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Mitigating interference algorithm as a solutions in cognitive radio networks

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Abstract

Efficient spectrum management in cognitive radio networks (CRNs) is crucial for optimizing spectrum utilization and minimizing interference. This paper presents an approach for mitigating interference algorithm solutions using queuing theory and Markov Decision Process (MDP) to enhance dynamic spectrum access. Queuing theory provides a structured model for analyzing spectrum availability, while Marcov Decision Process (MDP) enables adaptive decision-making under uncertainty. To validate the proposed approach, MATLAB and Minitab are utilized for simulation and performance analysis. MATLAB enables system modeling, algorithm implementation, and real-time evaluation, while Minitab facilitates statistical analysis of simulation results. The integration of these techniques improves spectrum efficiency, reduces collisions, and enhances Quality of Service (QoS) in CRNs. Future research can explore hybrid models incorporating machine learning for more adaptive spectrum management.

Keywords: Queuing Theory (Using Markov Decision Process; (MDP); Spectrum; Sensing; Secondary/Primary Users and Blockchain

1. Introduction

In recent years, the wireless communication landscape has witnessed explosive growth driven by the proliferation of mobile devices, the Internet of Things (IoT), and the increasing demand for high-speed, ubiquitous connectivity. This surge in wireless traffic has placed immense pressure on the radio frequency (RF) spectrum, a limited resource that is traditionally managed through static allocation policies. These policies, although effective in the past, have led to significant inefficiencies, with large portions of the spectrum either underutilized or heavily congested. Cognitive Radio Networks (CRNs) have emerged as a promising solution to address these inefficiencies by enabling dynamic spectrum access (DSA), where secondary users (SUs) can opportunistically utilize spectrum bands temporarily unused by primary users (PUs).

The concept of cognitive radio, introduced by Joseph Mitola in the late 1990s, revolutionized the approach to spectrum management. Unlike traditional radios, cognitive radios are equipped with the ability to sense their environment, learn from it, and make intelligent decisions regarding spectrum usage in real time. This adaptability is the cornerstone of Cognitive Radio Networks, allowing them to improve spectrum utilization and coexistence with minimal interference to licensed users. However, realizing the full potential of Cognitive Radio Networks requires solving a complex set of challenges, many of which demand innovative algorithmic solutions.

Formulating these algorithmic solutions involves addressing several critical aspects of Cognitive Radio Network operation. Spectrum sensing is fundamental, as it enables cognitive radios to detect the presence of primary users and identify available spectrum opportunities. However, accurate spectrum sensing is challenging due to factors such as noise, fading, and hidden node problems. To overcome these challenges, advanced techniques such as cooperative sensing, where multiple cognitive radios collaborate to improve detection accuracy, are often employed.

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Once spectrum opportunities are identified, dynamic spectrum access (DSA) mechanisms must be designed to allow secondary users to access the spectrum efficiently while minimizing the risk of interference with primary users. This requires sophisticated decision-making algorithms that can balance multiple objectives, such as maximizing throughput, minimizing delay, and ensuring fairness among users. These algorithms must operate in real-time, adapting to the constantly changing spectrum environment.

The advent of Cognitive Radio Networks (CRNs) has marked a significant evolution in wireless communication, addressing the inefficiencies associated with static spectrum allocation by enabling dynamic and opportunistic spectrum access. CRNs leverage the capability of cognitive radios to sense, learn, and adapt to their environment, allowing secondary users (SUs) to utilize spectrum bands that are temporarily unoccupied by primary users (PUs). This dynamic approach has the potential to alleviate spectrum congestion and improve overall spectrum utilization. However, achieving these benefits requires addressing a range of complex challenges through sophisticated algorithmic solutions.

The formulation of effective algorithms for CRNs involves tackling several key areas, spectrum sensing, dynamic spectrum access (DSA), spectrum management, and security. Spectrum sensing, which involves detecting the presence of primary users and identifying available spectrum, is crucial for ensuring that secondary users do not interfere with licensed communications. Advanced sensing techniques, such as cooperative sensing and machine learning-based methods, have been proposed to enhance accuracy and reliability in challenging environments (Zhao & Sadler, 2012; Zhang et al., 2015).

