

Genetic Approaches for Citizens Broadband Radio Service Channel Allocation

Ahmed N. H. Alnuaimy 

Department of Mechatronics Engineering, Al-Khwarizmi College of Engineering, University of Baghdad, Baghdad 10013, Iraq

Corresponding Author Email: ahmed.n@kecbu.uobaghdad.edu.iq



Copyright: ©2026 The author. This article is published by IETA and is licensed under the CC BY 4.0 license (<http://creativecommons.org/licenses/by/4.0/>).

<https://doi.org/10.18280/jesa.590104>

ABSTRACT

Received: 3 October 2025

Revised: 24 November 2025

Accepted: 1 December 2025

Available online: 31 January 2026

Keywords:

Citizens Broadband Radio Service, channel allocation, genetic algorithms, cognitive radio

This study compares four different algorithms for solving the Citizens Broadband Radio Service (CBRS) allocation channel problem, namely the Hungarian, Auction, Linear programming, and genetic algorithms (GAs). The Hungarian approach is a popular assignment algorithm that is mainly used in other combinatorial optimization problems. The Auction can be regarded in some sense as a Hungarian algorithm, which provides an improvement to the solution to the problem. The linear programming algorithms are algorithmic linear optimization methods aimed at solving specific allocation problems; on the other hand, GAs use heuristic iterative evolution-based concepts when searching for problem solutions. As a performance measure for all of these algorithms, large-scale simulations were performed, and the channel allocation costs were obtained and analyzed. Through the intermediate stages of simulations and evaluations, we validate that Linear Programming and GAs are superior in cost minimization in channel allocation as compared to Hungarian and Auction approaches. This study contributes to optimizing channel allocation approaches within the CBRS framework, drawing the map for more efficient and cost-effective wireless communication systems.

1. INTRODUCTION

The demand for the resources of the spectrum has reached the highest levels in the history of the wireless communication industry. The electromagnetic spectrum is a limited and valuable resource that is divided into different frequency bands used for different wireless communications services. Since conventional methods of spectrum allocation cannot satisfy the ever-growing needs, the future of communication will be oriented towards new strategies, such as spectrum sharing or resource allocation.

Spectrum sharing may be defined as the practice of enabling numerous users or systems to operate on the same frequency bands at the same time and place. In the past, spectrum distribution has generally been controlled by means of exclusive licensing systems, featuring the assignment of bands to services or operators. Such an arrangement may, however, result in spectrum wastes since licensed spectrum may be predominantly unoccupied for long periods. Spectrum sharing was developed to increase spectral efficiency and allows sharing of spectrum by many users or services as long as one or more users or services can be serviced by the existing spectrum [1].

Spectrum sharing means allowing more users and/or systems to exist and utilize the same frequency bands at the same time with the efficient use of the spectrum resource [2]. Nonetheless, in the past, the provision of spectrum has mainly been on an exclusive 'licensing' basis whereby frequency bands have been allocated to dedicated users, for example, telecommunication companies only. Thus far this policy has

created inefficiencies, resulting in the fact that great parts of the spectrum are hardly used, while other parts are overcrowded and suffer from scarcity.

The demand for a given resource grows constantly; as a solution, spectrum sharing deals with those challenges since it allows multiple users, technologies, or services to use the same frequency bands, however, on a more or less fragmented basis and depending on the instant demand. To strengthen efficiency in spectrum usage, the resources available are increased in a way that minimizes interference and optimizes use of the spectrum allowing for a wider population to have access to the spectrum resources.

Resource allocation in wireless communication refers to allocating resources such as time slots, spectrum, power, and modulation schemes among users or devices in a network [3]. The communication system's performance will be optimized when resources are available and are utilized appropriately to satisfy the users' quality of service (QoS) requirements of different users.

Wireless communication resource allocation means addressing such parameters as bandwidth, power, time, and code assignments horizontally between users or applications. In light of improving system capacity and satisfying user experience and QoS requirements, resource allocation is a crucial factor. Factors such as the designated user, the channel state, data rate, and the level of congestion in the network are some of the factors considered by the allocation strategies [4].

The purpose of these strategies is to achieve a balance between providing services to as many users as possible, providing equal distribution, and achieving maximum

efficiency. However, due to the emergence of new technologies like 5 Generation (5G) and beyond, how resources are utilized has become more sophisticated, and this requires intelligent algorithms and adaptive techniques to deal with diverse and rapidly changing communication scenarios [5]. Spectrum sharing and resource allocation bring both challenges and opportunities in the case of wireless communication. The challenges include managing interference scenarios that may arise when there are coexisting users, equitable distribution among the different users, and finding robust algorithms to handle the dynamic requirements of the spectrum access. Also, that challenge of ensuring spectrum rights should also be dealt with considering that new approaches to spectrum allocation should be permitted under appropriate legal and policy frameworks.

In addition, spectrum sharing and resource allocation can lead to a better spectrum utilization and growth in new wireless services, as well as new applications such as Internet of Things (IoT), smart cities, and industrial automation [3]. That's why technologies like cognitive radio, machine learning, and dynamic spectrum access (DSA) are used, which allow more variety and flexibility in the effective resource use.

Wireless communication is one of the most important aspects of the advancement of many organizations, which is enabled through spectrum sharing and resource allocation, while the electromagnetic spectrum is limited resource. These ideas are among the most promising today and will not only enable significant change to the way spectrum is managed and allocated, but used as well. Such advanced technology combined with communication requirements will also rely on effective spectrum sharing and resource allocation as key enablers for the development of strong, efficient and prepared wireless networks of the future [5].

This paper looks into and evaluates several algorithms that relate to channel allocation in wireless communication systems. Channel allocation is a resource allocation of maximum importance, which consists of efficiently assigning frequency channels to users, devices or services while minimizing interference and QoS limitations.

It is intended to optimize the limited spectrum resource, through the use of reliable and efficient communication. The selection of an optimal channel allocation algorithm heavily affects the performance of the wireless networks. Various algorithms differ in the design complexity, adaptability to changes, fairness and efficiency of the networks.

2. SPECTRUM SHARING

Spectrum sharing, shown in Figure 1, is use to refer to the ability for a number of users or systems or services to use the same frequency spectrum at the same time and in an effective style. The electromagnetic spectrum which comprises of various frequencies is a scarce and essential resource for wireless communication technologies including radio, television, cellular network, Wi-Fi and others [6]. With the rate of growth of demand for wireless services increasing, it becomes imperative to make effective use of the limited spectrum resource available.

Speaking about the traditional methods of spectrum allocation, it uses an exclusive licensing method. This is where specific frequency bands are set aside and assigned to specific entities and that entity has an exclusive right to use that frequency band. This is however not very efficient since there

are some underutilized bands while others experience congestion [7].

To deal with these issues, systems are developed that allow various users and systems to access the same frequency bands automatically and in a coordinated fashion [8].

