# Energy-Efficient Resource Allocation for Cognitive Radio Networks: A Genetic Algorithm Approach

Yasmeen Zaied, Mona Shokair, Saed Abdelatty and Waleed Saad

***Abstract*—Cognitive radio networks, where secondary users opportunistically share spectrum resources with prime users to improve spectrum utilization, energy-efficient resource allocation is a critical concern. In order to solve the optimization problem of optimizing network lifetime while satisfying energy limitations for both primary and secondary users, a genetic algorithm-based method is presented in this paper. The network consists of a time-division multiple access (TDMA) frame with a variable number of time slots, a primary user base station, a secondary user base station, primary users, and secondary users. The effectiveness of the genetic algorithm in identifying solutions that strike a balance between energy consumption and energy harvesting, improving network lifetime, is demonstrated by simulation results. Additionally, the study explores the effects of altering the number of primary and secondary users, as well as time slots, on the optimization process.**

***Keywords*—Wireless Sensor Networks (WSN), Cognitive radio routing, energy harvesting, wireless-powered communication network,**

## I. Introduction

The demand for extra spectrum has increased as wireless communication applications have expanded. Using Cognitive Radio (CR) to address underutilization in the licensed band to provide the spectrum's optimal applications [1]. There are two sorts of licensed users in CR networks. users in the channel have a high priority (Primary users, PUs). Unlicensed users (also known as Secondary Users, or SUs) with Cognitive Radio capabilities constitute a different category. White spaces are areas of the spectrum that are underutilized and detected by secondary users when primary users are not using them for a specified period of time. If the licensed user's activation is detected once again, SU must change its operating channels. [2].

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A large number of applications require sensors that can be networked and communicated with each other, hence producing a WSN [3]. WSNs is a system that contains a greater number of distributed sensor nodes. Those nodes allow for sensing over wider geographical regions with higher efficiency [4]. It also can be computed and communicated with other sensors or base stations by wireless technique as in [5] and [6].

(WPCN) Refers to The wireless power communication network is allowed by radio-frequency and enabled by wireless energy transfer [7]. The model of WPCN is an access node with a stable power supply and makes two operations, One energy transfer operation is called an energy transfer operation it's called the downlink (DL), and the other is an information transmission operation that is called the uplink (UL) [8]. In fact a transmission protocol for the WPCN is called the "harvest-then-transmit" (HTT) protocol [9].

In this paper, resource allocation issues in cognitive radio networks are addressed using a genetic algorithm-based method. The proposed methodology focuses on optimizing the allocation of energy resources for the cognitive radio network within a scheduled time-division multiple access (TDMA) framework.

Furthermore, the study of varying the number of primary and secondary users, as well as the number of time slots is discussed. Moreover, different transmission scenarios are explored.

The main contributions of this paper are:

- Formulating an optimization problem that seeks to maximize the network lifetime.
- developing a genetic algorithm to solve the optimization problem of the scheduled TDMA framework.
- Investigating the impact of varying the number of PUs, SUs, and time slots on the total network lifetime.

In this paper, a genetic algorithm-based approach is proposed to address the optimization problem of optimizing network lifetime while satisfying energy constraints for both primary and secondary users.

The rest of this paper is structured as follows: Section II presents a detailed system modeling and problem formulation, highlighting the constraints and objectives of energy- efficient resource allocation. Section III introduces the genetic algorithm methodology to solve the optimization problem. In Section IV, the simulation results are discussed. Finally, Section V concludes the paper.

