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Performance Evaluation and Optimisation of Spectrum Management in Communication Systems by GA

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Abstract

Whilst wireless communication technologies proliferate, putting extra demand on the finite radio frequency spectrum and leading to issues of congestion, underutilisation and interference, this dissertation presents a modern spectrum management model on the binary genetic algorithm (BGA) capable of improving detection accuracy and adaptive spectrum access in cognitive radio networks (CRNs). BGA follows binary encoding to determine optimum weighting factors for secondary users in a CRN scenario with a much faster performance and better reliability than conventional genetic approaches. In the cooperative spectrum-sensing scheme proposed in this paper, multiple secondary users will forward their local sensing outcomes to a fusion centre in which BGA optimisation will fine-tune the weighting coefficients throughout the soft decision fusion mechanism. The algorithm then evolves from one generation to the next through the application of selection, crossover and mutation operations to discover the best configuration. Extensive simulation experiments were conducted to study the effects of the critical genetic parameters of mutation probability, crossover rate and population size on detection capability. The results indicate that the optimised BGA framework can achieve detection probability close to 96%, false alarm rate of 0.1, mutation rate of 0.12 and bit error rate of around 7×10^{-5} even when the signal-to-noise ratio is extremely low at –15 dB. In addition, the comparative evaluation showed the definite superiority of the proposed algorithm when tested against conventional algorithms, such as energy detection, matched filtering and neural network-based convolutions, when subjected to challenging and noise-prone conditions. The work further affirms the applicability of evolutionary algorithms in enhancing the cognitive intelligence of CRs and presents a scalable solution for spectrum management in existing 5G systems and future 6G frameworks.

Keywords: *Cognitive Radio; Crossover; Detection Rate; Dynamic Spectrum Access; Genetic Algorithm; Optimisation; Spectrum Sensing*

1. Introduction

Considerable changes in social automation and connectivity have been brought about by groundbreaking advances in technology related to wireless communication infrastructures. Changes in this area are responsible for the exponential increase in the number of connected devices and user demands, thereby complicating and aggravating problems of spectrum congestion and the efficient use of limited frequency resources. Additionally, all these limitations affect the overall performance and quality of service of modern-day wireless networks [1,2].

The modern generation of wireless technology is evolving to meet the insatiable appetite for ever-increasing data transfer rates along with low latencies and the efficient usage of the available spectrum as well as 3G rendering mobile multimedia capabilities, thus establishing 2G as digital voice communications. Advanced methods such as LTE, OFDM and MIMO were utilised by 4G implementations to provide services for data at high speeds. Although modern-day 5G networks offer technical advantages and opportunities, they also came with problems regarding propagation caused by its very wide frequency ranges: under 1 GHz, mid-band (1-6 GHz) and even millimetre-wave spectra [2,3]. The frequency allocation implemented in the 5G implementation strategy is illustrated in Fig. 1.

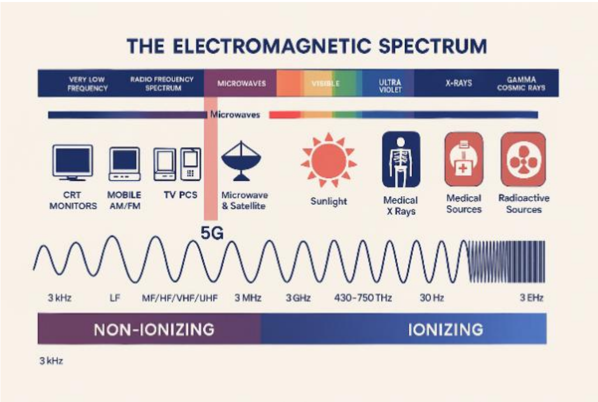

Fig. 1. 5G-based electromagnetic spectral part [3]

Spectral crunch refers to the limitation of a static system employing spectrum allocation with the power of current extreme growth in mobile connectivity. Therefore, DSA technologies play an important role in addressing that domain. In particular, they enable wireless devices to intelligently exploit available frequency bands depending on real-time changes in the environment. This opportunistic access of DSA considerably enhances spectral efficiency through the fair treatment of different users and minimum interference. A few characteristic application scenarios of DSA implementation emphasising its important role in the prevalent modern wireless architecture are shown in Fig. 2 [4,5].

