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The Impact of Servers Reliability on the Characteristics of Cognitive Radio Systems*

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Abstract

The current paper presents a finite-source retrial queuing system that models a Cognitive Radio Network (CRN) dealing with two types of requests (primary and secondary) attached to two interconnected, non-independent frequency bands. An orbit and a First In First Out queue are assigned to the second and first service units, respectively. The first server is meant to handle requests coming from Primary Users (PUs), the second one is built for the requests of Secondary Users (SUs). The newly generated primary requests are directed to the Primary Service Unit. In case of an idle status, the service process of these jobs can start immediately. If it is busy with a licensed request, the last generated packet is routed to the FIFO queue. However, if the channel is busy with an unlicensed request, its service is discontinued and the latter request must be returned to the Secondary Service Unit. Depending on the status of the units, the suspended jobs are added to either the server or the orbit. If an SU request discovers an idle status in the Secondary Channel Service (SCS), the service can be resumed right

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away, however, If the SCS is busy, the new request might attempt joining the Primary Channel Service (PCS). Assuming the PCS is idle, the low priority packet can opportunistically be hosted by the high-priority server, otherwise, it needs to join the orbit. From orbit, the deferred requests retry to be served after a random time. It should be noted that the secondary service unit is non-reliable, which means that the server is subject to random failures depending on whether it is busy or idle. We decided to assume that only the secondary server of our system is unreliable, since having both servers unreliable is another case study and due to the limitation of pages we have focus our analysis on the secondary part of the system to demonstrate the positive effect of sharing the channels cognitively. The novelty of this work is to investigate the impact of the failure time distribution of the SCS, distinguishing its state (idle or busy). Our approach is based on simulation to study the effects of the mentioned two scenarios on different performance measures of the system, using several distributions (Pareto, gamma, log-normal, hyper-exponential and hypo-exponential). Multiple figures illustrate the problem in the question.

Keywords: Finite source queuing systems, simulation, Cognitive Radio Networks, performance and reliability measures, non-reliable servers

1. Introduction

The main objective of our model "Cognitive Radio Network" is to utilize the free portions of the licensed frequency bands for the benefit of secondary customers. Further details are given in [1, 5, 7, 9, 10, 13, 16, 17, 19]. In this queuing system, we consider two elements; a first subsystem is intended for the jobs of Primary Users (PU) with a finite number of sources. In this subsystem, each source generates a primary call for the PUs after an exponentially distributed time; the latter requests are forwarded to a single server Primary Channel Service (PCS) with a preemptive discipline (FIFO queue) to start the service, assuming that the service time is also exponentially distributed. The second component of the system is set up for Secondary Users (SU) requests coming from a finite source and forwarded to Secondary Channel Service (SCS), presuming that the arrival and service times of the secondary users are exponentially distributed. In order to test the usability, the generated licensed tasks are targeting the PCS. If this service unit is unoccupied, the service starts immediately. However, if the PCS is busy with another primary task, this last task joins a First In First Out (FIFO) queue. In case of having a second job is being handled in the primary unit, it disconnects immediately and will be routed back to the Secondary Channel Service. Depending on the status of the secondary channel, the aborted job either restarts the service on its original server "SCS" or is added to the retrial queue (Orbit). Besides, the secondary channel also receives low priority requests. If the aimed unit is idle, the service may start immediately. Otherwise, these secondary requests will attempt to join opportunistically the primary unit. If the last unit is idle, the secondary requests will have the opportunity to start. If not, they will automatically enter the orbit. From the orbit, the postponed requests retry to receive service after an exponentially distributed random interval. Numerous studies have examined the CRN based on different scenarios. Using the example of paper [2], the authors have used some theoretical queuing approaches on a finite source cognitive radio network with two channels (primary and secondary) to investigate the main performance measures of this system using a tool-based approach. However, a similar study [14] analyzed a single server network that was subject to failures and repairs. With this type of network, some difficulties could arise during periods of high utilization, as the failure of a single server could affect the entire system. Using primary and secondary service channels and a retrial queue, the authors of [10] assumed that both channels of the presented system were subject to random failures and repairs. In this paper, the authors aimed to illustrate the influence of different distributions (exponential, hypo-, and hyper-exponential) on such a system's main performance measures. As an extended work, the authors of [18] added the gamma distribution to the above-mentioned distributions. In [11] and [12] the hypo-, hyper-exponential distributions were implemented, assuming that the secondary queries of the CRN are subject to collisions and that the two services of such a system are unreliable.

However, in this investigation, we are assuming that only the secondary unit is unreliable and differentiating the failures (idle or busy state).

After a deep immersion in many similar investigations and studies, we did not find any papers that dealt with the unreliability in such model, distinguishing the failures in a busy and idle state. Consequently, several figures will illustrate the impact of the various distributions on the performance measures of the second part of the system, using stochastic simulation.

