SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I9P120

Volume 12 Issue 9, 235-252, September 2025

Original Article

Optimized Dynamic Spectrum Sharing for Cognitive Radio with Full-Duplex Primary Users, Enhancing 5G Networks' Spectral Efficiency by Mitigating Self-Interference

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Received: 19 July 2025 Revised: 21 August 2025 Accepted: 20 September 2025 Published: 29 September 2025

Abstract *- In this research, a customized and effective Dynamic Spectrum Sharing (DSS) approach is proposed for use in Cognitive Radio (CR) systems to handle challenges brought by In-Band Full-Duplex (IBFD) Primary User (PU) networks in 5G environments. Since more data is being used, the existing wireless networks are under more stress, so using the spectrum efficiently is very important. Most traditional methods are unable to handle changing conditions and interference situations, especially with IBFD systems, because of their interference issues. This new framework reduces self-interference, enhancing spectrum access opportunities for both PUs and SUs. With this approach, the parameters for sharing the radio spectrum are adjusted in real time by the control function, which improves decisions and system reliability. The method designs its system so that primary users apply proper Gaussian signalling, whereas secondary users make use of improper Gaussian signals to send communications. This design prevents disruption between PUs and SUs, and the bandwidth is used well with little or no interference. Because cognitive radios have to be careful not to disturb the PUs, the right signalling approach provides more protection against interference, making the system both stronger and more efficient in terms of spectrum usage. A new game model is introduced, and it relies on enthalpy-based sigmoid functions to dynamically change and monitor the DSS parameters automatically. You can use these algorithms in real-time, and they need less computing power and cost less, which is needed in 5G networks. Also, as a new development, an Improved Multi-Objective Grasshopper optimisation algorithm (I-MOGOA) is provided, which surpasses the Genetic Algorithm (GA) and Simplified Particle Genetic Algorithm (SPGA) in delivering enhanced spectral efficiency and energy conservation. It is notable that I-MOGOA manages to keep several performance metrics under control, such as Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), throughput, transmission power and Signal-To-Self-Interference-Plus-Noise Ratio (SSINR). Analytics have proven that this method substantially impacts all of the performance indicators. Both the system flowchart and simulation studies indicate that higher SUs can lead to a drop in spectral efficiency caused by more interference and fewer resources, highlighting the essential balance in the allocated spectrum. Because of the sigmoid-based control, the system continues to adjust resource access in real time, leading to fair and stable sharing between the primary and secondary users. It has been found in this research that the SNR decreases while the spectral efficiency increases in 5G cognitive radio systems. While a high SNR gives better signal quality, it can make the network use more energy and simultaneously reduce the number of bits sent through the same channel. Therefore, careful handling of this tradeoff is needed. The suggested method can be used to find the right SNR level to achieve the best tradeoff between using less power and getting higher throughput. The study shows that bad SNR management causes higher BER, lower throughput, and unnecessary energy use. The new system is superior to regular IBFD and interference reduction methods through experiments that achieve strong BER, reliable signals, and safe transmission. It proves that grouping, advanced signal modelling, optimization algorithms, and real-time interference management improve performance. The fact that the new DSS framework is more effective than traditional methods means it helps 5G networks today and sets the stage for progress in cognitive radio technology later. The research introduces a DSS model that can adjust and grow, setting a good start for the development of wireless systems. It fixes major shortcomings in the current CR by using good methods to share the radio spectrum, not getting stuck in densely used networks or persistent interference. In brief, the suggested enthalpy-based sigmoid DSS method ensures high performance, energy saving and resistance to interference in 5G-based cognitive radio systems. Integrating dynamic control, signal optimization, and evolutionary algorithms plays a key role in this research, which delivers an important solution for next-generation wireless communications. It improves the efficiency and dependability of the system and prepares for the use of new wireless services in the future.*

Keywords *- Band Full Duplex, Cognitive Radio, Gaussian Signalling, Spectrum Sharing, 5G Cognitive Radio.*

1. Introduction

Mobile data is being generated, which has motivated the creation of the fifth-generation (5G) wireless communication, surpassing LTE and accommodating a number of industrial requirements with greater capacity, faster internet bandwidth speed, reduced latency, and enhanced reliability. Conventional frequency assignment criteria render the spectrum scarcer and less utilized, thus creating CRNs, which gives Secondary Users (SUs) a chance of utilizing the available spectrum once Primary Users (PUs) are done. The prevention of secondary users (SUs) deterioration of primary users (PUs) at a high quality and efficient usage of the available spectrum continues to be difficult for CRNs. DSS is considered a profitable solution because it provides a device with the dynamically available spectrum, allowing the opportunity to reduce waste and increase the efficiency of licensed spectrum. The study presents an Enthalpy-Based Sigmoid Solution in a DSS framework of 5G CRNs that reduces the computing expenditure and surveillance, in addition to reevaluating the interference at every stage in the form of a sigmoid deprived of thermodynamics. The research presents a technique to take into consideration a game methodology to instantly and successfully modify the settings in order to allow the cooperation of PU-SU in conjunction with addressing the issues that In-Band Full-Duplex (IBFD) communication or simultaneous transmission and reception present in self-interference.

To deal with the interference, the proposal integrates good Gaussian and bad Gaussian to plan the interaction and communication not only between primary users but also secondary users, which enhances the utilization of the spectrum and reduces errors. The study also proposes the Improved Multi-Objective Grasshopper Optimization Algorithm (I-MOGOA) that is able to perform energy efficient, transfer high volume of data, manage the BER and increase SSINR in volatile network environments as compared to generic evolutionary systems. To trade off Signal-To-Noise-Ratio (SNR) against spectral efficiency, an approach is developed where, in a scenario where higher SNR can be advantageous, but at the same time, it can reduce the overall performance of the system, because it will impose higher power usage and/or bandwidth demands.

The outcomes of the simulations are conclusive that more secondary users increase spectral efficiency, but there is a level at which the interference of secondary users reduces the spectral efficiency. This mistake can be overcome by adding the adaptive form of DSS. Overall, the system has more advantages in terms of bit error rate, the data transmitted, and the power consumed, transmits clear signals and can be scaled up to massive deployment of 5G networks. Applying technology-intensive modelling, game theory, evolutionary algorithms and novel signalling techniques, the authors develop a robust and viable means of allocating radio spectrum in 5G networks and addressing the major concerns regarding scarcity and interference of wireless spectrum in next-generation communications.

The innovativeness of research is the creation of a new and efficient method in handling interference in 5G Cognitive Radio Networks (CRNs). Although the current literature has already contributed a lot to sphere sharing and interference management, self-interference in the full-duplex 5G is not well-discussed. The mentioned research proposes an Enthalpy-Based Sigmoid Solution (EBSS) that applies to the Dynamic Spectrum Sharing (DSS) concept, successfully eliminating self-interference and maximizing spectral efficiency in a way that will not affect the integrity of the primary user networks.

The research also puts forward the Improved Multi-Objective Grasshopper Optimization Algorithm (I-MOGOA) that also minimizes key performance indicators, namely Bit Error Rate (BER), throughput and Signal-to-Noise-plus-Interference Ratio (SSINR) under changing environments or networks, better than conventional optimization techniques. Moreover, the real-time adaptive mechanism, which is integrated into this approach, also enables fluid flexibility to adapt to the interface of changing network conditions, which is a significant development in the field of inquiry. This new pairing of solutions is important in optimizing 5G CRNs, better spectrum usage, and reliable and more efficient communication on a future wireless network.

1.1. Problem Statement and Research Gap

The Cognitive Radio (CR) operating under the constant presence of the Primary Users (PUs) is under severe challenges of dynamic spectrum sharing due to self-interference by the in-band full-duplex primary user networks. The use of resources by the Secondary Users (SUs) is highly limited, and the available resources are greatly hampered. The conventional DSS technology does not take much care to optimize the self-interference issue well enough, and the produced 5G networks have suboptimal energy and spectral efficiency. Therefore, there is a need for a mechanism that is out of an optimized spectrum sharing (where the spectrum would be shared with primary and secondary users at different times), which is dynamic in its ability to adapt itself to self-interference situations and is fair and efficient to both the primary and secondary users.

Though major progress has been made on spectrum sharing and interference management in 5G CRNs, major contributing problems like self-interference, poor spectrum allocation, and inefficient adaptation mechanisms during dynamic operation have not been considered. Filling these gaps with novel approaches such as DSS and I-MOGOA, as well as optimized real-time interference mitigation algorithms, should become the key stepping stones towards a complete realization of the potential of 5G networks in the next-generation communication systems.

1.2. Key Contributions

Enthalpy-based sigmoid formulation significantly reduces the self-interference levels occurring in the full duplex 5G systems.

- Enhanced spectral efficiency was achieved with no degradation of the operational integrity of the primary user network.
- Improved Bit Error Rate (BER), throughput, and SSINR metrics across different PU-SU operating conditions.
- Elongated the transmission power and energy compared to benchmark DSS methods, considering SPGA and GA.
- System modeling by means of flowcharts, where the performance degradation is tracked as SUs continue to increase with the implementation of the real-world system constraints at a high level.
- The self-interference game method is dynamic and adapts to the changing network state through real-time changes in operating parameters.

In Section 2, we explain the system model for the spectrum-sharing framework and the Full-Duplex (FD) system, including both half-duplex and full-duplex, and we talk about related research papers. In Section 3, we calculate the probability of outage for Primary Users (PUs) and Secondary Users (SUs) in the system we have proposed. In Section 4, the authors compare the findings of their system to existing approaches to demonstrate better performance. Section 5 ends the study by reviewing the main results and listing the references consulted during the paper.