Dynamic spectrum access mechanisms are essential for enabling efficient and fair utilization of spectrum resources among multiple users. Algorithms for DSA must address the trade-offs between maximizing throughput, minimizing interference, and ensuring fairness. Recent advancements include the application of Markov Decision Processes (MDPs) and reinforcement learning to optimize spectrum access strategies in real-time (Bianchi et al., 2017; Li et al., 2019). These approaches model the uncertainty and dynamic nature of the spectrum environment, providing robust solutions for adaptive spectrum management.

Spectrum management involves the allocation and reallocation of spectrum resources among competing secondary users. Game theory has been increasingly employed to model the interactions between users and design mechanisms that achieve equilibrium in both cooperative and competitive scenarios (Kumar et al., 2016). Security in CRNs is another critical concern, as the shared nature of the spectrum exposes networks to various threats, including jamming, eavesdropping, and spectrum sensing data falsification. Algorithmic solutions for security must address these vulnerabilities by developing robust protocols and detection mechanisms (Nguyen et al., 2018; Zhang et al., 2020).

The integration of emerging technologies, such as artificial intelligence (AI) and blockchain, is also shaping the future of CRNs. AI techniques, particularly machine learning, are being utilized to develop adaptive algorithms for spectrum sensing and management (Mao et al., 2021). Blockchain technology offers a decentralized and secure framework for spectrum sharing and transaction logging, ensuring transparency and integrity in spectrum usage (Mokhtar et al., 2020).

The aims are to provide a comprehensive overview of the algorithmic solutions formulated to address the various challenges in CRNs. Another critical challenge in CRNs is spectrum management, which involves the allocation and reallocation of spectrum resources among multiple secondary users. Traditional resource allocation algorithms are often inadequate for CRNs due to their dynamic and heterogeneous nature. As a result, more advanced approaches, such as game theory, auction-based mechanisms, and machine learning, have been explored to address these complexities. Game theory, for instance, provides a framework for modeling and analyzing the interactions between multiple cognitive radios, allowing for the design of strategies that achieve equilibrium in competitive or cooperative scenarios.

As the demand for wireless services continues to grow, the need for efficient, adaptable, and secure spectrum management solutions will only become more critical, making the formulation of effective algorithms a crucial area of research in the field of cognitive radio networks.

By developing and implementing these algorithmic solutions, CRNs can achieve enhanced adaptability, reliability, and efficiency, making them indispensable in the future landscape of wireless communication.

Formulating these algorithmic solutions involves addressing several key challenges. Spectrum sensing is critical for detecting the presence of primary users and identifying available spectrum bands. However, spectrum sensing must be accurate and fast, even in the presence of noise, fading, and other signal impairments. Dynamic Spectrum Access (DSA) is another crucial aspect, where secondary users must decide when and how to access the spectrum, balancing the need for efficient communication with the obligation to avoid interference. Spectrum management involves the allocation and reallocation of spectrum resources among multiple users in a way that maximizes overall network performance while ensuring fairness and adherence to regulatory constraints.

Cognitive Radio Networks (CRNs) represent a transformative approach to addressing the limitations of traditional spectrum management. By allowing secondary users (SUs) to opportunistically access unused spectrum bands without interfering with primary users (PUs), CRNs promise to enhance spectrum utilization and address the growing demand for wireless communication. Algorithmic advancements in CRNs have evolved significantly over the past decade, driven by the need for efficient, adaptive, and secure solutions in dynamic spectrum environments. Spectrum sensing, a fundamental component of CRNs, involves detecting and identifying available spectrum while avoiding interference with PUs. Recent developments in this area include advanced cooperative sensing techniques and machine learning-based approaches that improve detection accuracy and reliability (Zhang et al., 2017; Li et al., 2020).