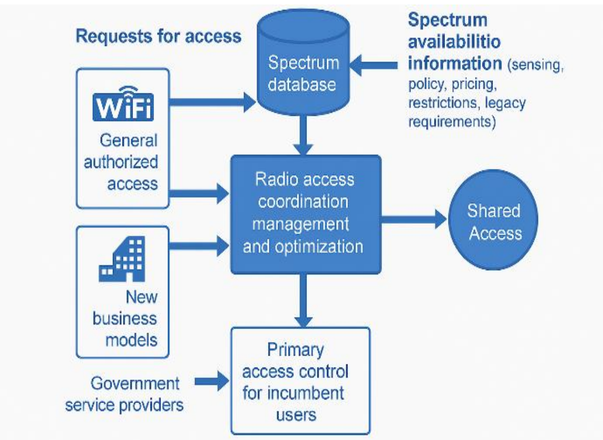

Fig. 2. DSA applications

CR innovation will be most instrumental in promoting DSA applications that enable radios to detect, characterise and adapt to the spectrum conditions. CR devices are capable of detecting unutilised frequency bands, also known as *spectrum holes* or *white spaces*, to access them dynamically without affecting any primary licensed user. This facility draws best applicability in densely populated metropolitan areas, where spectra congestion is at its worst [6].

The facilities and capabilities of telecommunication systems have witnessed dramatic changes via the AI and ML in the application of predicting traffic patterns and adjustment of sensing algorithms, thus improving performance. Past studies have shown that the next advanced generation systems networks (i.e. 6G) allow new applications with different requirements in the dynamic allocation of resources [7, 8].

Achieving high performance with good quality requires strong optimisation algorithms that are capable of managing nonlinear and dynamic situations. Advancements in 6G devices and the application of terahertz frequency range may sound futuristic, but it could also lead to greater complexities in the distribution and management of the spectrum. This makes genetic algorithms (Gas) one of the more promising bio-inspired methods for improving precision in spectrum sensing and resource allocation within cognitive radio networks (CRNs) [9–11].

In this paper, we present an improved GA-based detection system to enhance detection performance and spectrum utilisation efficiency. The effectiveness of the proposed method is tested against earlier established techniques, which appeared in various papers, via simulative comparison with the aim of establishing its superiority in the stage of variety of wireless medium. The particular contributions of this work are as follows:

1) Formulating a genetic algorithm-based joint detection model that enhances the accuracy of smart selection fusion methodologies;
2) Using a fitness-based choice, multipoint crossing and genetic variation to improve on the weighting vector for secondary users (SUs); and
3) Testing performance by extensive simulations, thus ensuring good detection reliability even under low SNR.

The tuning of genetic factors, such as population, mutation and crossover frequency, will have tremendous impacts on overall performance in demonstrating GA's capability for real-time CR optimisation.

The remaining parts of this work are organised as follows: Section 2 presents a brief overview of GA with CRN, Section 3 discusses the details related to the introduced system model, Section 4 talks about the simulation outcomes, Section 5 talks about the comparison of the proposal with the current state of the art and finally, Section 6 ends the paper by presenting the conclusions.

2. Background

GAs are a category of biologically inspired techniques for optimisation based on the principles underlying biological evolution. Because of their versatility and robustness, GAs are widely used to deal with difficult, multiple optimisation problems. In today's mobile communication systems, GAs have also been remarkably effective in optimising RF utilisation. A GA starts off with a heterogeneous population of possible solutions, each represented as a chromosome. The actions are then evaluated by a fitness function as the measure of the efficiencies of each in dealing with the problem at hand. Next, this population is subjected to several generational successions under the operations of selection, crossover and mutation, similar to actual genetic processes [12–14].

Through succeeding generations, the population approaches optimal or near-optimal solutions by preserving and enhancing the most fit people. In wireless systems, genetic algorithms have shown significant potential in numerous critical domains, including spectrum allocation, which involves the successful allocation of frequency bands to reduce interference whilst satisfying the demands of diverse users. CRNs have an enhanced precision in identifying main users (PUs) and selecting suitable transmission bands based on environmental circumstances [15]. Power control and spectrum sharing involves the optimisation of transmission power and resource allocation procedures to enhance reliability and mitigate cochannel interference. Although successful, Gas are sensitive to specific design factors, such as mutation rate, crossover frequency and the number of individuals, thus requiring meticulous adjustment to guarantee convergence and prevent premature stagnation [16]. In signal processing, GAs have demonstrated promising outcomes in complex situations involving multiple-input multiple-output (MIMO) systems and intricate modulation schemes (e.g. M-PSK), by effectively manoeuvering through noisy signal environments and improving detection performance [17–19].

In conclusion, GAs offer a versatile and effective framework for dynamic spectrum management, especially in future-oriented communication networks in which real-time improvement is critical [20].