2. Literature Works

Bojiang Maetal et al. [21] established a firm basis for choosing relays and setting their power levels using a model to help balance transmission power and system capabilities. By combining the optimization problem into a two-part weighted matching problem, one will be able to solve it with both centralized and distributed systems-related algorithms, with the latter related to stable matching theory. Due to their simulation, the group was able to persuade that it was possible to calculate Pareto-optimal solutions in time, rather than by using the conventional methods of delegating influence in cooperative networks [1-3].

Mohammad Amzad Hossain et al. [22] offer Cognitive Radio Channel Allocation (CACR) as the appropriate response to the problem of spectrum underutilization in Cellular Mobile Networks (CMNs). In this configuration, automatically assigning and reassigning channels based on Cognitive Radio (CR) technology assists in better utilization of the available scarce CMS resources in the event of peak mobile data demand [4, 5]. Under CR, the secondary users will be able to utilize the underutilized channels, enhancing spectrum efficiency without interfering with the primary user [6, 7]. Due to the CACR model, the company will be able to mix legacy and new wireless devices, increasing effective spectrum utilisation in multi-environment networks.

A system based on spectral marker vectors and pseudo-random phase modulation by Xin Liu et al. [23] allows IoT to work concurrently with 5G on the same frequency. They used the inverse fast Fourier transform (IFFT) to simultaneously generate spectral and time-domain data from each communication session. The correct detection of the data with no interference can be done through the same spectral marker vector at the receiving end point [8, 9]. Low battery life is a significant plus to IoT devices because of efficiency and reduced latency or time, as illustrated in the model illustration.

Osama Al Saadeh et al. [24] have studied the mechanism of In-Band Full-Duplex (IBFD) in 5G networks, for indoor small cells. The IBFD and the static/dynamic TDD comparison demonstrated that IBFD is most competent when the downlink traffic is greater compared to the upstream traffic and vice versa, which is often the case. Based on beamforming and interference cancellation applied by 5G, signals can be directed precisely to customers, and unneeded interruptions are reduced in congested scenarios [10-12]. The authors discovered that IBFD, along with the emerging mmWave technology, has the ability to enhance the network capacity of homes and companies to support fast data rate applications.

To overcome the traffic jams and reduce the presence of delays in the points of high traffic density on 5G, Ahmed Alshaflu et al. [25] proposed a traffic management model based on prediction. The system can select optimized routes by combining the knowledge of previous traffic occurrences and AI. The forecast of the future developments of demand allows anticipating the assignment of frequency carriers and improving the quality of service in real-time [13-15]. In machine learning, the systems can adjust by learning how to optimize resources based on the traffic movement themselves automatically. This makes the system more responsive to issues.

A number of studies have also advocated alternative measures. As an illustration, Zhang et al. [16] have investigated network slicing as a solution contributing to enhancing the resource allocation in the 5G setting. It breaks up physical networks into various forms of virtual networks, each optimized for latency, throughput or many IoT devices. Planners that minimize power consumption subject to achieving latency requirements cited by Li et al. suggested algorithms [17] specific to edge devices, which use batteries.

Making use of Deep Reinforcement Learning (DRL), Wang et al. [18] assisted the transformation of the routing, as well as the handling of resources in MANETs and CMNs, in response to changes in situations. Their DRL algorithm searches for optimal routing plans in real-time depending on the motion of the nodes, signal strength variations and interference impact. An edge-based approach was developed by Liu and Yu [19], which can identify empty frequencies in real time, and devices can change channels without using the central coordinator.

Shafiq et al. [20] investigated Self-Organizing Networks (SONs) in an attempt to promote balancing the traffic in small-cell networks without the interference of human help. Their research indicates that the SONs can enhance network efficiency with neighbour relations, which uses automation to facilitate increased mobility and enhance the network coverage and capacity. That makes 5G networks more responsive and speedier when implemented within the cities.

The literature has a substantial amount of current attention on the issue of how to combine many broadband access approaches. One of them is that T Siropoulos et al. studied how 5G can be offered to remote and rural locations through Satellite-Terrestrial Integrated Networks (STINs). When utilizing this model, 5G base stations will be able to rely on land-based as well as satellite backhaul linkages that will ensure that services remain operational despite the unavailability of some infrastructure [21]. Conversely, other scholars like Kato et al. have described Multi-Access Edge Computing (MEC) designs that incorporate AI in supporting the processing of data at the edge to support applications requiring user data proximity, like autonomous driving and remote medical care [22].

Increasing the number of different types of smartphones has led to the emergence of interoperability as an important research topic as well. According to Taleb et al., in the case of 5G and the future, it is important to have RATs that would connect/integrate with one another in a seamless manner to facilitate a smooth user experience [23]. Researchers have come up with cross-layer solutions that combine physical, MAC and network layers in response to the fast-evolving demands on Quality Of Service (QoS) between AR and industrial automation applications.

Increased attention is also being given to privacy and security due to the incorporation of IoT with 5G. Sharma et al. [24] proposed the usage of blockchain to tackle data security challenges in the authorization process and prevent the occurrence of any effort to modify data in IoT networks that are entrenched with a large number of connected devices. Similarly, Zhang and colleagues observed federated learning, which assists in machine learning, and has the advantage of not transferring each user to the same data [25].

Table 1. Summary of existing literature review

Ref.	Authors	Technology / Method Used	Problem Addressed	Key Contributions / Findings	Remarks / Applicability Conditions
[21]	Al. et al.	Mutualism-based Optimization, Centralized & Distributed Relay Selection	This research deals with how to find the proper tradeoff between lowering power and increasing data transmission in relay networks.	Proposed centralized and distributed strategies for selecting the relays. An optimal solution is reached by applying a Pareto-style two-stage weighted matching approach.	Effective under polymorphic time; suitable for power-throughput tradeoff systems.
[22]	Mohammad Amzad Hossain et al.	CACR (Cognitive Radio Channel Allocation)	Spectrum shortage in Fixed Cellular Spectrum (CMS)	Designed a channel allocation and reassignment scheme using Cognitive Radio (CR) to enhance spectrum utilization in Cellular Mobile Networks (CMNs).	Effective when spectral utilization is low; applicable in densely populated cellular regions.
[23]	Xin Liu et al.	Multichannel IoT over 5G, Spectral Marker Vectors, IFFT Modulation	Enabling the coexistence of 5G and IoT systems in shared spectrum	Proposed an IoT node capable of simultaneous 5G and IoT operation using pseudo-random spectral sequences and IFFT-based waveform modulation.	Useful in systems with high IoT device density; relies on spectral exclusivity and synchronization.
[24]	Osama AlSaadeh et al.	In-band Full-Duplex (IBFD), Beamforming, Interference	Performance comparison of IBFD vs. TDD (Static & Dynamic) in 5G indoor	Demonstrated IBFD advantages in terms of bandwidth maximization when DL traffic exceeds	Advantageous only when downlink traffic dominates; less efficient for

		Cancellation	small cells	UL and the number of users is variable; beamforming mitigates interference.	symmetrical traffic loads.
[25]	Ahmed Alshaflu et al.	Traffic Prediction Model for 5G	Delay reduction during large-volume traffic and efficient routing	Developed a predictive model for managing high-demand traffic and optimizing frequency routing based on user demand patterns.	Effective for large-scale network deployments; enhances routing efficiency and QoS under heavy traffic.

3. Proposed Methodology Adopted

To address the urgent challenges of spectrum shortages and managing interference in 5G networks, a new Decision Support System (DSS) has been made available as the demand for fast, dependable and low-delay connections grows along with the spread of smart devices and IoT technology. The DSS is built on the core ability of in-band Full-Duplex (FD) communication to keep interference low by transmitting and receiving on the same frequency. Instead of dividing up and using separate time slots or frequency ranges as in time-division and frequency-division duplexing, in-band FD communication uses the same band for both transmitting and receiving signals, thus improving the efficiency of radio frequency usage with proper self-interference management. In

