OPTIMIZATION OF FALSE ALARM RATE AND MISDETECTION RATE FOR A DESIRED THRESHOLD VOLTAGE IN COOPERATIVE COMMUNICATION

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ABSTRACT

Cooperative communication systems (CCSs) involves collaboration among sensor nodes to transmit data more effectively, especially in scenarios with limited resources or challenging environmental conditions. Optimizing the total error rate (TER) for cooperative communication in wireless sensor networks (WSNs) is a critical task to enhance the reliability and efficiency of data transmission. The link quality of a WSN can be improved by cooperative relaying with a relatively low TER. In this paper, real-coded genetic algorithm (RGA) and particle swarm optimization (PSO) are used in WSNs to reduce TER. The number of nodes is varied from 1 to 16, SNR is varied from 0 dB to 20 dB, threshold is varied from 25 mV to 35 mV and mutation rate is 0.1. Minimum TER is obtained for a threshold of 25 mV to 35 mV compared to TER obtained without optimization. The optimization method provides significant improvements to achieve the desired threshold voltage with minimum false alarm rate and misdetection rate, which enhances the overall performance of the CCS in WSNs.

KEYWORDS

Cooperative communication, Cognitive radio, Optimization, RGA, PSO, Error rate.

1. INTRODUCTION

In CCS, the source node (SN) apart from sending the signal to the destination node (DN), also relays it to an intermediate node. Subsequently, this relay node (RN) forwards the signal either to another relay node or directly to the destination node using various relaying protocols [1].This technology utilizes mobile relay nodes to augment the capacity of specific users. This principle entails categorizing the system into three types of nodes: the SN, the DN and the RN [2]. In this setup, all relay nodes function as both receiving and sending antennas for particular user nodes. Consequently, the network can be conceptualized similarly to a multiple input and multiple output (MIMO) system [3]-[4]. The CCS involves 2 phases of transmission [5]. Phase I: The users distribute the source data with control information among the remaining users. Phase II: The users collectively re-transmit the data to the desired destination.

In a relay system, one user is the SN, while the other user is the RN and both the users can interchange their roles at various time intervals [6]. As outlined earlier, during Phase I, the SN user will broadcast information to both the RN and the DN. Subsequently, in Phase II, the RN can independently forward data or collaborate with the SN to enhance reception at the DN. Coordination is vital in a CCS, especially since antennas are distributed across various terminal devices, unlike centralized MIMO systems [7]. Excessive coordination may lead to a reduction in system bandwidth, but this cost is consistently offset by the substantial diversity gain achieved under high signal-to-noise ratio (SNR) conditions [5]. The expense of coordination may escalate with the number of cooperating users. Therefore, designing an efficient user-to-user communication method is necessary for a successful cooperation [5], [8]. In order to achieve energy-efficient transmission, a cooperative spectrum sensing (CSS) technique based on PSO is developed for cognitive WSNs [9]-[10]. The enhanced performance and flexibility of a re-configurable unmanned aerial vehicle relay-communication system is proposed in [11]. The optimization of energy efficiency in wireless networks beyond 5G through the integration of visible light and RF bands, employing non-orthogonal multiple access schemes for downlink using visible light to enhance data rates for cell-edge users *via* cooperative communications strategies is

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explored in [12]. The challenges of energy constraints and security concerns in WSNs are addressed in [13]. A study on maximization of energy efficiency for the cooperative-communication system achieved by optimizing both the packet size and the modulation level is reported in [14]. To extend communication coverage, the use of energy harvesting-based combined information and power transfer is reported in [15]-[16]. The performance of the energy-detection mechanism can be evaluated based on the misdetection rate and the false-alarm rate [17]. The investigation of spectral monitoring over Rayliegh fading channels is presented in [18]. The impact of cooperative-spectrum sensing and dynamic-threshold selection on the performance of a cognitive radio network in fading environments, comparing the receiver operating characteristics for cooperative and non-cooperative scenarios and demonstrating improvements in detection probability, error probability with dynamic-threshold selection is discussed in [19].The spectrum sensing in cognitive radio using energy detection over various wireless communication channels is presented in [20]. A comprehensive review of optimization algorithms, including evolutionary, swarm intelligence and metaheuristic approaches, for enhancing wireless sensor network (WSN) node localization, evaluating their accuracy, scalability, computational complexity and robustness across different deployment scenarios is presented in [21]. In [22], authors presented a VLSI-based power-optimization model for wireless sensor networks using FPGA technology, designed to lower energy consumption by employing a collaborative unit with parallel processing and a smart power component, leading to improved efficiency compared to processor-based WSN implementations. In [23], authors proposed a PSO-based scheduling approach to maximize the lifetime of wireless sensor networks by addressing the non-disjoint sets cover problem, demonstrating competitive performance and optimal solutions compared to state-of-the-art algorithms. The research gap is to enhance the data rate in cooperative-communication system, by minimizing the TER for a desired threshold voltage.