2. System Model

Figure 1 shows a queueing cognitive radio system with the following assumptions. Consider two interconnected subsystems, where the licensed requests are generated by a finite number of sources N_1. These sources generate primary calls corresponding to an exponentially distributed time with an average value of λ_1 which are sent to the primary service unit. If the server is idle, the service starts immediately. If the server is busy, the call joins a preemptive priority queue. The primary service time is supposed to be exponentially distributed random variable with a mean μ_1.

For the secondary part, the number of sources is denoted by N_2. Each source generates low priority calls according to an exponentially distributed time with a mean value of N_2/λ_2. The secondary service time is exponentially distributed with a parameter μ_2. We assume that the secondary service unit is non-reliable, which means that the server is subject to random failures depending on whether it is in a busy or idle state. The secondary service unit may fail after a time, which is generally distributed with a rate θ_2 during idle state and γ_2 during a busy state. The operating time (or inter-failure time) during the busy or idle state is supposed to be hyper-exponential, hypo-exponential, gamma, lognormal and Pareto distributed random variables. Similarly, for repair time, the rate is σ_2. The retrial time of the secondary customers is supposed to be exponentially distributed random variable with a parameter ν/N_2.

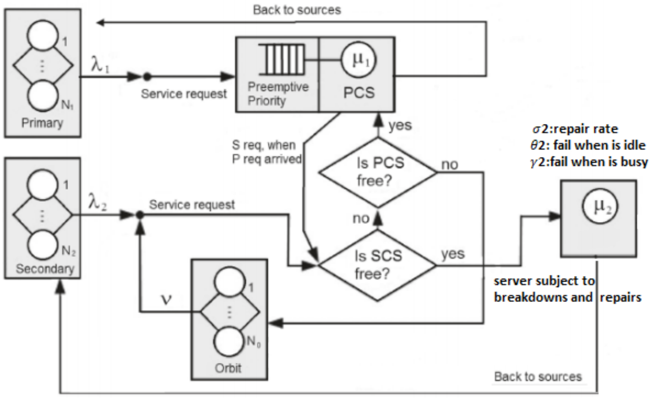

Figure 1. Finite-source retrial queuing system: Modeling the Cognitive Radio Network with unreliability.

Table 1. Parameters of the simulation.

Parameters	Notation
Primary sources	N_1
Secondary Sources	N_2
Primary arrival rate	λ_1
Secondary arrival rate	λ_2
Primary service rate	μ_1
Secondary service rate	μ_2
Retrial rate	ν
Failure rate while idle	θ_2
Failure rate while busy	γ_2
Repair rate	σ_2

Assuming that all random variables included in the system are exponentially distributed except the failure and repair times which are generally distributed random variables, we created a stochastic simulation program written in C coding language with SimPack [6] libraries. All the numerical results were collected by the validation of the simulation outputs. The input parameters are displayed in Table 1. It should be noted that the batch-mean approach was used in our simulation for the estimations of the characteristic of the system. This approach is a popular technique of confidence interval that is used for the analysis of the performance of the steady-state simulation. For instance, see [3, 4, 8, 15].

3. Simulation Results

Performance modelling and analysis of systems with non-reliability has been investigated using asymptotic methods in [14]. Since the authors have supposed that the inter-event times were exponentially distributed, the stationary state has been reached by the construction of a continuous Markov chain.

This paper deals with a more general situation allowing non-exponential distributions. Therefore, the simulation approach is the most efficient method which helps us in performance modelling and analysis when the steady-state equations are not solvable.

For a better understanding of numerical results, we presume that in our system the disrupted secondary service from the PCS due to the arrival of PUs or from the SCS due to server failure will be repeated from the beginning (non-intelligent). Furthermore, the failure of the service unit will not obstruct the system and free sources will continue to create new jobs.

In this paper, we have performed several simulations runs in order to investigate the impact of the operating and the repair times distribution on the behaviour of the system. Mainly, we have investigated separately the cases when the server fails during idle or busy state. Many scenarios might be treated using our introduced model, however, due to the limitation of pages, we have assumed only the following three scenarios:

Scenario 1: SCS repair time is generally distributed, assuming that the operating time is Exponentially distributed.

Scenario 2: SCS operating time is generally distributed when server fails during idle state, assuming that the repair time is Exponentially distributed.

Scenario 3: SCS operating time is generally distributed when server fails during busy state, assuming that the repair time is Exponentially distributed.

Table 2. Numerical values of the model parameters.

N_1	N_2	λ_1	λ_2/N_2	μ_1	μ_2	ν/N_2	θ_2	γ_2	σ_2
10	10	0.01	x-axis	1	1	0.01	0.1	0.1	1

All the numerical values of parameters for the statistical methods are defined in Table 2 and were collected based on some previous works dealing with the same model, such as [1, 9, 12]. Furthermore, different set of parameters were used, however the output result from these input parameters has the most significant impact.

3.1. Repair Time is Generally Distributed

Firstly, our aim is to investigate how the various distributions of repair times, where the mean and variance are equal, effect the performance analysis. Depending on the square coefficient of variation, the investigation is split into two parts.

Table 3 represents the input parameters for the distributions of the repair times. These parameters are chosen according to the squared coefficient of variation.