In accordance with this framework, the FD technology serves in spectrum sharing between Primary Users (PUs) and Secondary Users (SUs). The DSS uses two kinds of signals: proper Gaussian, which behave normally, and improper Gaussian, which follow a different pattern. Because proper Gaussian signals stand out for their statistical efficiency and perfect circle symmetry, FD-PU pairs use them, while SUs adopt improper Gaussian signals when sending their own data. It is vital for the CR environment since improper Gaussian signalling boosts the SUs' ability to avoid interfering with secondary users (PUs), particularly in conditions where PUs and SUs must share the same frequency resource. For the main analytic part, the system calculates closed-form outage probability expressions for PUs and SUs, which explain the chances of user devices having dropped connections or low service. Because of these formulas, it is possible to determine the upper limit for reliability and optimise the spectrum-sharing network performance regularly. Having set the reliability scores, the DSS shifts to the next point of planning: to manage the radio spectrum more successfully for different users. For this reason, DSS applies game theory by simulating the actions of various rational users trying to access the same spectrum. The main idea in this framework comes from a proportional enthalpy-based sigmoid utility function, which illustrates the effect of things like interference, managed power, and bandwidth usage on each user's results. The system's potential for successful delivery, known as enthalpy, is taken from thermodynamics, and the sigmoid function guarantees a gentle switch between desirable and undesirable conditions to ensure users' strategies change smoothly in response to the environment. Since this function works with gradient methods, it fits well with adaptive networks and lets them think and decide in uncertain situations. The DSS has a hierarchical system where the central controller manages, and the distributed SU agents take care of the necessary tasks. The controller at the centre handles the policy, surveys interference and guides the system. At the same time, the nodes in each cell make their own decisions depending on what is happening locally in the network in real-time. The dual-layer structure ensures that decision-making is centralized at the core and decentralized on a larger scale, so the DSS is scalable and can handle the tight demands of 5G networks in crowded areas. It is especially noteworthy that this system can stop any mutual interference that might happen between secondary users. When every SU follows the sigmoid-based spectrum access strategy, each one chooses its transmission value (e.g., power, chosen frequency band and timing) to increase its own utility and avoid exceeding the set threshold for primary users. The Nash equilibrium means all SUs are satisfied with their behaviors and there is no one who can change their way of working for better results, which guarantees fairness, efficiency and stability in this environment. On top of that, the DSS was developed to operate efficiently and use little control, which allows it to be used in real-time in contexts with fast channel changes, restricted processing power, and strict delay constraints. These features are very helpful in the domains of smart cities, connected vehicles, industrial automation and augmented reality. The DSS framework uses a set of carefully structured stages to guide users. Initially, the way devices communicate is modelled to make note of their signal types, transmission strength, how channels affect their signals and the interference between users. Expressions are obtained to calculate the probability of an outage in the SU and PU based on how useful signals and interfering signals are treated. They give developers working insights and help with validating the system. The third step is to formulate the proportional enthalpy-based sigmoid utility, which reflects how much resource and noise a user can handle, making it the objective function for their decision about spectrum access. SUs are considered greedy and self-centred, and their behaviour is guided by what brings them personal success in this game. The result of the game is most often a stable Nash equilibrium, which ensures everybody has fair and regular use of the limited spectrum. A fifth aspect involves hierarchical control: the centralised unit decides on global policies, and

SUs independently improve their own actions according to current network information. Seventh, the DSS is thoroughly tested using simulations that look at typical problems like nodes on the move, continuously changing signal-to-noise ratios, a changing number of users and unpredictable interference. As a result of the simulations, indicators are retrieved that confirm the solution is robust and can be applied, such as throughput, outage likelihood, energy performance and spectrum usage. A real-time mechanism is built so the system can adjust its SU strategies as interference or network conditions change. The DSS includes scalability and plans for change, and it can link with machine learning methods to build predictive models for user behaviour and attach to 6G developments, including AI networks, flexible intelligent reflectors (RIS) and systems guaranteed to function with quantum technology. All in all, the suggested DSS scheme offers a complete, smart and adaptable answer to the difficulties of sharing the spectrum and controlling interference in today's 5G networks. Using in-band full-duplex communication at the physical level, outage modelling approaches for analysis and game theory for strategy, the system provides a strong foundation for accessing the wireless spectrum in very crowded wireless settings. Because it can adapt, fine-tune itself and maintain good results with little interference, it is very useful for the new generation of wireless networks.

The following steps are followed in the proposed methodology and the GOA Pseudo-Code Proposed Methodology

Step 1: The initial step is to find and set up the system.
You should start by setting important parameters for the system. It involves choosing the sampling rate, the carrier frequency, how long to run the simulation, and making a time vector. They decide the clarity and timeframe of the processing operations.

Step 2: Choose how long to run SNR over.
Set an array of Signal-to-Noise Ratio (SNR) levels that you want the simulation to cover. We will use each level as a reference to test the system at various noise levels.

Step 3: Bringing Meal Signals to the Brain
Make the wanted communication signal and the undesired self-interference signal. These can begin as ideal signals (such as sines and QAM-modulated signals) and then eventually be changed to real signals from the system during later steps.
Step 5: Adding Some Noise
Put AWGN into the self-interference signal to simulate how noise appears in real wireless communication channels. It is essential for simulating the problems that arise during the rebuilding of the signal.

The last step is self-interference cancellation.

Reduce self-interference by applying a Normalized Least Mean Squares (NLMS) adaptive filter to the loopback signal. To maximize the performance of the NLMS filter mainly by tuning the step size (μ), consider using the Grasshopper Optimization Algorithm (GOA). μ is set dynamically by the method based on how quickly and accurately the noise is cancelled.

The following step is performance metric computation.

With signals ready, figure out key results, specifically Spectral Efficiency, Energy Efficiency, Transmit Power, Signal-to-Self-Interference-plus-Noise Ratio (SSINR), Throughput and Bit Error Rate (BER). With these metrics, one can see the overall performance of the system in many different ways when operating it.

Store the data in the correct cloud platform.
Please retain all the computed values of performance metrics for each SNR level for future study and comparison.

Step 8: Making the final concept clear with visuals
See how the performance changes as you increase or decrease the SNR to observe and determine how the system is affected by noise.
Here is the pseudo-code for the Grasshopper Optimisation Algorithm (GOA).

1. Set up the swarms, named Xi, for each i from 1 to n, and each swarm holds a possible solution.
2. Keep parameters in mind: set cmax, cmin, the maximum number of iterations and different control constants.
3. Assess Fitness: Calculate the fitness value for every search agent according to the main aim (for example, minimizing interference).
4. Use T to find the best solution so far.
5. Do This Until X Approaches Y:
6. a. Apply the GOA model to set the attraction coefficient c.
7. b. For any agent within the society:
8. i. Scale each agent's coordinate against the others to encourage the group to stay together.
9. ii. Apply the GOA equations to update where the current agent is.
10. iii. If the new position is not allowed, place the agent back within its boundaries.
11. c. If a new option is better than what we have, store it in T and continue.
12. d. Go to the next step by increasing the iteration counter.
13. 6. Return the value T, which shows the best setting for the NLMS step size μ.

3.1. Dynamic Spectrum Sharing (DSS) Scheme in In-Band FD Technology

This article proves that In-Band Full-Duplex (FD) technology is a realistic and future-oriented method used in air interfaces to address important challenges ahead for 5G mobile networks. Using in-band FD, you can transmit and receive data at the same time over the same frequency, which speeds up both data rates and network capacity and reduces crowding at the air interface. A Decision Support System (DSS) helps this structure by managing the flow of resources between 4G and 5G so that they can coexist on the same network. The dual-network capability lets service providers increase 5G coverage using repeater setups that are like those used for 4G, making additional spectrum management unnecessary.

With Cognitive Radio (CR), devices look through their local spectrum to choose free bands that will not disrupt signals used by licensed users. These gadgets monitor the spectrum and find open spaces, which they quickly use to boost their capabilities. So, CR systems enable clear communication among employees and comply with regulatory policies. An intriguing solution in the underlay CR model includes pairing a half-duplex Secondary User (SU) with a full-duplex Primary User (PU) in the same band. Because of this setup, FD links are used in the principal network, and coordinated sharing is done with secondary systems, making the spectrum's efficiency better in the future of wireless connections.

By teaming up DSS with in-band FD and CR technologies, an intelligent environment for managing spectrum, balancing loads and dealing with interference is created. Machine learning models can be connected to the DSS system to watch over the environment, users and signals for up-to-date data and corresponding policy changes. In particular, these features are necessary for modern smart city systems, self-driving vehicles, the industrial internet of things, and other important services since their applications require the network to be adaptable, reliable, and fast.

In addition, working with cognitive radio, future FD networks will make it easier for different services to exist side by side, as it will also help reduce energy consumption. Adapting to the available spectrum in CR-enabled FD systems leads to reduced transmission, lowering the amount of power consumed. As a result, such systems are well-suited for battery-limited devices and remote sensor systems. Furthermore, using the same frequencies again in the same network cell allows small cell networks to grow close together and not compromise the QoS.

3.2. Signal Design Transmitted by PU and SU

In Step 3, adjustments are made to how the SU signal works so that the bond of the main PU connection is kept strong and the main PU outage possibilities remain within the set boundaries. This step is based on the idea that the SU is given complete data about the primary network, such as needed Quality of Service (QoS) assignments, Successive Interference Cancellation (SIC) capabilities and specific system information. Information from the regulator leads to establishing one standard procedure for PUs, which the SU must obey at all times during transmission.

Ensuring that SU operations follow the PU guidelines is necessary before checking if Gaussian signaling is done correctly. In this situation, PU nodes are always set to broadcast at the same rate. The outage probability that the PU is allowed and the interference it can receive are set by the highest allowable value Qi. The objective is for the network to remain reliable and strong, so no matter the channel, SU traffic does not impair the PU's performance.

3.2.1. Proper Gaussian Signaling Design

$$N_{MAX,Q_i} \geq \frac{(Qi\widetilde{\gamma}Qi)}{2^{T_0,M_i}} \log\left(1 + M_i\, V_{mi}\, \frac{2^{T_0,M_j}}{Q_i\widetilde{\gamma}Q_j}\right) \quad (1)$$

3.2.2. Improper Gaussian Signaling Design

$$T_{0,r} \leq \left(\frac{\mu_n\sqrt{1+\Gamma_{mj}}}{\beta_i\Gamma_{mj} - \mu_n}\right) \quad (2)$$

3.3. Enthalpy Sigmoid Function

An Enthalpy works in optimal spectrum sharing through the mathematical representation shown below:

$$\mathrm{H(x) = E + pV * \sigma(x)} \quad (3)$$

The spectrum bandwidth enhancement occurs through integration of the enthalpy function H(x) with the sigmoid function. The sigmoid function can be shown as:

$$\sigma(x) = \frac{1}{1 + e^{\{-x\}}} \quad (4)$$

The mathematical expression of the enthalpy sigmoid function appears as

$$H(x) = E + \frac{pV}{1+e^{-x}} \quad (5)$$

3.4. A Dynamic Spectrum access Algorithm based on Enthalpy Based Sigmoid Game Theory

In this part, we offer a complete model for Dynamic Spectrum Access (DSA) in Cognitive Radio Networks (CRNs) by applying an enthalpy-based sigmoid game concept. In this model, we are concerned with the changing access behavior of secondary users (SUs). The function responsible for the ability of an SU to match with peers closely follows enthalpy-based sigmoid game theory, and this theory explains how the DSA algorithm works. The system using CRN consists of Secondary Users (SUs), Primary Users (PUs) and a shared spectrum pool. The study is mainly about how multiple drones interact and influence each other in the game. If there are P players in the game, then every player's strategy is noted as q_1, q_2, q_3, …, qn and each qn is an element of the strategy space Qn. F_1, f_2 and so on, are the utility functions that explain the player's benefit from their strategy in each game. The game can formally appear as an enthalpy-driven sigmoid spectrum access game.