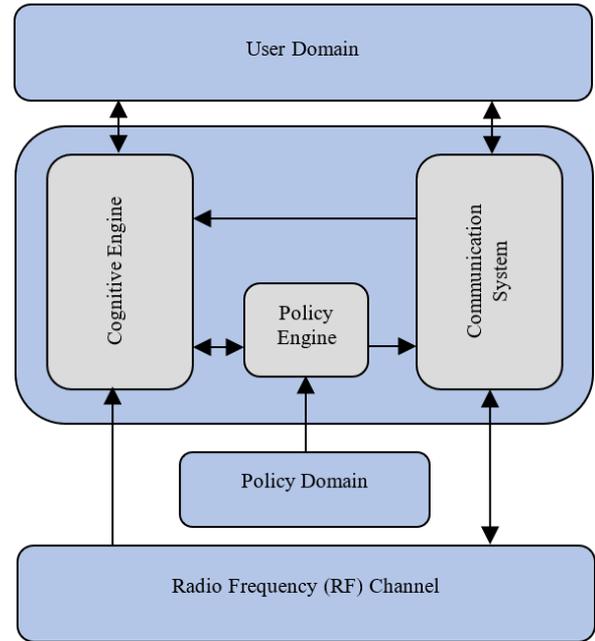


Figure 1. Sharing spectrum architecture

There are some approaches to spectrum sharing:

(1) Licensed Shared Access (LSA): Known as this approach, licensed users, such as mobile network operators, lease or share their spectrum resources with the lower demand authorized users whenever they are available. This increases the spectrum utilization since the QoS for the primary users is not guaranteed to be compromised.

(2) Unlicensed Spectrum: Unlicensed spectrum is a spectrum that can be used by anyone without having the need to have a formal licensing. There are technologies such as Wi-Fi and Bluetooth that operate in unlicensed bands and thus several devices do not require centralized coordinators to share the spectrum.

(3) DSA: DSA includes such technologies as cognitive devices to scan the spectrum and look for currently available frequencies. An instance is Cognitive radio, in which intelligent radios shift their operating frequency to unutilized or unoccupied bands.

(4) Geolocation Database: Some frequencies are reservable for shared use but the unique frequencies are reserved because of geographic peculiarity. Geolocation databases help in ensuring that the devices do not interfere with others by choosing channels that are as per the frequencies available in that particular location.

(5) Spectrum Sharing Frameworks: Different bodies and regulatory authorities have embarked on developing frameworks and structures for dynamic spectrum sharing. Such frameworks include rules, protocols, and other technical specifications that allow devices to use the spectrum resource and share it in an orderly manner.

The practice of Sharing of the spectrum has a number of advantages that mitigate practice of scarcity of spectrum, ubiquity of wireless demands and over dependence of the available spectra. These advantages include:

- **Improved Spectrum Utilization:** Users of the wireless service would rely on the same few spectrum bands, so through spectrum sharing many users can use the same band simultaneously [9]. This assists in improving the overall purpose of the spectrum.

- **Improved Accessibility:** Spectrum sharing helps to expand the number of simultaneous users and devices using the same frequency bands [7]. Addressing the increased need for wireless communication services in the crowded and busy hour regions.

- **Quick Deployment of Services:** Similarly, spectrum sharing means new services and technologies can be rolled out faster. Instead of waiting for innovators to be granted exclusively available licenses, they can spin unlicensed or shared spectrum to bring new wireless services in the shortest time frame.

- **Reduced Cost:** Many operators end up incurring high costs when acquiring exclusive spectrum rights, particularly for the most competitive bands. Through multi-users permitted access to the spectrum, spectrum sharing eases up financial burden, reduces entry for new players, thus enhancing competition.

- **Utilization of Flexible Resources:** The authors address that DSA and cognitive radio are spectrum sharing mechanisms that increase resource efficiency and allow frequencies to be utilized where and when demanded or the nature of the channel permits [8]. Such an adjustment makes certain that the resources are only wasted when they are really not required.

- **Access to Wireless Services in Remote Areas:** Ensuring seamless wireless penetration in unserved/underserved regions can be achieved through spectrum sharing eliminating the need for extensive infrastructures. With shared spectrum, the connectivity solutions can be inexpensive and narrow the digital divide.

- It has been established that spectrum sharing promotes the development of new wireless technologies, services and applications through testing of ideas (usually considered test bed concepts for new devices or services). Novel applications and solutions can be tested by developers and researchers; thus, many different wireless services are created and these are often of great value [10].

- **Efficient Use of Licensed Spectrum:** LSA offers fairness because it permits primary licensed spectrum holders to share their spectrum during low demand periods. Through this method, the requirement for primary users or primary services is completely preserved and an appropriate quantity of licensed spectrum is utilized [9, 10].

- **Mitigation of Spectrum Scarcity:** With the growing need for wireless services, the aspect of spectrum scarcity is worrying. Adequate and effective spectrum sharing helps to avoid this scarcity by making optimal use of the available resource and postponing the demand for the allocation of more spectrum.

- **Sustainable Development:** Through spectrum sharing, the need to seek for new spectrum allocation is eliminated, thereby making its use more in accordance with the principles of sustainable development.

Thus, sharing the spectrum is beneficial in many ways to cope with the increasing demand for wireless communication services and the limited availability of spectrum resources [11]. Specifically, by enhancing spectrum efficiency, bandwidth expansion, cost reduction and fueling creativity, spectrum sharing advances the wireless technology development and broadens connectivity issues to people and business entities.

3. CITIZENS BROADBAND RADIO SERVICE

Considered a technology that operates in a band of frequencies of 3550 – 3700 MHz, the Citizens' Broadband Radio Service (CBRS) system allows a large population to have equal opportunities without monopolizing resources in the microwaves. The potential of CBRS is that it unlocks availability of broadband for users, thus it alters the characteristics of radio resources by devising means and providing access to multiple and coexisting users without requiring static assignment of channels or frequency-shifted links. CBRS was considered part of the government system within the band of 3.5 GHz, which has since been released for commercial purposes [12]. In its implementation, CBRS is arranged in 3 tiered models (as shown in Figure 2), which depict the different classes of users and their level of privilege with regard to the use of spectrum access systems:

- **Incumbent Access:** This is a tier that is only available for a few government and military users. Although these institutions are assumed to be subordinate system operators, they are the main users of the CBRS spectrum.

- **Priority Access License (PAL):** Commercially licensed authorities acquired through auction qualifiers operate at this tier. PAL licensees possess secondary access rights, which gives them higher privilege than General Authorized Access (GAA) users.

- **GAA:** All users who use GAA operate in an opportunistic manner since they do not have exclusive licenses. They can dynamically access the available spectrum when the higher priority access users are not using them.

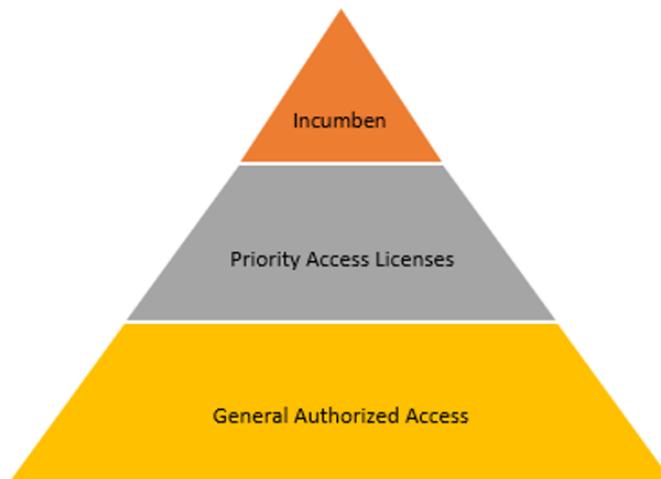


Figure 2. CBRS three-tiered spectrum access

The CBRS architecture deploys a spectrum access system (SAS) that automatically performs operations such as assigning frequency bands, interference minimization, and user coordination. SAS makes sure that PAL and GAA users are able to coexist without interfering with the incumbent users or with each other [13].

