant \mathrm{M} \\ \dfrac{G_2 - M}{L - M} & \text{if } \mathrm{M} < G_2 \leqslant \mathrm{L} \\ \dfrac{G_2 - L}{VL - L} & \text{if } \mathrm{L} < G_2 < \mathrm{VL} \\ 100 & \text{if } \mathrm{VL} \leqslant G_2 \end{cases} \tag{9}$$

$\mu_o(G_2)$ is called membership degree of G_2 in γ_2.

The inference rules provided in Table 5 are based on fuzzy inputs and outputs of Equation-7 are also mathematically represented in Equation-10 and Equation-11 as linguistic statements.

$$f(\beta_1, \beta_2, \beta_3) : [0 \quad 100] \rightarrow R1 \; and \; f(\gamma_2) : [0 \quad 100] \rightarrow R2 \tag{10}$$

$$(G_2 \in R1) = \mu_{R1}(G_2) \; and \; (G_2 \in R2) = \mu_{R2}(G_2) \tag{11}$$

The inference rules provided in Table 5 are based on fuzzy inputs, and the union of these rules generates final outcome, which can be written in mathematical form as under in Equation-12:-

$$R_1 \cup R_2 \cup R_3 \ldots\ldots \cup R_{27} = \bigcup_{i=1}^{27} R_j \tag{12}$$

where R_j is the result obtained after applying the ith rule, which is among the one of the twenty-seven rules as elaborated in Table 5. Furthermore, the Rule Review mode Fig.10 shows a particular single scenario, while the Fig.11 illustrates the complete input-output surface of FuzzyRuleBase2.

The proposed GFCO approach is evaluated for known REB, as well as for the SACA algorithm, which was chosen since it is a based study. For each algorithm, REB, SACA, and GFCO repeated rounds of each method were carried out in two scenarios i.e. scenario-I and scenario-II, and after the intervals of 10, i.e. 10, 20, 30, 40, 50, results of a number of competitive nodes/sensors were recorded for scenario-II, while for scenario-I after the interval of 1 i.e. 1, 2, 3, 4, 5, 6, 7, 8, 9 results of competitive nodes or sensors were recorded. In a REB algorithm, a node or sensor that generates data typically sends a data packet and then waits for an ACK from the destination node. This implies that many transmissions may be conceived simultaneously. The chance of collision is larger in the conventional methodology (REB) than in alternative ways because each contending node or sensor tries to access this material. Therefore, the transmission of huge data packets increases the duration of collisions and the time needed for re-transmission when the medium is not allocated, resulting in under-utilization of the resources available. In a congested network, backoff interval, sometimes referred to as waiting time, is inversely correlated with the quantity of retransmissions. The intended data delivery will be delayed if there is an abnormally lengthy waiting period, which will lead to a significant number of re-transmissions.

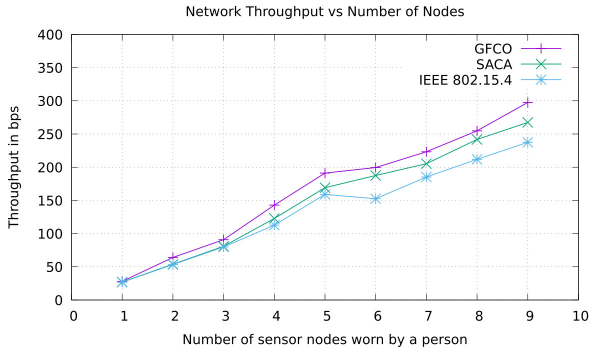


FIGURE 12. Scenario-I: Throughput of GFCO, SACA and REB.

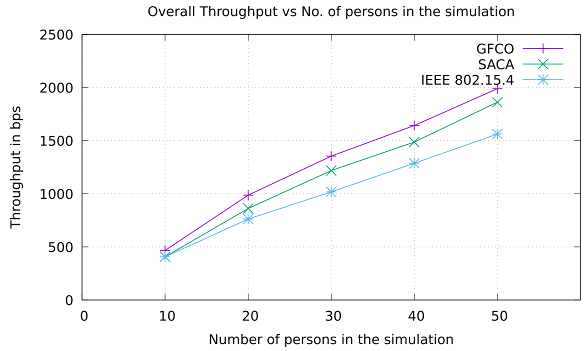


FIGURE 13. Scenario-II: Throughput of GFCO, SACA and REB.