3. System Model

The significant role of sensing stage in the CRN systems is highly affected due to bad environments (e.g., fading and additive white Gaussian noise (AWGN)) in communication channels. The soft decision fusion (SDF)-based cooperative scheme is employed so as to improve detection reliability. The architecture consists of multiple SUs, so-called relays, forwarding sensed information to a central fusion centre (FC). The redesigned cooperative system model with updated notations is shown in Fig. 2 [21–25].

3.1. Primary-relay channel modelling

Each secondary user performs local spectrum sensing to detect the presence of a primary user (PU). The sensing process is formulated as a binary hypothesis test:

Under the null hypothesis H_0 (no PU signal):

$r_k[m] = \eta_k[m]$, …(1)

Under alternative hypothesis H_1 (PU present):

$r_k[m] = \alpha_k \cdot s[m] + \eta_k[m]$, …(2)

where rk[m] denotes the m-th received signal sample at the k-th SU. The variable ηk[m] represents the AWGN at SU-k, assumed to have zero mean with variance $\sigma^2\eta_k$. In addition, αk denotes the sensing channel gain between the primary user and the kth SU, incorporating effects, such as shadowing and multipath fading. The PU's transmitted signal s[m] is modelled as a zero-mean Gaussian random process with variance $\sigma^2 s$. Table 1 provides a reference for the variables used in Fig. 3, along with their corresponding definitions, as described in the system model.

Table 1,
Variable definitions used

Variable	Definition
$s[m]$	Signal transmitted by the primary user (PU)
α_k	Channel gain between PU and the k-th Secondary User (SU_k)
$r_k[m]$	Received signal at the k-th secondary user (SU)
$\eta_k[m]$	Noise at the k-th SU (AWGN)
τ_k	Transmit power of SU_k
β_k	Channel gain between SU_k and fusion centre (FC)
$\xi_k[m]$	Noise at the FC from SU_k
$y_k[m]$	Signal received at FC from SU_k
Z_k	Energy detection result of SU_k at the FC
λ_k	Weighting coefficient assigned to SU_k
Z	Final global test statistic at the FC

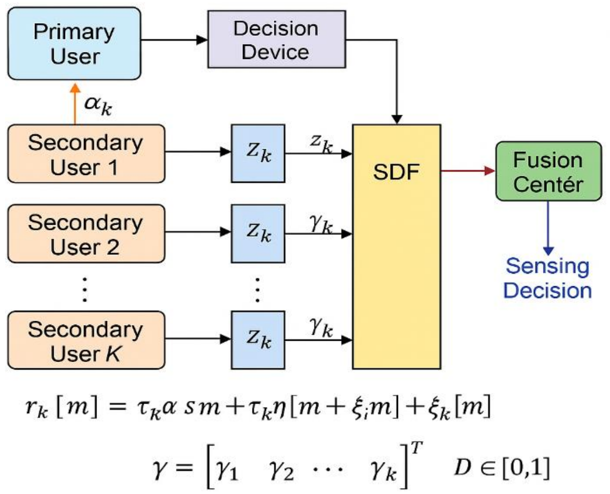

Fig. 3. Cooperative sensing system model using updated variable notations.

3.2. Relay-fusion channel modelling

This subsection describes the transmission from SU to FC as seen in Equation 3:

$$y_k[m]= \tau_k \cdot \beta_k \cdot r_k[m] + \xi_k[m], \qquad \ldots(3)$$

where τk is the transmission power of SU-k, βk is the amplitude gain of the reporting channel between SU-k and the FC and $\xi k[m]$ is the AWGN at the FC from SU-k, as well as a zero-mean variance of $\sigma^2 \xi_k$. Substituting the hypotheses into (3), under H_0:

$$y_k[m] = \tau_k \cdot \beta_k \cdot \eta_k[m] + \xi_k[m], \qquad \ldots(4)$$

$$y_k[m] = \tau_k \cdot \beta k \cdot \alpha_k \cdot s[m] + \tau_k \cdot \beta_k \cdot \eta_k[m] + \xi_k[m] \qquad \ldots(5)$$

However, under H_1:

$$Z_k = \Sigma\{m=1\}^N |y_k[m]|^2. \qquad \ldots(6)$$

Let Zk denote the energy estimate computed at the FC from SU-k's signal:

This test statistic Zk approximates a Gaussian distribution via the central limit theorem. Its statistical parameters under each hypothesis are given as follows, where μ_{0k} and μ_{1k} are the expected values of Zk under H_0 and H_1, respectively:

$$\mu_{0k} = N \cdot (\tau_{k^2} \cdot \beta_{k^2} \cdot \sigma^2 \eta_k + \sigma^2 \xi_k), \qquad \ldots(7)$$

$$\mu_{1k} = N \cdot (\tau_{k^2} \cdot \beta_{k^2} \cdot \alpha_{k^2} \cdot \sigma^2 s) + \mu_{0k}. \qquad \ldots(8)$$