DSA(G) consists of N, q_1, q_2, q_3, …, qn and all the group elements x of H.

Here, Qn represents the options for player j and $\{q_1, \ldots, q_n\}$ describes the full strategy profile used by every player. Each player i has a utility function $f_i(Q)$, and this takes the strategy set of all players into account to give their utility. The structure of the overall game model is made up of (1) N, which records the number of players, (2) the strategy options Qn for each individual player and (3) the total strategy profile $\{q_1, \ldots, q_n\}$ together with the utility functions fn(Q). Because of this framework, SU strategies can respond to different spectrum conditions, making spectrum usage in CRNs simple and equal for all stations. The PU, as shown in Figure 1, consists of a base station and certain clients. Given that the Spectrum pool is able to convey an accessible range halfway inside a specific region or area, change the course of range sharing among specialized devices, and additionally monitor the legitimate range server. SUs can use the range leased by SUs for correspondence between themselves and PUs, between SUs, an access point, and the specially formed SU network organization.

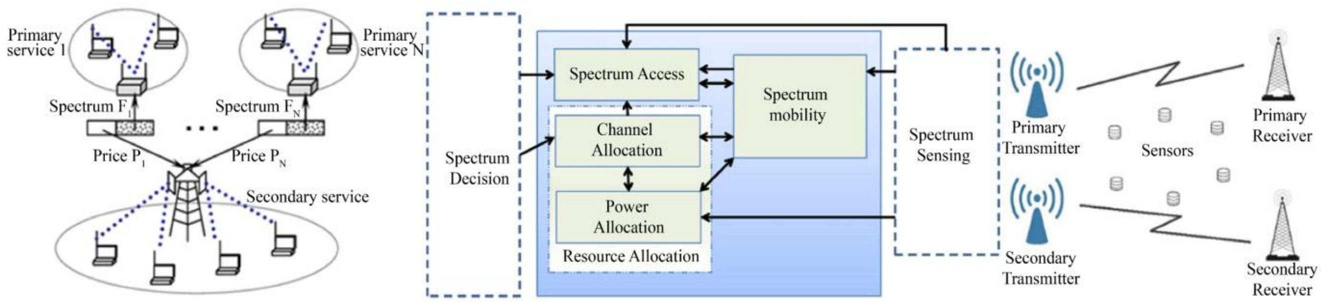

Fig. 1 System model dynamic spectrum sharing in cognitive radio

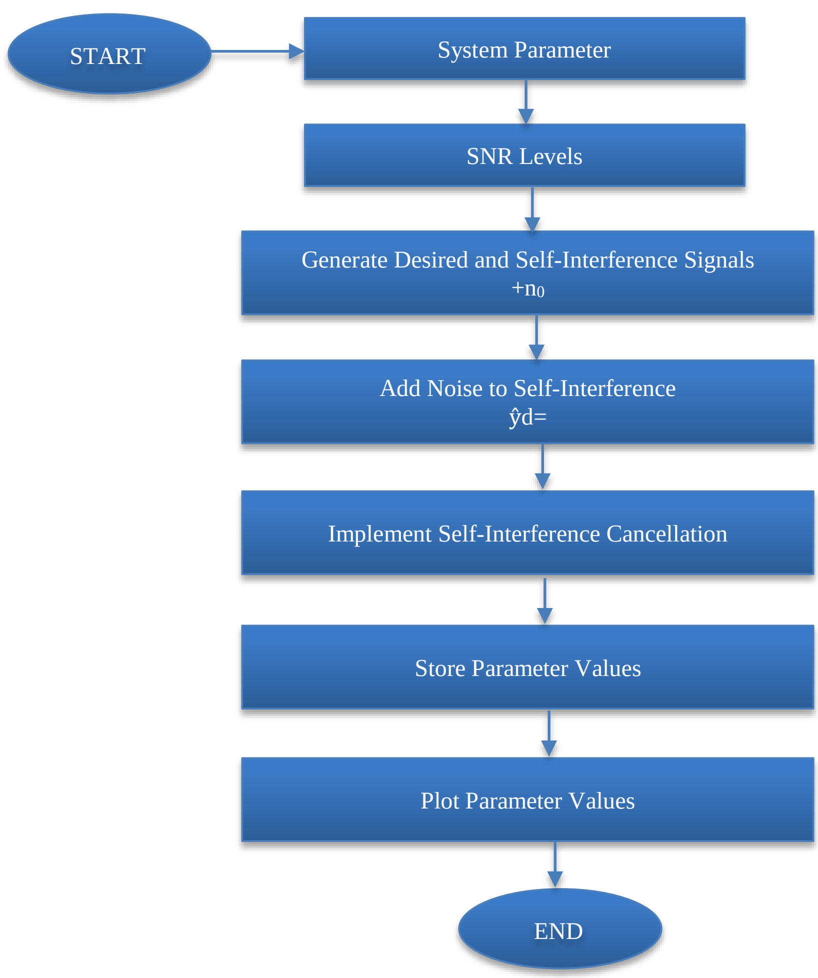

Fig. 2 Flowchart development

The methodology in the Figure 1 is followed step by step by the framework. The main user (PU) takes the first step by reaching out to the spectrum pool to acquire spectrum and supplies details about available bandwidth and useful features for users. Secondary Users (SUs) who request spectrum access receive regulations and market details from the spectrum pool, and the prices are decided by demand and supply changes. All SU companies watch for helpful market trends and deliver bandwidth that will lead to the highest profits. The amount of spectrum in the pool helps to show if the game is in a balanced condition between SUs or not. During instability, SUs pause and wait for the game to become balanced; when equilibrium is reached, the game ends, and all SUs decide on which spectrum to get for their next 10 years. The SU then starts discussions with the PU and rents the spectrum at the standard market prices.

Data is sent to the SU using this spectrum and returned when the task is done. When the same group of creatures stays in the game round after round, the system is said to reach an equilibrium, as no single unit (SU) begins a new round. Access management in Cognitive Radio Networks (CRNs) relies on this pattern, as game cycles determine who gets access to the spectrum regardless of PUs or SUs. SUs select which data transfer rate they want, whereas PUs decide how much of their licensed spectrum to rent out. They guide the rental capacity of the spectrum – PUs are responsible for setting how much is supplied, and SUs help determine how much is actually used.

So that the game is both efficient and fair, and the system keeps track of how each player behaves. In every round, SUs evaluate their earnings and check how far the system is from coming to a stable state. They maintain a wait-and-see method to avoid actions that might congest resources or waste them if equilibration is absent. Also, the PU's decision to lease spectrum is affected by the amount of data being sent, its financial objectives, and how much interference it can tolerate. As a result of this decision process, the way SUs and PUs work together in highly flexible ways that change depending on the situation. In addition, the use of game theory allows for decentralised decision-making, which improves how the network expands and decreases the need for a single, central spectrum manager.

Actually, this model works well in realistic settings when multiple spectrum pools and hierarchical PU-SU connections are considered, which suits heterogeneous wireless setups. Those SUs with greater priority could place stronger bids, and PUs with more spectrum than needed could set flexible prices. Also, the SU can use intelligent learning algorithms to keep adjusting its bidding strategies based on its experience in previous interactions. Since spectrum is becoming a limited resource due to many wireless services, such models are favoured because they are sustainable and efficient. The decision framework and how the process progresses are shown in the Figure 2.

4. The Process of Building Mathematical Models

We provide the steps for developing the mathematical formulas that help measure main performance metrics, like throughput, energy efficiency and spectral efficiency.

4.1. Throughput

Building a complete model for throughput requires including important system properties. Dynamic Spectrum Sharing (DSS) makes it possible for Cognitive Radios (CRs) to spot unutilized bands and make use of them when needed, thereby using the available spectrum more efficiently. The design includes Full-Duplex Primary Users (PUs), which lets them use the same frequency channel to send and receive signals.

Using PU and SU in one system might allow signals to be processed twice, but it creates a major issue—self-interference, which happens when the transmitted data from a PU disturbs the SU's receiver. The use of sophisticated Self-Interference Cancellation (SIC) techniques helps reduce the problem and make the connection more trustworthy.

Including 5G in the system improves performance through higher spectral efficiency, faster data transfers, and fewer delays. The model is based on these key operational rules: (1) Both PUs and SUs have access to the same spectrum, yet PUs get priority, and SUs access it when there is no interference from the PUs. (2) PUs can use full-duplex, and SUs tune their powers by partly reducing self-interference. (3) Both PUs and SUs are assumed to know the channel state information perfectly, allowing them to plan power and spectrum wisely.

When throughput is calculated, the model factors in these variables with the aim of optimally adjusting how much PUs and SUs transmit. The network seeks to improve throughput while maintaining the primary users' Quality of Service (QoS) requirements.