Table 3. Parameters of the distribution.

Distribution		Hyper	Hypo	Gamma	Pareto	Log-normal
Figure 5,6,7	**Mean**	N/A	1	1	1	1
	Variance	N/A	0.68	0.68	0.68	0.68
	Parameters	N/A	$\lambda_1 = 1.25$ $\lambda_2 = 5$	$\alpha = 1.4705$ $\beta = 1.4705$	$\alpha = 2.75181$ $k = 0.61116$	$m = 0.72027$ $\sigma = -0.25939$
Figure 2,3,4	**Mean**	1	N/A	1	1	1
	Variance	2.56	N/A	2.56	2.56	2.56
	Parameters	$\lambda_1 = 0.6619$ $\lambda_2 = 1.33803, p = 0.3309$	N/A	$\alpha = 0.3906$ $\beta = 0.3906$	$\alpha = 2.1792$ $k = 0.5411$	$m = 1.1268$ $\sigma = -0.6348$

Squared coefficient of variation is greater than one

Figure 2, Figure 3 and Figure 4 illustrate the impact of the server's repair time distribution on the mean sojourn time of secondary customers, total utilization of secondary server and mean service time of secondary customers, respectively. These measures are displayed in function of the arrival intensity of the secondary customers. Figures show an important impact of the repair times distribution on these features. In Figure 2, the log-normal distribution gives a higher value of the mean response time while the gamma distribution provides the smallest value of the mean. However, since the gamma distribution generates small values using the mentioned input parameters, the server is recovered faster, thus, the greater value of the utilization is shown in Figure 3. Similarly, in Figure 4 the highest value of the mean service time is provided by the gamma distribution since the system is most of the time in operational mode.

The explanation of the results might depend on the observed random variable. For instance, the behaviour of mean total of primary and secondary service time will change in case of changing the distributions mean and variance. The analysis of the performance measures of such a system using simulation allows us to investigate the characteristics that are almost impossible to analyse analytically. However, our explanation of the results is as follows:

In Figure 2 the repair time is generally distributed. If we see the graph of the Probability Density Function of the lognormal and gamma distribution, the relative likelihood of the random variable x (repair time) is clearly greater in the case of the lognormal distribution than in the case of the gamma which means that the repair time will take more likely greater values in case it is lognormally distributed. Thus, it involves greater response time of the customers considering that the server takes longer time to be repaired. On the other side, Figure 3 shows that the utilization of the server while the repair time is lognormally distributed has smaller values than when it is gamma distributed because the server is most of the time down and not occupied by a customer.

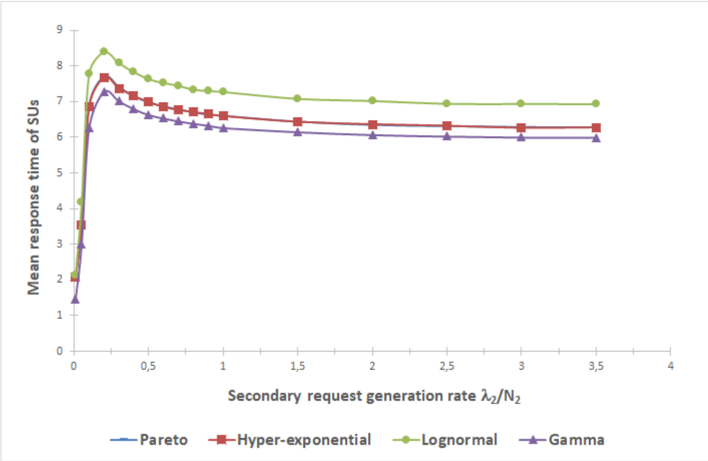

Figure 2. The effect of repair time distributions on the mean sojourn time of cognitive users vs secondary arrival rate.

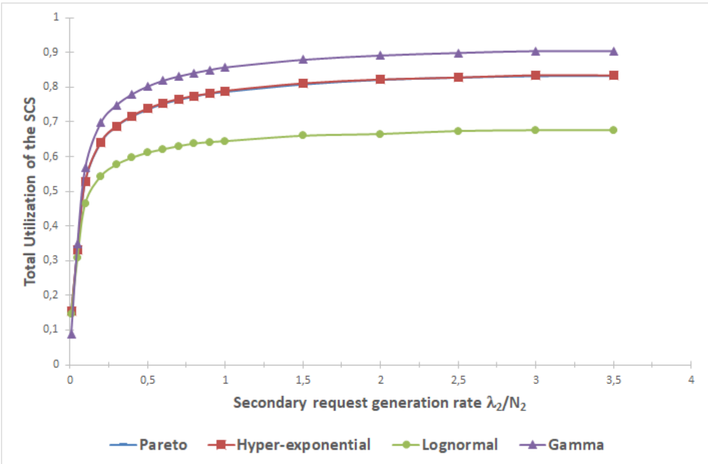

Figure 3. The effect of repair time distributions on total utilization of the secondary server vs secondary arrival rate.