2. METHODOLOGY

2.1 Aim of the Research Work

The current work aims to enhance the efficiency and reliability of cooperative-communication systems (CCSs) in wireless sensor networks (WSNs) by optimizing the total error rate (TER). It focuses on using particle-swarm optimization (PSO) and real-coded genetic algorithms (RGAs) to achieve these improvements.

2.2 System Model

A cooperative-communication network comprising K cognitive radios (CRs) with a common receiver is examined and illustrated in Figure 1. Here, spectrum sensing is performed by each CR independently, followed by transmitting local decisions to the shared receiver.

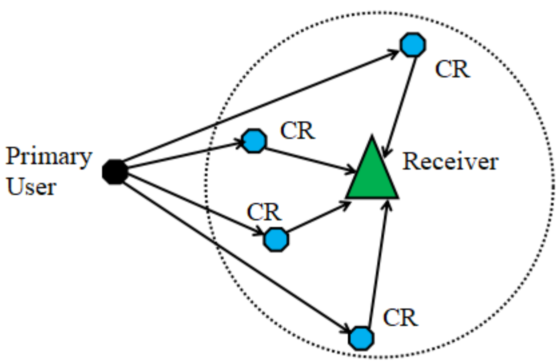

Figure 1. Spectrum-sensing model in a cooperative CR.

The receiver then consolidates all available information regarding decisions to deduce the presence or absence of the primary user (PU). Spectrum sensing essentially involves a binary hypothesis-testing problem:

H_0 : PU is not present.
H_1 : PU is present.

Considering sensing of spectrum only at i^{th} CR, the sensing method may choose any of the following 2 hypotheses.

$$x_i(t) = \begin{cases} w_i(t), & H_o \\ h_i(t)s(t) + w_i(t), & H_1 \end{cases} \tag{1}$$

where, $x_i(t)$ is the received signal in time slot t, at the i^{th} CR , s(t) is PU signal , $w_i(t)$ is additive white Gaussian noise (AWGN) and the complex sensing-channel gain between the i^{th} CR and the PU is $h_i(t)$. Here, it is considered that the sensing time is lower compared to the channel's coherence time. In the process of sensing, sensing channel $h_i(t)$ is time-invariant; that is, $h_i(t) = h_i$. Again, it is assumed that during spectrum sensing, the PU's state remains constant. The energy-detection approach is the best choice for identifying zero-mean constellation signals for an unknown previous information of the PU signal [17]. The probabilities of average false alarm, average detection and average misdetection over AWGN channels for the i^{th} CR with the energy detector are provided, accordingly, by [24].

$$P_{f,i} = \frac{\Gamma\left(u, \frac{\lambda_i}{2}\right)}{\Gamma(u)} \tag{2}$$

$$P_{d,i} = Q_u\left(\sqrt{2\gamma_i}, \sqrt{\lambda_i}\right) \tag{3}$$

$$P_{m,i} = 1 - P_{d,i} \tag{4}$$

Here, 'u' is the energy detector's time-bandwidth product and λ_i and γ_i stand for the energy-detection threshold (mV) and instantaneous SNR at the i^{th} CR, respectively. Q_u (n,x) is the generalized Marcum Q-function and Γ(n, x) is the incomplete gamma function, given by:

$$\Gamma(n, x) = \int_x^{\infty} t^{n-1} e^{-t} dt \tag{5}$$

$$Q_u(n, x) = \frac{1}{n^{u-1}} \int_x^{\infty} t^u e^{-\frac{t^2+n^2}{2}} I_{u-1}(nt) dt \tag{6}$$

I_{u-1} represents the first-kind modified Bessel function of u-1 order.

In CSS, each node takes a binary decision according to its local observations and then sends one bit of the decision D_i (1 representing PU presence, 0 for PU absence) to the common receiver *via* an error-free channel. All 1-bit decisions are combined at the common receiver using a logic rule:

$$Y = \sum_{i=1}^{K} D_i \begin{cases} \geq n, & Hd_1 \\ < n, & Hd_o \end{cases} \tag{7}$$

where Hd_1 and Hd_0 are the inferences of the common receiver that the PU signal is transmitted or not, respectively. The threshold integer 'n' represents the "n-out-of-K" voting rule. The AND rule is applicable to the case of n=K and the OR rule for n=1.