Dynamic spectrum access mechanisms are crucial for enabling SUs to utilize spectrum resources efficiently. Recent work has applied Markov Decision Processes (MDPs) and reinforcement learning to optimize spectrum access in real-time, accounting for the stochastic nature of spectrum availability and user behaviors (Xiao et al., 2019; Zhang et al., 2021). These algorithms help balance trade-offs between maximizing throughput, minimizing interference, and ensuring fair spectrum allocation.

Spectrum management, involving the allocation and reallocation of spectrum resources, has also seen significant advancements. Game theory has been extensively applied to model the interactions among multiple cognitive radios, offering insights into cooperative and competitive strategies for spectrum sharing (Kumar et al., 2015).

Security remains a critical concern in CRNs due to the shared nature of the spectrum and the potential for malicious activities. Recent research has focused on developing robust security protocols and detection mechanisms to safeguard CRNs against threats such as jamming and spectrum sensing data falsification (Nguyen et al., 2021; Zhang et al., 2022).

The integration of emerging technologies, such as artificial intelligence (AI) and blockchain, is also shaping the future of CRNs. AI techniques, including machine learning and reinforcement learning, are being employed to develop adaptive algorithms that enhance spectrum sensing and management (Mao et al., 2021). Blockchain technology offers a decentralized and transparent framework for secure spectrum sharing, improving the integrity and efficiency of spectrum transactions thus improving efficiency (Mokhtar et al., 2021).

2. Literature Review: Formulating algorithmic solution involves addressing several key challenges for Cognitive Radio Networks

2.1. Spectrum Sensing

Spectrum sensing is a fundamental component of Cognitive Radio Networks (CRNs), enabling cognitive radios to detect and identify spectrum opportunities while avoiding interference with primary users (PUs). Accurate spectrum sensing is crucial for the efficient operation of CRNs. Various algorithmic solutions have been proposed to enhance sensing performance under different conditions.

Early work focused on traditional spectrum sensing techniques, such as energy detection, matched filtering, and cyclostationary feature detection (Zhao & Sadler, 2012). Energy detection, while simple and widely used, suffers from limitations in low signal-to-noise ratio (SNR) conditions and can be prone to false alarms. To address these issues, cooperative sensing has been proposed, where multiple cognitive radios collaborate to improve detection accuracy. For example, Zhang et al. (2017) introduced a cooperative spectrum sensing scheme that leverages fusion rules to aggregate sensing reports from multiple nodes, enhancing the overall detection performance.

2.2. Dynamic Spectrum Access (DSA)

Dynamic Spectrum Access (DSA) involves the strategies and algorithms used by cognitive radios to access spectrum resources efficiently while minimizing interference with PUs. DSA mechanisms must address the dynamic nature of spectrum availability and user behavior.

2.3. Markov Decision Processes (MDPs)

have been widely used to model and optimize spectrum access strategies. Xiao et al. (2019) applied MDPs to develop algorithms for optimal spectrum access, considering the probabilistic nature of spectrum availability and user actions. This approach enables cognitive radios to make informed decisions on when and how to access spectrum resources, balancing throughput and interference considerations.

Reinforcement learning has also been employed to improve DSA mechanisms. Zhang et al. (2021) explored reinforcement learning techniques for dynamic spectrum access, focusing on algorithms that adapt based on real-time feedback and changing spectrum conditions. These algorithms allow cognitive radios to learn optimal access strategies through trial and error, improving performance over time.

2.4. Spectrum Management

Spectrum management encompasses the allocation and reallocation of spectrum resources among multiple secondary users. Effective spectrum management is essential for ensuring fair and efficient spectrum usage.

Game theory has been extensively applied to spectrum management problems. Kumar et al. (2015) reviewed various game-theoretic approaches for spectrum sharing, including cooperative and non-cooperative games. Game theory provides a framework for modeling interactions between cognitive radios and designing strategies that achieve equilibrium in competitive and cooperative scenarios.