The global test statistic Z at the fusion centre is a weighted linear combination of all individual energy statistics:

$$Z = \Sigma\{k=1\}^K \lambda_k \cdot Z_k, \qquad \ldots(9)$$

where λ_k is the weight assigned to SU-k, satisfying the normalisation constraint $\Sigma\ \lambda k^2 = 1$. The performance is characterised using the Q-function:

$$Pf = Q((\beta - \mu_0) / \sigma_0), \qquad \ldots(10)$$

$$Pd = Q((\beta - \mu_1) / \sigma_1). \qquad \ldots(11)$$

Each SU forwards its observations to the FC through an orthogonal reporting channel. The received signal at the FC from the k-th SU is given by:

where β is the detection threshold at the FC and (σ_0, σ_1) are the standard deviations of Z under H_0 and H_1, respectively.

3.3. Conventional weighting strategies in SDF

The following classical methods are used to define the weighting coefficients λk:

- Equal gain combining (EGC): $\lambda k=1/\sqrt{K}$, assigning equal weight to all SUs.
- Maximal ratio combining (MRC): $\lambda k \propto SNRk$, where SNRk is the signal-to-noise ratio at SU-k.
- Normal deflection coefficient (NDC): $\lambda \propto \Sigma_0^{-1} \cdot \theta$, where $\theta = \mu_1 - \mu_0$.
- Modified deflection coefficient (MDC): $\lambda \propto \Sigma_1^{-1} \cdot \theta$, using covariance under H_1 instead.

These strategies aim to enhance detection probability by emphasising more reliable SU measurements in the fusion process.

3.4. Proposed BGA-based cooperative spectrum sensing

To enhance detection performance and spectrum utilisation in CRNs, a binary genetic algorithm (BGA) was employed to optimise the weighting coefficients used in the SDF process. The proposed BGA-based model operates by evolving a population of candidate weighting vectors through successive generations, guided by fitness-driven selection, crossover and mutation operations, selection and genetics. The model is capable of addressing straightforward tasks (e.g. image generation and highly complex challenges), including deep learning optimisation and stochastic problem solving. GA deals with a set of possible solutions, each representing a particular answer to the problem in question.

The procedure starts with an initial random population of the encoded solutions termed *genomes*. Next, these solutions are evolved to different generations using biologically motivated operations for selection, crossover and mutation. The quality of each genome is assessed using a fitness evaluation function relevant to the specific problem.

If the stopping criterion has not yet been met, individuals with higher fitness values are selected to form the next generation. These individuals undergo crossover to exchange genetic material and mutation to introduce variability. The offspring produced by this process are then evaluated, and the most promising amongst them are carried forward.

The abovementioned evolutionary loop continues until a predefined condition is satisfied (e.g. reaching a maximum number of generations or achieving a target performance). A conceptual overview of this procedure is shown in Fig. 4. The strategy generates a seed group of potential solutions and normalises them to meet restrictions, aiming to optimise identification effectiveness by determining the ideal collection of grading vector elements. If the algorithm exceeds the specified limit, the most effective scalar values are then selected.

Let C S and L1, L2…LC be the soft decisions of S1, S2…SC, respectively, on the presence of signals, where C is the complete number of SUs. Yi represents the weighting vector of the ith individual that consists of Y1, Y2….YC. In the case of ||Yi ||=1, dp is the detection rate. The fitness value for the ith individual is defined as: .

The objective of the selection step is to use crossover and mutation to identify the most advantageous genomes for replication. A higher fitting value indicates a superior option:

$$\mathrm{Fun}_i = d_P(Yi). \qquad \ldots(12)$$

Here, the Roulette Wheel selection approach is employed. The notation pi represents the probability of choosing the ith individuals.

$$d_i = \frac{\mathrm{FUN}_i}{\sum_{i-1}^{individuals} \mathrm{FUN}_i} \qquad \ldots(13)$$