For an AWGN environment, one can assume that $\gamma_1 = \ldots = \gamma_K = \gamma$. Again, it can be assumed that all CRs use the same threshold λ, that is, $\lambda_1 = \ldots = \lambda_K = \lambda$. For an AWGN channel, $P_{d,i}$ (denoted as P_d) is independent of i. For a Rayleigh fading channel, P_d represents the average $P_{d,i}$ over the statistics of γ_i . For both types of channels, we have $P_m = 1 - P_d$. So, the probability of false alarm and probability of misdetection are given by [24]:

$$Q_f = P\left(\frac{Hd_1}{H_0}\right) = \sum_{l=n}^{K} \binom{K}{l} P_f^l (1 - P_f)^{K-l} \tag{8}$$

$$Q_m = P\left(\frac{Hd_0}{H_1}\right) = 1 - \sum_{l=n}^{K} \binom{K}{l} P_d^l (1 - P_d)^{K-l} \tag{9}$$

The total error rate (TER) is given by: $$TER = Q_f + Q_m \qquad (10)$$

Figure 2 and Figure 3 show that the optimal voting rule across all of the simulated detection threshold ranges is n = 5 for AWGN channel and n=2 for Rayleigh channel. Though, for very small fixed thresholds, the AND rule is the optimal rule; i.e., n = 10. For fixed extremely large thresholds, it is the OR rule; i.e., n = 1, that is found to be optimal. The comparison of n values to obtain min TER w.r.t threshold values at various SNRs ranging from 0-15 dB in both AWGN channel and Rayleigh channel is depicted in Table 1.

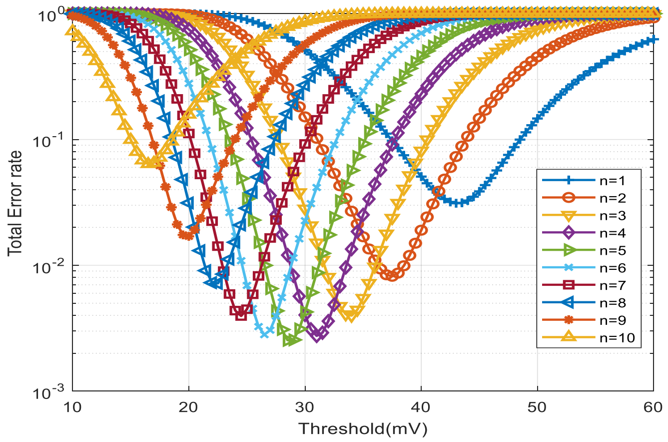

Figure 2. TER of CSS in 10-dB AWGN channel; n is voting rule, K = 10.

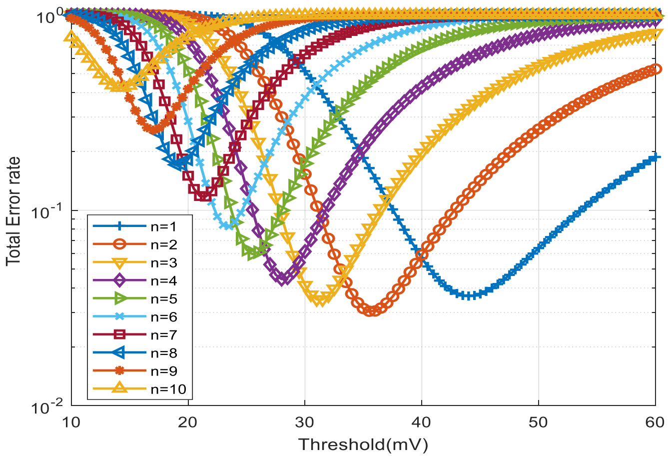

Figure 3. TER of CSS in 10-dB Rayleigh channel; n is voting rule, K = 10.

Table 1. Comparison of n values to get minimum TER w.r.t threshold values at various SNRs

SNR (dB)	Parameter	AWGN Channel	Rayleigh Channel
0	Threshold (mV)	23	25
	Minimum TER	0.696261	0.702793
	n	4	3
5	Threshold (mV)	23.5	30
	Minimum TER	0.2575	0.306736
	n	5	2
10	Threshold (mV)	29	36
	Minimum TER	0.00255473	0.030527
	n	5	2
15	Threshold (mV)	44	44
	Minimum TER	$3.19*10^{-12}$	0.00039336
	n	5	2

Optimal Voting Rule: To obtain the optimal number of CR, TER should be minimized based on [25].

$$n_{optimal} = \min\left(K, \left\lceil \frac{K}{1+\alpha} \right\rceil\right) \tag{11}$$

$$\text{where } \alpha = \frac{\ln\left(\frac{P_f}{1-P_m}\right)}{\ln\left(\frac{P_m}{1-P_f}\right)} \text{ and [.] is the ceiling function.} \tag{12}$$

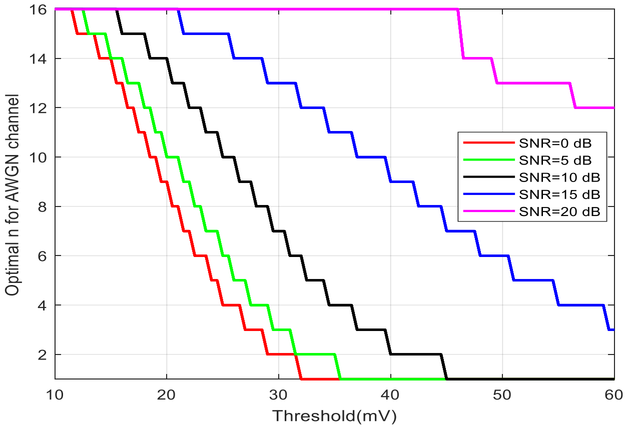

Figure 4. Optimal n *vs.* threshold of CSS for K=16 in AWGN channel.