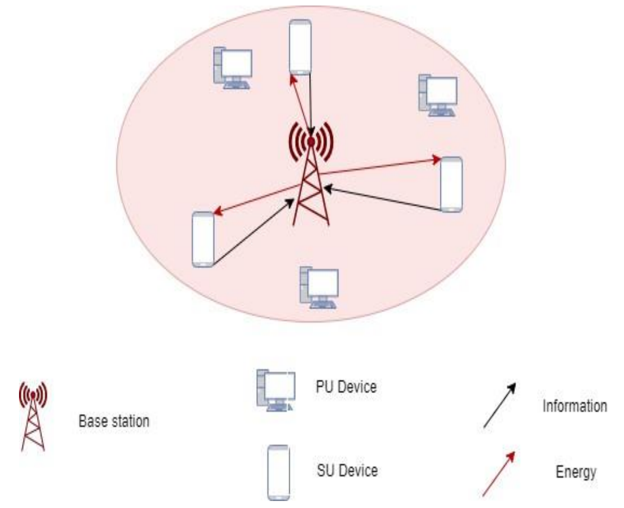


*Fig. 1 Schematic of the cognitivev radio network modeling.*

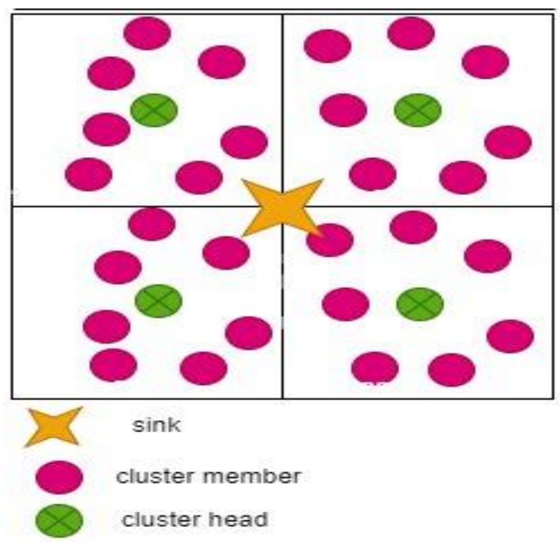


*Fig. 2 Schematic of the WSN network modeling.*

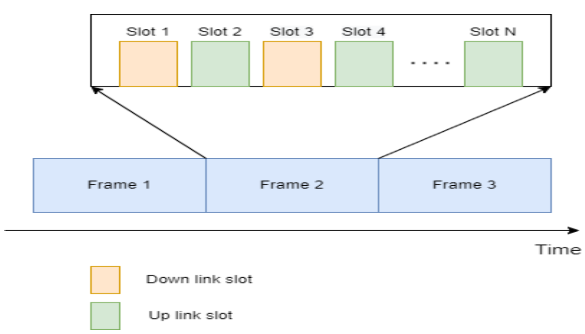


*Fig. 3 The basic communication timeline of the CRN*

## II. Related Work

Ref. [7] investigated the scheduling optimization problem for energy harvesting to meet the energy requirements of the links in a wireless-powered network. An alternating minimized algorithm was addressed.

By concentrating on node selection criteria for spectrum sensing in such networks, Ref. [10] uses an iterative algorithm to identify the nodes that sense the spectrum in order to maximize the lifetime of cognitive sensor networks.

The minimal cluster head separation distance, an ART1 neural networks-based cluster head election, and a cluster head rotation system were investigated in [11] to increase the network lifetime.

In [12] by balancing energy consumption across a broader network region utilizing geographical routing protocols, a decentralized routing technique dubbed the game theoretic energy balance routing was presented to increase network lifetime. By tackling the load balance issue at both region and node levels, the proposed protocol's goal is to cause sensor nodes to exhaust their energy roughly at the same time.

Ref. [13] discussed how to maximize the lifetime of the networks by best decisions about sensor placement, activity planning, data routing, and sink mobility. A mathematical optimization framework (SAMDP) that takes into account sensor placement was made. The authors in [13] made a provision for activity scheduling, data, and mobile sink routing decisions. Then two mathematical solutions, useful heuristics were suggested.

The authors in [14] provided a combined method that uses a novel spectrum sensing strategy to improve network implementation, including network lifetime, energy consumption, and packet delivery. They offered an inter- and intra-cluster communication model as well as a clustering algorithm to address the energy utilization issue. A posterior transition probability-based model for spectrum sensing was also presented.

A Drop factor-based energy-efficient routing strategy (DF-BEER) was discussed in [15], A novel routing approach makes routing decisions based on metrics for packet drop ratio and power dissipation. By avoiding nodes with a high drop factor, this technique lowers the drop ratio and increases network lifetime.

