Greedy versus Dynamic Channel Aggregation Strategy in CRNs: Markov Models and Performance Evaluation

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Abstract. In cognitive radio networks, channel aggregation techniques which aggregate several channels together as one channel have been proposed in many MAC protocols. In this paper, we consider elastic data traffic and spectrum adaptation for channel aggregation, and propose two new strategies named as *Greedy* and *Dynamic* respectively. The performance of channel aggregation represented by these strategies is evaluated using continuous time Markov chain models. Moreover, simulation results based on various traffic distributions are utilized in order to evaluate the validity and preciseness of the mathematical models.

Keywords: Cognitive radio networks, channel aggregation strategy, continuous time Markov chain models, performance evaluation.

1 Introduction

In Cognitive Radio Networks (CRNs) [1], when multiple channels are available, Secondary Users (SUs) can decide to aggregate them together as one channel to support services with higher data rate or still to treat them as individual channels. The former alternative, channel aggregation, has been proposed in many Media Access Control (MAC) protocols [2–4] in CRNs.

The research work on spectrum access in CRNs can be categorized into two phases. The first phase is MAC protocol design itself, which aims at proposing feasible schemes to make CRNs access spectrum more efficiently [2–4]. The second phase is to build analytical models in order to help us better understand the dynamics behind these schemes and evaluate the performance of different strategies [5–9]. In this study, we mainly focus on the second phase and analyze the performance of channel aggregation represented by two new strategies, i.e., the *Greedy* strategy and the *Dynamic* strategy, when spectrum adaptation is enabled. This work is motivated by the observation that the performance of SU networks with various channel aggregation strategies is not thoroughly analyzed through mathematical models. For example, in [5–7], the performance of an SU network when a channel for Primary Users (PUs) can be divided into several channels for SUs is analyzed based on a Continuous Time Markov Chain (CTMC) model. In [8, 9], the performance of several channel aggregation strategies when spectrum adaptation is not enabled is studied through CTMC models. However, none of them analyze channel aggregation with spectrum adaptation systematically through mathematical modeling.

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The meaning of spectrum adaptation is twofold. On the one hand, it is inherited from spectrum handover, allowing SUs to switch an ongoing SU service to a channel that is not occupied by PUs or SUs, when PUs appear on the current channel. On the other hand, it is meant that an ongoing SU service can adjust the number of aggregated channels according to the availability of channels as well as other SUs' activities. Since spectrum adaptation is potentially more appropriate for CRNs, we propose two channel aggregation strategies with spectrum adaptation in which SUs greedily or dynamically aggregate a number of available channels. Based on the proposed strategies, we present CTMC models to analyze their performance. Then, numerical results obtained from mathematical models and simulations are analyzed and compared. Finally, the results under various traffic distributions are examined by simulations and compared with the analytical results.

The rest of this paper is organized as follows. The system model and channel aggregation strategies are described in Sec. 2. In Sec. 3, CTMC models are built in order to analyze the performance of these strategies. Numerical results and corresponding discussions are presented in Sec. 4. Finally, the paper is concluded in Sec. 5.

2 System Model and Channel Aggregation Strategies

2.1 System Model and Assumptions

Two types of radios, PUs and SUs, operate in the same spectrum band consisting of M channels for PUs. The channels are allocated to PUs, and can be utilized by SUs when they are not occupied. SUs must release the channel upon a PU appearance. Each PU service occupies only one channel while SUs may aggregate multiple channels, N ($N \leq M$), for a service (a packet, flow or session) transmission. The aggregated channels can be either adjacent or separated in the spectrum domain.

We assume that there is a protocol with ignorable overhead working behind to support channel aggregation and spectrum adaptation, and SUs can sense PUs activities precisely. It is further assumed that the sensing and spectrum adaptation latency is much shorter than the duration between service events. We thus assume that the arrival or departure of services will not happen during the sensing and spectrum adaptation period. In the following analyses, we focus on the performance of the *secondary network*.

2.2 Channel Aggregation Strategies

In what follows, the $Greedy$ and the $Dynamic$ strategies are proposed. In the strategy descriptions, two parameters, W, V are utilized to indicate the lower bound and the upper bound of the number of aggregated channels respectively. Let N denote the number of channels that an SU service aggregates. This number can vary from one SU service to another and even vary along time for a single SU service.