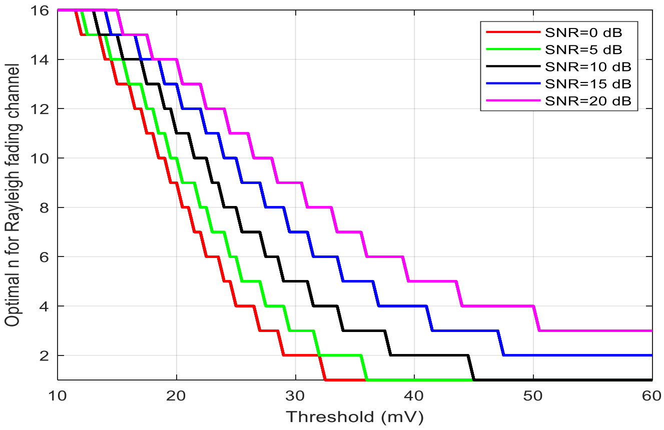

Figure 5. Optimal n *vs.* threshold of CSS for K=16 in Rayleigh channel.

The plot of n *versus* detection threshold determined by Equation 11 is displayed in Figure 4 and Figure 5, for various SNRs varying from 0-20 dB for K=16.

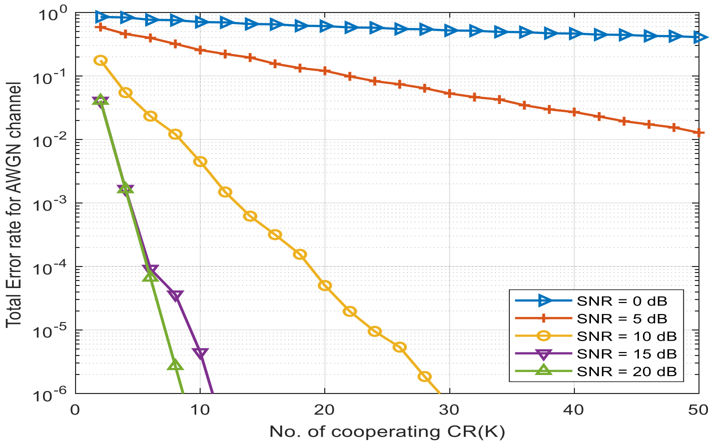

Figure 6. TER *vs.* number of cooperating CRs with λ = 25 mV in AWGN channel.

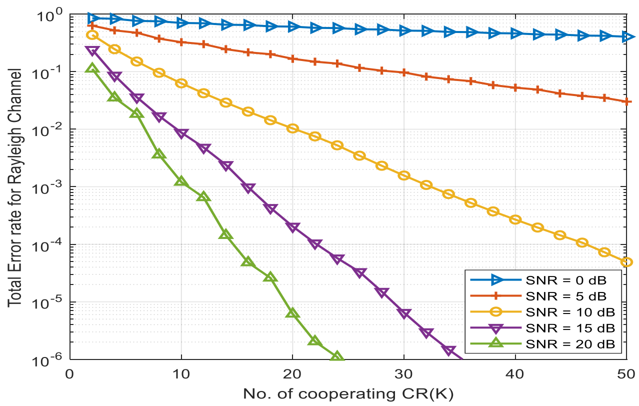

Figure 7. TER *vs.* number of cooperating CRs with λ = 25 mV in Rayleigh channel.

According to Figure 6, in an AWGN channel for a threshold of 25 mV at SNR= 20 dB, 15 dB and 10 dB, respectively, the least numbers of CRs needed to achieve the error-rate objective of 0.001 are 4, 4 and 13. According to Figure 7, in a Rayleigh channel for a threshold of 25 mV at SNR= 20 dB, 15 dB and 10 dB, respectively, the least numbers of CRs needed to achieve the error rate objective of 0.001 are 10, 16 and 33.