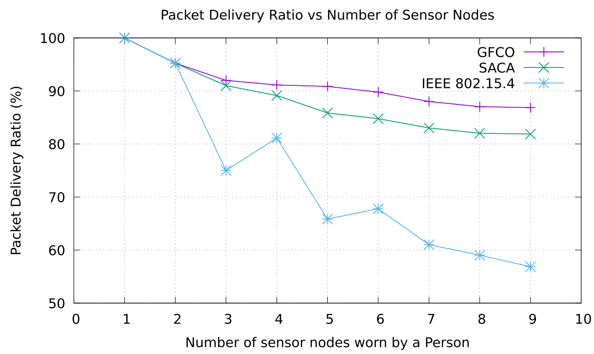


FIGURE 14. Scenario-I: PDR of GFCO, SACA and REB.

B. SIMULATION METRICS

The efficiency of the proposed GFCO technique, as well as the competing REB and SACA algorithms, was assessed using the metrics indicated below throughout the experimental situations.

1) Throughput: Throughput is computed by sum of the number of successful packets transmitted on average packet size dividing the total time spent on this process by the several nodes or sensors in the network.

$$Throughput = \Sigma \frac{(SuccesfulPkt) * (AvgPktSize)}{(TotalTime)} \quad (13)$$

2) Packet Delivery Ratio (PDR): The overall amount of transmission attempts made by the different nodes and sensors in the system is divided to determine the number of successful transmissions.

$$PDR = \frac{(SuccesfulTransmission)}{(TransmissionAttempts)} \quad (14)$$

3) Packet Loss Ratio (PLR): In this case, the total number of transmission attempts made by all nodes and sensors (due to collisions and transmission faults) is divided by the number of unsuccessful transmissions to calculate the number of failed transmissions.

$$PLR = \frac{(UnsuccesfulTransmission)}{(TransmissionAttempts)} \quad (15)$$

4) Packet Delay (PD): The time difference between packets being received at the destination and being sent at the source node/sensor is used to calculate it.

$$PD = (PktRecievedTime) - (PktSendingTime) \quad (16)$$

C. RESULTS EVALUATION

The results of the experimental process are examined in this section. In total, the results of experimental are compared with those obtained for REB and SACA for the suggested GFCO approach.

1) THROUGHPUT

Fig.12 and Fig.13 shows the simulated findings of scenario-I and II for the throughput of the proposed GFCO, SACA, and REB algorithms, respectively. These figures demonstrate that the suggested GFCO technique generated 15.11% and 12.06% on average superior results, hence substantially enhancing the throughput than the comparing techniques. With a confidence interval of 0.95 achieved by employing the method, the figure clearly shows that the suggested GFCO strategy significantly boosted the throughput when compared to the other two algorithms. We noticed that the suggested GFCO considerably improved the throughput and beat the other two algorithms in accordance with the Fig.12 and Fig.13.

2) PACKET DELIVERY RATIO (PDR)

Fig.14 and Fig.15 shows the simulated findings of scenario-I and II for the PDR of the proposed GFCO, SACA, and REB algorithms, respectively. These figures demonstrate that the suggested GFCO technique generated 3.11% and 9.0% on average superior results, hence substantially enhancing the PDR. With a confidence interval of 0.95 achieved by utilising the method, the figure clearly shows that the suggested GFCO approach significantly raised the PDR when compared to the other two algorithms.