***Greedy* $\boldsymbol{W \leq N \leq V}$:** In this strategy, an SU is to aggregate up to V channels at the time when it tries to access channels if the number of idle channels is larger than or equal to W. During an SU service period, if any channels become idle, ongoing SU services with fewer than V channels will greedily aggregate those newly available ones up to V. Moreover, if there is no idle channel upon a PU arrival, ongoing SU services will adjust downwards the number of channels, as long as its remaining number is still not fewer than W. If a PU takes any one of these channels that is in use by an ongoing SU service with exactly W channels when no idle channel exists currently, the service is forced to terminate. Upon the arrival of a new SU service request, if there are fewer than W idle channels, the request will be blocked.

In the presence of multiple ongoing SU services that can utilize newly vacant channels, the one that currently has the minimum number of aggregated channels will occupy them first. If the SU service with the minimum number reaches the upper bound V after adjusting and there are still vacant channels, other SU services will occupy the remaining ones according to the same principle, until all those newly vacant channels are utilized or all of the ongoing SU services aggregate V channels. For example, assume that four channels become idle while there are two ongoing SU services occupying one and two channels respectively, in *Greedy* $1 \leq N \leq 4$. The ongoing SU service with one channel will then acquire three of the four idle channels and reach the upper bound. Since there is still one idle channel left, the other ongoing SU service with two channels will use this one.

Dynamic $\boldsymbol{W \leq N \leq V}$**:** In this strategy, SU services react in the same way as in the *Greedy* strategy when PU services arrive and when PU or SU services depart. However, upon an SU arrival, if there are not enough idle channels, instead of blocking it, ongoing SU services will share their occupied channels to the newcomer, as long as they can still keep at least W channels and the number of channels is sufficient for the new SU service to commence after sharing.

With this strategy, when a new SU service needs the channels shared by ongoing SU services to commence and there are several ongoing SU services, the one that occupies the maximum number will release its channels first. If the one with maximum number cannot provide enough channels by itself, the one with the second maximum number will share its channels then, and so on. The new SU service will aggregate W channels initially if it needs the channels shared by ongoing SU services to join the network. If the number of idle channels together with the number of channels that can be released by all ongoing SU services is still lower than W, the request is blocked.

In summary, ongoing SU services are given higher priority to finish their transmission first in the *Greedy* strategy while the access opportunities are more fairly shared among SUs in the *Dynamic* strategy. A special case of these strategies is $W = V = 1$, i.e., without channel aggregation. We denote it as *No aggregation* in our numerical results presented later.

3 CTMC Models for the Channel Aggregation Strategies

To model different strategies, we develop CTMCs by assuming that the service arrivals of SUs and PUs to these channels are Poisson processes with arrival rates λ_S and λ_P respectively. Correspondingly, the service times are exponentially distributed with service rates μ_S and μ_P in one channel. The newly arrived PU services will access channels that are not occupied by PU services with the same probability. Elastic traffic is considered, which means that the service time will be reduced if more channels are utilized for the same service. Assume further that all the channels are homogeneous. Therefore, the service rate of N aggregated channels is $N\mu_S$. The unit for these parameters can be service/time unit. Given concrete values to these parameters, the results can be expressed, e.g., in Mbps. For this reason, the unit of capacity is not explicitly expressed in our analysis.

For both of the *Greedy* and *Dynamic* strategies, the states of the CTMC models can be represented by $\boldsymbol{x} = (i, j_W, ..., j_k, ..., j_V)$, where i is the total number of PU services while j_k is the number of SU services that aggregate k channels in the system. We denote by $b(\boldsymbol{x})$ the total number of used channels at state $\boldsymbol{x}$ as $b(\boldsymbol{x}) = i + \sum_{k=W}^{V} kj_k$.