Squared coefficient of variation is less than one

In this part, let us investigate and compare the effect of the repair time distribution on the same features shown above, but in this situation, we replace the hyper-exponential distribution by the hypo-exponential distribution and set new parameters that their coefficient of variation is less than one.

Similarly, Figure 5, Figure 6 and Figure 7 show the effect of the repair time distribution on the mean response/service time of secondary calls and utilization of

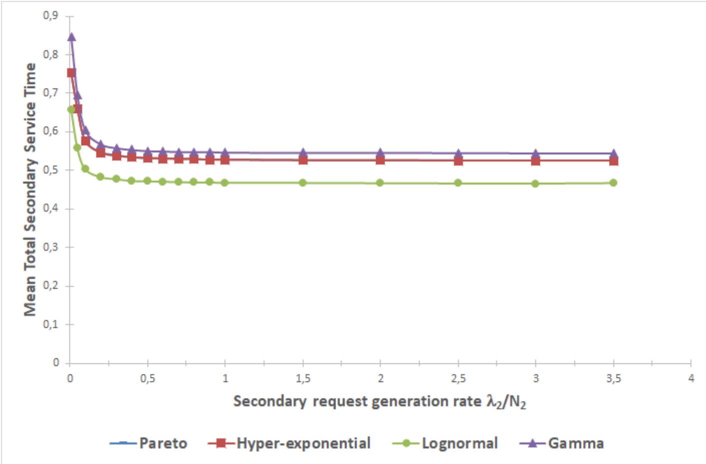

Figure 4. The effect of repair time distributions on total utilization of the secondary server vs secondary arrival rate.

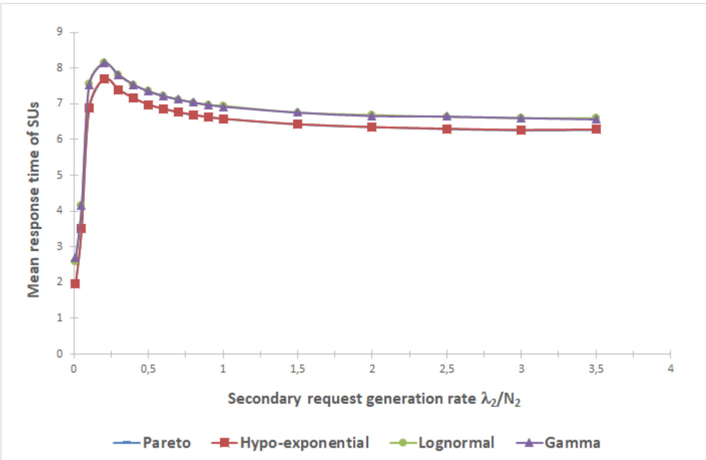

Figure 5. The impact of repair time distributions on the mean response time of SUS vs λ_2/N_2.

SCS versus secondary request generation rate. In this case where the distribution have their $C_x^2 < 1$, the difference in the values of the performance measures is between two groups of distributions. Pareto and hypo-exponential give similar values of the estimations. These values are greater than the one resulted from the log-normal and gamma distribution. The explanation of the illustrated impact of the distributions is similar as the case of squared coefficient of variation greater than 1.

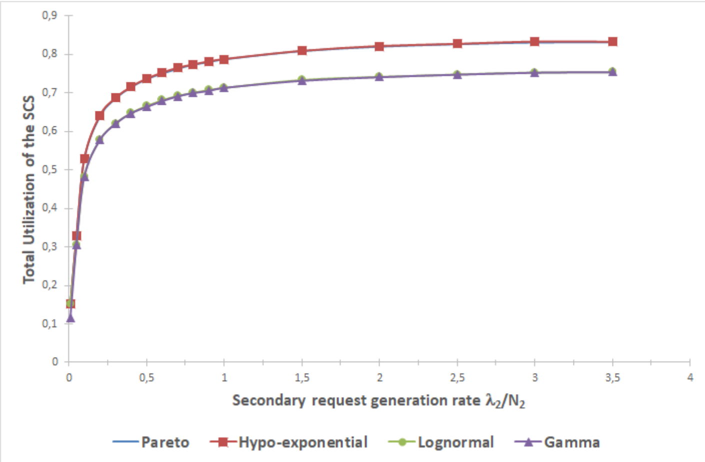

Figure 6. The impact of repair time distributions on the total utilization of secondary server vs λ_2/N_2.

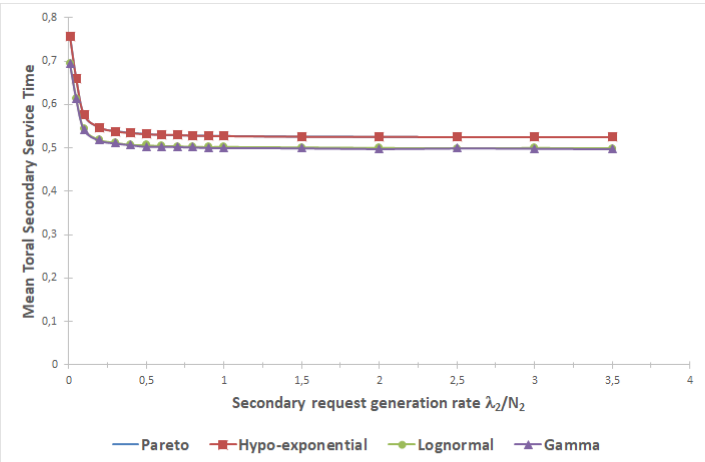

Figure 7. The impact of repair time distributions on the mean total secondary service time vs λ_2/N_2.