3) PACKET LOSS RATIO (PLR)

Fig.16 and Fig.17 shows the simulated findings of scenario-I and II for the PLR of the proposed GFCO, SACA, and REB algorithms, respectively. These figures demonstrate that the suggested GFCO technique generated 3.11% and 9.0% on

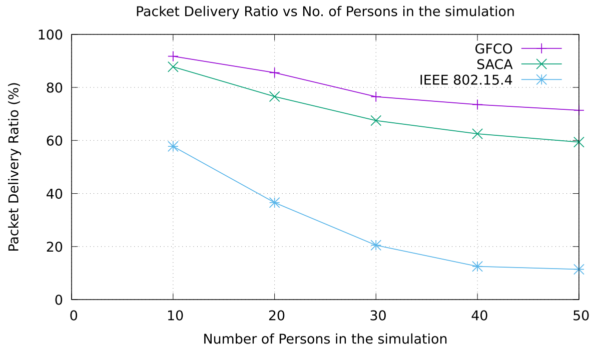


FIGURE 15. Scenario-II: PDR of GFCO, SACA and REB.

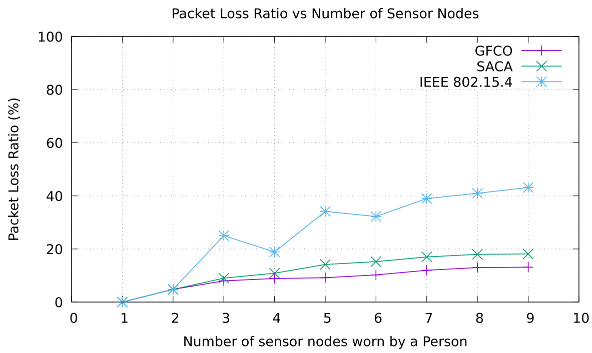


FIGURE 16. Scenario-I: PLR of GFCO, SACA and REB.

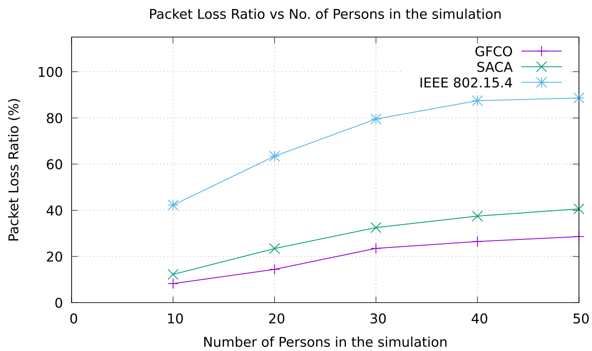


FIGURE 17. Scenario-II: PLR of GFCO, SACA and REB.

average superior results, hence GFCO substantially reduced the PLR. With a confidence interval of 0.95 achieved by utilising the method, the figure clearly shows that the suggested GFCO approach significantly lowered the PLR when compared to the other two algorithms. As shown in Fig.16 and Fig.17, the results of simulations with various numbers of nodes/sensors show that the proposed GFCO significantly reduced the PLR and outperformed the other two techniques. The PLR is decreased as a result of this strategy since it makes collisions less likely. The simulated output value is noticeably better than SACA and REB when compared to those two variables.

4) PACKET DELAY (PD)

Fig.18 and Fig.19 shows the simulated results of scenario-I and II for the PD of the proposed GFCO, SACA,

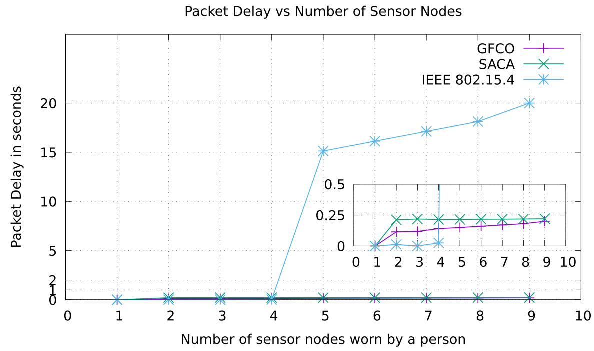


FIGURE 18. Scenario-I: PD of GFCO, SACA and REB.