3.1 CTMC Analysis for the Greedy $W \leq N \leq V$ Strategy

Given concrete values of M, V and W, the feasible states of the CTMC model for the *Greedy* strategy can be expressed as a combination of two categories. The first category refers to the states with vacant channels, i.e., when $b(\boldsymbol{x}) < M$. The second category follows $b(\boldsymbol{x}) = M$. Denote the set of states in the second category by C, the feasible states of this strategy, $\mathcal{S}$, can be expressed as $\mathcal{S} := \{(i, 0, ..., 0, j_V)|b(\boldsymbol{x}) < M\} \cup C$. Since the state set C is not obvious, we propose an algorithm to construct it in an iterative manner, as illustrated in Alg. 1. The state transitions can be found in Table 1. Based on the balance and the normalization equations, the state probability, $\pi(\boldsymbol{x})$, can be calculated and the following performance parameters can be further obtained.

Algorithm 1. To acquire state set C

$C := \{\boldsymbol{x} \,|b(\boldsymbol{x}) = M, j_V = \left\lfloor \frac{(M-i)}{V} \right\rfloor, j_k = 1, k = M - i - Vj_V\}$,
$F := \{(i+1, j_W, \ldots, j_p + 1, j_{p+1} - 1, \ldots, j_V) \mid \forall (i, j_W, \ldots, j_p, j_{p+1}, \ldots, j_V) \in C$, $p \in \{W, \ldots, V-1\}, j_{p+1} > 0\}$,
$D_o := F - F \cap C, C := C \cup D_o$,
while $D_o \neq \emptyset$ **do**
  $F := \{(i+1, j_W, \ldots, j_p + 1, j_{p+1} - 1, \ldots, j_V) \mid \forall (i, j_W, \ldots, j_p, j_{p+1}, \ldots, j_V) \in D_o$, $p \in \{W, \ldots, V-1\}, j_{p+1} > 0\}$,
  $D := F - F \cap C, C := C \cup D, D_o := D$.
end while

The blocking probability of SU services, P_b, is given by

$$P_b = \sum_{\boldsymbol{x} \in \mathcal{S}, M - b(\boldsymbol{x}) < W} \pi(\boldsymbol{x}). \tag{1}$$

The capacity of the secondary network, ρ, is the average number of SU service completions per time unit [5], as follows,

$$\rho = \sum_{\boldsymbol{x} \in \mathcal{S}} \sum_{k=W}^{V} kj_k \mu_S \pi(\boldsymbol{x}). \tag{2}$$

Table 1. Transitions from a generic state $\boldsymbol{x} = (i, j_W, \ldots, j_k, \ldots, j_V)$ of *Greedy* $W \le N \le V$, $W \le k \le V$

