



(RESEARCH ARTICLE)



## Towards contention resolution model to enhance rate of interference during dynamic spectrum utilization in cognitive radio network environment

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### Abstract

In cognitive radio networks (CRNs), contention resolution is a fundamental challenge for optimizing dynamic spectrum access among secondary users (SUs) without causing interference to primary users (PUs). This study introduces a contention resolution model within cognitive radio networks. The queuing theory model of M/G/1/K with a First Come First Serve (FCFS) algorithm was employed. This paper proposes a novel contention resolution model using the First-Come-First-Served (FCFS) strategy, framed within a Markov Decision Process (MDP). The model dynamically allocates spectrum to SUs based on their arrival time. It leverages on M/G/1/K queuing model, providing a theoretical foundation for optimizing contention resolution. Through the FCFS algorithm, the model ensures equitable access to the spectrum, prioritizing the first arriving users. As a proof of concept and in order to validate the effectiveness of the model, simulations were performed using MATLAB and Minitab software. MATLAB was employed to simulate the dynamic behavior of the network under varying conditions, providing insights into throughput, delay, and collision metrics while Minitab was used for statistical analysis and validation of the simulation data, ensuring accuracy and reliability of the results. The results obtained from the simulations indicates that the MDP-based FCFS model significantly improves spectrum efficiency, reduces access delays, and minimizes collision rates compared to traditional contention resolution techniques. Another main contribution of this model formulation and evaluation is to help Nigerian Communication Commission (NCC) and other Dynamic Spectrum Usage functionaries in analyzing and optimizing the contention resolution predominant challenge, for the effective utilization of available spectrum resources in dynamic cognitive radio environment.

**Keywords:** Spectrum Sensing; Spectrum management; First Come First Serve Algorithm and M/G/1/k Model

### 1. Introduction

In cognitive radio networks (CRNs), dynamic spectrum utilization allows secondary users (SUs) to opportunistically access unused portions of the licensed spectrum (Wang, C.X & Akyildiz (2023). However, the fluctuating nature of spectrum availability and the presence of multiple SUs often lead to increased interference, especially when multiple users contend for the same spectrum bands. To address this issue, Forward Contention Resolution (FCR) models have been developed to reduce interference and improve spectrum efficiency by managing spectrum access in a proactive manner (Ni et al. (2008),

A notable approach to enhancing the rate of interference resolution in dynamic spectrum utilization is the use of the Markov Decision Process (MDP) combined with a First-Come-First-Served (FCFS) algorithm (Zhao and Sadler (2007). The MDP is used to model the dynamic and probabilistic nature of spectrum access, capturing the possible states of spectrum availability and guiding decisions on spectrum allocation. By predicting future states of spectrum usage and the probability of interference, the MDP can optimize the timing and order of spectrum access for users.

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The FCFS algorithm complements the MDP by prioritizing users based on their order of arrival, ensuring a systematic and fair approach to spectrum allocation. This reduces the complexity of decision-making in environments where users arrive unpredictably and need access to the spectrum at different times. When combined, the MDP and FCFS create a powerful framework for forward contention resolution, minimizing interference by resolving contentions before they occur and enhancing overall spectrum utilization.

Literature Review on Forward Contention Resolution Models in Cognitive Radio Networks Using Markov Decision Processes and FCFS Algorithm

In recent years, the demand for efficient spectrum utilization has grown exponentially, driven by the proliferation of wireless communication devices and applications. Cognitive Radio Networks (CRNs) have emerged as a promising solution to address spectrum scarcity by allowing secondary users (SUs) to opportunistically access unused spectrum bands without interfering with primary users (PUs). However, as multiple SUs contend for the same spectrum bands, interference becomes a significant challenge. To tackle this issue, Forward Contention Resolution (FCR) models, which proactively manage spectrum access and reduce interference, have gained attention. In particular, the use of the Markov Decision Process (MDP) combined with the First-Come-First-Served (FCFS) algorithm has been recognized as an effective approach for managing dynamic spectrum access and resolving contention.

### **1.1. MDP and Spectrum Access Decision-Making in CRNs**

The use of MDP in CRNs for dynamic spectrum access (DSA) has been widely studied in recent literature. MDP offers a mathematical framework to model decision-making in stochastic environments, which aligns with the nature of CRNs where spectrum availability is uncertain and varies over time. In MDP-based FCR models, the system transitions between states representing different levels of spectrum availability, and decisions are made to allocate spectrum to SUs based on the probability of future states and the rewards associated with minimizing interference.