In this scenario, the expected phenomenon was obtained such the property of having a maximum value of the mean. Also, increasing the arrival intensity involves higher utilization of the server and lower mean service time.

3.2. Operating Time is Generally Distributed

In this scenario, we analyze the distributions of operating times depending on the square coefficient of variation, this part is divided into two subsections.

Table 4 represents the input parameters for the distributions of the inter-failure times.

Table 4. Parameters of the distribution.

Distribution		Hyper	Hypo	Gamma	Pareto	Log-normal
Figure 11,12,13,17,18,19	**Mean**	N/A	10	10	10	10
	Variance	N/A	0.68	0.68	0.68	0.68
	Parameters	N/A	$\lambda_1 = 0.125$ $\lambda_2 = 0.5$	$\alpha = 1.470588$ $\beta = 0.14705$	$\alpha = 2.57181$ $k = 6.111689$	$m = 0.72027$ $\sigma = 2.043088$
Figure 8,9,10,14,15,16	**Mean**	10	N/A	10	10	10
	Variance	2.56	N/A	2.56	2.56	2.56
	Parameters	$\lambda_1 = 0.132392$ $\lambda_2 = 0.133804, p = 0.33098$	N/A	$\alpha = 0.390625$ $\beta = 0.0390625$	$\alpha = 2.1892$ $k = 5.4321$	$m = 1.667705$ $\sigma = 1.12684$

Server fails during idle state

Let's consider the inter-failure time of the server during an idle state generally distributed and all the other involved random variables are exponentially distributed.

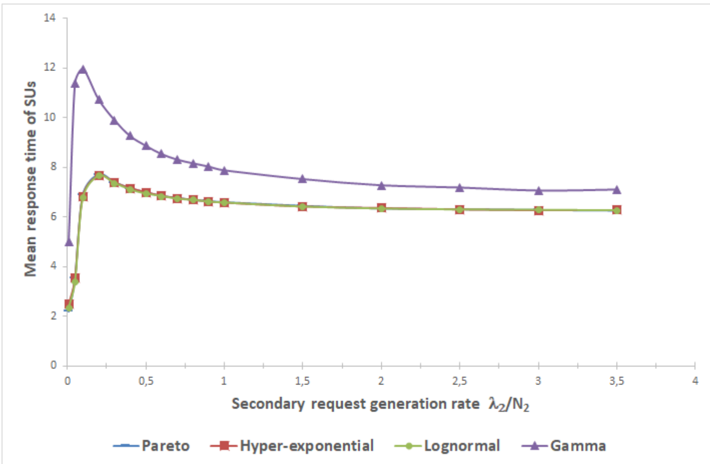

Figure 8. The effect of the operating time distributions on the mean sojourn time of cognitive users vs secondary request generation rate.

Figure 8, Figure 9 and Figure 10 illustrate the impact of the failure time distribution during idle state on the mean response time, utilization of the SCS and PCS respectively while the running parameter is λ_2/N_2. The distributions on the figures have their $C_x^2 > 1$. Despite the gamma distribution, which involves a big difference in the estimation of the mean sojourn time and the utilization, the other distributions have no effect on the performance. An impact of the gamma distribution as well on the utilization of the primary channel can be seen in Figure 10. The generated inter-failure times from gamma distribution make the server more often non-operational and the impact can be seen even on the utilization of the primary service channel.

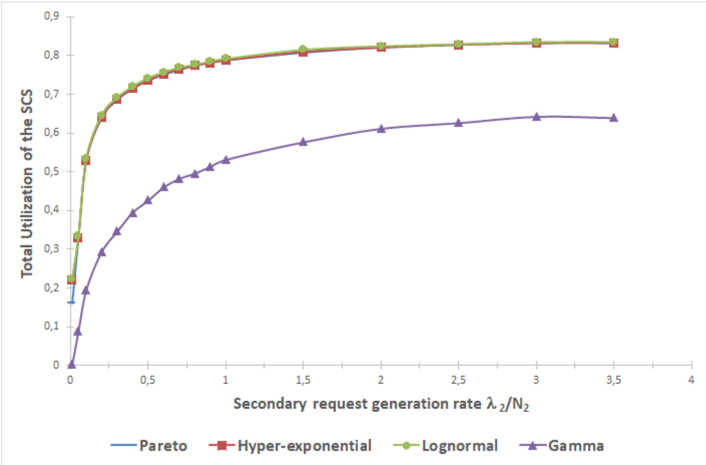

Figure 9. The effect of the operating time distributions on the utilization of SCS vs secondary arrival rate.