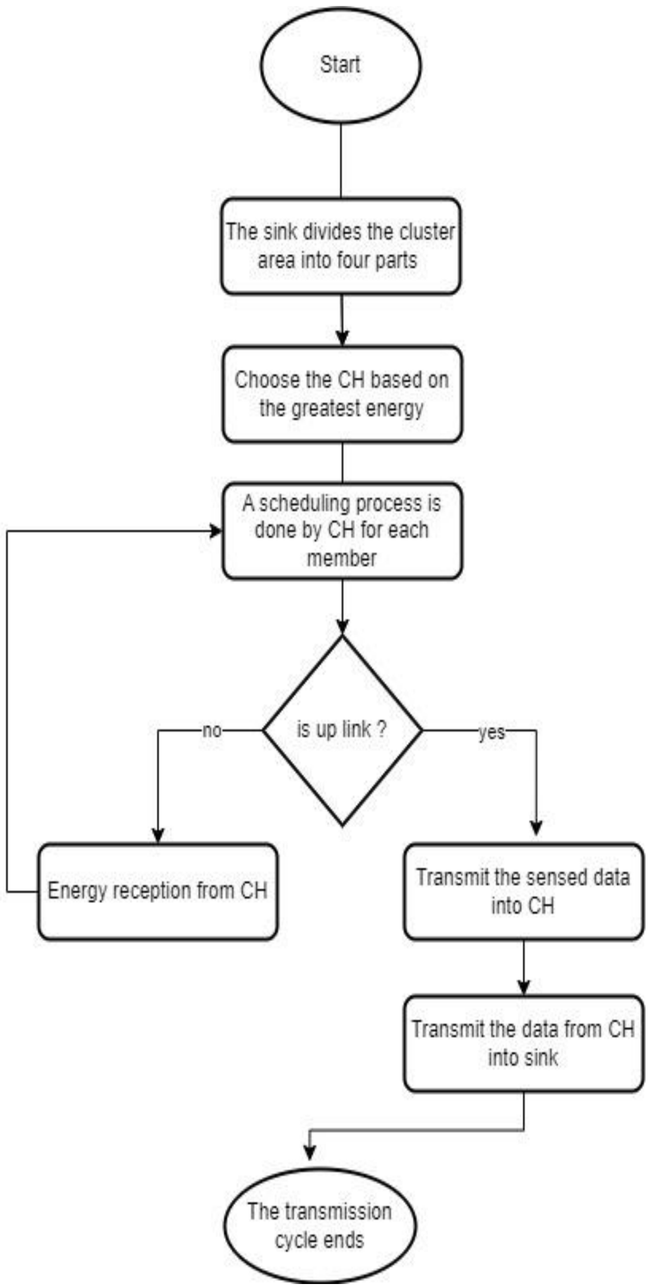


***Fig. 4** . flowchart of CWSN with scheduling process modeling.*

## III. System Model and Problem Formulation

### A. network System Model

The cognitive system model. is shown in Fig. 1. 1. In this research model, adopted that all points in the WS network are SUs. The network uses a Time Division Multiple Access (TDMA) frame with $S$ slots and consists of one base station (BS), $N$ main users (PU), and $M$ secondary users (SU). As seen in Fig. 2, According to [5], The WSN is divided into four clusters by the sink. Each cluster contains a number of cluster members and cluster head (CH), and all of these points represent the secondary users. Sink chooses the node with the most energy left in each cluster to serve as the CH. CH determines when to send each member by creating a TDMA frame based on their individual needs. the secondary users as seen in Fig. 3,transmit information over the uplink while collecting energy over the downlink Note that the power consumption during the communication process follows the radio model in [5],. The steps of scheduling in CWSN are also shown in the flowchart in Fig.4.

### B. Problem Formulation

In fact, the optimization problem can be framed as a constrained optimization problem with the goal of maximizing the cognitive radio network lifetime while ensuring that the energy requirements of all users are met. The network lifetime can be defined as the time duration for which the cognitive radio network can operate effectively or meet the quality-of-service requirements. Therefore, the objective function can be formed as maximization of the total network lifetime, which can be represented as the sum of the lifetimes of all users in the network. It is worth mentioning that the lifetime of each user can be defined based on their energy consumption and energy harvesting rate.