2.5. Security in CRNs

Security is a critical aspect of CRNs, given their shared nature and susceptibility to various threats. Ensuring secure operation is essential for maintaining the integrity and reliability of CRNs.

Recent research has focused on developing robust security protocols and detection mechanisms. Nguyen et al. (2021) provided a comprehensive survey of security and privacy issues in CRNs, highlighting threats such as jamming, eavesdropping, and spectrum sensing data falsification. They reviewed various security solutions, including cryptographic techniques and anomaly detection methods, to address these vulnerabilities.

viii. Blockchain technology has been explored as a solution for secure spectrum sharing. Mokhtar et al. (2021) examined the integration of blockchain into CRNs to provide decentralized and transparent spectrum management. Blockchain can enhance the security and trustworthiness of spectrum transactions by ensuring tamper-proof records and decentralized control.

2.6. Emerging Technologies

The integration of emerging technologies such as artificial intelligence (AI) and blockchain is shaping the future of CRNs. AI techniques, particularly machine learning, are being utilized to develop adaptive algorithms for spectrum sensing and management. Mao et al. (2021) reviewed the application of machine learning in CRNs, highlighting its potential to enhance spectrum access, management, and security.

Blockchain technology offers a decentralized approach to spectrum sharing, improving transparency and security. Mokhtar et al. (2021) discussed the use of blockchain for spectrum management, emphasizing its ability to provide secure and efficient spectrum transactions through smart contracts and decentralized ledgers.

3. Research Methodology

The M/G/1/K queuing model is a widely used queuing model that is applied to analyze the performance of a single-server queue with finite capacity (K). In the context of cognitive radio networks, the M/G/1/K queuing model is used to study the performance metrics such as average delay, packet loss probability, and throughput in a contention-based access scheme. It helps in understanding how the system behaves under different traffic loads and buffer sizes. Integrating signal strength in this queuing model with FCFS algorithm, a framework statistically validates the contention resolution model process in cognitive radio.

The M/G/1/K queuing model can be used to analyze and optimize the performance of contention resolution algorithms, such as channel access protocols, by considering the following parameters: the p arrival rate of users, the service time distribution, and the maximum number of users that can be served simultaneously (K).

- Arrival rate (λ): This represents the rate at which users arrive and request access to the channels. In a cognitive radio network, this can vary depending on factors like user density and traffic patterns.
- Service time distribution (G): This represents the distribution of time required to serve a user's request. In a cognitive radio network, this can vary depending on factors like channel availability and interference conditions.
- Maximum number of users (K): This represents the maximum number of users that can be served simultaneously. In a cognitive radio network, this can depend on factors like the number of available channels and the network's capacity.

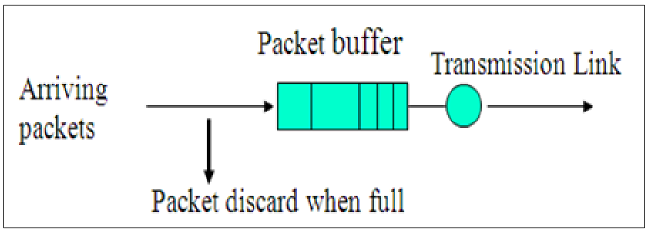

Figure 1 Basic Queuing Model for First Come First Serve (FCFS)

The service time of a SU customer shall be dependent on the channel transmission rate (which is time-varying), PU activity, resource allocation scheme, number of SUs, number of PU channels, and sensing errors, etc.

We define the system state at time t to be the number in the system at that instant.

Consider the imbedded Markov Chain of system states at these time instants when the SU leaves from the system after transmitting. At a time instant ti , the system state will be the number of SUs left behind in the system when the SU leaves. Note that will range between 0 and since the departure of the job cannot leave the system completely full, i.e. with system state K.