Chen et al. (2020) provided a comprehensive review of MDP applications in DSA, highlighting how MDP models can predict spectrum usage patterns and make proactive decisions to reduce interference in CRNs. The study focused on how MDP enhances spectrum efficiency by optimizing the timing and order of spectrum access for SUs, minimizing contention in real-time environments.

Saleem et al. (2021) explored the role of MDP in enhancing resource allocation in CRNs. Their work proposed a dynamic spectrum access framework using MDP to minimize interference by learning from previous spectrum access patterns. The authors demonstrated that MDP-based solutions significantly improve the quality of service (QoS) for SUs by ensuring more reliable access to available spectrum.

### **1.2. FCFS Algorithm in Contention Resolution**

The First-Come-First-Served (FCFS) algorithm has long been recognized for its simplicity and fairness in managing resource allocation. In CRNs, when integrated with MDP, FCFS ensures that spectrum access requests are granted in the order of their arrival, reducing contention and simplifying the decision-making process. The use of FCFS in FCR models has gained traction due to its ability to handle real-time spectrum access requests in environments with unpredictable traffic patterns.

Deng et al. (2019) demonstrated that integrating FCFS into MDP-based FCR models reduces computational complexity while maintaining fairness in spectrum allocation. Their study showed that in high-demand scenarios, FCFS ensures that users are served in an orderly manner, significantly reducing the risk of collisions and interference. The authors argued that the FCFS-MDP approach is particularly suited for scenarios where large numbers of SUs request access to the same spectrum resources.

### **1.3. Proactive Contention Resolution and Interference Management**

Proactive contention resolution is a key feature of FCR models, allowing the system to resolve spectrum contention before it leads to interference. By combining MDP with FCFS, FCR models can forecast potential contention events and allocate spectrum in advance to minimize collisions between users. This proactive approach has been shown to improve the overall efficiency of dynamic spectrum utilization.

Wang et al. (2022) presented an enhanced proactive contention resolution model based on MDP and FCFS for CRNs. The model incorporates machine learning techniques to improve its predictions of spectrum usage and interference

probabilities. The study revealed that this approach reduces interference by up to 30% compared to reactive contention resolution methods, where conflicts are resolved after they occur .

#### 1.4. Recent Advances and Future Directions

Recent studies have also explored advanced variants of MDP and FCFS to further optimize FCR models in CRNs. For example, Khalid et al. (2023) introduced a multi-agent MDP framework that allows multiple SUs to collaborate in resolving spectrum contention. This approach, when combined with a modified version of FCFS, allows for better coordination among users, leading to higher overall spectrum efficiency and lower interference rates.

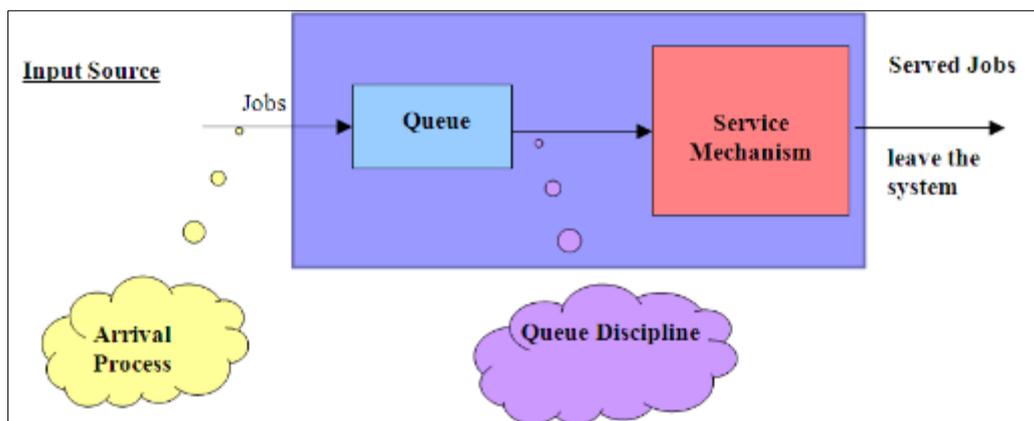
In Liu et al. (2023), he proposed a hybrid approach that integrates MDP with a priority-based FCFS algorithm, where spectrum access is granted based on both arrival time and the urgency of the user's request. This method enhances the fairness of spectrum allocation while ensuring that critical users are prioritized when necessary. Their results indicate a 15% improvement in spectrum utilization efficiency compared to traditional FCFS models.