Activity	Dest. state	Trans. rate	Conditions
PU departs, and an SU service with k channel(s) uses the vacant channel	$(i-1, j_W, \ldots, j_k-1, j_{k+1}+1, \ldots, j_V)$	$i\mu_P$	$j_k > 0$, $k = \min\{r \mid j_r > 0, W \le r \le V-1\}$; $i > 0$; $V > 1$.
PU departs, and SUs cannot use the vacant channel	$(i-1, j_W, \ldots, j_k, \ldots, j_V)$	$i\mu_P$	$j_k = 0, \forall k < V$; $i > 0$.
SU with k channel(s) departs. Other SU services, if exist, cannot use the vacant channel(s)	$(i, j_W, \ldots, j_k - 1, \ldots, j_V)$	$kj_k\mu_S$	$j_k = 1$, $k < V$; $j_m = 0$, $\forall m < V$ and $m \ne k$. Or $j_k > 0$, $k = V$; $j_m = 0$, $\forall m < V$.
SU with k channel(s) departs. An SU service with minimum number of aggregated channels, h, uses all the vacant channel(s)	$(i, j_W, \ldots, j_h - 1, \ldots, j_k-1, \ldots, j_l + 1, \ldots, j_V)$	$kj_k\mu_S$	$j_k > 1$; $h = \min\{r \mid j_r > 0, W \le r \le V-1\}$; $l = k+h \le V$; $V > 1$. Or $j_k = 1$; $h = \min\{r \mid j_r > 0, r \in \{W, \ldots, k-1, k+1, \ldots, V-1\}\}$; $l = k+h \le V$; $V > 1$.
…	…	…	…
SU with k channel(s) departs. All rest SU services with fewer than V channels use the vacant channel(s) and achieve the upper bound V.	$(i, 0, \ldots, 0, \ldots, 0, \ldots, j_V + q)$	$kj_k\mu_S$	$q = \sum_{m=W}^{V-1} j_m - 1$; $k \ge \sum_{m=W}^{V-1}(V-m)j_m - (V-k)$; $V > 1$.
PU arrives when a vacant channel exists	$(i+1, j_W, \ldots, j_k, \ldots, j_V)$	λ_P	$b(\boldsymbol{x}) < M$.
PU arrives. An SU service with k channels reduces its aggregated channels	$(i+1, j_W, \ldots, j_{k-1}+1, j_k-1, \ldots, j_V)$	$\dfrac{kj_k}{M-i}\lambda_P$	$b(\boldsymbol{x}) = M$; $j_k > 0$, $k > W$; $V > 1$.
PU arrives and an SU service is terminated. No spectrum adaptation is needed	$(i+1, j_W - 1, \ldots, j_k, \ldots, j_V)$	$\dfrac{Wj_W}{M-i}\lambda_P$	$j_W = 1$; $j_k = 0$, $W+1 \le k \le V-1$; $b(\boldsymbol{x}) = M$; $W > 1$. Or $j_W \ge 1$; $b(\boldsymbol{x}) = M$; $W = 1$. Or $j_W \ge 1$; $b(\boldsymbol{x}) = M$; $W = V$.
PU arrives. An SU service is terminated and provides vacant channel(s). The SU service with minimum number of aggregated channels, h, could use the vacant channel(s)	$(i+1, j_W - 1, \ldots, j_h - 1, \ldots, j_l + 1, \ldots, j_V)$	$\dfrac{Wj_W}{M-i}\lambda_P$	$j_W > 1$; $h = W$; $l = h+W-1 \le V$; $W > 1$; $b(\boldsymbol{x}) = M$; $V > 1$. Or $j_W = 1$; $h = \min\{r \mid j_r > 0, W+1 \le r \le V-1\}$; $l = h+W-1 \le V$; $W > 1$; $b(\boldsymbol{x}) = M$; $V > 1$.
…	…	…	…
PU arrives and an SU service is terminated. All rest ongoing SU services with fewer than V channels use the vacant channel(s) and achieve the upper bound V	$(i+1, 0, \ldots, 0, \ldots, 0, \ldots, j_V + q)$	$\dfrac{Wj_W}{M-i}\lambda_P$	$b(\boldsymbol{x}) = M$; $q = \sum_{m=W}^{V-1} j_m - 1$; $W - 1 \ge \sum_{m=W}^{V-1}(V-m)j_m - (V-W)$; $W > 1$; $V > 1$.
SU arrives	$(i, j_W, \ldots, j_k + 1, \ldots, j_V)$	λ_S	$k = \min\{M - b(\boldsymbol{x}), V\} \ge W$.

The average service rate per commenced SU service, μ_{ps}, is defined as the capacity divided by the average number of commenced SU services,

$$\mu_{ps} = \rho / \sum_{\boldsymbol{x} \in \mathcal{S}} \sum_{k=W}^{V} j_k \pi(\boldsymbol{x}). \tag{3}$$

The forced termination probability, P_f, which represents the fraction of the forced terminations over those commenced SU services, is given by

$$P_f = R_f / \lambda_S^* = \sum_{\substack{\boldsymbol{x} \in \mathcal{S}, b(\boldsymbol{x})=M, \\ j_W > 0, i < M}} \frac{\lambda_P W j_W}{(M-i)\lambda_S^*} \pi(\boldsymbol{x}), \tag{4}$$

where R_f is the forced termination rate and $\lambda_S^* = (1 - P_b)\lambda_S$.

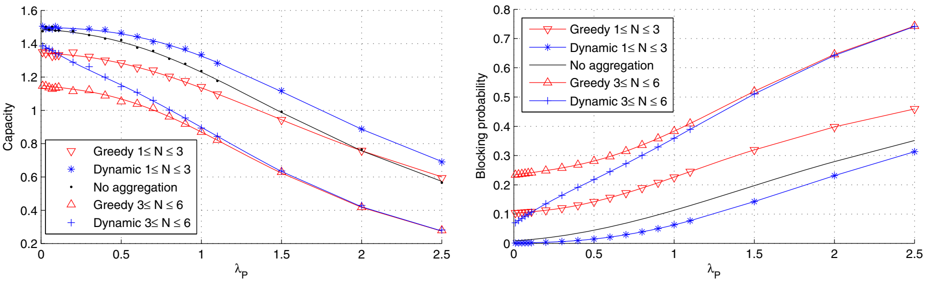
3.2 CTMC Analysis for the Dynamic $W \leq N \leq V$ Strategy