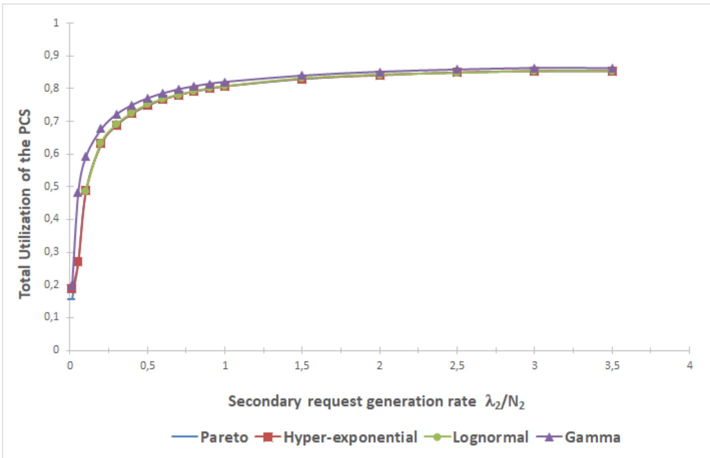

Figure 10. The impact of the operating time distributions on the utilization of PCS vs secondary arrival rate.

Figure 11, Figure 12 and Figure 13 illustrate the same features as the figures above in this section, but in this time, we replaced the hyper-exponential distribution by the hypo-exponential distribution in order to investigate the case of distinguished distributions with $C_x^2 < 1$. With this set of parameters, the relative difference between gamma and the other distributions is very small comparing with the corresponding figures above. Still a small impact can be seen on the mean residence time and utilization of the SCS but there no effect on the PCS.

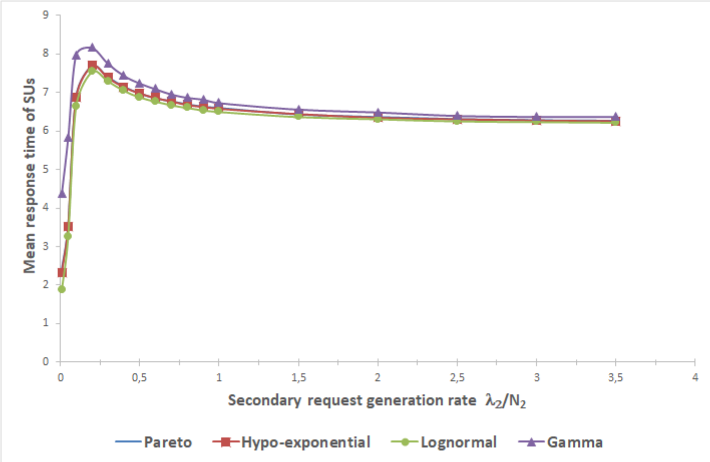

Figure 11. The effect of the operating time distributions on the mean sojourn time of cognitive users vs λ_2/N_2.

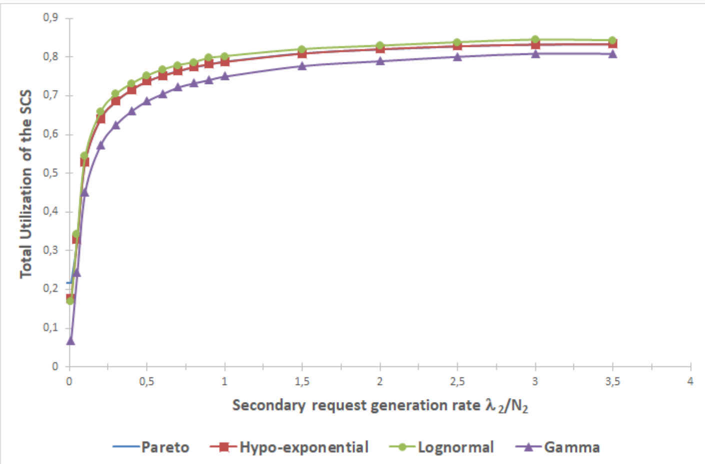

Figure 12. The impact of the operating time distributions on the utilization of SCS vs secondary arrival rate.

Server fails during busy state

In the last scenario of our investigation, we suppose the failure time of the server during a busy state generally distributed and all the other involved random vari-

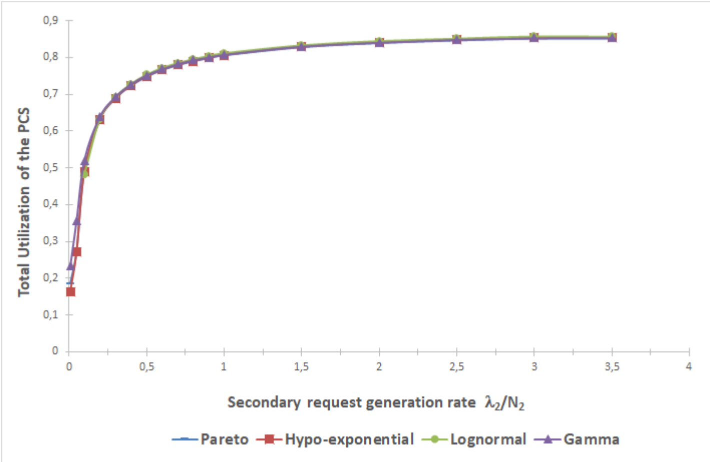

Figure 13. The effect of the failure time distributions on the utilization of primary server vs secondary arrival rate.

ables exponentially distributed. Similarly, as the above investigation, we will start with the hyper-exponential distribution and set the gamma, Pareto and log-normal with $C_x^2 > 1$.