The optimization problem can be written as [16]:

$$\boldsymbol{Maximize}: \sum_{\{i=1\}}^{\{N\}} T_{\{pu\}}^{i} + \sum_{\{j=1\}}^{\{M\}} T_{\{su\}}^{j} \qquad (1)$$

**Subject to:**

- $E_{\{pu\}}^{i} \cdot T_{\{pu\}}^{i} = E_{\{pu\}}^{i} \cdot S, \quad \forall i$
- $E_{\{su\}}^{j} \cdot T_{\{su\}}^{j} = H_{\{su\}}^{j} \cdot S + E_{\{su\}}^{j} \cdot S, \quad \forall j$
- $\sum_{\{i=1\}}^{\{N\}} E_{\{pu\}}^{i} \cdot S + \sum_{\{j=1\}}^{\{M\}} \left(E_{\{su\}}^{j} + H_{\{su\}}^{j}\right) \cdot S \le E$
- $T\_\{pu\}^\wedge i \geq 0, \forall i$
- $T\_\{su\}^\wedge j \geq 0, \forall j$

The problem variables can be denoted as follows:

• $T_{\{pu\}}^{i}$: Lifetime of primary user i.

• $T_{\{su\}}^{j}$: Lifetime of secondary user j.

•$E_{\{su\}}^{j}$: Energy consumed by primary user i during each TDMA frame.

•$E_{\{su\}}^{j}$: Energy consumed by secondary user j during each TDMA frame.

Where $H_{\{su\}}^{j}$ is the energy harvested by secondary user $\boldsymbol{j}$ during each TDMA frame, and $\boldsymbol{E}$ is the total available energy. By maximizing lives, the goal function aims to increase network longevity the lifetimes of each PU and SU in the network (Assuming that the energy consumption and harvesting rates are constants). The lifetimes of each PU and SU can be represented as:

$$T_{\{pu\}}^{i} = E_{\{pu\}}^{i} * S/E \tag{2}$$

$$T_{\{su\}}^{j} = \left(E_{\{su\}}^{j} + \min\left(H_{\{su\}}^{\{max\}}, E - sum\left(E_{\{pu\}}^{i}\right)\right)\right) * S/E \tag{3}$$

The first two energy constraints in the optimization problem confirm the equality of the total energy consumed over the lifetime for the PU or the SU with the total consumed and harvested energies per slot over the TDMA frame. The next inequality constraint ensures that the total energy consumed by all users can't exceed the total available energy within each TDMA frame. Finally, the last two constraints satisfy that the lifetime of each user should be a positive value.

## IV. Solution Method

To solve the given optimization problem, metaheuristic technique is used. In this paper, the Genetic Algorithm (GA) can be adapted to solve the optimization problem and hence, to find values for $E_{\{pu\}}^{i}$, $E_{\{su\}}^{j}$, $T_{\{pu\}}^{i}$, and $T_{\{su\}}^{j}$that maximize the total network lifetime while satisfying all the given constraints. The pseudo-code representation of the GA can be represented as follows:

• Define the required parameters and constants, *N, M, S,* maximum energy consumption for PU and SU, GA parameters.
• Initialize each variable with random values for variables$E_{\{pu\}}^{i}$ and $E_{\{su\}}^{j}$.
• Repeat until stopping condition is met:
  – Select parents for reproduction using tournament selection.
  – Perform crossover and mutation functions to create new individuals (This is to randomly modify some variables within their bounds).
  – Evaluate fitness of new individuals
  – Replace worst individuals in population with new children
• Return the best solution found.

*Table 1 SIMULATION PARAMETERS*

| Parameter | Symbol | value |
|---|---|---|
| The primary user's number | N | 5 |
| The secondary user's number | M | 20 |
| The slots in TDMA frame number | S | 10 |
| Max. energy consumption for primary users | $E_{\{pu\}}^{max}$ | 10 |
| Max. energy consumption for secondary users | $E_{\{su\}}^{max}$ | 5 |
| Max. energy harvesting for secondary users | $H_{\{su\}}^{max}$ | 3 |
| population size (GA Parameter) | __ | 100 |
| max generations (GA Parameter) | __ | 1000 |
| mutation rate (GA Parameters) | __ | 0.1 |

## V. COMPLEXITY ANALYSIS

The complexity analysis of the proposed solution depends on several factors (i.e.,the optimization problem size, the population size, the number of generations, and the fitness function).

From the given pseudo-code representation of the GA in the previous Section, firstly the initialization process is performed. Then, the loop continues to run for the number of loop generations or until a stopping condition is met. The loop consists of several functions which are; parents selection, crossover, mutation, fitness function evaluation, and replacement.

Therefore, the complexity is a function of (number of generations multiplied by the complexity of [Selection + Crossover + Mutation + Evaluation + Replacement]).