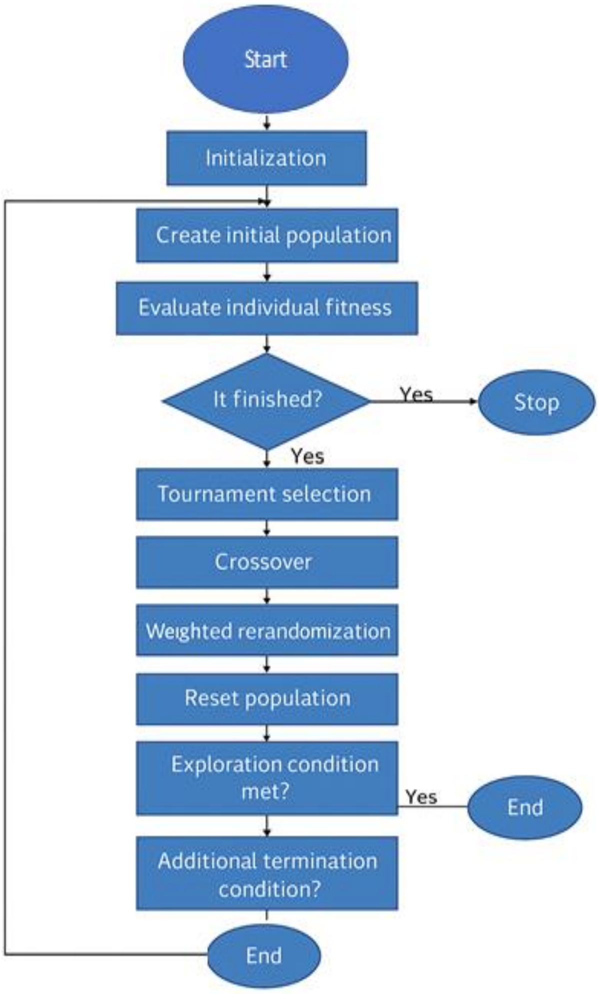

Fig. 4. Flowchart of the proposed GA

Based on privilege, the genes that have the greatest likelihood of occurring will be passed down to the following population. Crossover occurs following the selection procedure. The crossover procedure commences by pairing the chosen genes from the existing generation to produce a new progeny population. These partnerships, equivalent to biological parents, are selected randomly out of the current pool via a statistical picking technique. A randomly selected function, such as rand, is then employed to ascertain candidate numbers, which are subsequently rounded to the nearest integers to align with real chromosome positions within a certain population size (e.g. 5 individuals).

After selecting both parental genomes, a multipoint crossover approach is employed, in which genetic material is exchanged between pairs at several randomly established crossover locations.

This process mimics the biological process of genetic recombination, thus promoting diversity and helping the algorithm explore a broader solution space. In the tested configuration, sample random values (i.e. (0.67, 0.23) and (0.12, 0.91)) are generated to guide the selection and crossover points. The resulting selected chromosomes for crossover are indexed as x = [2, 4] and y = [5, 1], representing the parental combinations for that iteration. The complete crossover and mutation procedures are depicted in Figs. 5 and 6, respectively. These figures offer a visual analogy similar to shuffling and splitting strands of DNA to create new genetic expressions in the next generation of solutions.

Before the crossover (x)

101100	101011	----	101100

offspring1 after the crossover

101100	110011	----	101100

Before the crossover (y)

100100	110010	----	100100

offspring2 after the crossover

100100	101010	----	100100

Fig. 5. BGA crossover operation

Now due to the mutation:

101100	**101011**	----	101100	Before the mutation
101100	**101111**	----	101100	After the mutation

Fig. 6. The operation of mutation

In the case of BGA mutation, all the parameters that might be changed are ≈ (mutation rate * population * bit size * number of variables). At a pace of a single chromosomal bit at a time, the suggested bit switches into the matching bipolar digit after the row and column numbers are randomly selected. The process by which BGA mutations work is presented in Fig. 4. The mutation procedure contributes to the creation of a new search space. In summary, the following is how the suggested GA-based system for collaborative spectral monitoring operates from A to G:

A: Place t is set to 0 to produce an arbitrary population of genomes. Every population genome is (C*X) bits long, where C represents the overall number of SUs in the system and X represents the bits in every genome.

B: Each chromosome will be decoded into an array that corresponds to it in the arbitrary group. The identification accuracy is enhanced via the weighted parameters set of Y= [Y1 Y2 Y3,…Yi]T; Y ≥ 0 satisfying the criterion ||Yi||=1.

C: The weighted parameter array should be normalised by combining:

D: Most suitable genomes (P*α) will be identified (where α is an amount specifying a percentage of P that is below one) by calculating the value of fitness of each balanced decoded weighted vector (Y) and ranking them based on this value.

$$\vec{Y} = \frac{\bar{Y}}{\sqrt{\sum_{i=1}^{C}(Y_i)^2}}, \qquad \ldots(14)$$

E: Return the updated solution (P*(1-α)) via the GA's selection, crossover and mutation processes and set t=t+1.

F: Combine the recently replicated chromosomes with the most promising parental chromosomes to create an additional batch of genes.