Long-term evolution networks or so-called LTE private networks, smart IoT deployments, fixed wireless broadband and industrial applications are among the different solutions made possible and supported by the CBRS architecture. It encourages spectrum sharing, whereby organizations can benefit from spectrum that has been lying idle without violating any interference rules. Due to its advantages, CBRS has come into the limelight following its ability of enhancing connectivity levels, promote creativity ultimately meeting the

increasing demand for wireless services more effectively.

The range of recent studies related to channel allocation for the CBRS have centered on the aspects of enhanced efficiency, and ease of scalability as well as the capacity for real time adaption to the instantaneous dynamics of the environment. Some key advancements include:

- **Machine Learning and Artificial Intelligence:** These algorithms have become popular factored in the dynamic spectrum allocation. These algorithms are well suited in a scenario in which most of the channel settings are automatic, owing to the fact that feedback is put in place by the system to indicate the best utilization of all frequencies. It is very important for such networks to be adaptive as the traffic is often unpredictable as is the case with the CBRS networks where there are several users transmitting signals over the same frequency band.

- **Deep Learning for Prediction:** The forecasting of spectrum based on demand and even predicting any interference is bound to be much easier with the neural networks. Hence, channels are preemptively provided and allocated using historical data, which in return aids in congestion reduction and improves service quality due to the best channels being allocated.

- **Hybrid Algorithms, including Auction-Hybrid Models,** combine the auction algorithms with other related ones such as linear programming, game theory among others for optimal channel distribution in terms of fairness and efficiency. It uses auction information in real time as well as the current network to maximize the allocation of channels.

- **Genetic Algorithm + Linear Programming:** Currently, there are frameworks that incorporate GAs and linear programming, where the GAs handle the global search and the linear programming deals with further optimization making it relevant for immediate allocation.

4. CBRS RESOURCE ALLOCATION

In CBRS, resource allocation as observed above in Figure 3 entails coordination and proportional usage of the frequencies within the PAL and GAA levels and make sure that they are not misused. Winning PAL holders then have exclusive access to their frequency blocks allocated to them within the specified geographic area [14]. PAL is won through competitive bidding. The Federal Communications Commission (FCC) offers territorial and band segments for sell at competitive bidding. There are areas with licenses to bid in them and the most qualified gets the license [14]. The winning PAL holders then have exclusive access to their allocated frequency blocks within the designated geographic area. GAA spectrum is unlicensed in nature, meaning there is no need to obtain a license like there is for technologies such as Wi-Fi. Nevertheless, GAA users are subject to rules that mitigate the potential for harmful interference to PAL licensees and non-primary users. GAA devices can sense when higher tier users are operating and refrain from using their frequency if it is necessary to avoid interference.

Dynamic Spectrum Sharing: The distinct feature of CBRS is its specific concept of dynamic spectrum sharing. It confers that the PAL users and the GAA users operate in the same bands but PAL users have preference over GAA users. The GAA users are required to move that portion of the spectrum to avoid interference [15]. If the GAA users are parasitic and scope that spectrum first, then GAA users would be denied

significantly access to that portion of the spectrum.

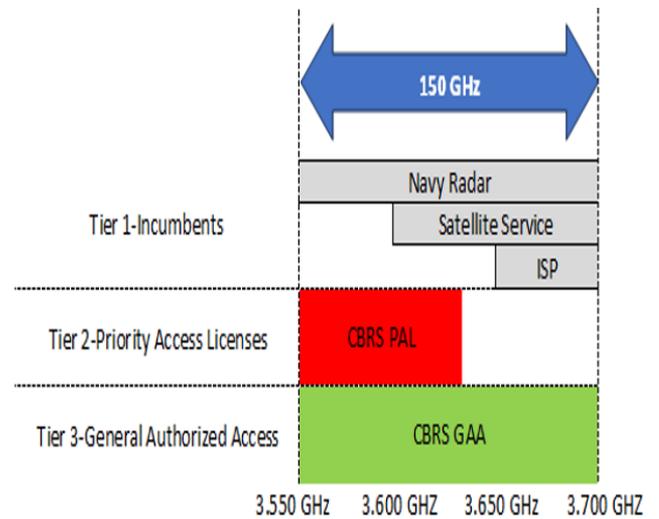


Figure 3. CBRS channels allocation

The allocation of PALs in the continuing block of the CBRS is the responsibility of the FCC. The FCC organizes competitive auctions in which, in designated areas, the parties bid for licenses for the right to utilize specific frequency blocks. This mechanism of auctions is intended to ensure that spectrum licenses are allocated to those who will make the best use of them [16].

The auction process requires that a number of rounds of bidding should occur, during which different parties may bid for specific areas and/or specific frequency blocks. And thus, bidding goes on until there are no more bids, and the highest bidders are awarded the price. The money obtained from these auctions is turned into Russia's asset management [17].

Such auction-based mechanisms or methods are user-based in nature, take into consideration the fact that user demand for spectrum resources is never the same over different geographical locations and over different frequency bands. It also enables those with deep pockets to buy priority access to the spectrum, which can lead to better access to the spectrum.

The Hungarian algorithm belongs to the class of and solves the so-called assignment problems. It is applicable especially if one has a matrix of costs or values associated with assigning resources to tasks and one wants to minimize the costs [18]. In spectrum sharing, users could be represented as tasks needing assignment and frequency bands as resources needing assignment with the algorithm tasked with looking for the best assignment that minimizes interference or maximizes efficiency. But the Hungarian algorithm may be less effective when there are many arbitrary limits that could rather be addressed to auctions.

Linear programming is another algorithm designed to optimize mathematical functions that operate under defined linear constraints. In spectrum allocation, one could define the allocation problem as a linear program whose objective is to achieve the maximum values for a certain parameter (e.g., efficiency) within certain limits (e.g., no interference). Compared to the Hungarian algorithm, linear programming can be more complex in taking into account such limits and preferences. Nevertheless, it may require some extent of modelling in order to precisely capture the nature of spectrum sharing [18].

5. AUCTION ALGORITHM FOR RESOURCE ALLOCATION

The auction algorithm can be viewed as a means of allocating the resources to bidders according to their valuations in the most efficient way. This is an iterative market-based technique where the possible assigns between agents and items are determined by means of competitive bidding, which is illustrated in Figure 4. It is suitable for problems that are sparse or large-scale and finds an optimal assignment quickly. This allows for a cycle of bidding, allocation and price change to take place. It is worth mentioning that this is a broad formulation, some practical implementations would go beyond this and may include dealing with ties, and bidders' strategies, among others [16].



Figure 4. Auction algorithm diagram

Let N be the bidders and M be the resources which are going to be distributed. Each Shannon bidder i has a certain valuation v_{ij} for every resource j . For each resource j , set the prices $p_j = 0$, and bidders make bids depending both on the value they have placed on each resource and the current prices. Bidders' i 's bid for resource j is:

$$b_{ij} = v_{ij} - p_j \quad (1)$$

if their bid is positive ($b_{ij} > 0$), allocate each resource to the highest bidder by setting $x_{ij} = 1$, where x_{ij} is a binary variable indicating allocation of resource j to bidder i . Update prices based on the difference between the highest bid and the second-highest bid for each resource:

$$p_j = p_j - step \times (b_{max_j} - b_{second_{max_j}}) \quad (2)$$

where, $step$ is a parameter controlling the rate of price adjustment. Repeat the auction steps until convergence criteria are met, such as when no bidder wants to change their allocation or after a predetermined number of iterations.

$$\sum_{i=1}^N \sum_{j=1}^M v_{ij} x_{ij} \quad (3)$$

Subject to constraints:

(1) Each resource is allocated to at most one bidder:

$$\sum_{j=1}^N x_{ij} \leq 1, \forall j$$

(2) Each bidder is allocated at most one resource:

$$\sum_{j=1}^M x_{ij} \leq 1, \forall j$$

where, x_{ij} is binary: $x_{ij} \in \{0,1\}$.