The complexity of the initialization process can be considered as O(population size * (N + M)). While, the complexity of the Selection process of the two parents is O(2 * population size) = O(population size). For the Crossover process, just a single-point crossover operation is performed. Hence, its complexity is O(1). Whereas, the complexity of the Mutation can be written as O(N + M). For the fineness function evaluation process, the complexity is the same as the initialization process which is O(population size * (N + M)). Finally, the complexity of the Replacement function can be calculated as O(1) as it just identifies the best solution. In summary, the overall time complexity of the proposed solution is O(number of generations * (population size * (N + M) + population size + 1 + N + M + population size * (N + M) + 1)) which is can be approximated into: O(number of generations * (population size * (N + M))).

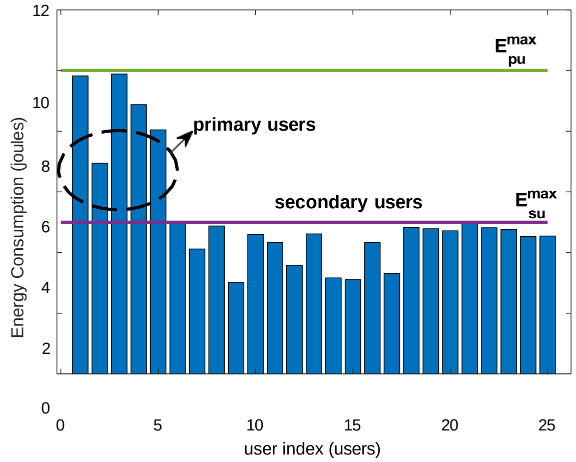


**Fig. 5**. The optimum values for Energy consumption for both primary and secondary users.

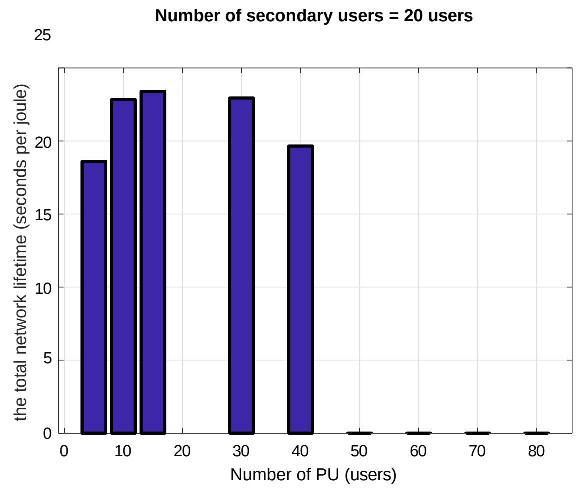


**Fig. 7**. The impact of total number of PU on the total network life time (The number of SU = 20 users).

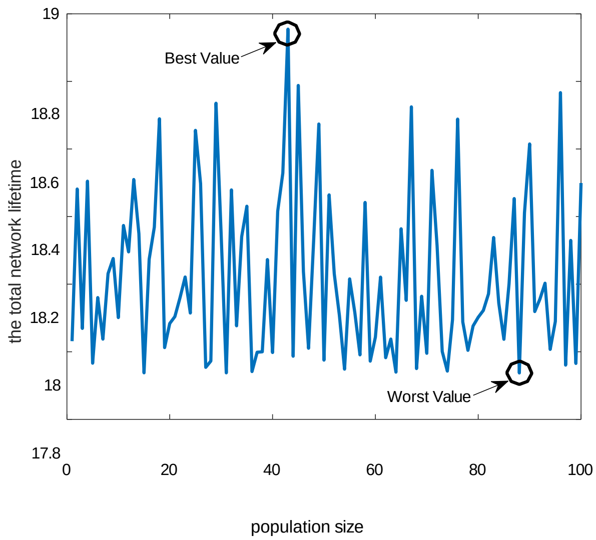


**Fig.6.** The total network life time (fitness function).

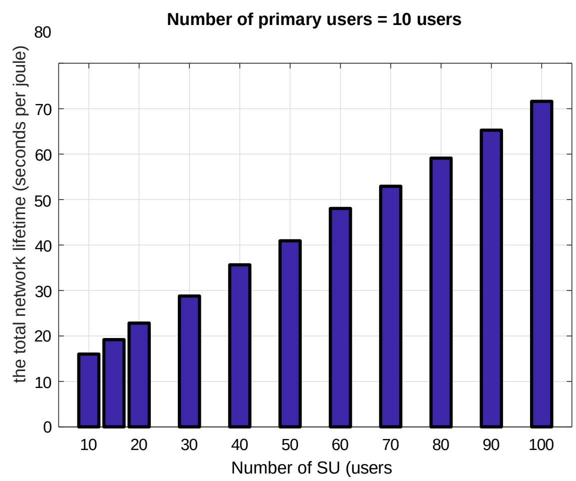


**Fig.8**. The impact of total number of SU on the total network life time (The number of PU = 10 users)

## VI. SIMULATION AND EVALUATION RESULTS

Extensive MATLAB programs have been executed to implement the solution of the given optimization problem using GA. By using Processor: 11th Gen Intel(R) Core (TM) i5-1135G7 @ 2.4 GHz RAM: 8.00 GB Operating system: Microsoft Windows 11 Home. The simulation parameters are listed in the following Table I [17].

For the given simulation parameters, the optimum energy consumption values for the 5 primary users and for the 20 secondary users are [9.82; 6.95; 9.89; 8.88; 8.04; 4.97; 4.12; 4.88; 3.01; 4.60; 4.34; 3.58; 4.61; 3.16; 3.10; 4.33; 3.31; 4.83; 4.78; 4.72; 4.98; 4.82; 4.76; 4.52; 4.54], respectively. This can be shown in Fig. 5.

The fitness function (the total network life time) is drawn in Fig. 6. From this figure, the best value for the total network life time while considering constraints is 18.95. While the worst value is 17.94.

The effect of varying the number of primary users and secondary users on the GA optimization process are studied in Fig. 7 and Fig. 8, respectively. It is observed that with the increase of the secondary users, the total life time of the network can be increased due to the increased value of the harvesting energies. While, the degradation occurs when the number of primary users exceeds the number of the secondary users. That is due to the energy consumption is more than harvested energies.

Furthermore, the effect of the scheduled or the non-scheduled transmission scenarios is studied as shown in Fig. 9 and Fig. 10. From these results, the scheduled transmission over TDMA frames scenario behaves better total network life time compared with non-scheduled transmission scenario. That is due to the benefits of scheduled transmission such as; spectrum utilization, quality of service guarantees, and less consumed energy