Let be the number of arrivals (from the Poisson arrival process) in the service time. The equations for the corresponding Markov Chain can then be written as

$$\begin{aligned} n_{i+1} &= \min\{a_{i+1}, K-1\} && for \quad n_i = 0 \\ &= \min\{n_i - 1 + a_{i+1}, K-1\} && for \quad n_i = 1, \ldots, (K-1) \end{aligned} \quad (1)$$

The transition probabilities of the imbedded Markov Chain at equilibrium are defined to be

$$p_{d,jk} = P\{n_{i+1} = j\}; \quad 0 \le j, k \le K-1 \qquad (2)$$

Let be the probability of k SU arrivals to the queue during a service time.

$$\alpha_k = \int_{t=0}^{\infty} \frac{(\lambda t)^k}{k!} e^{\lambda t} b(t) dt \qquad (3)$$

where the pdf of the service time is given as b(t).

The transition probability pd, jk for the two cases $j = 0$ and $j = 1, \ldots, K-1$ will be found separately using the values of α_k found in (3). The expressions for these are given in (4) and (5), respectively, based on the observation that the final state k cannot exceed $K-1$.

$$p_{d,jk} = \begin{cases} \alpha_k; & 0 \le k \le K-2 \\ \sum_{m=K-1}^{\infty} \alpha_m & k = K-1 \end{cases} \qquad j = 0 \quad (4)$$

$$p_{d,jk} = \begin{cases} \alpha_{k-j+1}; & j-1 \le k \le K-2 \\ \sum_{m=K-j}^{\infty} \alpha_m & k = K-1 \end{cases} \qquad j = 0 \quad (5)$$

The equilibrium state probabilities pd,k k=0,1....,K-1 at the departure instants may be calculated Using the transition probabilities of (4) and (5), along with the normalization condition as follows.

$$p_{d,k} = \sum_{j=0}^{K-1} p_{d,j} p_{d,jk} \qquad k = 0,1,\ldots,K-1 \qquad (6)$$

$$\sum_{k=0}^{K-1} p_{d,k} = 1 \qquad (Normalization\ condition) \qquad (7)$$

The transition probabilities pd, jk of (4) and (5) may now be substituted in (5) and (6), giving a set of linear equations that may be solved to get the corresponding state probabilities. Note that only K independent equations are needed, as there are only K unknowns (i.e. pd, k k=0,1,......,K-1) to be found. This set of K-1 equations is summarized in (8).

$$\begin{cases} p_{d,k} = p_{d,0}\alpha_k + \sum_{j=1}^{K+1} p_{d,j}\alpha_{k-j+1} & k = 0,1,\ldots,K-2 \\ \sum_{k=0}^{K-1} p_{d,k} = 1 \end{cases} \qquad (8)$$

Alternatively, one can solve first for the normalized variables (pd,k /pd,0) using and then solve for pd,0 using the normalisation condition to get

$$\frac{p_{d,k+1}}{p_{d,0}} = \frac{1}{\alpha_0}\left[\frac{p_{d,k}}{p_{d,0}} + \sum_{j=1}^{k}\frac{p_{d,j}}{p_{d,0}}\alpha_{k-j+1} - \alpha_k\right] \qquad k = 0,\ldots K-2 \qquad (9)$$

$$p_{d,0} = \frac{1}{\sum_{k=0}^{K-1}\frac{p_{d,k}}{p_{d,0}}} \qquad (10)$$

We use this and the values obtained earlier for (pd,k /pd,0), to obtain the actual state probabilities pd,k k=1,......, K-1 at the SU transmission instants.