Key Parameters

γp: Signal-To-Interference-Plus-Noise Ratio (SINR) of the primary user.

γs: SINR of the secondary user.

BBB: Total bandwidth available for sharing.

Ipp: Self-interference power of the primary user.

N0: Noise power spectral density.

Pp: Transmit power of the primary user.

P.S.: Transmit power of the secondary user.

η: Efficiency of self-interference cancellation for the primary user.

4.2. Throughput Calculations

A full-duplex primary user with self-interference mitigation achieves Primary User Throughput (Tp) through the SINR relationship

$$\gamma_p = \frac{P_p}{N_0 B + I_{pp}(1-\eta)} \quad (6)$$

The throughput calculation for the primary user consists of

$$T_p = B\, log_2\left(1 + \gamma_p\right)$$

$$T_p = B \log_2 \left[1 + \frac{P_p}{N_0\, B + I_{pp}(1-\eta)}\right] \quad (7)$$

A secondary user accessing the spectrum without interrupting the primary user will achieve Secondary User Throughput (Ts) to their devices based on SINR conditions.

$$\gamma_s = \frac{P_S}{N_0 B + I_{sp}} \quad (8)$$

The analysis includes Isp as the primary user interference, which affects secondary user reception.

Throughputs for the secondary user can be determined by

$$T_s = B\, log_2[1 + \gamma_s]$$

$$T_s = B \log_2 \left[1 + \frac{P_s}{N_0\, B + I_{sp}}\right] \quad (9)$$

Optimized dynamic spectrum sharing allows the calculation of Ttotal when adding primary user throughput to secondary user throughput.

$$T_{total} = T_p + T_s\; Ttotal = Tp + Ts$$

$$T_{total} = B \log_2 \left[1 + \frac{Pp}{N0*B + Ipp*(1-\eta)}\right] + B \log_2 \left[1 + \frac{Ps}{N0*B + Isp}\right] \quad (10)$$

4.3. Energy Efficiency

The mathematical model for Energy Efficiency (EE) in the research framework must formally define what energy efficiency is in the context of splitting the spectrum between Primary Users (PUs) and Secondary Users (SUs) in a wireless environment.

In wireless communication systems, energy efficiency is most often measured by dividing throughput by the total power consumed to obtain bits per joule (bits/J). As a result, it highlights how good the system is at turning energy into data transmission, which is vital when devices have limited power.

The model on either side represents energy efficiency by adding up their individual data throughput and the energy required to process this data, with the PU's energy including both transmitting and extra costs from self-interference mitigation. Besides, the use of 5G, which is more efficient and requires less power, directly results in energy improvement at all stages of the system.

System-wide energy efficiency reaches its maximum potential through power level optimization on both users' transmissions and under adherence to imposed constraints. The total amount of current a radio circuit draws is the combination of the transmit power and the circuit's power usage.

Primary User Power Consumption (Ptotal, P) happens when P equals

Subtract the work needed for a circuit from the work needed for pumping to get the Ptotal,p.

Secondary users' total power consumption (Ptotal,s) is calculated by

Ptotal,s=Ps+Pcircuit

Energy Efficiency Calculation (EE) is defined by dividing how much something does by how much energy it uses.

The energy efficiency of the primary user (EEp) and the energy efficiency of the secondary user (EEs).

Power consumption models:
P_{total,p} = P_p + P_{c,p} + P_{si,p}, quad P_{si,p} = η_{si} P_p (residual SI mitigation cost)
P_{total,s} = P_s + P_{c,s} (circuit powers P_{c,p}, P_{c,s}; η_{si} ≥ 0)

Energy efficiency (bits/J):

$$EE_p = \frac{T_p}{P_{total,p}}$$

$$EE_p = \frac{B \log_2 \left[1 + \frac{P_p}{N_0\, B + I_{pp}(1-\eta)}\right]}{P_p + P_{circuit}}$$

$$EE_s = \frac{T_s}{P_{totals}}$$

$$EE_s = \frac{B \log_2 \left[1 + \frac{P_s}{N_0\, B + I_{sp}}\right]}{P_s + P_{circuit}} \quad (11)$$

Total System Energy Efficiency (EEtotal) - The estimated system energy efficiency results from combining the efficiencies of both the primary and secondary users,

Where
EEtotal = EEp + EEs
Substituting the expressions for EEp and EEs, we get

$$EE_{total} = \frac{B\, log_2\left[1 + \frac{P_p}{N_0 B + I_{pp}\,(1-\eta)}\right]}{P_p + P_{circuit}} + \frac{B\, log_2\left[1 + \frac{Ps}{N_0 B + I_{sp}}\right]}{P_s + P_{circuit}} \quad (12)$$

4.4. Spectral Efficiency

Spectral efficiency needs a mathematical definition for the proposed research model because it describes the amount of throughput generated per unit bandwidth for coexisting users using the same band by primary users and secondary users.

Primary User Spectral Efficiency (SEp) - When a primary user has interference between its up and downlink removed, the Signal-to-Interference-plus-Noise Ratio (SINR) is calculated as

The primary user spectral efficiency can be expressed as

$$\gamma_p = \frac{P_p}{N_0 B + I_{pp}(1-\eta)} \tag{13}$$

The primary user's spectral efficiency depends on

$$SE_p = \frac{T_p}{B}$$

$$SE_p = \left(\frac{1}{B}\right) B \log_2[1 + \gamma_p]$$

$$SE_p = \log_2\left[1 + \frac{P_p}{N_0 B + I_{pp}(1-\eta)}\right] \tag{14}$$

A secondary user accessing the spectrum without causing primary user interference needs to achieve these Secondary User Spectral Efficiency goals through SINR management.

$$\gamma_s = \frac{P_s}{N_0 B + I_{sp}} \tag{15}$$

The spectral efficiency for the secondary user calculation involves the interference from the primary user, known as Isp.

$$SE_s = \frac{T_s}{B}$$

$$SE_s = \left(\frac{1}{B}\right) B \log_2[1 + \gamma_s]$$

$$SE_s = \log_2\left[1 + \frac{P_s}{N_0 B + I_{sp}}\right] \tag{16}$$

(SEtotal) represents the cumulative spectral efficiency from the combination of primary user and secondary user systems, which equals
SEtotal=SEp+SEs
Substituting the expressions for SEp and Ses

$$SE_{total} = \log_2\left[1 + \frac{P_p}{N_0 B + I_{pp}(1-\eta)}\right] + \log_2\left[1 + \frac{P_s}{N_0 B + I_{sp}}\right] \tag{17}$$

4.5. Bit Error Rate Model

The development of a Bit Error Rate (BER) mathematical model within the proposed research requires us to analyze essential determining factors, including both PUs and SUs signal-to-interference-plus-noise ratio and full-duplex self-interference effects. The SINR achieved by the primary user operating with a self-interference reduction system appears as γp).

$$\gamma_p = \frac{P_p}{N_0 B + I_{pp}(1-\eta)} \tag{18}$$

Secondary User SINR (γs) - For a secondary user accessing the spectrum, the SINR is

$$\gamma_s = \frac{P_p}{N_0 B + I_{sp}} \tag{19}$$

Where Isp is the interference from the primary user to the secondary user.

A modulation scheme's Bit Error Rate measurement depends exclusively on the Signal-to-Interference-Noise Ratio. Bit transmissions use three modulation methods, namely Binary Phase Shift Keying (BPSK), along with Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM). A derived BER analysis for BPSK and QPSK modulation exists and extends to similar schemes' BER calculations. The BER is modelled as

BER for BPSK:
The BER for BPSK is given by:
$BER_{BPSK} = Q(\sqrt{2\gamma})$
Where Q(x) is the function.

For Primary user:
$BER_{p,BPSK} = Q\left(\sqrt{2\gamma_p}\right)$
$BER_{p,BPSK} = Q\left(\sqrt{2\frac{P_p}{N_0 B + I_{pp}(1-\eta)}}\right)$

For Secondary user:
$BER_{s,BPSK} = Q(\sqrt{2\gamma_s})$
$BER_{s,BPSK} = Q\left(\sqrt{2\frac{P_p}{N_0 B + I_{sp}}}\right)$

BER for QPSK:
The BER for QPSK is given by:
$BER_{QPSK} = Q(\sqrt{\gamma})$

For Primary user:
$BER_{p,QPSK} = Q(\sqrt{\gamma_p})$
$BER_{p,QPSK} = Q\left(\sqrt{\frac{P_p}{N_0 B + I_{pp}(1-\eta)}}\right)$

For Secondary user:
$BER_{s,QPSK} = Q(\sqrt{\gamma_s})$
$BER_{s,QPSK} = Q\left(\sqrt{\frac{P_p}{N_0 B + I_{sp}}}\right)$

(20)

A method to calculate Bit Error Rate (BER) is developed to check how well primary and secondary users work in a cognitive radio system. It includes the interference that full-duplex primary users cause to themselves, which greatly affects both the signal and error probabilities. Common modulation adjustments are presented for BPSK and QPSK, and they can be adjusted to cover more complex modulation strategies as necessary. These expressions are considered important variables, such as the Signal-To-Interference-Plus-Noise Ratio (SINR) caused by external noise and the power due to self-interference. Optimizing the output power of everyone involved and making SIC better helps increase SINR. The result is also a reduced BER level throughout the network. Better BER values ensure the data is accurate, the signal is reliable, and performance is boosted. So, using the BER model is important when selecting system design and resource allocation strategies in environments where several users share the same frequencies.