Additionally, the impact of varying the number of the time slots (S) on the GA optimization process for different numbers of primary users and secondary users is discussed. As shown in Fig. 11, the total network lifetime is increased with the increase of the number of the TDMA slots ($S$). That is due to the increased opportunities for both primary and secondary users to transmit and harvest energy.

In this research, we relied on studying the effect of scheduling on the transmission information process and receiving energy using GA in Cognitive Radio networks. While other studies dealt with different methods using GA in Cognitive Radio networks also as well, as shown in Table 2.

## I. CONCLUSIONS

In this paper, the critical challenge of energy-efficient resource allocation in cognitive radio networks (CRNs) through a tailored genetic algorithm approach have addressed. The offered methodology has aimed to maximize the network lifetime while ensuring equitable energy distribution among

primary users (PUs) and secondary users (SUs) operating within a scheduled time-division multiple access (TDMA) framework. It effectively has balanced the energy consumption and harvesting, leading to optimized resource allocation decisions.

*Table 2 Comparison of the different studies used GA in CRN*

| **Proposal** | **Description** | **Results are discussed** | **Simulation program** | **Ref.** |
|---|---|---|---|---|
| A Modified Genetic Algorithm for Resource Allocation in Cognitive Radio Networks in the Presence of Primary Users | This study aims to optimize SU's network performance while PU is present. Modified GA by Changes in the fitness function seeks to achieve optimal resource distribution and network throughput. | The suggested method's value produced a better outcome than the random one. | MATLAB | [18] |
| Energy-Efficient Resource Allocation for Heterogeneous Cognitive Radio Network based on Two-Tier Crossover Genetic Algorithm | They provide a two-tier crossover genetic algorithm strategy based on crossover to get the best result in terms of power and bandwidth. | The result achieves a good trade-off between capacity and energy. | MATLAB | [19] |
| Optimized cognitive radio network using genetic algorithm and artificial bee colony algorithm | The artificial bee colony (ABC) technique incorporates a meta-heuristic optimization approach to improve spectrum allocation for increased efficacy and fairness. | higher normalized throughput by 5.58 and 3.31% for 2 number of available channels | MATLAB | [20] |
| Optimized neural network for spectrum prediction using genetic algorithm in cognitive radio networks | Here, the genetic algorithm is utilized to minimize the aggressive weight structural pattern and improve the neural cognitive radio networks. | results proved high prediction accuracy and lessen the prediction error values | MATLAB | [21] |
| On the Effectiveness of using Genetic Algorithm for Spectrum Allocation in Cognitive Radio Networks | The performance of the Genetic Algorithms under various parameter values is assessed using two usage functions, namely Mean-Reward and Max-Proportional-Fair. | the parameters of the GA can achieve up to 90% and 62% improvements in speed and error, respectively, as compared to the GA used in the literature. | MATLAB | [22] |