G: Following the procedures outlined in Steps B and C, decipher and standardise the genetic material from the freshly created population. Repeat step D to determine every chromosome's value for fitness, then finish the iteration if t equals the preset value ngener. If not, proceed to E.

4. Experimental Scenarios

To determine the ideal arrangement for GA, numerous tests were executed by systematically altering essential factors. The assessment concentrated on the impact of these setups on detection accuracy and overall performance. The examined factors included mutation rate, population size, bits per variable and crossover rate. The GA method was executed with multiple settings of an identical factor to determine the ideal array of values. The experiments were conducted using MATLAB®.

4.1. Parameter tuning and experimental setup

The parameters utilised for testing are listed in Table 2. The best-performing configuration, based on detection probability and convergence speed, is shown in Table 3.

Table 2,
Testing parameters

Variable	Value
Rate of mutation	[0.02, 0.12, 0.17, 0.21, 0.28, 0.31, 0.4]
Size of population	[6, 12, 18, 24, 30]
No. bit per variable	[2, 4, 8, 16, 32]
Rate of crossover	[0.52, 0.54, 0.62, 0.64, 0.8]

Table 3,
Obtained best results

Variable	Value
Rate of mutation	0.12
Size of population	30
No. bit per variable	16
Rate of crossover	0.64

4.2. Simulation results and observations

Using the optimised parameters, simulations were conducted over 250 generations with population sizes of 35 and 24 SUs. The mutation probability, crossover portion and false alarm rate (Pf) were set at 0.05, 0.75 and 0.01, respectively. Using the best settings determined in the preceding section, the simulation will run the suggested GA approach. The value of fitness determines its identification likelihood, as shown in Fig. 7. It is observed how the GA option meets the greatest achievable answer, which is 100%. The subsequent settings were employed by BGA as follows: 250 generations to come, 35 population length as minor with 24 SUs, 0.05 chance of mutation, 0.75 population for gestation and 0.01 for Pf.

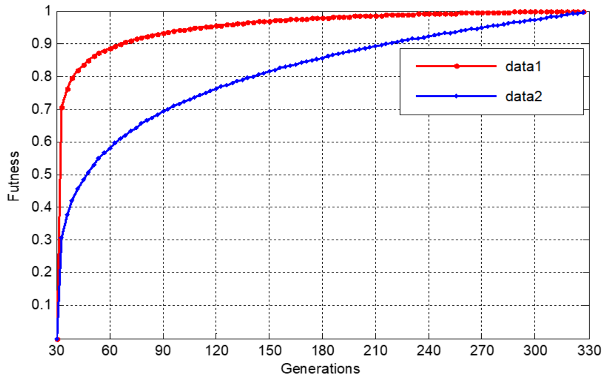

Fig. 7. Sample of obtained results

In Fig. 7, data 1 represents the results of the proposed method, while data 2 is the mean fitness binary. The effect of mutation rate on overall performance is clearly noticed in Fig. 8, which shows direct proportionality between the detection rate and the mutation rate. Similarly, direct proportionality between the generation number and the fitness function is shown in Fig. 9.

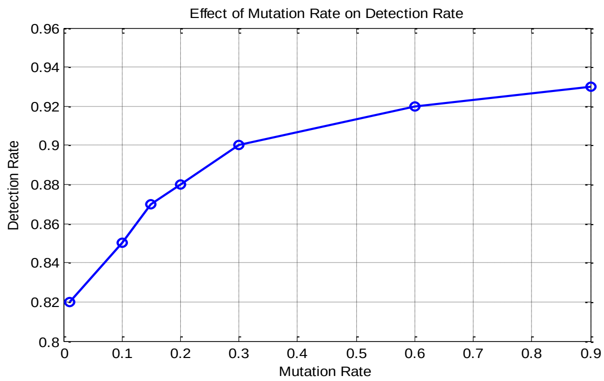

Fig. 8. Direct proportionality between the detection and the mutation rate

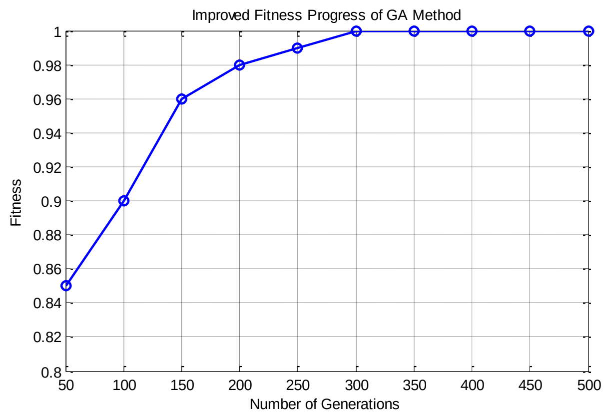

Fig. 9. Relation between the generation number and the fitness function.