6. HUNGARIAN ALGORITHM FOR RESOURCE ALLOCATION

The Hungarian algorithm effectively addresses the assignment issue in polynomial time via the transformation of the cost matrix through series of reductions and optimality checks. It ensures a globally optimal one-to-one pairing. Let n be the number of agents and m be the number of tasks, then C be an $n \times m$ cost matrix, where c_{ij} represents the cost or benefit of assigning agent i to task j .

$$C'_{ij} = C_{ij} - \min(C_{ij}) \text{ for all } i, j \quad (4)$$

$$C''_{ij} = C'_{ij} - \min(C'_{ij}) \text{ for all } i, j \quad (5)$$

Next, on the cover of the zeros use a process known as Munkres' theorem which seeks to cover the minimum number of lines that span the points that must be crossed and update the remaining elements.

$C'''_{ij} = C''_{ij}$ if the row i is not marked and column j is not marked. $C'''_{ij} = C''_{ij} + \min_k$ if k is not marked (C''_{ik}).

This adjusted matrix will only have zeros in relation to the best assignments. These zero numerals are meant to be the ideal sortation and so the matrix ought to structure desirable sorts that remove the required costs. Such an assertion may be seen directly from the matrix. Figure 5 shows the diagram of Hungarian algorithm.

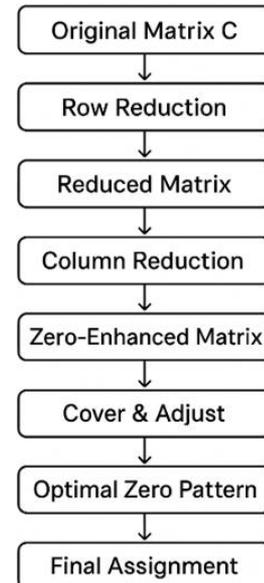


Figure 5. Hungarian algorithm diagram

The Hungarian algorithm includes resource allocation scenarios where you want to optimally match a set of agents to a set of tasks based on cost or benefit.

7. LINEAR ALGORITHM FOR RESOURCE ALLOCATION

A systematic approach to solving optimization problems is what is referred to as Linear programming. Linear programming solvers such as software tools can easily determine optimum allocation of resources that best serves the objectives of the system within the limits set by the constraints of the system. In this case, several algorithms include the Simplex method or the Interior-Point method are utilized for optimization purposes in the feasible region obtained by the constraints [14].

More formally, N are the available resources and M users of those resources, then there exists an allocation of these resources which should be carried in order to corollary a linear function of the decision variables. However, even these constraints are not unlimited since they will depend on the potential resources available or the users' requirements [5].

Let x_{ij} represent the amount of resource i allocated to user j . The goal is to optimize an objective function $f(x_{ij})$ subject to linear constraints. Maximization Problem is:

$$f(x_{ij}) = \sum_{i=1}^N \sum_{j=1}^M c_{ij} x_{ij} \quad (6)$$

Which subject to constraints:

(1) Resource Constraints: Ensure that the total allocation of each resource doesn't exceed its capacity: $\sum_{j=1}^M x_{ij} \leq R_i, \forall i$, where R_i is the capacity resource i .

(2) User Constraints: Ensure that the total allocation to each user doesn't exceed their demand: $\sum_{i=1}^N x_{ij} \leq D_i, \forall j$, where D_i is the demand of user j .

(3) Non-Negativity: Allocation values cannot be negative: $x_{ij} \geq 0$.

8. GENETIC ALGORITHM FOR RESOURCE ALLOCATION

Genetic algorithms (GAs) are algorithms for optimizing processes that work in a similar manner to biological evolution's fittest survive method. They excel especially well in optimal resource allocation due to the characteristics [19]. The main concept underlying GAs is that a population of individuals, which consists of numerous potential solutions, should be developed. Each individual is formed and represented as a combination of parameters known collectively as a chromosome or simply a genotype. These chromosomes are then scored using a fitness function that ranks solutions according to how optimally they meet the goals of the problem [20].

The GA works as follows: there are rounds known as generation in which the algorithms perform genetic operations such as selecting, crossing (recombination) and mutant to generate a new individual. It will be noticed that sometimes this algorithm produces satisfactory results and even successive generations improve responses further harmoniously succeeding to the optimal resolution.

Let us now focus on a simple problem of resource allocation as representation. Consider resources N and tasks M , participating in resource usage with task completion and profit registered. The tasks are performed in such a manner that the profit is maximized, with resource allocations being confined within limits. The goal is to allocate resources to tasks in a way that maximizes the total profit while respecting the resource constraints. The objective is to find a binary allocation matrix X of size $M \times N$, where X_{ij} equals 1 if resource j is allocated to task i and 0 otherwise. We want to maximize the total profit:

$$\sum_{i=1}^M \sum_{j=1}^N X_{ij} P_i \quad (7)$$

where, P_i is the Profit associated with task i . The total profit should be subjected to the following constraints:

(1) Each task is allocated to exactly one resource:

$$\sum_{j=1}^N X_{ij} = 1 \text{ for } i = 1, 2, \dots, M \quad (8)$$

(2) Resource availability constraints:

$$\sum_{i=1}^M X_{ij} \leq 1 \text{ for } j = 1, 2, \dots, N \quad (9)$$

where, C_{ij} is the resource requirement of task i for resource j and R_j is the amount of available resource j .

The GA is an option for incorporating into the spectrum management of CBRS either within the SAS or as an external operator-side optimization module depicted in Figure 6. When it is used in the internal context, the GA is considered as part of the SAS decision-making mechanism, taking the complete state of CBRS registrations, incumbent activities, PAL protection areas, and interference models into account to facilitate the creation of the most suitable channel and power assignments. This method provides very close integration along with efficient access to reliable information, on the other hand, it does necessitate cooperation with SAS vendors and compliance with rigorous testing, certification, regulatory, and operational procedures. On the other hand, operators can incorporate GAs in the external network controllers to suggest channel configurations and then submit them to the SAS through standard Grant Request and Grant Update procedures. This approach maintains the regulatory limits, while allowing operators to include local traffic, and QoS policies.

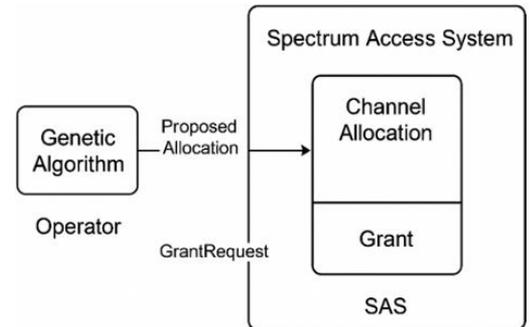


Figure 6. Genetic algorithm for spectrum access system

The extent to which GA-based CBRS allocation can be applied pivots on the algorithm's ability to adhere to the SAS

constraints and operate at the right timescales. The regulatory frameworks that set the rules for the incumbent protection, PAL priority, power limits, and interference thresholds should be expressed as either hard constraints for the GA or as very high penalties in the GA's fitness function so that all the candidate solutions are SAS-compliant. In terms of practical deployment, GAs are very compatible with medium-timescale optimization, like periodic channel reassignment, PAL planning, or congestion mitigation, where the time it takes for convergence is acceptable and the problem of excessive grant churn can be lessened through reassignment penalties. The existing industry support for advanced SAS optimization and operator-side orchestration frameworks signals a strong deployment feasibility, with GAs providing a flexible way to enhance spectral efficiency without losing compatibility with the CBRS operational and regulatory architecture. A sensitivity analysis was carried out to assess the robustness of the GA by methodically changing key hyperparameters such as population size (N), mutation rate (m), crossover rate (c), selection pressure, and elitism. Each parameter was varied around its baseline value while the others were kept constant, and several independent runs (R) were done to reflect stochastic variability. For every configuration, the average and standard deviation of the best fitness over replications were calculated as:

$$\overline{f^{best}} = \frac{1}{R} \sum_{i=1}^R f_i^{best} \quad (10)$$

$$s = \sqrt{\frac{1}{R-1} \sum_{i=1}^R (f_i^{best} - \overline{f^{best}})^2} \quad (11)$$