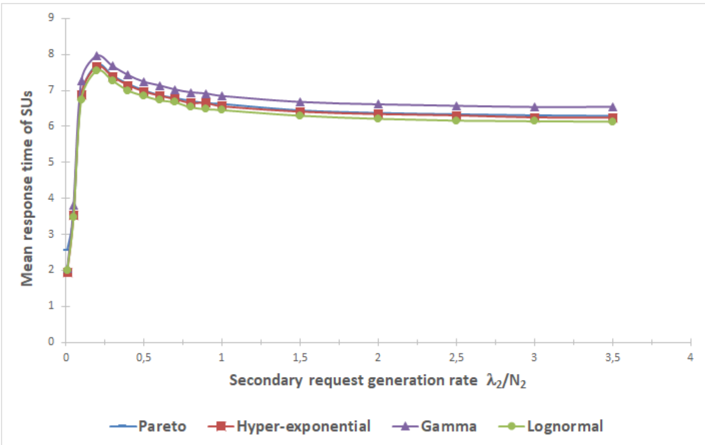

Figure 14. The effect of the operating time distributions on the mean sojourn time of cognitive users vs λ_2/N_2.

Figure 14, Figure 15 and Figure 16 display the effect of the inter-failure time distribution during busy state on the mean sojourn time, utilization of the SCS and PCS respectively versus λ_2/N_2. Figure 14 shows the impact of the distribution where the gamma gives a higher value of the mean response but the log-normal gives the smallest value. In Figure 15, the gamma distribution provides the lowest utilization of the server as expected.

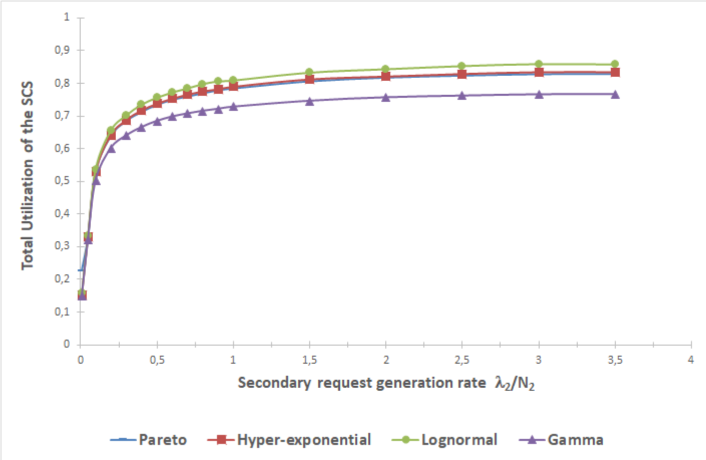

Figure 15. The impact of the operating time distributions on the utilization of SCS vs secondary arrival rate.

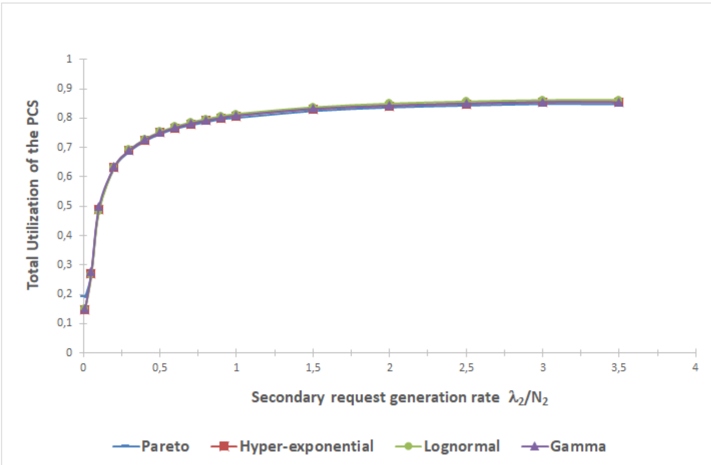

Figure 16. The effect of the failure time distributions on the utilization of primary server vs secondary arrival rate.

In Figure 17, Figure 18 and Figure 19. The hypo-exponential distribution takes place instead of the hyper-exponential. The figures illustrate the same estimation as Figure 14, Figure 15, and Figure 16, respectively. In this case, we notice an opposite behaviour of scenario 2 where the inter-failure time during idle state was generally distributed. In this later, the relative difference of the estimations caused by the gamma distribution was smaller in the case of the hypo-exponential distribution. However, in this scenario, we see the figures that the relative difference between the estimations is greater in the case of the hypo-exponential distribution and smaller in the case of the hyper-exponential distribution.