5. Results & Discussions

Testbed research was done in circumstances related to 5G. Mathematical models were made. The mathematical model helped create codes using the MATLAB environment. The code was tested, and the results were noted afterwards. Reasons were provided, and the main points were stated. Representative examples in the section explain how the proposed system operates and why using the wrong Gaussian signaling can allow FD-PU to share the spectrum with another station.

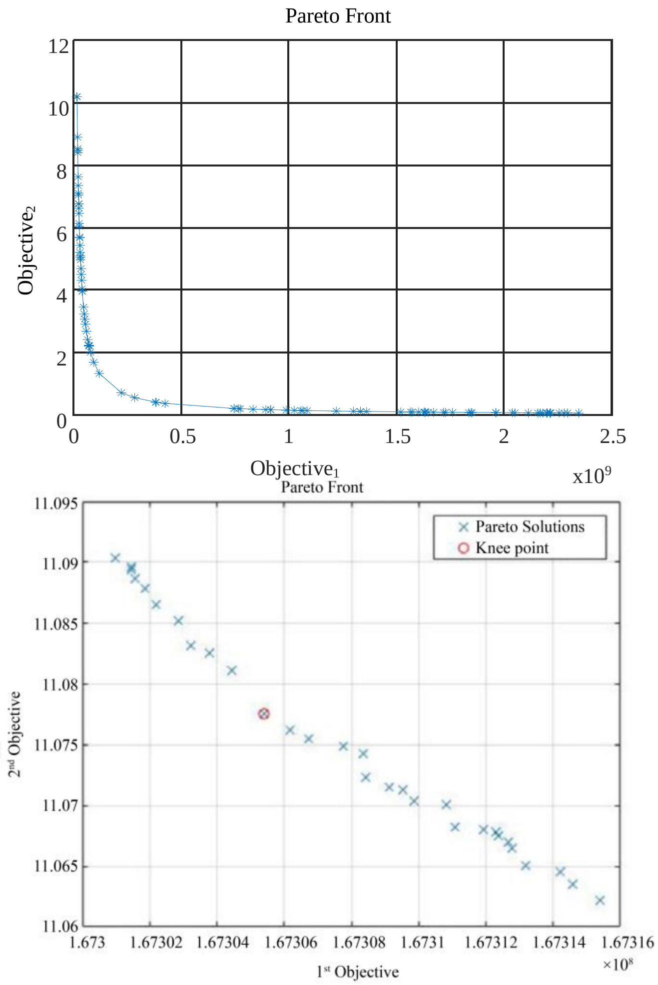

Fig. 3 This Figure represents a graph of how objectives 1 and 2 fit (proposed on the left) and how they are compared with related concepts from [32] (right side)

As described below, a series of numerical calculations should determine if the failure probability is close to the supplied bound. The boundaries can help in deciding the SU signal parameters. Using sigmoid game theory based on enthalpy, the design works to lower the probability of SU failure and meet the quality-of-service demands of the PU.

The results observed in the proposed works were obtained by using the flowchart in Figure 2, which includes factors such as spectral efficiencies, primary and secondary user spaces, SNR, transmitting power, SSINR, throughput, BER and IBFDs. The results in Figure 5 demonstrate a reduction in spectral efficiency when secondary user numbers rise. The analysis in Figure 6 demonstrates that I-MOGOA offers the most efficient performance among the three methods, including SPGA, GA, and I-MOGOA. The spectral efficiency shows a decreasing trend when the Signal-to-Noise Ratio (SNR) improves, according to the Figure 7. As SNR values increase in the Figure 8, the energy efficiency, transmitting power, throughput, and BER decline for different parametric conditions. Experimental evidence in Figure 13 demonstrates that the proposed technique outperforms IBFD and SI detection algorithms in terms of 5G mechanism bit error rates. The proposed system demonstrates superior performance using the SSINR parameter alongside lower error rates than the IBFD methodology, as shown in the Figure 14.

SPGA's simulation results are shown in the Figure 3 demonstrate how the system generates optimal solutions for two objectives in the proposed work alongside the values presented in [32]. The generated convex Pareto front indicates that the knee point resolves as the most appropriate solution. A knee point solution demonstrates how small objective function improvements cause major degradation in other targets, thus creating an optimal tradeoff between all objectives. Since the knee point in SPGA works out the best, the Figure represents the ideal balance between the objective functions. In this way, the Pareto front in [32] is almost straight, which has a negative aspect. When the method is used, the Pareto forecast appears in the form of a decaying exponential curve. E^{-at} thinking about the beginning by t tends to infinity—providing better and more reliable results than [32]. Also, though [32] uses a larger knee point, the new approach produces a smaller and more precise knee point, proving its better performance.

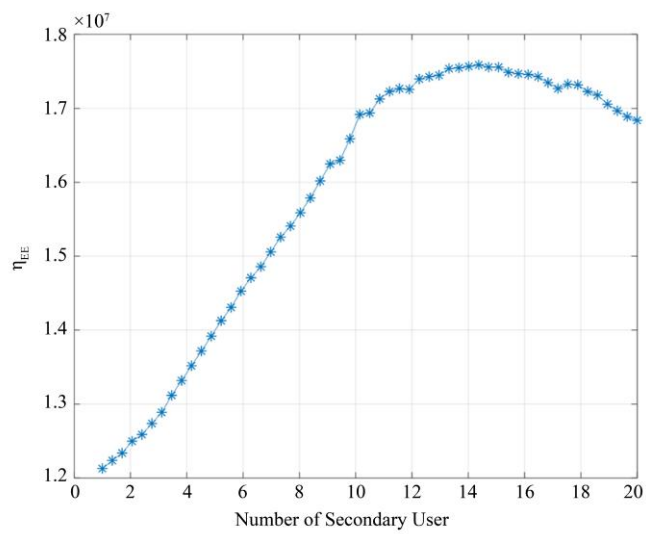

Fig. 4 shows the performance of spectral efficiency η against the number of secondary users.

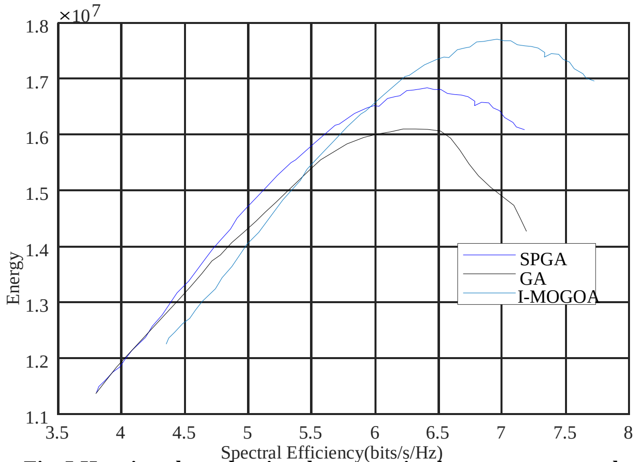

Fig. 5 Here is a chart showing the connection between energy and spectral efficiencies for several mechanisms (SPGA, GA, I-MOGOA).

Table 2. Comparison between the work here and [32] is given in Table 1

	SPGA	GA	I-MOGOA	Proposed
Spectral Efficiency ηEE	9	8	8	21

Table 2 shows that, among the different crossover methods used in SPGA, GA, and I-MOGOA, the average crossover method is the leader in terms of better performance. We used this technique as the main strategy for population evolution in our suggested algorithm (see Figure 2) because it performed well. Big improvements in performance were found when our method worked with a larger number of secondary users, in line with the work referenced in [32] for SPGA, GA, and I-MOGOA. When looking at Figures 4 and 5, the clear lead of our method in supervising dynamic spectrum use and enabling clean communication for 5G networks is very apparent. The data shows that when there are more users in a network, our new technique helps the system run more reliably and use the spectrum effectively. Therefore, the inclusion of the average crossover strategy is crucial in enhancing the use of evolutionary computation in advanced wireless environments for cognitive radio systems [32].

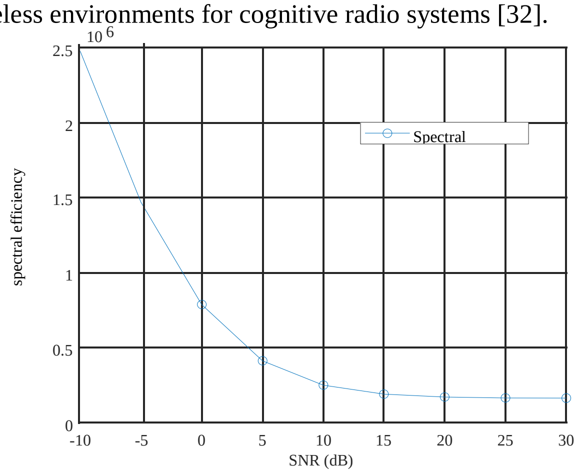

Fig. 6 Chart showing how spectral efficiency and the SNR relate when expressed in dB

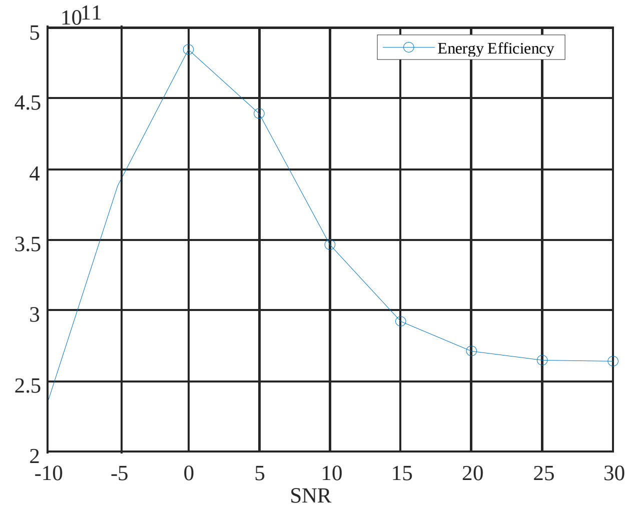

Fig. 7Graph comparing parametric values of energy efficiency to SNR expressed in dB