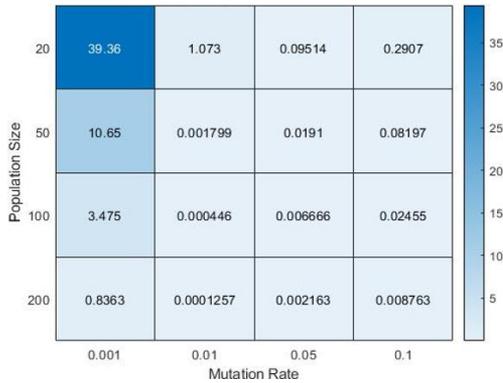


Figure 7. Mean final fitness

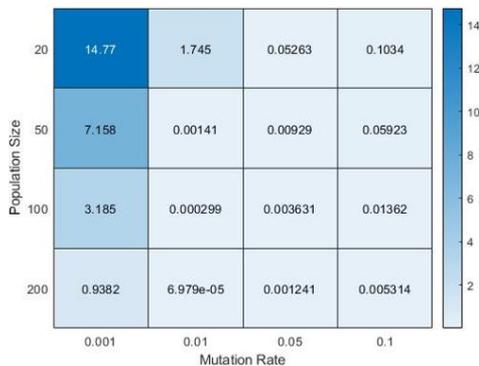


Figure 8. Standard deviation final fitness

The convergence speed was expressed in terms of the

average generation G_{95} at which 95% of the final best fitness was reached for the first time. The results showed that population size and mutation rate had the strongest impact on both solution quality and convergence behavior: larger populations decreased variability and increased stability, while moderate mutation rates ($0.005 \leq m \leq 0.05$) were effective in maintaining diversity without hurting convergence. Selection pressure and crossover rate had less impact but showed significant interactions with population size. The algorithm, however, continued to deliver high-quality solutions across the tested intervals with little sensitivity to slight parameter changes, thus verifying the robustness of the selected GA configuration. The sensitivity analysis depicted in Figures 7 and 8 unmistakably showed trends in performance related to the two major GA parameters under review: population size and mutation rate. Throughout the entire range of settings, it was a steady case of the larger the population, the better both the mean final fitness of Figure 7 and the stability of convergence of Figure 8.

Smaller populations ($N = 20$ or $N = 50$) showed higher variance through replications, which was a sign of their larger risk of premature convergence and being highly influenced by random initialization. On the other hand, larger populations ($N = 100-200$) managed to reach lower average objective values along with lower standard deviations, indicating that the diversity in genes has made the algorithm more efficient in searching the whole area.

The mutation rate had a notable impact on performance. The extremely low mutation rates like $m = 0.001$, in most cases, resulted in stagnation because there was no sufficient diversity in the search process to exit local optima. On the other hand, the very high mutation $m = 0.1$ caused the opposite effect by creating a lot of randomness; thus, there was a high mean fitness value and a large range of different results. The findings suggest that an intermediate range of mutation rates (approximately $m = 0.01$ to 0.05) is the best compromise between exploration and exploitation. The heatmaps in this region showed lower mean fitness and reduced standard deviation, which indicates that the performance was robust and reliable.

The interaction effects between population size and mutation rate have emphasized that the GA is most stable when both parameters are tuned together. To be more specific, larger populations are able to accept a bit higher mutation rate without losing their performance, while small populations will get very unstable with even a small increase in mutation. In general, the GA keeps its great robustness when using moderate population sizes and mutation rates. The results, therefore, confirm that the parameter defaults are a good choice and the algorithm, in fact, has the ability to resist the influences of extreme parameter settings in a wide but reasonable range of parameters.

9. RESULT

In our cultural simulation context, we recognize that there are four PALs and three GAAs. Each PAL operator has a distinct number of PAL users who are dispersed randomly and are provided with a set of randomly allocated unoccupied spectrum region as given in Table 1 [3]. Furthermore, we assume in our model that a GAA user is only able to make demand requests for up to two channels from the PAL operators.

Table 1. Priority Access License (PAL) and General Authorized Access (GAA) users' classification and their quality of service (QoS) requirements

Operator	Available Channels	Bandwidth (Kbps)	Cost	Packet Loss	Delay (ms)	Interference (dB)
PAL1	7	5500–6000	130–150	<1	50–60	-30
PAL2	7	1500–2000	80–100	<1	40–45	-30
PAL3	7	1000–1200	60–80	<1	40–45	-30
PAL4	7	3000–3500	140–160	<1	50–60	-30
GAA1	8	2000–2500	100	<2	55	-40
GAA2	8	500–1000	60	<3	50	-40
GAA3	8	1500–2000	100	<1	45	-40

The focus of this paper is the problem of assigning the non-utilized PAL reserved frequency channels to GAA users while protecting the PAL users from excessive interference with the aim of obtaining enhanced transmission rates at low tariffs. These applications have varying requirements in terms of delays, bandwidth, and packet loss rates. GAA users across different industries will have varying QoS requirements that cater to their specific application, such as video streaming, voice calls, and file transfer. This means that there is a need to make use of the unused PAL reserved channels and their associations with PAL network characteristics and GAA user service demands. In addition, when a GAA user uses a PAL channel that has been reserved for GAA use, this always results in the introduction of interference to the PAL users affecting their QoS. Thus, the SAS has to set an interference limit for GAA use to ensure that the QoS for PAL users is not compromised.

But this time cost seemed to be the dominant parameter in the channel allocation process, specifically through the use of allocation algorithms for CBRS whereby MATLAB software was used to simulate the allocations.

The main approach in this research is the GA. Before using a GA to solve the resource allocation problem formulated in this study, the following items must be specified:

(1) Chromosome Encoding: A chromosome is a potential solution on how to allocate resources. It could be represented by a binary matrix X , with the components X_{ij} for some i, j where $1 \leq i \leq m$ and $1 \leq j \leq n$, equal to either 0 or 1 if resource j is assigned to task i .

(2) Goal Function: A goal function helps to assess how elegant a solution is. In this case, it calculates the aggregate profit focused on the available resources.

(3) Survivor Selection: The selection of individuals in the new population is usually determined by how fit the individuals are in the population. Those characterized with high fitness are in most cases selected.

(4) Recombination: Recombination or cross over uniquely features two parent solutions to give one or many child solutions. For resource allocation, this may involve two parents' allocation matrices being merged.

(5) Chromosome Mutation: This is the process that randomizes chromosomes of an individual and introduces small random differences in responses to genes.

(6) Stopping Criteria: Identify events that signal the end of the algorithm, including the number of generations reaching a certain point or exceed a predetermined fitness threshold.

The GA works in the following way:

(1) Create a random collection of possible solutions as the initial population.

(2) Apply the fitness function to each solution and analyze the outcome.

(3) Use a selection pressure based on the fitness of

individuals for the next generation.