Let $\mathcal{S}$ be the set of feasible states of this strategy, as $\mathcal{S} := \{(i, 0, ..., 0, j_V) | i + V j_V < M\} \cup \{\boldsymbol{x} \; | b(\boldsymbol{x}) = M\}$. For a generic state $(i, j_W, ..., j_k, ..., j_V)$ in this strategy, transitions corresponding to PU arrivals, PU and SU departures are exactly the same as those in the *Greedy* strategy, which are specified in Table 1. The difference is that the *Dynamic* strategy has various destination states when an SU service arrives. Therefore, we only show in Table 2 the corresponding transitions when an SU service arrives for *Dynamic* $W \leq N \leq V$, where the arrival rate is λ_S. Again, based on the above analysis, the state probability of $\pi(\boldsymbol{x})$ can be obtained and then ρ, μ_{ps}, and P_f can be computed by Eqs. (2), (3) and (4) respectively, while the blocking probability becomes,

$$P_b = \sum_{\boldsymbol{x} \in \mathcal{S}, \; M - b(\boldsymbol{x}) + \sum_{k=W+1}^{V} (k-W) j_k < W} \pi(\boldsymbol{x}). \tag{5}$$

Table 2. Transitions from a generic state $\boldsymbol{x} = (i, j_W, \ldots, j_k, \ldots, j_V)$ of *Dynamic* $W \leq N \leq V$, $W \leq k \leq V$ when an SU service arrives

Activity	Dest. state	Conditions
SU arrives when enough idle channels exist	$(i, j_W, \ldots, j_k + 1, \ldots, j_V)$	$k = \min\{M - b(\boldsymbol{x}), V\} \geq W$.
SU arrives. The ongoing SU service with the maximum number of channels, m, gives channel(s) to the newcomer	$(i, j_W + 1, \ldots, j_n + 1, \ldots, j_m - 1, \ldots, j_V)$	$m = \max\{r \| j_r > 0, W + 1 \leq r \leq V\}$; $n = m - [W - (M - b(\boldsymbol{x}))]$, $W \leq n < m$; $V > 1$.
...	...	...
SU arrives. All ongoing SU services that aggregate more than W channels give channel(s) to the newcomer	$(i, j_W + q, 0, \ldots, 0, j_n + 1, 0, \ldots, 0)$	$q = \sum_{m=W+1}^{V} j_m$; $n = \sum_{m=W+1}^{V} (m - W) j_m + M - b(\boldsymbol{x})$, $W \leq n < \min\{r \| j_r > 0, W + 1 \leq r \leq V\}$; $V > 1$.



(a) System capacity (b) Blocking probability

Fig. 1. System capacity and blocking probability as a function of λ_P

4 Numerical Results and Discussions

In this section, the obtained numerical results for these strategies are presented. In the first part, ρ, P_b, μ_{ps}, and P_f are examined and mathematical results are verified by simulations. In the second part, the results under various traffic distributions are illustrated.

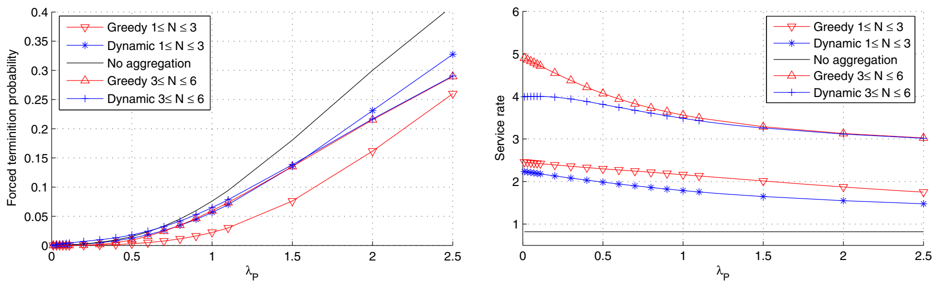
4.1 Performance Comparison among Different Strategies

Numerical results for ρ, P_b, P_f, and μ_{ps} as a function of λ_P are illustrated in Fig. 1 and Fig. 2, given $M = 6$, $\lambda_S = 1.5$, $\mu_S = 0.82$, and $\mu_P = 0.5$. To compare the impact of different threshold values, we plot two groups of results for each strategy, i.e., $1 \leq N \leq 3$ and $3 \leq N \leq 6$. The results of $No\ aggregation$ are also shown for comparison.