Considering a system at equilibrium, let pa,k k=0,1,.....,K be the probability that a newly arriving SU, irrespective of whether it finally joins the queue or not, finds k SUs waiting in the queue. For this system, let pk k=0,1,.....,K be the probability that the queue has k SUs in it at an arbitrarily chosen instant of time. We will have that

$$p_k = p_{a,k} \qquad k = 0,1,\ldots,K \qquad (11)$$

We can also define pac, k k=0,1,.....K-1 as the equilibrium probability of the system state k as seen by an arrival which does actually enter the queue. Based on the fact, that the state of the queue can change by at most ±1 because of these arrivals and the departures from it, we can claim that

$$p_{d,k} = p_{ac,k} \qquad k = 0,\ldots,K-1 \qquad (12)$$

Using PB as the equilibrium probability that an arrival is blocked (because the queue is full, i.e.

$$p_k = p_{a,k} = (1-p_B)p_{ac,k} = (1-p_B)p_{d,k} \quad k = 0,\ldots K-1 \qquad (13)$$

Note that this may also be confirmed by observing that

$$\sum_{k=0}^{K-1} p_{a,k} = 1 - p_B = \sum_{k=0}^{K-1} (1 - p_B) p_{ac,k}$$

$$\text{since} \sum_{k=0}^{K} p_{a,k} = 1 \text{ and} \sum_{k=0}^{K-1} p_{ac,k} = 1$$

Let $\overline{X}$ be the mean service time of a SU in the queue. The traffic load ρ offered to the queue will then be given by $\rho = \lambda \overline{X}$. Since the average arrival rate of SUs actually entering the queue (also the average departure rate of SUs leaving the queue) is $\lambda_c = \lambda(1 - p_B)$, the actual traffic throughput of the queue will be $\rho_c = \rho(1 - p_B)$.

This implies that the probability p0 of finding the queue empty at an arbitrary time will be

$$p_0 = 1 - \rho_c$$

Using (13) for the case k=0, we can then write

$$1 - \rho(1 - p_B) = (1 - p_B) p_{d,0} \qquad (14)$$

The blocking probability PB (or pK) can be found using (14) as

$$P_B = 1 - \frac{1}{p_{d,0} + \rho} \qquad (15)$$

Using the values of pd,k and the results of (13) and (15), the equilibrium state distribution pk, k=0,1,....(K-1) of the queue at arbitrary time instants may then be shown to be

$$p_k = \frac{1}{p_{d,0} + \rho} p_{d,k} \quad k = 0, \ldots K - 1 \qquad (16)$$

The equilibrium state distribution may now be used to find the mean number N in the system as

$$N = \sum_{k=0}^{K} k p_k = \frac{1}{p_{d,0} + \rho} \sum_{k=0}^{K-1} p_{d,k} + K\left(1 - \frac{1}{(p_{d,0} + \rho)}\right) \qquad (17)$$

Note that the effective arrival rate λ_c to the queue will be given by

$$\lambda_c = \lambda(1 - P_B) = \frac{\lambda}{p_{d,0} + \rho} \qquad (18)$$

Using this and Little's result, the mean total time spent in system by a SU actually entering the queue will be

$$W = \frac{N}{\lambda_c} = \frac{\sum_{k=0}^{K-1} p_{d,k} + K[(p_{d,0} + \rho) - 1]}{\lambda} \qquad (19)$$

This may be used to get the mean time spent waiting in the queue Wq as

$$W_q = W - \overline{X} = \frac{1}{\lambda}\sum_{k=0}^{K-1} p_{d,k} + \frac{K}{\lambda}\left(p_{d,0} + \rho - 1\right) - \overline{X} \qquad (20)$$

where $\overline{X}$ is the mean service time. The second moment of the time spent waiting in queue is given by

From the Table 1, the 3-D show the relationships that exist among the three parameters, that is Arrival time, Service rate and traffic intensity. This relationship signifies how signal sensing of spectrum for contention determine the signal. That is, between arrival time to traffic intensity the signal is decreasing possible from the environment. When signal – to noise is high in an environment the interference level becomes low as shown in table 1 using arrival time and service rate. The First Come First Serve is incorporated into the signal to determine arrival in the queue as in Figure 1.