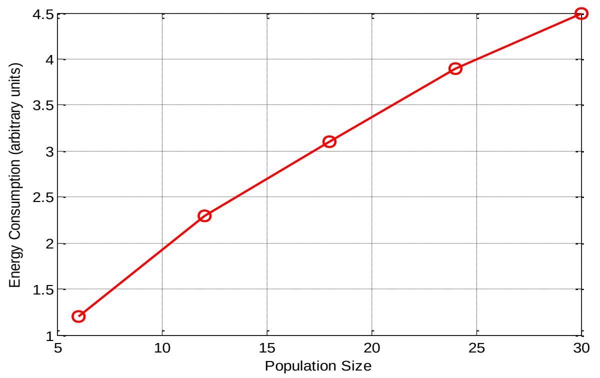

Fig. 10. Energy consumption vs. population

The relationship between population size and energy consumption in the proposed GA framework is shown in Fig. 10. As the population size increases, the energy consumption exhibits a proportional growth due to the higher number of individuals being processed in each generation. This trend is also linked with the high computational snowball associated with larger populations. Thus, there is a trade-off between improving detection performance and minimising energy costs when implementing real-time detection.

5. Proposal and Other Methods: Comparative Analysis

To test the efficiency of the proposed GA-based algorithm, several standard spectrum-sensing techniques were considered for comparison: energy detection (ED), matched filter (MF) and convolutional neural networks (CNNs). The evaluation was done under common simulation parameters of 8 MHz bandwidth, 10 ms sensing time duration and 10 dBm primary transmission power. The system was assumed to be under a very harsh noise environment of SNR ratios below −15 dB.

5.1. Detection rate vs. false alarm rate

As shown in Fig. 11, the proposed GA approach achieved a pd of 90% with a pf of 0.04, outperforming CNNs (83%), mf (70%) and ED (58%). This outstanding performance underscores GA's strength in optimisation and adaptability in the sensing process.

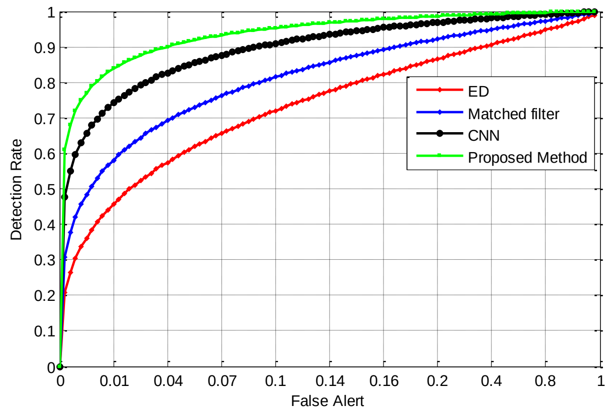

Fig. 11. Comparative analysis of the suggested and traditional methodologies

5.2. ROC performance comparison

The automated technique provides better detection probability over a wide range of false alarm rates, as seen from the ROC curves in Fig. 12. This is further evidence of the reliability and robustness of the proposed model under varying operational conditions. For the comparison, we used standard deflection factor (SDF), normal deflection coefficient (NDC), modified deflection coefficient criterion (MDC), maximal ratio combining technique (MRC0 and equal gain combining technique (EGC).

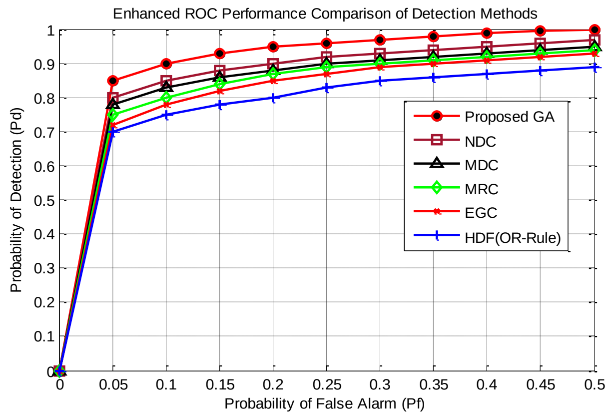

Fig. 12. Comparative analysis of the proposal against alternative methods

5.3. Bit error rate analysis

As shown in Fig. 13, the BER of the GA model was markedly least (10^{-5}). This result further validates the method's resilience to noise and channel degradation, particularly in low-SNR conditions.