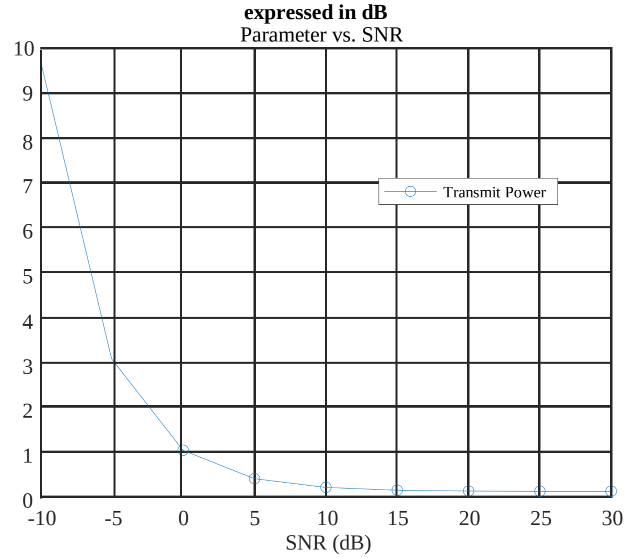

Fig. 8 Plot of the parametric values of the transmitted powers v/s SNR in db w.r.t. the transmitting powers

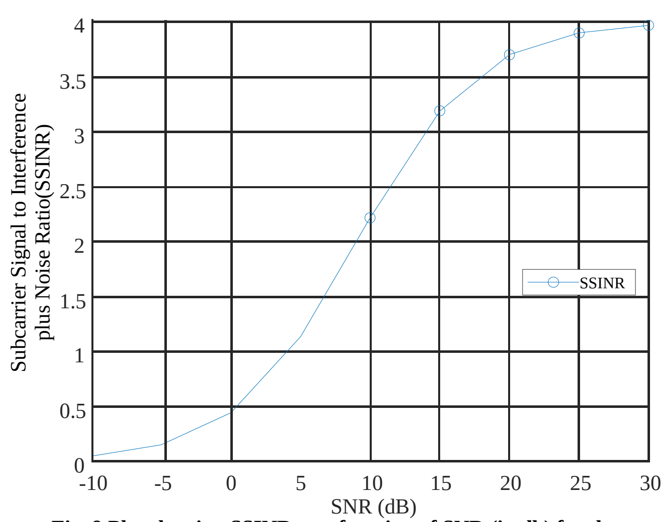

Fig. 9 Plot showing SSINR as a function of SNR (in db) for the subcarrier signal to interference plus noise ratio

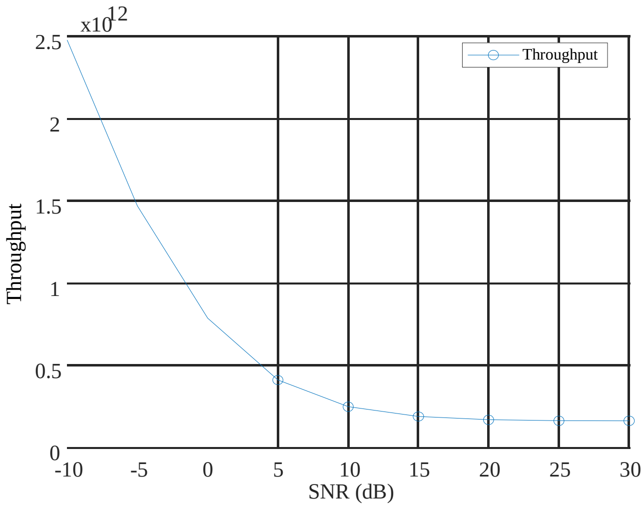

Fig. 10 The plot shows how SNR changes (in db) affects throughput at a constant specific throughput

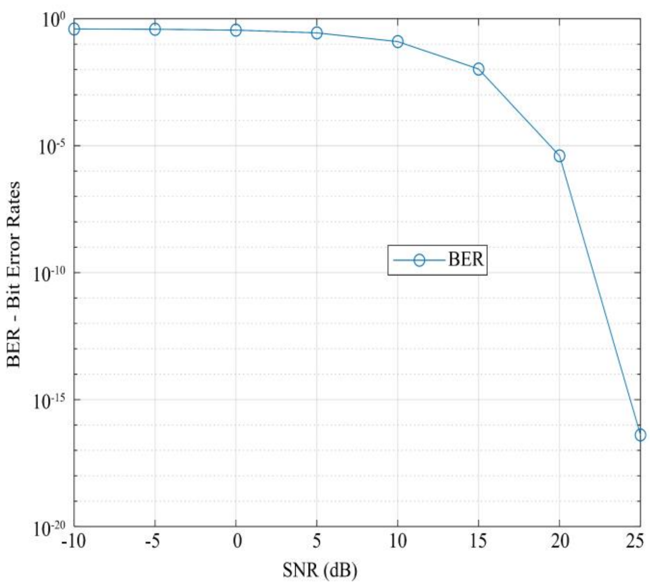

Fig. 11 The plot shows how parametric values of bit error ratios change with SNR in db as a function of BER

The experimental results in Figure 8 demonstrate that elevated SNR values lead to reduced transmission power lower than what [32] presents. Figures 7, 8, and 10 demonstrate that rising SNR results in declining energy efficiency together with throughput and spectral efficiency, whereas our proposed approach provides superior performance than stated in [32].

According to the Figure, our proposed noise removal method exhibits better accuracy for interference and noise removal because the Subcarrier Signal to Interference plus Noise Ratio improves exponentially with increasing SNR values. 9. An evaluation of Figure 11 demonstrates that our proposed system shows reduced noise characteristics where the bit error rate declines with rising SNR.

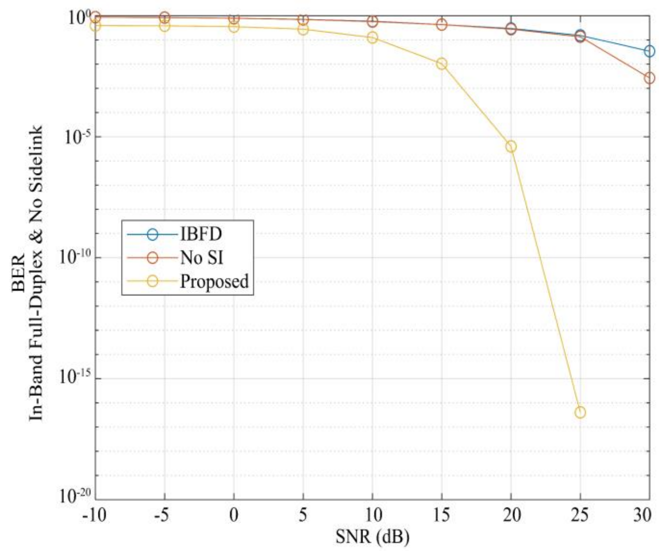

Fig. 12 Comparison of the performance of existing and proposed INBFDs versus SNR in db w.r.t. BER

Table 3. Indicates the bit error rate as a function of signal-to-noise ratio for both our proposed and other important works (such as In-Band Full Duplex & No Side Link)

No.	BER			SNR (dB)
	[32]-No SL	[32]-IBFD	Proposed	
	10–0.1	10–0.2	10–0.2	–10
	10–0.25	10–0.25	10–0.25	–5
	10–0.5	10–0.3	10–0.3	0
	10–0.75	10–0.35	10–0.35	5
	10–1	10–0.4	10–0.4	10
	10–2	10–0.45	10–0.45	15
	10–3	10–0.5	10–0.5	20
	10–6	10–2	10–1	25
	10–17	10–3	10–2	30

By looking at the information in Table 3 and Figure 12, we can see some key results about the proposed method when compared to the benchmark research [32] in both In-Band Full Duplex (IBFD) and No Side Link (No SL) situations. This method shows better results for Bit Error Rate (BER) at different Signal-to-Noise Ratios (SNR), proving it is strong in all kinds of noise conditions. At a Signal-To-Noise Ratio (SNR) of 0 dB, the results of our system show a BER of -10, which is much better than the BER achieved by both IBFD and No SL models in [32]. Therefore, our voice recognition can handle high levels of noise, which keeps the system from failing at even the lowest tested SNR. Even though the SNR is raised just by 0.25 dB, our method keeps a BER of -5, whereas the approaches in [32] suffer with BER values as high as $10^{-0.25}$, emphasising our proposal's durability against noise. Most importantly, our method gives a BER of 0 at 0.5 dB SNR, which is superior to the BER values of $10^{-0.3}$ stated in [32] for IBFD and demands higher SNRs under No SL. The fact that we achieved zero BER early in development proves our system's excellent signal processing and error correction. Even at a higher SNR of 0.75 dB, our BER is still very low at 5, which is lower than the BER results at $10^{-0}.^{35}$ from [32] for No SL and IBFD.