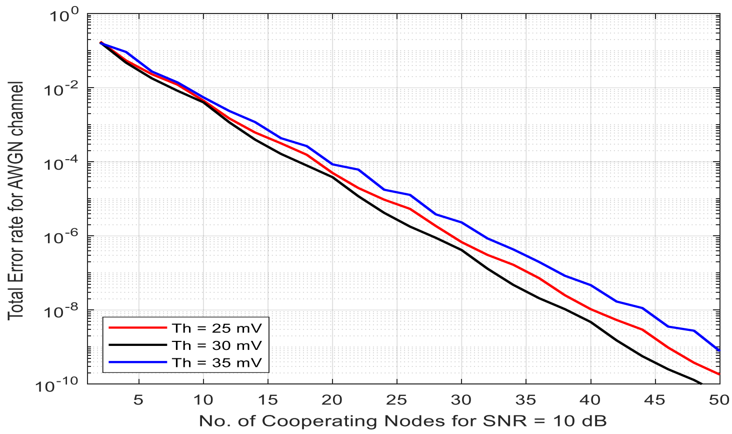

Figure 8. TER vs. number of cooperating CRs in AWGN channel.

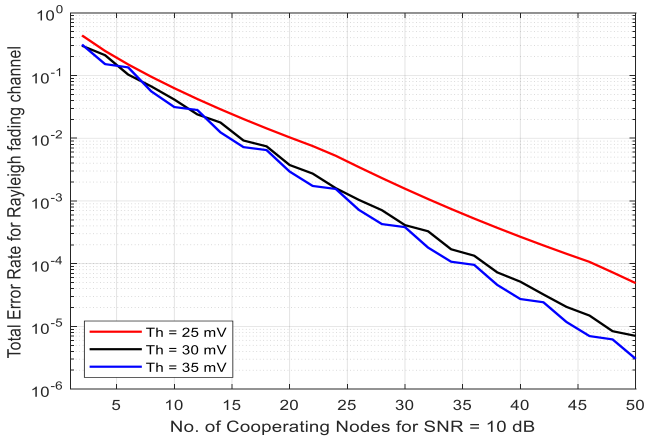

Figure 9. TER *vs.* number of cooperating CRs in Rayleigh channel.

According to Figure 8, in an AWGN channel for an SNR of 10 dB at threshold values of 25, 30 and 35 mV, respectively, the least numbers of CRs needed to achieve the error-rate objective of 0.001 are 13, 12 and 15. According to Figure 9, in a Rayleigh channel for an SNR of 10 dB at threshold values of 25, 30 and 35 mV, respectively, the least numbers of CRs needed to achieve the error-rate objective of 0.001 are 32, 27 and 25.

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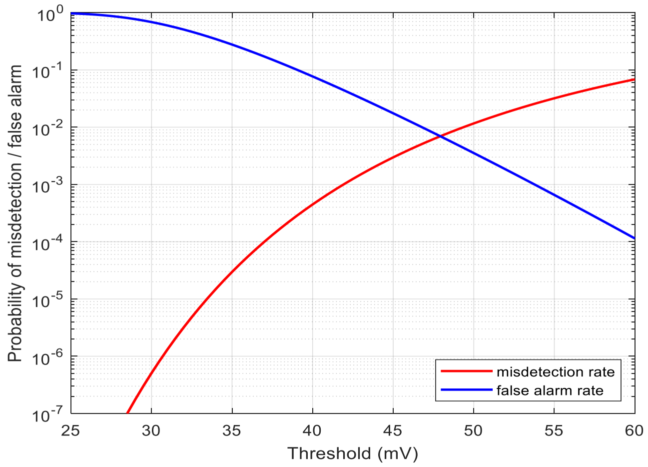


Figure 10. Trade-off between misdetection rate and false-alarm rate.

According to Figure 10, the lowering of the threshold voltage reduces the misdetection rate and increases the false-alarm rate as per Equation 8. Raising the threshold voltage reduces the false-alarm rate and increases the misdetection rate as per Equation 9. The aim is to minimize TER as given in Equation 10, which is the sum of false-alarm rate and misdetection rate. In Equation 11, optimal-voting rule has been implemented to optimize this balance to minimize TER.

2.3 Optimization of TER in Cooperative Spectrum Sensing

Here, two optimization techniques are used to optimize TER: PSO and RGA, where the variable parameters are optimal number of nodes, SNR and threshold.

The GA is a stochastic approach rooted in evolutionary-optimization principles, endeavoring to locate global minima through the emulation of genetics and natural selection. The RGA operates on continuous variables cost function optimization with natural selection and genetic recombination [26], [28]. Adjustments to the RGA involve modifying operator or parameter values. Chromosomes are populated by a group of genes with random values ranging from 0 to 1, constituting the initial population [27], [29]. The population size should balance the need for diversity with computational feasibility. A typical range is 20 to 100 individuals, but larger sizes may be used in complex problems or where more resources are available. In this work, the population size is 20.