Table 1 Result of Contention Model from the Simulated Speculation

S/N	**Arrival Time (λ)**	**Service Rate (μ)**	**Traffic Intensity (P)**	**Number of Sus (Lq)**	**Meantime in the Queue (Wq)per Secs**
1	0.100	0.111	0.901	8.19	81.90
2	0.067	0.071	0.944	15.81	235.92
3	0.05	0.053	0.943	15.72	314.47

Table 2 Result of Analysis in Contention Model using MANITAB Software of OP Model to validate Sensing (Transmission)

S/N	**Threshold (T)**	**Arrival Time (λ)**	**Service Rate (μ)**	**Traffic Intensity (P)**	**Number of Sus (Lq)**	**Meantime in the Queue (Wq)**
1.	0.39	0.10000	0.11100	0.9010	8.190	81.90
2.	0.58	0.06700	0.07100	0.9440	15.810	235.92
3.	0.78	0.05000	0.05300	0.9430	15.720	314.47

Where $0 \leq$ Threshold < 1. The threshold is established based on the desired signal-to noise ratio (SNR), Where the threshold represents the minimum acceptable signal strength for a channel is considered during sensing. That is, the threshold value lies between zero (with zero inclusive) and one (with one exclusive). With this in mind, we have randomly assigned threshold values to each level of the five variables: arrival time (λ), service rate (μ), Traffic Intensity (P), Number of Sus (Lq), and Meantime in the Queue (Wq).

We seek a specific multiple linear regression model whose general form assumes:

$$\hat{T} = \hat{\beta}_0 + \hat{\beta}_1\lambda + \hat{\beta}_2\mu + \hat{\beta}_3 P + \hat{\beta}_4(Lq) + \hat{\beta}_5(Wq) \qquad (21)$$

where: $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\beta}_5$ are parameter estimates of the model.

In order to develop this model, the data in the Table 2 is used in MINITAB Software (version 17) to obtain a specific multiple linear regression model which assumed the general form in equation (A), and which describes the Contention Model. The result of this analyses is presented below, alongside the developed model given as equation (B) known as OP model.

$$\hat{T} = 9.7 + 38\lambda - 47\mu - 8.6P - 0.0096(Lq) + 0.00001(Wq) - OP\ Model \quad (22)$$

Source: Okwong, A.E (2024)

Regression analysis: Threshold (T versus arrival time, service rate, traffic intensity

Table 3 Regression analysis: Threshold (T versus arrival time, service rate, traffic intensity

Analysis of Variance					
Source	DF Adj	SS Adj	MS	F-Value	P-Value
Regression		5 0.162128	0.032426	0.30	0.890
Arrival Time (λ)	1	0.000742	0.000742	0.01	0.938
Service Rate (μ)	1	0.001287	0.001287	0.01	0.918
Traffic Intensity (P)	1	0.002395	0.002395	0.02	0.889
Number of Sus (Lq)	1	0.003344	0.003344	0.03	0.869
Meantime in the Queue (Wq)	1	0.000001	0.000001	0.00	0.998
Error	4	0.432122	0.108031		
Total	9	0.594250			
Model	Summary	S	R-sq	R-sq(adj)	R-sq(pred)
0.328680	27.28%			0.00%	0.00%

Table 4 Regression analysis

Coefficients					
Term	**Coef**	**Coef**	**SE Coef**	**P-Value**	**VIF**
Constant	9.7	54.4	0.18	0.867	
Arrival Time (λ)	38	464	0.08	0.938	11982.77
Service Rate (μ)	-8.6	58.0	-0.11	0.918	13505.73
Traffic Intensity (P)	-0.0096	0.0544	-0.15	0.889	177.90
Number of Sus (Lq)	-0.0096	0.0544	-0.18	0.869	56.37
Meantime in the Queue (Wq)	0.000001	0.000060	0.00	0.998	12.56

Regression Equation

Threshold (T) = 9.7 + 38 Arrival Time (λ) - 47 Service Rate (μ) - 8.6 Traffic Intensity (P)

- 0.0096 Number of Sus (Lq) + 0.000001 Meantime in the Queue (Wq)