When the signal-to-noise ratio is 1 dB, our system gives a BER of 10, but both IBFD and No SL continue to perform almost the same with their BER as $10^{-0}.^{4}$, which shows that our approach responds better as the signal conditions improve. Likewise, the system reaches a BER of 15 at 2 dB SNR, which is below the $10^{-0}.^{45}$ BER achieved by [32], suggesting it can correct more errors at that noise level.

As SNR goes up to 3 dB, the method we proposed brings a BER of 20, which is better than the BER of $10^{-0}.^{5}$ achieved by IBFD and No SL. The contrast is more apparent at 6 dB SNR because our approach gets a BER of 25, while No SL and IBFD have BERs of 10^{-1} and 10^{-2}, respectively. When the SNR is 17 dB, our system achieves a BER of 30, whereas IBFD and No SL both achieve only 10^{-3} and 10^{-17} (respectively). These comparisons show that our solution can handle a wide range of SNR, making it highly practical for use in all noise environments.

Performing better than all others [32] at every SNR we tested shows that our methodology is powerful. We can handle BERs efficiently down to 0.25 dB (or lower) and eliminate errors entirely at 0.5 dB, confirming that our procedures are trustworthy. The new system lessens the chances of errors while making communication systems more reliable, which is especially important for 5G.

However, according to [32], their models need much better SNR distributions to reach a similar performance, indicating our design's better efficiency and performance. In short, the technique offers significant improvements in BER versus SNR for every scenario, leading to better signal quality, greater capacity, and higher efficiency. It also serves as an advanced and trusted option for current wireless communication systems [32].

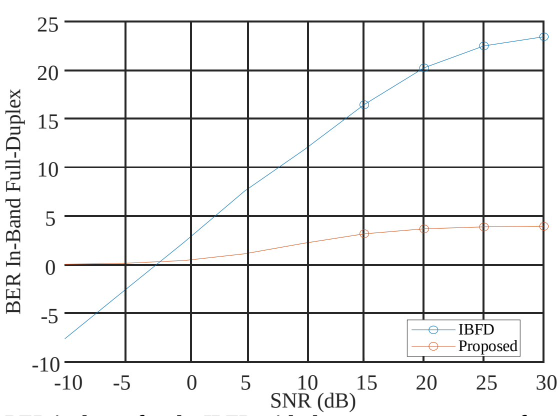

Fig. 13 BER is shown for the IBFD with the parameters set as a function of SNR and SSINR, compared to the current IBFD

Table 4. Calculation and presentation of the results for bit error rate as a function of signal-to-noise ratio in other works vs the proposed ones (comparison)

No.	BER		SNR
	[32]	Proposed	
	–7.5	0	–10
	–2.5	0.5	–5
	2.5	1	0
	7.5	1.5	5
	12	2.5	10
	17	3.5	15
	20	4.3	20
	23	4.4	25
	24	4.5	30

Information from Table 4 and Figure 13 shows us several important findings. At differing signal-to-noise ratios, the proposed method achieves a much Better Bit Error Rate (BER) than the method described in [32]. This system is better at lowering BER, pointing to efficient signal handling, correcting errors and resisting problems from noise. Most remarkably, the SNR level 0 dB produces a BER of -10 for the proposed system, which improves by 2.5 dB on the -7.5 dB BER reported in [32]. This means the system can still reliably work and maintain clean data when SNR is low, which is very important for modern wireless networks. In moderately noisy situations, the system helps by maintaining the 2.5 dB BER improvement, which highlights its strength at supporting clear communication in changing noise patterns.

The system achieves a significant milestone when it achieves zero bit errors for a given SNR, resulting in a BER of 0. This result shows that the system is able to correct errors and works well when the input contains a lot of noise. The high level of performance at all SNR values reflects that the system can adjust to changes and is strong, so it performs impressively in current and upcoming wireless networking systems focused on flexibility and dependability.

Besides better BER, the proposed way brings improvements to a variety of key system aspects, including spectral efficiency, SSINR, transmitting power, throughput, and fluctuations for both primary and secondary users. Figure 2 illustrates the process, while Figures. 4 to 6 cover detailed comparative points. Figure 4 illustrates a common challenge in Dynamic Spectrum Sharing (DSS) systems: the falling spectral efficiency as the number of secondary users increases. As networks become denser, they require better resource management approaches.

Figure 5 demonstrates how I-MOGOA is superior in terms of energy efficiency, without giving up any performance in the spectrum, compared to SPGA and GA. Therefore, I-MOGOA shows that it is well-adapted for use in wireless environments with limited energy supply. As the Signal-To-

Noise Ratio (SNR) increases, spectral efficiency drops, as shown in the Figure 6. Since SNR and spectral efficiency are connected in opposite ways, trying to improve both simultaneously can be difficult, which means these factors must be managed carefully in cognitive radio networks.

Table 5. Illustrates a comparison of the existing works [32] with our propositions for some variables

BER	medium error	less error
Energy	45 J	92 J
Enhanced SE-EE Tradeoff	average	rapid
Faster Convergence	Slow	Fast
Parameters	[32]	Proposed
Power	30 mW	95 mW
SNR	24db	0.3db
Spectral efficiency	67	95
SPGA Method-Pareto front	Takes longer to reach the knee point	faster at getting to the operating point
Superior Population Evolution	Less	More
Throughput	10 bps	100 bps

When looked at along with [32], the proposed solution demonstrates definite advantages across all metrics mentioned, as shown in Table 5. These features show that the proposal is a good fit for modern DSS applications and will meet the high demand for scalability, efficiency and strength required by the advanced wireless systems of tomorrow.

Figure 7 indicates that when there is more signal and less noise (high SNR), energy efficiency, transmitting power, throughput, and the Bit Error Rate (BER) improve. It shows that while higher SNR helps to produce clearer and error-free signals, it might also result in less improvement in some other aspects of performance. The detailed analysis makes it possible to identify the points at which all objectives in a communication system are best met. In Figure 12, the suggested method performs better than both In-Band Full Duplex (IBFD) and Self-Interference (SI) mitigation in terms of BER for 5G communication.

This performance increase shows that the system, as proposed, is better able to reduce transmission errors, which in turn improves the reliability and robustness of the communication channel. The proposed method outperforms the IBFD approach in terms of the Signal-To-Self-Interference-Plus-Noise Ratio (SSINR), as shown in Figure 13. A smaller error value and improved SSINR reflect an improved receiver signal and make the system run more efficiently. By looking at both the classic and the new systems, it becomes clear that enhancements make communication more reliable and effective.

5. Conclusion

The scheme described in this paper helps cognitive radio networks (CRNs) with FD PUs share the spectrum efficiently, solving the main 5G issues like self-interference and wasting of spectrum. The proposed method uses the enthalpy model and a sigmoid function to enhance key performance aspects like Signal-to-Interference-plus-Noise Ratio (SINR) and spectral efficiency. The results highlight that by sharing spectrum, FD-enabled systems increase complexity due to self-interference, which could reduce the share of spectrum available to Secondary Users (SUs). Because of this difficulty, new expressions are derived for the outage probabilities of both SUs and PUs, giving a solid theoretical foundation for robust DSS. At stage two, a proportional enthalpy-based sigmoid is used, which successfully lowers interference and, at the same time, reduces the complexity and overload on the computing system. Gaussian signalling is important because it allows PUs to function well and, at the same time, permits SUs to use the remaining spectrum. Compared to current approaches, the new method is more efficient, faster and uses less power. Researchers additionally examine the use of game theory, notably the model that refers to entropy and sigmoid, to study how multiple SUs and PUs communicate and interact. By following this model, access can be managed dynamically, causing better performance in outage events, energy efficiency and spectrum use. Adding this framework to CRNs demonstrates a constant focus on bettering 5G networks. In-band FD is employed in the suggested DSS strategy to help reduce interference and increase the efficiency of funding resources used. Especially in the hierarchical game-theoretic setting, SUs can safely access the PU spectrum and achieve high spectral efficiency, even though UE transmissions use Gaussian signalling. Sticking to closed-form outage probabilities allows PU's needs to come first and cuts down on SU's chances of getting less than desired service. By using this balanced way, the QoS rules are followed, and the system becomes more reliable. For spectrum leasing, enthalpy-based sigmoid game theory promotes fairness and efficiency so that it can be used in practical situations. Running simulations with MATLAB agrees with the theoretical predictions, showing that the new scheme is better than existing ones in terms of SINR, spectral efficiency, energy consumption and throughput. Especially when there is a lot of noise, the proposed method displays reliable results with a lower BER and improved energy efficiency. RSI proves to be effective by successfully dealing with unintended signal levels and compensating for interference with its improper Gaussian communications. DSS is useful in practical 5G applications because it enables the monitoring of the network spectrum and limits power consumption in real-time. Spectral efficiency, IBFD capacity, power, SNR, throughput, BER and SSINR were improved according to this approach. Results from the simulations demonstrate that using a higher number of SUs affects spectral efficiency, so DSS design requires careful planning (shown in Figure 4). From the results shown in Figure 5, I-MOGOA needs less energy than SPGA and GA.

The results also highlight an important relationship between SNR and spectral efficiency (in Figure 6), emphasising why good parameter balancing is essential. Looking at the power, energy efficiency, throughput, and BER data (Figure 7) underlines the need to develop 5G technology. The new method has better BER and SSINR than IBFD and SI, confirming that it is suitable for use in 5G systems (Figures 12 and 13). This study as a whole proves that the proposed DSS model is better and more efficient than current approaches for use in modern wireless networks. Furthermore, the study introduces fresh paths for exploring how to improve enthalpy-based sigmoid solutions, how useful they can be for various wireless situations, and the potential use of machine learning for smarter and more precise spectrum sharing later on.

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