Each chromosome's cost within this population is assessed and those with the most favorable values are chosen for the natural-selection process, while the others are discarded. Offspring are generated from these chosen-parent chromosomes. The weight 'z' is determined through the utilization of a random number 'r' and the cross-over operator 'µ' as [26]-[27]. The cross-over rate is typically set between 0.7 and 0.9, with values closer to 1 being preferred for problems where exploration is more important. In this work, the cross-over rate is 0.9.

$$z = \begin{cases} (2r)^{\frac{1}{1+\mu}} & \text{if } r > 0.5 \\ \left(\dfrac{1}{2(1-r)}\right)^{\frac{1}{1+\mu}} & \text{otherwise} \end{cases} \tag{13}$$

New offspring are:

$$\begin{aligned} Offspring1 &= \frac{(1+z)\,parent_1 + (1-z)\,parent_2}{2} \\ Offspring2 &= \frac{(1-z)\,parent_1 + (1+z)\,parent_2}{2} \end{aligned} \tag{14}$$

A sub-set of randomly chosen chromosomes undergoes mutation using the mutation operator 'η' and mutation weight 'm', The mutation rate is typically kept between 0.01 and 0.1, depending on the complexity of the problem. In this work, the mutation rate is 0.1. For large or complex search spaces, a higher mutation rate might be appropriate, where,

$$m = \begin{cases} (2r)^{\frac{1}{1+\eta}} - 1 & \text{if } r \le 0.5 \\ 1\text{-}[2(1\text{-}r)]^{\frac{1}{1+\eta}} & \text{otherwise} \end{cases} \tag{15}$$

The PSO algorithm, another variant of evolutionary algorithms, is employed to discover optimal settings or parameters necessary for obtaining a desired objective [30]-[31]. Each distinct solution within the search space of the objective function is denoted as a particle, with the initial collection of random particles forming the starting position of the swarm. These particles have the capability to assess their current fitness or positions through optimization functions. Swarms, composed of randomly generated solutions, iteratively explore the design space towards finding the optimal solution. Each particle's velocity is modified according to solution of individual best position, termed as particle best (pbest) and the best value encountered so far by any particle in the particle swarm optimizer, termed as global best (gbest). Every particle has a velocity vector $v_j(l)$ and a position vector $y_j(l)$. The equation for updating velocity is given by [30]-[31]:

$$v_j(l+1) = w \times v_j(l) + c_1 \times rand \times [pbest - y_j(l)] + c_2 \times rand \times [gbest - y_j(l)] \tag{16}$$

and the position update equation is:

$$y_j(l+1) = y_j(l) + v_j(l+1) \tag{17}$$

where, v_j - particle velocity of j^{th} iteration, w - inertia weight factor, which is a random number between (0,1), y_j - current particle position, c_1 ,c_2 are cognitive parameter and social parameter, generally, $c_1 + c_2 = 4$. Typically, $c_1 = c_2 = 2$ is a common choice, though in some cases, a slight imbalance (e.g., c_1=1.5, c_2=2.5) can promote better exploration early on, followed by stronger exploitation later. In this work, c_1=1.65, c_2 =2.35. At each iteration, the particle adjusts its position and velocity according to the procedures mentioned above in order to achieve the best solution.

2.4 Algorithm for the Implementation of PSO to Optimize TER

Step-1: Initialize parameters, like size of population, iteration number, inertia weight, personal and global learning coefficients and limit of velocity.

Step-2: Compute fitness by applying the cost function of TER (Equation 10) to each particle for both pbest and gbest solutions.

Step-3: Continuously update the velocity and position of every particle using Equation 16 and Equation 17 and repeat steps 3 and 4 until the convergence of population.

Step-4: Choose the gbest solution based on the minimum value of the cost function TER.

2.5 Algorithm for the Implementation of RGA to Optimize TER

Step-1: Initialize variables, like optimal node number, SNR and threshold. Establish upper and lower bounds of parameters along with defining the population size, mutation rate and number of generations.

Step-2: Compute fitness by applying the cost function of TER (Equation 10).

Step-3: The process involves selection, arithmetic crossover, mutation and computation of temporary fitness.

Step-4: Repeat step 3 until the convergence of population.

Step 5: Choose the threshold value with the best fitness where the TER is minimized.

3. RESULTS

The cost-function plot for RGA and PSO optimization are depicted in Figure 11.