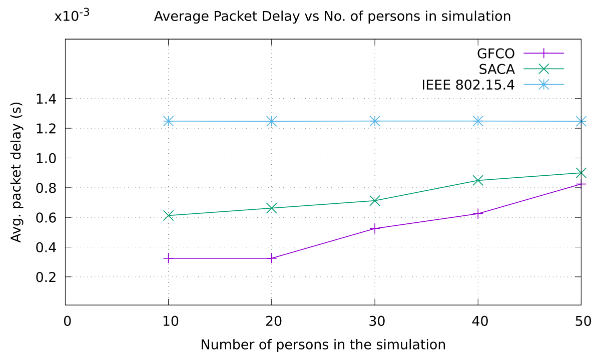


FIGURE 19. Scenario-II: PD of GFCO, SACA and REB.

and REB algorithms, respectively. These figures demonstrate that the suggested GFCO technique generated 5.52% and 2.23% on average superior results, hence the GFCO technique substantially reduced the packet delay. With a confidence interval of 0.95 produced by employing the method, the data clearly show that the suggested GFCO approach significantly lowered the PD when compared to the other two algorithms. As shown in Fig.18 and Fig.19, the results of simulations with various numbers of nodes/sensors show that the recommended GFCO strategy significantly reduced the PD and outperformed the other two ways in both situations, i.e. scenario-I and scenario-II.

VI. CONCLUSION

We have conducted a thorough study of the available methodologies in the domain of 802.15.4 LR-WPANs for the goal of channel / CW_{size} optimization, and we have compared all of the techniques/approaches that we have studied. We introduced GFCO: A Genetic Fuzzy-Logic Channel Optimization approach for LR-WPAN is proposed. It employed FLC and GA, by doing so, GA optimally modified the FLC. Five algorithms were proposed for this purpose, Algorithm-1: GFCO for LR-WPAN, Algorithm-2: GA_1 for GFCO, Algorithm-3: FLC_1 for GFCO, Algorithm-4: GA_2 for GFCO, and Algorithm-5: FLC_2 for GFCO. The suggested GFCO approach was assessed for REB and SACA and implemented in NS-3.20 in conjunction with fuzzylite in two scenarios of a hospital environment. First scenario was implemented in randomly deployed 10 sensors on a person's body ($2 \times 2\ m^2$ area), whereas second scenario was implemented in $20 \times 20\ m^2$ area of a ward in hospital having 10 to 50 persons. The simulated outcomes of both scenarios were recorded for REB, SACA, and GFCO. These results were then utilised to compute the throughput, PDR, PLR, and PD, as well as to generate a graphical representation. The simulated testing results showed that the suggested GFCO strategy significantly improved performance and also attained the confidence interval of 95%.

In addition to providing a cutting-edge method for achieving the goal of performance enhancement through channel / CW_{size} optimisation for 802.15.4 LR-WPAN, the proposed GFCO technique will benefit the community at large and the medical community in particular by removing the barriers to performance improvement.

In Future we are interested to implement the proposed GFCO in larger testbed in another environment other than hospitals.

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CONFLICT OF INTEREST

The authors declare that they have no Conflict of interest.

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REFERENCES

[1] *IEEE Standard for Local and Metropolitan Area Networks—Part 15.4: Low-Rate Wireless Personal Area Networks (LR-WPANs)—Amendment 5: Physical Layer Specifications for Low Energy, Critical Infrastructure Monitoring Networks*, IEEE Standard 802.15.4k-2013 (Amendment to IEEE Standard 802.15.4-2011 as Amended by IEEE Standard 802.15.4e-2012, IEEE Standard 802.15.4f-2012, IEEE Standard 802.15.4g-2012, and IEEE Standard 802.15.4j-2013), Aug. 2013, pp. 1–149, doi: 10.1109/IEEESTD.2013.6581828.

[2] E. O. Addo, B. Kommey, and A. S. Agbemenu, "Wearable networks: Requirements," *Technol., Res. Trends*, vol. 12, no. 20, pp. 1–7, Mar. 2013.

[3] M. S. Akbar, H. Yu, and S. Cang, "Performance optimization of the IEEE 802.15.4-based link quality protocols for WBASNs/IoTs in a hospital environment using fuzzy logic," *IEEE Sensors J.*, vol. 19, no. 14, pp. 5865–5877, Jul. 2019.