(4) Use the crossover and mutation operators to form a new population.

(5) Continue with the last three steps until a given number of iterations is reached or specified conditions are met.

A number of key parameters were defined for the purpose of achieving better optimization of channel allocation using GA. Such characteristics as population size is equal to 50, which means that there were in each generation 50 possible solutions (chromosomes: represents a potential solution to the optimization problem, which is often encoded as a string of genes each representing a specific parameter of the solution) always fostering a variety of solution with dependence on computational resources. The number of generations in the population was 100 to allow enough repetitions for the improvement of solutions through evolution over time. A mutation rate of 0.01 (1%) was used, which means that a small percentage of the population will undergo random alterations. This was done so that diverseness would be introduced and limitation to the search space made would not take place. During the selection process, a tournament size of 5 was used: five solutions fought with each other, and one was chosen for reproduction. As it is known, GAs strongly advocates a survival of the fittest concept, which means only the best solutions should be selected for further computations. It is also critical that in the process of solving the problems the appropriate strategy maintains a competition among the selected solutions. The amount of the assignments did, as was necessary in terms of the cost matrix size, ensure that the algorithm covered the entire extent of the problem. These parameters acted together to shape the evolutionary process with respect to how thoroughly the search for potential solutions was carried out.

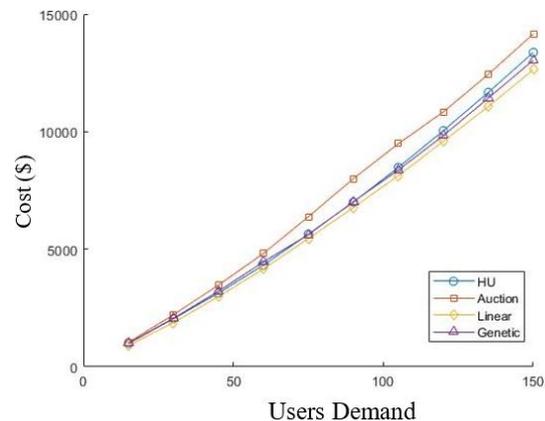


Figure 9. Net cost

In Figure 9, we show the results of the comparative analysis of the four considered algorithms for the cost matrix problem:

GA, Auction Algorithm, Hungarian Algorithm, and Linear Algorithm.

In the given study, the performance of the algorithms was primarily investigated with regards to quality and efficiency.

As results show, the GA has outperformed quite consistently the Auction algorithm in every aspect of solution and convergence. The solutions generated by the G were also in terms of total cost lesser and factors such as sensitivity to the initial population configuration were removed. This goes to show that compared to the Auction Algorithm GAs are more applicable in the course of addressing the cost matrix problem of resource allocations in CBRS system. The same can be said of the Hungarian Algorithm, as far as the solution quality is concerned, the commission rate was quite low. Although the assignment problem is efficiently solved by the Hungarian algorithm, the same matrix has provided suboptimal results in our study. The GA did however, take much of the search space into account which allowed it to derive more optimal solutions in tougher situations. The two other algorithms did not offer significant diversions when it came to solution quality; however, there was a keen edge on the Linear Algorithm with respect to the computational time used in solving the problem. Although most of the cost matrices were comparatively small in dimensions, the Linear Algorithm proved to be an optimal solution searching mechanism. The competition was such that the GA solutions were offered as fast constructive strategies, but the total time implications were relatively larger due suggesting higher computational times for bigger problems.

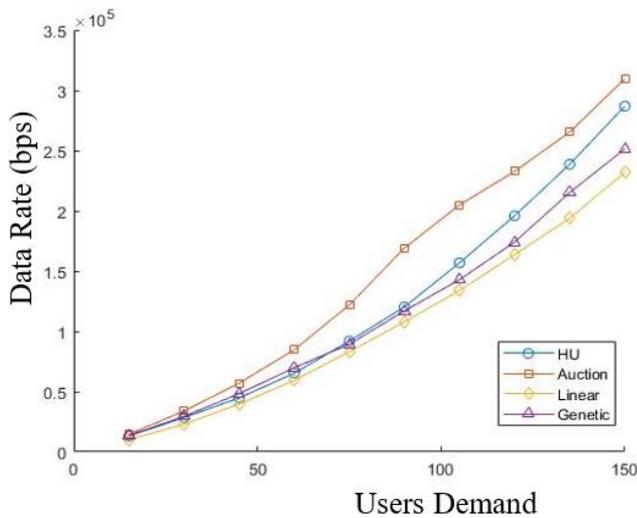


Figure 10. Net data rate

Even for the smaller versions of the problems, the Linear Algorithm is efficient. However, there is a problem when high-cost matrices come into the view, which makes the algorithm prone to a dramatic increase of complexity together with the increase in size of the problem. For many problems where the number of elements to be assigned is very large, it can also require very large computation times which may not be practical for most applications. The main disadvantage of the GA is that it works for a smaller number of elements than the GeAlgo as it works for larger number of elements and can shape larger search. This is of great use in assignment problems of a complex nature, where many viable solutions exist as well. Adaptability of the GA makes it a very useful algorithm to remember in unresolved problems of small to large in number of elements. Also, it is not that prone to the starting configuration so it is able to give good results for many

different situations. According to Figure 10, the Image GA and the Linear Algorithm achieved comparable solution quality for matrix data rate problems.

Both of them were able to achieve high data rate assignments but Linear algorithm i.e. LA had some efficiency as well. It consistently delivered optimal or near-optimal solutions for smaller data rate matrices and rapid implementation, which is a desired option in the case when there is a shortage of time.

GAs fit complex and changing environments like urban areas of high density with noise. Therefore, a broad range of solutions could be exploited as shown in Figure 11. GA can deal with nonlinear objectives and constraints, interference management as such, therefore they are very robust in very complex situations. Yet, in congested urban area with a significant amount of noise and low latency requirements, Auction algorithms can facilitate rapid channel assignment however cause high amount of noise as well as poor spectrum utilization. Hungarian algorithms provide solutions in a fairly stable and calmer environment but cannot perform effectively in a high noise environment characterized by dynamism. Linear Programming and GAs are best in reducing noise and handling complexities but are disadvantageous in the aspect of speed and time hence not much applicable in real time applications unless optimized.

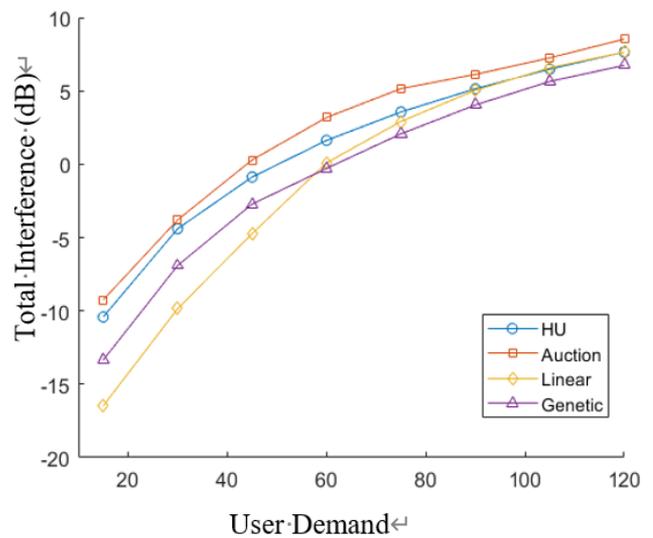


Figure 11. Net interference

The processing time for all the algorithms for efficient channel allocation in the considered model of the CBRS system is presented in Figure 12. The time also varies with the type of the algorithm used in the conceding channels in the CBRS algorithm and least core constraints. The first in this row is the Hungarians algorithm, specialized in the optimal configuration of resources, as a rule, quickly operated on the small and medium problems. Above them come the linear programming algorithms more slowly than auctions and Hungarian methods, but more flexible and accurate for the allocation tasks, which makes them more applicable for the changing restrictions of the model of the CBRS system. GAs, on the other hand, tend to be the slowest because it takes so long to get to multiple generations that nothing gets stuck on one set of chromosomes to converge on factories while also processing a beautiful and complicated channel allocation problem. Genomic algorithms preserve linear overlap goals at the cost of longer processing times but are able to solve the

problem in dynamic conditions.