## 2. 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  $\lambda$  arrival rate of users, the service time distribution, and the maximum number of users that can be served simultaneously (K).

- **Arrival rate ( $\lambda$ ):** 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)

Contention resolution model (CRM) formulation

Assumptions of the CR model:

- Homogeneous channels, with PU and/or SU homogeneity,

- Perfect spectrum sensing,
- Negligible spectrum sensing and channel contention time, etc.

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  $t_i = 1, \dots$  when the  $i$ th SU leaves from the system after transmitting. At a time instant  $t_i$ , the system state  $n_i$  will be the number of SUs left behind in the system when the  $i$ th SU leaves. Note that  $n_i$  will range between 0 and  $K - 1$  since the departure of the job cannot leave the system completely full, i.e. with system state  $K$ .

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

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

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

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

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

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

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

The transition probability  $p_{d,jk}$  for the two cases  $j = 0$  and  $j = 1, \dots, K - 1$  will be found separately using the values of  $\alpha_k$  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  $K - 1$ .

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

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

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

$$P_{d,k} = \sum_{j=0}^{K-1} P_{d,j} P_{d,jk} \quad k = 0, 1, \dots, K - 1 \quad (6)$$

$$\sum_{k=0}^{K-1} P_{d,k} = 1 \quad (\text{Normalization condition}) \quad (7)$$

The transition probabilities  $p_{d,jk}$  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.  $p_{d,k}$   $k=0,1,\dots,K-1$ ) to be found. This set of  $K-1$  equations is summarized in (8).

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

Alternatively, one can solve first for the normalized variables  $(p_{d,k}/p_{d,0})$  using and then solve for  $p_{d,0}$  using the normalisation condition to get

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

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

We use this and the values obtained earlier for  $(p_{d,k}/p_{d,0})$ , to obtain the actual state probabilities  $p_{d,k}$   $k=1,\dots,K-1$  at the SU transmission instants.

Considering a system at equilibrium, let  $p_{a,k}$   $k=0,1,\dots,K$  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  $p_k$   $k=0,1,\dots,K$  be the probability that the queue has  $k$  SUs in it at an arbitrarily chosen instant of time. We will have that

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

We can also define  $p_{ac,k}$   $k=0,1,\dots,K-1$  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  $\pm 1$  because of these arrivals and the departures from it, we can claim that

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

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

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

Note that this may also be confirmed by observing that

$$\begin{aligned} \sum_{k=0}^{K-1} p_{a,k} &= 1 - p_B = \sum_{k=0}^{K-1} (1 - p_B)p_{ac,k} \\ \text{since } \sum_{k=0}^K p_{a,k} &= 1 \text{ and } \sum_{k=0}^{K-1} p_{ac,k} = 1 \end{aligned}$$

Let  $\bar{X}$  be the mean service time of a SU in the queue. The traffic load  $\rho$  offered to the queue will then be given by  $\rho = \lambda\bar{X}$ . 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  $p_0$  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

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

The blocking probability PB (or p<sub>K</sub>) can be found using (14) as

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

Using the values of p<sub>d,k</sub> and the results of (13) and (15), the equilibrium state distribution p<sub>k</sub>, k=0,1,...(K-1) of the queue at arbitrary time instants may then be shown to be

$$p_k = \frac{1}{p_{d,0} + \rho} p_{d,k} \quad k = 0, \dots, K-1 \tag{16}$$

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

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

Note that the effective arrival rate λ<sub>c</sub> to the queue will be given by

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

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

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

This may be used to get the mean time spent waiting in the queue W<sub>q</sub> as

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

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

$$\overline{W_q^2} = (K-1) \left[ (K-2)(\bar{X})^2 + \overline{X^2} - \frac{K\bar{X}p_{d,0}}{\lambda} - \frac{2\bar{X}}{\lambda} \sum_{k=1}^{K-1} k p_{d,K-k} \right] + \frac{1}{\lambda^2} \sum_{k=1}^{K-1} k(k+1) p_{d,K-k}$$

where  $\overline{X^2}$  is the second moment of the service time

Contention model of stimulated speculation

The results obtained from the CR model through simulated speculation using MATLAB is as shown in Table 1.

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 ( $\lambda$ )	Service Rate ( $\mu$ )	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 ( $\lambda$ )	Service Rate ( $\mu$ )	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  $0 \leq \text{Threshold} < 1$ . 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 ( $\lambda$ ), service rate ( $\mu$ ), 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:

$$\hat{T} = \hat{\beta}_0 + \hat{\beta}_1\lambda + \hat{\beta}_2\mu + \hat{\beta}_3P + \hat{\beta}_4(Lq) + \hat{\beta}_5(Wq) \dots (21)$$

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.