[4] R. Casagrande, R. Moraes, C. Montez, A. S. Morales, and L. Rech, "Interference of IEEE 802.11n networks upon IEEE 802.15.4-based WBANs: An experimental study," in *Proc. IEEE 16th Int. Conf. Ind. Informat. (INDIN)*, Jul. 2018, pp. 388–393.

[5] P. Baronti, P. Pillai, V. W. C. Chook, S. Chessa, A. Gotta, and Y. F. Hu, "Wireless sensor networks: A survey on the state of the art and the 802.15.4 and ZigBee standards," *Comput. Commun.*, vol. 30, no. 7, pp. 1655–1695, May 2007.

[6] M. Elappila, S. Chinara, and D. R. Parhi, "Survivability aware channel allocation in WSN for IoT applications," *Pervas. Mobile Comput.*, vol. 61, Jan. 2020, Art. no. 101107.

[7] S. Pushpan and B. Velusamy, "Fuzzy-based dynamic time slot allocation for wireless body area networks," *Sensors*, vol. 19, no. 9, p. 2112, May 2019.

[8] F. Masud, A. Abdullah, A. Altameem, G. Abdul-Salaam, and F. Muchtar, "Traffic class prioritization-based slotted-CSMA/CA for IEEE 802.15.4 MAC in intra-WBANs," *Sensors*, vol. 19, no. 3, p. 466, Jan. 2019.

[9] S. Henna and M. A. Sarwar, "An adaptive backoff mechanism for IEEE 802.15.4 beacon-enabled wireless body area networks," *Wireless Commun. Mobile Comput.*, vol. 2018, pp. 1–15, Jun. 2018.

[10] S. M. Nekooei, G. Chen, and R. Rayudu, "Automatic design of fuzzy logic controllers for medium access control in wireless body area networks—An evolutionary approach," *Appl. Soft Comput.*, vol. 56, pp. 245–261, Jul. 2017.

[11] I. Bouazzi, J. Bhar, and M. Atri, "New CSMA/CA prioritisation based on fuzzy control mechanism," *Int. J. Intell. Eng. Inform.*, vol. 5, no. 3, pp. 253–266, 2017.

[12] S. Henna, M. Sajeel, F. Bashir, M. Asfand-e-yar, and M. Tauqir, "A fair contention access scheme for low-priority traffic in wireless body area networks," *Sensors*, vol. 17, no. 9, p. 1931, Aug. 2017.

[13] A. Al-Humairi and A. Probst, "Back-off time calculation algorithms in WSN," *Informatics*, vol. 3, no. 2, p. 9, Jun. 2016.

[14] A. Vutukuri, S. Bhattacharya, T. Raj, and V. Geetha, "Others enhanced back-off technique for IEEE 802.15. 4 WSN standard," in *Proc. Netw. Commun. (NetCom)*, 2014, pp. 21–29.

[15] Z. Dahham, A. Sali, and B. Ali, "An efficient backoff algorithm for IEEE 802.15. 4 wireless sensor networks," *Wireless Pers. Commun.*, vol. 75, pp. 2073–2088, Oct. 2014.

[16] J. Zhou, A. Guo, J. Xu, and S. Su, "An optimal fuzzy control medium access in wireless body area networks," *Neurocomputing*, vol. 142, pp. 107–114, Oct. 2014.

[17] K. A. Bhatti and S. Asghar, "Progressive fuzzy PSO-PID congestion control algorithm for WSNs," *Arabian J. Sci. Eng.*, vol. 48, no. 2, pp. 1157–1172, Feb. 2023, doi: 10.1007/s13369-022-06701-z.

[18] K. A. Bhatti, S. Asghar, and S. Naz, "Multi-objective fuzzy krill herd congestion control algorithm for WSN," *Multimedia Tools Appl.*, pp. 1–29, May 2023, doi: 10.1007/s11042-023-15200-8.

[19] S. Moulik, S. Misra, and C. Chakraborty, "Performance evaluation and delay-power trade-off analysis of ZigBee protocol," *IEEE Trans. Mobile Comput.*, vol. 18, no. 2, pp. 404–416, Feb. 2019.

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