The cost function is the TER of Equation 10, for RGA and PSO optimization. The aim is to minimize TER. The population size is 20, the iteration number is 100, the optimal number of nodes is varied from 1 to 16, SNR is varied from 0 dB to 20 dB, the threshold is varied from 25 mV to 35 mV and 0.1 is the mutation rate. The convergence of TER is shown in Figure 12 (a) and 12 (b). PSO generally

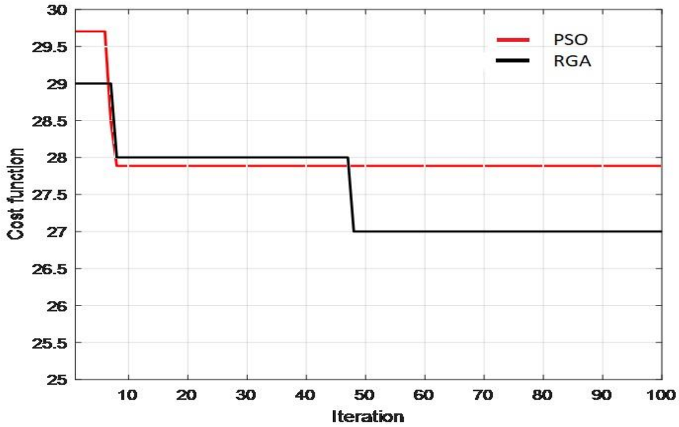
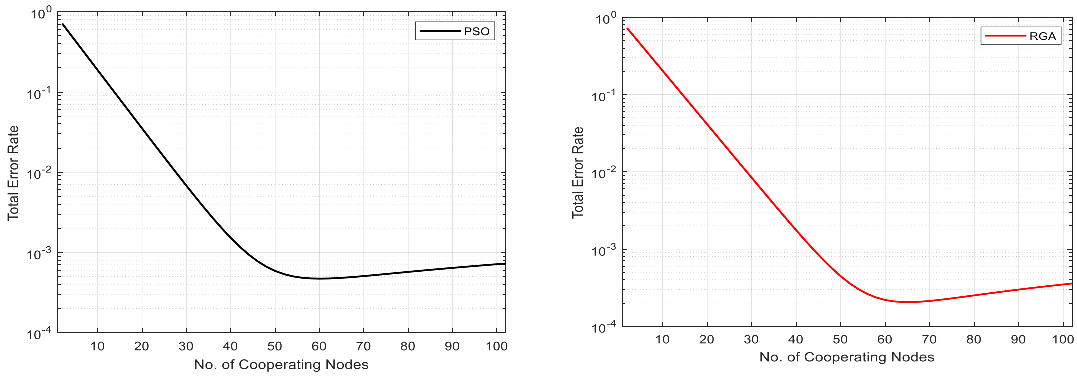


Figure 11. Cost function *vs.* iteration.



(a) (b)

Figure 12. Convergence of TER (a) PSO (b) RGA.

converges faster, but is more prone to local optima, whereas RGA provides better exploration at the cost of slower convergence. The stopping criterion is minimal value of cost function given in Equation 10 for both PSO and RGA algorithms, mentioned in step 4 of sub-section 2.4 for PSO algorithm and mentioned in step 4 of sub-section 2.5 for RGA algorithm.

The RGA and PSO optimized results of TER are compared with the results obtained without optimization [25], [32]-[34] in Figure 13.

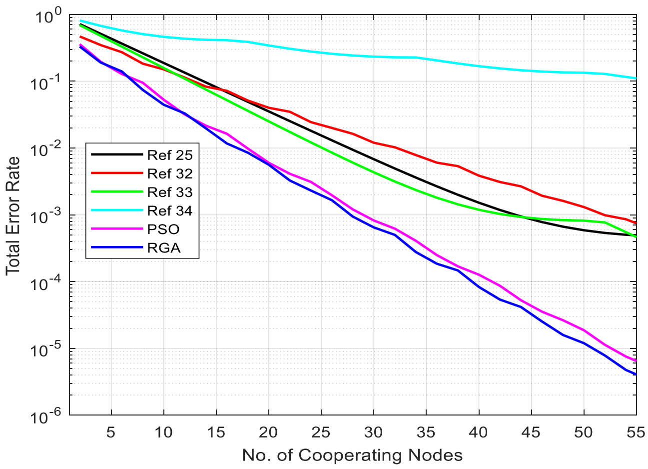


Figure 13. Comparison of TER with published results.

According to Figure 13, in a Rayleigh channel for SNR value of 10 dB, the least numbers of CRs needed to achieve the error-rate objective of 0.001 are 52, 44, 42, 29 and 27.