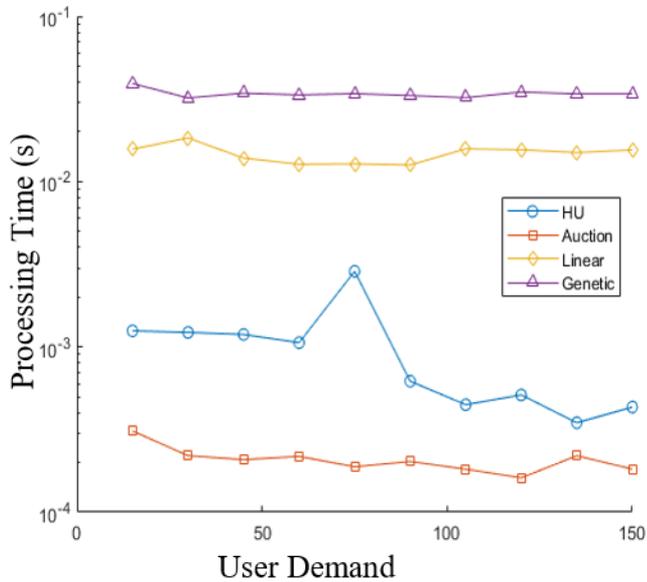


Figure 12. Processing time

Nonetheless, when the data rate matrix problems were solved, Data GA always surpassed Auction Algorithm and Hungarian Algorithm in every instance. It was able to arrive at solutions with much higher data rates in a lesser number of iterations. This implies that of all the approaches analyzed, it can be confidently stated that GA outperforms Auction Algorithm when it comes to data rate optimizations.

On the contrary, there are many potential issues and drawbacks with the application of Genetic and Auction Algorithm in the channel allocation for the CBRS system. GAs, particularly in large and dynamic environments with multiple users and devices, may take a long time to reach convergence. This may be an important limitation during CBRS real time deployments, in which quick channel allocation choices should be made. As the size of the problem grows, linear programming becomes computationally intensive. When hundreds or thousands of devices are communicating in a large CBRS network, the problem of allocation becomes unfeasible due to the linear programming paradigm. This is especially true in edge-based deployments where the resources for the processing units may be constrained.

Considering the case of GAs, their reiterative utility, as a consequence, leads to more processing delays which makes it difficult for applications that are real time in nature for the network involving fast changes. Instead, implementing GAs in practical CBRS systems would require optimizations or mixes with faster techniques for ensuring timeliness to real time requirements. Linear programming may not be efficient in a situation where requirements of the system are dynamic in nature such as movement of users, changes in the environment or even requests for reallocation of the spectrum.

Last but not least, CBRS utilizes SAS to centralize the management of spectrum and also protect incumbents. To add to the SAS, the genetic and linear algorithms have to be integrated in a way that does not interfere with the existing SAS; this makes things more complicated, in other words, the algorithms must be regulated. These algorithms must meet some regulatory requirements such as protection of non-active users which are sometimes considered at the level of the

automatic allocation of the channels leading to not optimal allocation being done.

10. DISCUSSIONS

This study had considered several simplifying assumptions that could impact the generalization and the application of the results obtained. First, the CBRS channel environment was simulated under quasi-static interference conditions, which means that it was assumed that user activity and the assignments of the incumbent SAS did not vary at sub-second timescales. In actual deployments, particularly in high-density urban areas or dynamic PAL-GAA coexistence situations, the availability of the channel could change very quickly, thus affecting the allocation decisions made. The path-loss and interference models that were utilized in the simulation are based on standardized propagation assumptions instead of using site-specific radio maps. Even though this simplification makes it easier to compare algorithms, it may not be able to depict all the irregularities in propagation, such as the loss caused by building penetration or the existence of localized hot spots of contention.

Limitations also arise regarding the baseline comparisons taken from the literature. The Hungarian algorithm, Auction algorithm and Linear Programming solver are mostly evaluated in their classical forms agreeing with the findings of the earlier studies; however, these baselines do not take into account CBRS-specific constraints such as Environmental Sensing Capability (ESC) triggers, dynamic SAS reallocation rules or real-time incumbent protection margins. The GA baseline chosen from previous studies goes the next step in assuming unconstrained mutation and crossover operations while real CBRS systems may need special-handling SAS-compliant constraint mechanisms. All these differences may lead to the performance being overestimated or underestimated depending on the actual field conditions. However, the limitations mentioned above are still overruled by the chosen baselines being the most referenced formulations in the existing literature on spectrum-allocation which justifies a comparative evaluation.

The results of the simulations carried out using MATLAB show that the GA was well-conceived and was able to withstand scrutiny due to its robustness. However, the actual application of the algorithm to real-world CBRS systems would necessitate taking into account the limitations of hardware and edge-computing capabilities. The GA is characterized by population-based structure and parallel fitness evaluations that are very easy to implement on modern embedded platforms. This includes Advanced RISC (Reduced Instruction Set Computing) Machine or ARM-based edge devices, Field-Programmable Gate Arrays (FPGAs), as well as small form factor units that are Graphics Processing Units (GPU) GPU-accelerated and commonly found in Radio Access Networks. The performance of the fitness evaluations can for example be distributed across several processing cores, which will then result in the decision-making process for channel allocation being almost instantaneous even in the case that the spectrum is dynamically changing. The lightest GA variants with the smallest chromosome sizes or the use of fixed-point arithmetic, hardware-friendly operators, etc. can be their implementations on FPGAs that will provide deterministically latencies and low power consumption capabilities that are especially necessary for densely located

CBRS deployments. The GA can be executed locally on the edge computing nodes that are collocated with the CBRS access points. This will result in less reliance on cloud resources and lower decision-making delay, which is a crucial aspect while reacting to quick interference changes or spectrum updates triggered by SAS. The modularity, low memory footprint, and intrinsic parallelism of the algorithm all point to its strong potential for efficient deployment on various hardware platforms apart from MATLAB, which, in turn, allows real-time, scalable, and energy-efficient operation in CBRS systems under practical conditions.

11. CONCLUSIONS

The results obtained indicate that the linear and GAs are superior to the Hungarian and Auction approaches in terms of cost reduction. The linear algorithm performs better because it focuses on solving the optimization problem through linear programming techniques, while the GA achieves better results due to efficient search space colonization followed by solution improvement over the generations. The linear versus GA comparison also showed that the linear algorithm is better than the GA in all cases except computational complexity. This evidence supports the conclusion that the linear algorithm is appropriate for cases where the allocation of CBRS channels is of type as listed in Table 1, where it is essential to avoid intensive computations. In general, the contribution of this research to the existing scholarship on CBRS channel allocation is aimed at evaluating and comparing central algorithms. The findings emphasize the significance of using the fitting algorithm to affect an economical channel allocation, with the linear and GAs proving rather more advantageous over the traditional Hungarian and Auction approaches.