Fits and Diagnostics for Unusual Observations

Threshold Std

Obs (T) Fit Resid Resid

1 0.390 0.390 0.000 0.01 X

7 0.780 0.779 0.001 0.64 X

X Unusual X

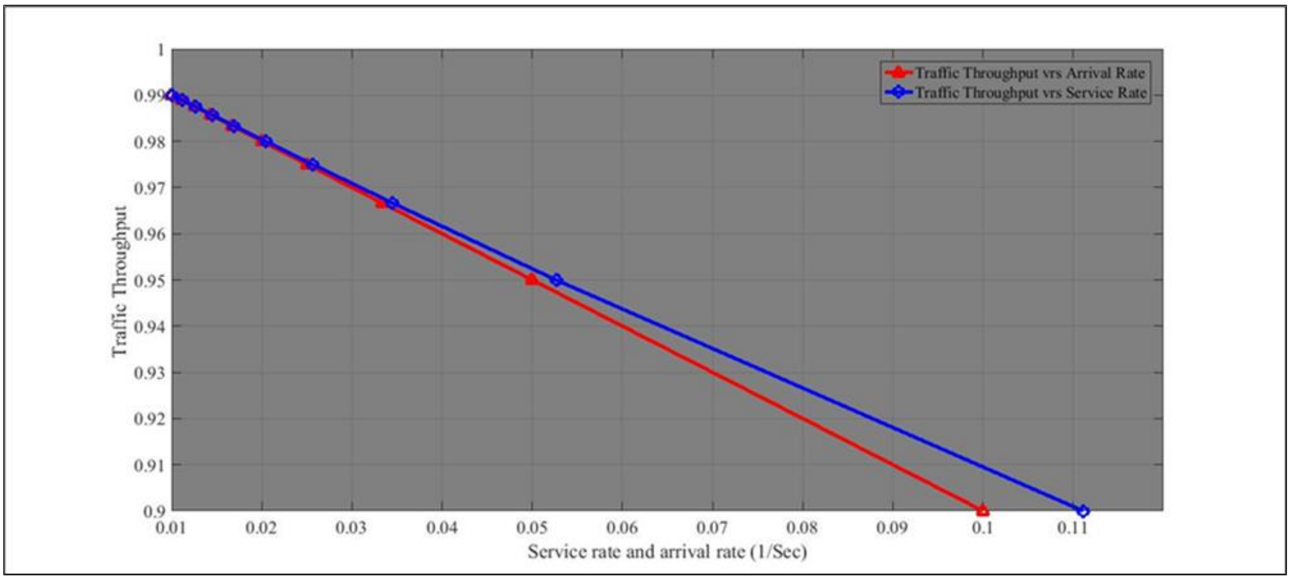

Figure 2 Traffic Throughput versus Service and Arrival Rate (secs)

4. Discussion of findings

In the above Figure 2, it shows the existing among the parameters in Table 2 used for obtaining the diagram.

Table 2 uses MINITAB version 17 to justify and validate Table 1. From the regression analysis general formula, we introduce the MINITAB software to derive a novel model formula of contention resolution model in cognitive radio network environment call OP regression analysis. Throughput (threshold) represents a minimum acceptable signal for successful communication. As seen in Fig 2 the interference level decreases, the signal decreases making it a challenge to reliably detect and decode signal.

Therefore, in contention, a higher interference environment necessitates a lower threshold to allow access only when the signal is relatively strong, minimizing the risk of interference with primary users. This show that the server is less congested and optimally used without contention and the traffic throughput (threshold) is $0 < T < 1$ for all conditions.

5. Conclusion

Mitigating interference algorithm solutions in cognitive radio networks (CRNs) using queuing theory and Markov Decision Process (MDP) is a robust approach to managing dynamic spectrum access efficiently. Queuing theory provides a mathematical foundation for modeling spectrum occupancy and traffic behavior, enabling precise estimation of available channels. Meanwhile, MDP offers a decision-making framework that optimally balances spectrum utilization and interference mitigation by considering probabilistic state transitions and rewards

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