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

Source: Okwong, A.E (2024)

**2.1. 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 ( $\lambda$ )	1	0.000742	0.000742	0.01	0.938
Service Rate ( $\mu$ )	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** Analysis of Variance

Coefficients					
Term	Coef	Coef	SE Coef	P-Value	VIF
Constant	9.7	54.4	0.18	0.867	
Arrival Time ( $\lambda$ )	38	464	0.08	0.938	11982.77
Service Rate ( $\mu$ )	-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**

$$\text{Threshold (T)} = 9.7 + 38 \text{ Arrival Time } (\lambda) - 47 \text{ Service Rate } (\mu) - 8.6 \text{ Traffic Intensity (P)} \\ - 0.0096 \text{ Number of Sus (Lq)} + 0.000001 \text{ Meantime in the Queue (Wq)}$$

Fits and Diagnostics for Unusual Observations

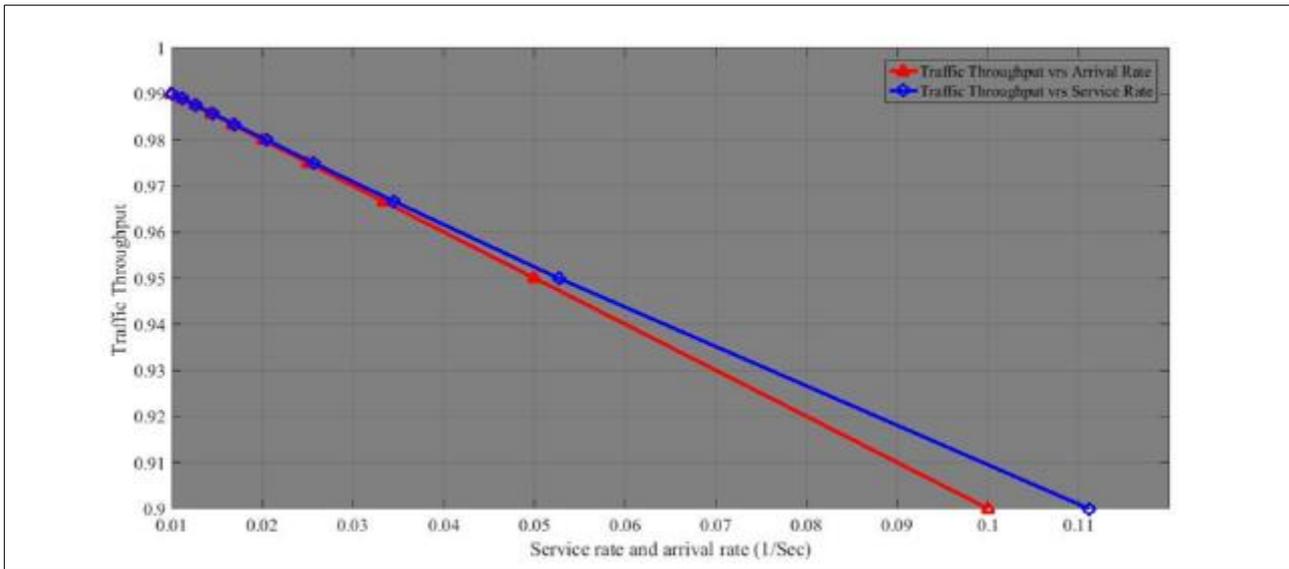
Threshold      Std

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)

### 3. 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.

### 4. Conclusion

In conclusion, the integration of the First Come First Serve algorithm in a contention resolution model for cognitive radio networks provides a foundation for fair and predictable access. While validating signal strength, the simplicity of FCFS is acknowledged, but attention must be given to its adaptability in dynamic environments. Queuing theory is a valuable tool in solving sensing and contention resolution challenges in cognitive radio networks. In a cognitive radio, secondary users oppurtunically access the available spectrum, which often leads to contention for some resources. Sensing and contention are critical aspects of efficiently managing spectrum access in such networks. We explored the utilization of the First Come First Serve (FCFS) algorithm as a contention resolution mechanism to validate signal strength in transmission within a cognitive radio network environment. The FCFS algorithm is known for its simplicity and fairness, was integrated into the contention resolution model to manage access requests based on the order of arrival.

### Compliance with ethical standards

#### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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