4. DISCUSSION

The research presented demonstrates the significant impact of PSO and RGA optimization techniques on the performance of cooperative communication systems in wireless sensor networks. By focusing on the optimization of TER, the study addresses a critical aspect of data-transmission reliability and efficiency in WSNs, particularly under constraints, such as limited resources and challenging environmental conditions.The study varies the number of nodes from 1 to 16 to analyze how the network density affects TER. The findings suggest that as the number of nodes increases, the cooperative relaying becomes more effective, leading to a reduction in TER. This can be attributed to the enhanced diversity and redundancy provided by additional nodes, which improves the overall link quality. The SNR is varied from 0 dB to 20 dB to observe its influence on TER. Higher SNR values typically result in better signal quality and lower error rates. The optimization techniques help in maintaining low TER even at lower SNR values, indicating the robustness of the CCS under different noise conditions. The threshold-voltage range of 25 mV to 35 mV is identified as optimal for minimizing TER. This range strikes a balance between sensitivity and noise immunity, ensuring that the nodes can effectively discriminate between signal and noise. The optimized threshold voltage significantly reduces false alarm and misdetection rates, which are crucial for reliable data transmission. The mutation rate of 0.1 used in the genetic algorithm ensures a good exploration of the solution space without causing excessive disruption to the convergence process. This rate is found to be effective in maintaining genetic diversity and preventing premature convergence to sub-optimal solutions. The computational complexity of RGA can be expressed as O(G * P * (C_f + log P)), where O() is the Big O order, P is the population size, G is the number of generations and C_f is the cost of evaluating the fitness function. In this work, P=20 and G=100. The computational complexity of PSO can be expressed as O(G * P * (C_f + 1)). In this work, P=20, G=100 and PSO generally has lower complexity per iteration compared to RGA since it avoids complex selection, crossover and mutation operations. Implementing RGA and PSO in real-world WSNs requires addressing hardware limitations by using lightweight versions of the algorithms that reduce computational and memory demands. Energy consumption is critical, so adaptive techniques should minimize computation time to preserve the battery life. Scalability can be achieved by using clustering or hierarchical approaches, ensuring that the algorithms perform efficiently even in large networks. The dynamic nature of WSNs necessitates fault-tolerant and adaptive versions of RGA and PSO to handle node failures and topology changes. Finally, multi-objective optimization and hybrid approaches can improve performance by balancing trade-offs between energy, coverage and network lifetime.

5. CONCLUSION

This paper has investigated the optimization of error rates, specifically focusing on false alarm and misdetection, within cooperative communication frameworks to meet a specified threshold voltage. The change of TER for a 50-node cooperative system in a WSN is presented here for both AWGN and Rayleigh channels. The effects of optimal number of nodes, SNR and threshold on TER are simulated. Furthermore, an efficient optimization approach that satisfies the given bound error has been assessed; it requires fewer cognitive radios than the total number used in cooperative spectrum sensing. Finally, the minimum TER is achieved using RGA optimization, as shown in Figure 13. This research contributes to the broader goal of improving communication efficiency and robustness in resource-constrained and challenging environments, paving the way for enhanced applications in various fields, such as environmental monitoring, healthcare and industrial automation.

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ملخص البحث:

تتضمّنُ أنظمة الاتّصالات التّعاونية التّنسيق بين عُقَد المجسّات لنقْل البيانات بشكلٍ أكثر فاعلية، وخصوصاً في السّيناريوهات الّتي تنْطوي على مصادر محدودةٍ وظروفٍ بيئيةٍ تحتوي على تحدِّياتٍ. وإنّ تحسين معدَّل الخطأ الكُلّيّ (TER) في الاتّصالات التّعاونية لتقريبه من القيمة المثالية في شبكات المجسّات اللاسلكية هو مهمَّة حاسمة من أجل تحسين موثوقية نقْل البيانات وفعاليته. ومن الممكن تحسين جودة الرّبط في تلك الشّبكات عن طريق نقْل البيانات تعاونياً بقيمةٍ منخفضةٍ قَدْر الإمكان لمعدَّلِ الخطأ الكُلّيّ (TER).

في هذه الورقة، نستخدم خوارزميةً جينية مرمَّزةً بشكلٍ حقيقي (RGA) إلى جانب تقنية التّحسين المرتكزة على سِرْبِ الجُزَيئات (PSO) في شبكات المجسّات اللاسلكية لخفْض قيمة مُعدّل الخطأ الكُلّيّ. ويتمُّ في هذه الدّراسة تغيير عدد العُقد بين 1 و 16، ونسبة الإشارة إلى الضّجيج بين 0dB و 20 dB. أمّا جُهْد العتبة فيجري تغييره بين 25 ميلي فولت و 35 ميلي فولت، بينما كان معدّل التّحوّل 0.1. ويتمُّ الحصول على القيمة الدنيا لمعدّل الخطأ الكُلّيّ لجُهْد عتبة يتراوح بين 25 ميلي فولت و 35 ميلي فولت مُقارنةً بقيمة معدذل الخطأ الكُلّيّ الّتي يتمُّ الحصول عليها دون إجراء عملية التّحسين. وقد برهنت عملية التّحسين على إحداث تحسيناتٍ ملحوظةٍ للحصول على جُهْد العتبة المرغوب بقيمةٍ دُنيا لمعدّل الإنذارات الكاذبة ومعدّل الكشف الخاطىء؛ من أجل تحسين الأداء الإجمالي لنظام الاتّصالات التّعاوني في شبكات المجسّات اللاسلكية.