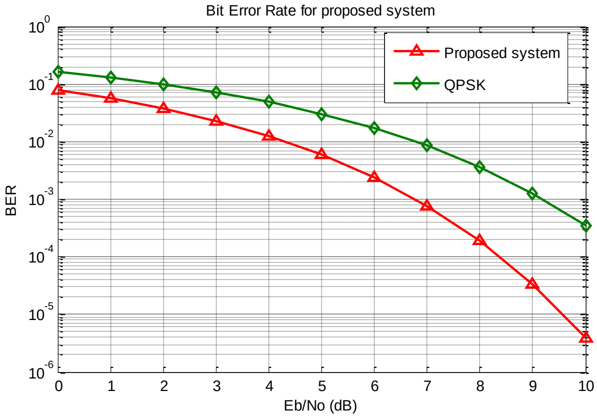

Fig. 13. BER of the proposed system

The proposed autonomy sensing method achieved equally or more competitive results than relative traditional techniques, rendering it quite versatile and adaptable to next-generation CRNs.

6. Conclusion

A methodology for spectrum sensing and resource allocation in CRNs through biological algorithms has been proposed in this paper in detail. BGA performance was evaluated for different settings and compared with other conventional spectrum-sensing approaches, such as ED, MF and CNNs. The results of the simulations demonstrated the advantage of the GA-based system in terms of detection accuracy with minimised false alarm rates along with low noise and channel variations.

In this research, we also developed a cooperative sensing model based on the GA, which enhances the performance of the soft-combining fusion scheme in the following ways: (1) fitness-based selection, multipoint crossover and (2) adaptive mutation for optimising the weighting vector for secondary users involved; (3) validation of performance through detailed simulation studies, which showcases improved detection reliability even at low signal-to-noise ratios; and (4) traditional versus deep learning methods are compared, and the performance of the GA model is validated against these algorithms.

The results demonstrate the ability of GAs to perform dynamic cognitive spectrum optimisation, while also emphasising that fine-tuning genetic parameters, such as population size, mutation rate and crossover frequency, may have drastic consequences for performance.

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تقييم الأداء وتحسين إدارة الطيف في أنظمة الاتصالات باستخدام الخوارزمية الجينية

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المستخلص

في ظل تزايد تقنيات الاتصالات اللاسلكية، مما يزيد من الطلب على طيف الترددات الراديوية المحدود، ويخفف حتى الآن من حدة مشاكل الازدحام ونقص الاستخدام والتداخل، تقدم هذه الأطروحة نموذجًا حديثًا لإدارة الطيف يعتمد على الخوارزمية الجينية الثنائية(BGA) ، القادرة على تحسين دقة الكشف والوصول التكيفي للطيف في شبكات الراديو المعرفية .(CRNs) تتبع BGA الترميز الثنائي لتحديد عوامل الترجيح المثلى للمستخدمين الثانويين في سيناريو CRN بأداء أسرع بكثير وموثوقية أفضل من الأساليب الجينية التقليدية. في مخطط استشعار الطيف التعاوني المقترح، سيُرسل العديد من المستخدمين الثانويين نتائج الاستشعار المحلية الخاصة بهم إلى مركز دمج حيث سيعمل تحسين BGA على ضبط معاملات الترجيح بدقة عبر آلية دمج القرار الناعم. تتطور الخوارزمية من جيل إلى آخر من خلال تطبيق عمليات الاختيار والتقاطع والطفرة لاكتشاف أفضل تكوين. أُجريت تجارب محاكاة مكثفة لدراسة آثار المعلمات الجينية الحرجة لاحتمالية الطفرة ومعدل التقاطع وحجم السكان على قدرة الكشف. أظهرت النتائج أن إطار عمل BGA المُحسَّن يُمكنه تحقيق احتمالية كشف تصل إلى ٩٦٪ تقريبًا، ومعدل إنذارات خاطئة يبلغ ٠,١، ومعدل طفرة يبلغ ٠,١٢، ومعدل خطأ بتات يبلغ حوالي ٧ × ١٠$^{-5}$ حتى عندما تكون نسبة الإشارة إلى الضوضاء منخفضة للغاية عند -١٥ ديسيبل. بالإضافة إلى ذلك، أظهر التقييم المقارن تفوقًا واضحًا للخوارزمية المقترحة عند اختبارها مقابل خوارزميات تقليدية مثل كشف الطاقة، والترشيح المتطابق، والالتواءات القائمة على الشبكات العصبية، وذلك عند تعريضها لظروف صعبة ومعرضة للضوضاء. كما يؤكد هذا العمل على إمكانية تطبيق الخوارزميات التطورية في تعزيز الذكاء المعرفي لأجهزةCR ، ويقدم حلاً قابلاً للتطوير لإدارة الطيف في أنظمة الجيل الخامس الحالية وأطر الجيل السادس المستقبلية.