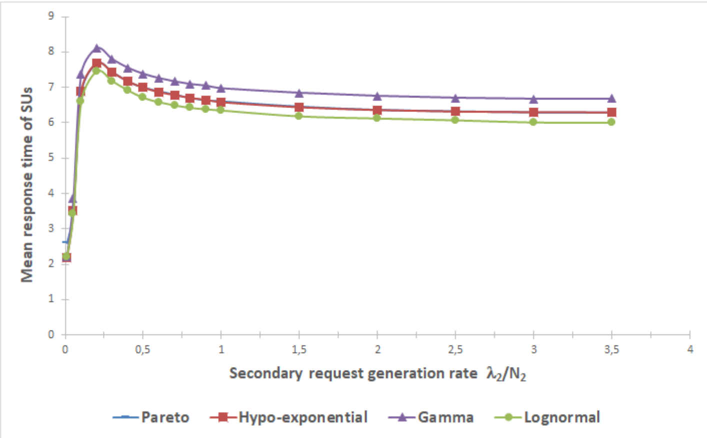

Figure 17. The effect of the operating time distributions on the mean sojourn time of cognitive users vs λ_2/N_2.

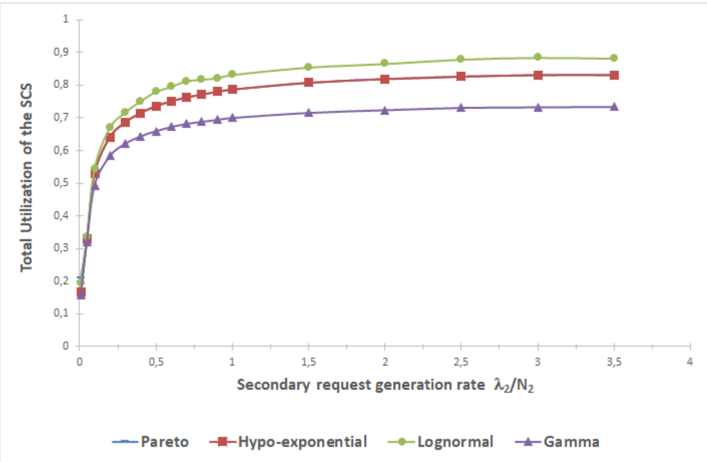

Figure 18. The impact of the operating time distributions on the utilization of SCS vs secondary arrival rate.

We notice from Figure 16 and Figure 19 that whether the squared coefficient of variation is greater or less than one, the distribution of the inter-failure time during busy state has no effect on the primary service channel.

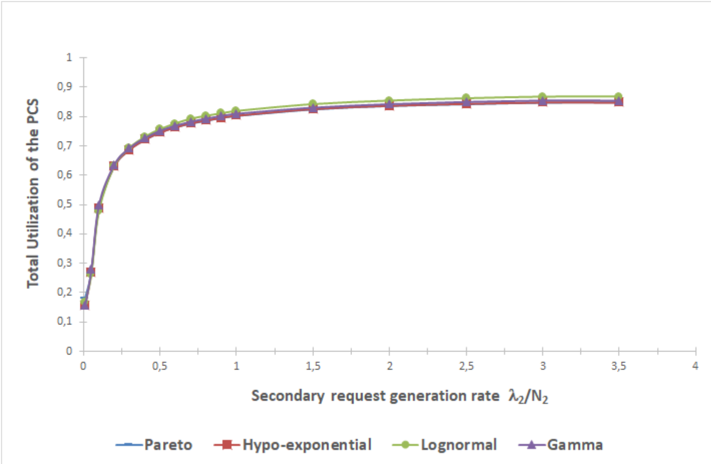

Figure 19. The effect of the failure time distributions on the utilization of primary server vs secondary arrival rate.

However, our explanation regarding the significant difference is shown in the figures is the following: let us consider the sample examples illustrated by Figure 8 and Figure 14 that show respectively the effect of the operating time distribution on the SU mean response time while the server breaks down during idle and busy state. The difference is significant when the arrival rate $\lambda_2/N_2 \in [0.1, 1]$. At this low arrival intensity, the server breaks down more likely during idle state, and the arrival customers during the repair time cannot join the service unit (Continues case study) which it involves greater response time. The difference can be seen while the operating time is gamma distributed because of the smallest values of that gamma distribution generates (Short operation time).

4. Conclusion

In this paper, we presented a finite-source retrial queueing system with two non-independent sub- systems to model cognitive radio network with primary and secondary service units subject to random break-downs and repairs. With the help of simulation, a detailed analysis has been performed in order to investigate the impact of the inter-failure time distribution separately during idle and busy state on the main performance measures of the system. In this paper, we have shown that the performance of the system depends on the state of the server at a random breakdown.

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