To conclude, on the basis of our comparative analysis in this study, Figures 9, 10 and 11 from the results section can be considered to favor the GA and the linear algorithm as the most appropriate algorithms for solving cost matrix problems, in relation to the size and complexity of the problem. It is evident that the linear algorithm takes relatively short time in executing the processes as depicted in Figure 12, and that makes it suitable for small problems, but for large and quite complex instance problems, the GA would be perfect. In this regard, both algorithms are superior to Auction and Hungarian Algorithms owing to the versatility and the breadth of the search space. As the nature of channel allocation continues to shift, especially in the hybrid environment of CBRS, future work should focus on combining different approaches. In particular, incorporating Linear Programming and GA allows for the creation of efficient solutions that provide optimal channel assignments as well as take into consideration the interference and the user requirements which may be constantly changing. Furthermore, the integration of the machine learning techniques into these hybrid models could be an area worth exploring performance enhancement. For example, if the MCL model is trained and tested on real-world data, supervised learning should be able to predict the expected interference databases and use them to minimize mashup channels. Applications utilizing reinforcement learning could be employed to adaptively enhance the allocation strategy over time, taking into account the results of earlier allocations instantaneously.

12. FUTURE WORK

The present research shows that GAs are very strong and versatile for CBRS channel allocation, but still, there are areas left for the integration of machine learning (ML) techniques in future work to improve performance, scalability, and adaptability in dynamic spectrum environments even more. One potential direction is to come up with a combined GA-ML framework where the machine learning models help the GA either by steering the search operations or by forecasting the allocation regions with high promise which, in turn, will shorten the going-round time and enhance the quality of the solution under extremely dynamic conditions.

REFERENCES

- [1] Pappa, P.C., Sarbhai, A., Baset, A., Kasera, S., Buddhikot, M. (2020). Spectrum sharing in CBRS using blockchain. In 2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), Delhi, India, pp. 631-639. <https://doi.org/10.1109/MASS50613.2020.00082>
- [2] Zahir, H. (2014). Implementation of energy detector for cognitive radio (Doctoral dissertation, MSc thesis, University of Baghdad).
- [3] Manosha, K.S., Joshi, S., Hänninen, T., Jokinen, M., Pirinen, P., Posti, H., Latva-aho, M. (2017). A channel allocation algorithm for citizens broadband radio service/spectrum access system. In 2017 European Conference on Networks and Communications (EuCNC), Oulu, Finland, pp. 1-6. <https://doi.org/10.1109/EuCNC.2017.7980711>
- [4] Jai, N., Li, S., Li, C., Hou, Y.T., Lou, W., Reed, J.H., Kompella, S. (2021). Optimal channel allocation in the CBRS band with shipborne radar incumbents. In 2021 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), Los Angeles, CA, USA, pp. 80-88. <https://doi.org/10.1109/DySPAN53946.2021.9677308>
- [5] Abbass, W., Hussain, R., Frnda, J., Khan, I.L., Javed, M.A., Malik, S.A. (2022). Optimal resource allocation for GAA users in spectrum access system using Q-learning algorithm. *IEEE Access*, 10: 60790-60804. <https://doi.org/10.1109/ACCESS.2022.3180753>
- [6] Liu, X., Lam, K.Y., Li, F., Zhao, J., Wang, L., Durrani, T.S. (2021). Spectrum sharing for 6G integrated satellite-terrestrial communication networks based on NOMA and CR. *IEEE Network*, 35(4): 28-34. <https://doi.org/10.1109/MNET.011.2100021>
- [7] Parvini, M., Zarif, A.H., Nouruzi, A., Mokari, N., Javan, M.R., Abbasi, B., Yanikomeroğlu, H. (2023). Spectrum sharing schemes from 4G to 5G and beyond: Protocol flow, regulation, ecosystem, economic. *IEEE Open Journal of the Communications Society*, 4: 464-517. <https://doi.org/10.1109/OJCOMS.2023.3238569>
- [8] Parvez, I., Sriyananda, M.G.S., Güvenç, İ., Bennis, M., Sarwat, A. (2016). CBRS spectrum sharing between LTE-U and WiFi: A multiarmed bandit approach. *Mobile Information Systems*, 2016(1): 5909801. <https://doi.org/10.1155/2016/5909801>
- [9] Zhang, L., Liang, Y.C., Xiao, M. (2018). Spectrum sharing for Internet of Things: A survey. *IEEE Wireless Communications*, 26(3): 132-139.

- <https://doi.org/10.1109/MWC.2018.1800259>
- [10] Sharmila, A., Dananjayan, P. (2019). Spectrum sharing techniques in cognitive radio networks—A survey. In 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, pp. 1-4. <https://doi.org/10.1109/ICSCAN.2019.8878714>
- [11] Wang, H., Wang, J., Ding, G., Xue, Z., Zhang, L., Xu, Y. (2020). Robust spectrum sharing in air-ground integrated networks: Opportunities and challenges. *IEEE Wireless Communications*, 27(3): 148-155. <https://doi.org/10.1109/MWC.001.1900398>
- [12] Quan, Z., Junpu, W., Xiuqing, W., Qingsheng, C. (2000). The working principle, application and current study of CBR. In Proceedings of the 3rd World Congress on Intelligent Control and Automation (Cat. No. 00EX393), Hefei, China, pp. 242-245. <https://doi.org/10.1109/WCICA.2000.859957>
- [13] Wu, J., Yu, Y. (2006). CBR-based load estimation for distribution networks. In MELECON 2006-2006 IEEE Mediterranean Electrotechnical Conference, pp. 952-955. <https://doi.org/10.1109/MELCON.2006.1653256>
- [14] Sahoo, A. (2017). Fair resource allocation in the citizens broadband radio service band. In 2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), Baltimore, MD, USA, pp. 1-2. <https://doi.org/10.1109/DySPAN.2017.7920768>
- [15] Hu, H., Chai, R. (2021). Blockchain-based hierarchical spectrum sharing architecture and resource allocation algorithm for CBRS system. In 2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall), Norman, OK, USA, pp. 1-5. <https://doi.org/10.1109/VTC2021-Fall52928.2021.9625435>
- [16] Devi, M., Sarma, N., Deka, S. (2023). Single-sided truthful auction mechanism for heterogeneous channel allocation in cognitive radio networks. *Wireless Networks*, 29(8): 3445-3467. <https://doi.org/10.1007/s11276-023-03412-7>
- [17] Rostom, M.A., Abd El-Malek, A.H., Elsabrouty, M., Abo-Zahhad, M. (2019). Cognitive radio users admission and channels allocation in 5G HetNets: A college-based matching and auction game approach. In 2019 International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Barcelona, Spain, pp. 1-6. <https://doi.org/10.1109/WiMOB.2019.8923171>
- [18] Chen, B., Lei, M., Zhao, M. (2016). An optimal resource allocation method for multi-user multi-relay DF cognitive radio networks. *IEEE Communications Letters*, 20(6): 1164-1167. <https://doi.org/10.1109/LCOMM.2016.2531699>
- [19] Xia, W., Shen, L. (2018). Joint resource allocation using evolutionary algorithms in heterogeneous mobile cloud computing networks. *China Communications*, 15(8): 189-204. <https://doi.org/10.1109/CC.2018.8438283>
- [20] Ferronato, J.J., Scalabrin, E.E., Carvalho, D.R. (2022). PM4SOS: Low-effort resource allocation optimization in a dynamic environment. In 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Prague, Czech Republic, pp. 1742-1747. <https://doi.org/10.1109/SMC53654.2022.9945393>