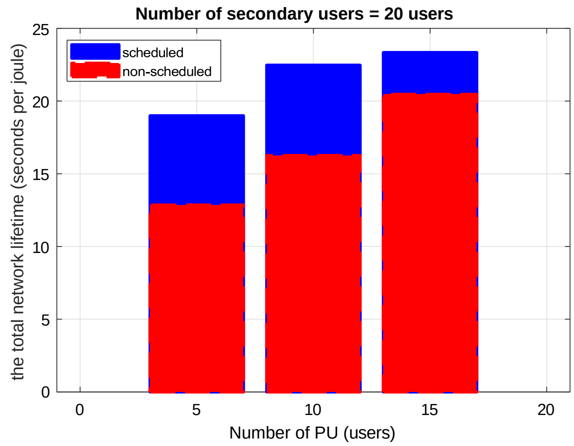


**Fig. 9**. The impact of scheduled or non-scheduled transmission scenarios (The number of SU = 20 users).

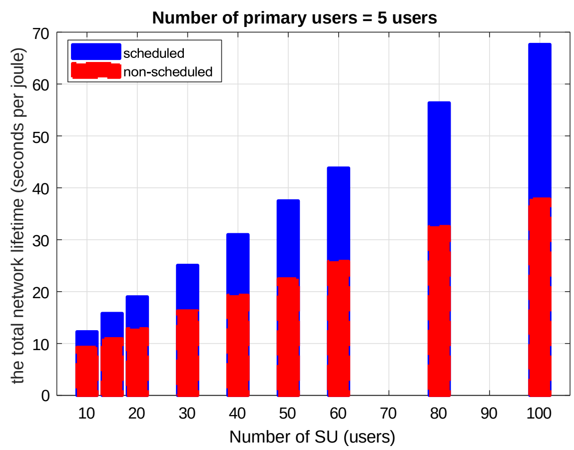


**Fig.10**. The impact of scheduled or non-scheduled transmission scenarios (The number of PU = 5 users).

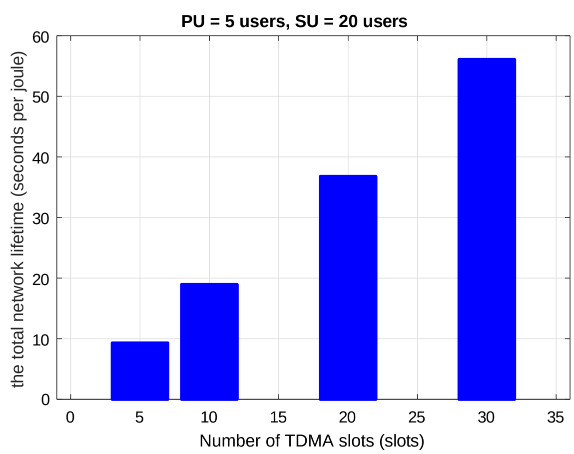


Fig.11. The impact of the number of TDMA slots $S$ (with PU = 5 users and SU = 20 users).

Also, through simulation-based evaluations, the algorithm has demonstrated its ability to study the impact of varying numbers of PUs, SUs, and time slots. The optimization problem of optimizing network lifetime while satisfying energy limitations for both primary and secondary users is addressed in this paper using a genetic algorithm-based approach.

In this study, we used GA to investigate how scheduling affects both the transmission information process and energy reception in Cognitive Radio networks. Other research focused on various techniques utilizing GA in cognitive radio networks. Then we mentioned a comparison of some studies that used the same method.

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