Model Verification and System Capacity. To verify the CTMC models, the simulation together with the analytical results of the capacity in the secondary network are plotted in Fig. 1 (a). More specifically, the solid lines are the analytical results while the marks are simulation results. The stochastic process is simulated by generating both PU and SU services according to the assumed distributions. From this figure, we can conclude that the simulation results precisely coincide with the analytical ones. In figures shown later, the analytical results have also been verified by simulations.

As shown in Fig. 1 (a), the system capacity of the secondary network decreases for all strategies as λ_P increases. Furthermore, only the $Dynamic$ strategy with a small value of W, i.e., $Dynamic\ 1 \leq N \leq 3$, can provide higher capacity than $No\ aggregation$ does and both of them can achieve capacity close to the offered load, i.e., $\lambda_S = 1.5$, when λ_P is small. Note that the system capacity of $Greedy\ 1 \leq N \leq 3$ becomes higher than that of the $No\ aggregation$ when $\lambda_P \geq 2$. However, this benefit is not of great significance since the corresponding blocking and forced termination probability is relatively high, which can be observed in Fig. 1 (b) and Fig. 2 (a). Among different strategies, $Dynamic$ strategies achieve higher capacity than the corresponding $Greedy$ strategies.

Comparing two groups of $1 \leq N \leq 3$ and $3 \leq N \leq 6$ in the same strategy, the results in the former group for each strategy have higher capacity. The reason is that



(a) Forced termination probability (b) Average service rate

Fig. 2. Forced termination probability and average service rate as a function of λ_P

in the latter group, the strategies require at least three vacant channels out of a total number of six channels, leading to wasted spectrum opportunities in comparison with the group of $1 \leq N \leq 3$.

Blocking Probability. Fig. 1 (b) depicts the blocking probability of SU services. One can observe that *Dynamic* $1 \leq N \leq 3$ has the lowest blocking probability since it needs only one channel for initiating an SU service and can adjust the number of aggregated channels when both PU and SU services are present. Similarly, *No aggregation* has the second lowest blocking probability among all strategies. Since the newly arrived SU service will be blocked while the ongoing ones will utilize as many available channels as possible in the *Greedy* strategies, they have higher blocking probability. Again, comparing the group $1 \leq N \leq 3$ with $3 \leq N \leq 6$, the blocking probability is generally higher in the latter one. The reason is straightforward since more channels are required in the latter case before a service request can be accepted.

Forced Termination Probability. To examine the forced termination probability of commenced SU services, we plot P_f in Fig. 2 (a). As expected, P_f becomes higher for all strategies as λ_P increases since PUs become more active. Comparing these strategies, the *Greedy* ones have the lowest P_f while the *Dynamic* strategies enjoy a lower P_f than *No aggregation*. The main reason that the *Greedy* strategies yield lower P_f than their *Dynamic* counterparts do is that the new SU requests will be simply blocked in the *Greedy* case when the number of idle channels is not sufficient for a newly arrived SU service. In contrast, in *Dynamic* ones, a new SU service can commence by utilizing channels donated by ongoing SU services. Therefore, the number of parallel SU services in the *Greedy* strategies is smaller. With the ability of reducing the number of channels for ongoing SU services in both cases, the *Greedy* strategies enjoy lower P_f than the *Dynamic* ones.

Average Service Rate per Commenced Service. Fig. 2 (b) illustrates the average service rate of the commenced SU services. As illustrated in this figure, the larger number of channels it aggregates, the higher average service rate a strategy can achieve. For *No aggregation*, the average service rate does not change with different λ_P since each SU service uses only one channel all the time, i.e., $\mu_{ps} = \mu_S$, while this rate

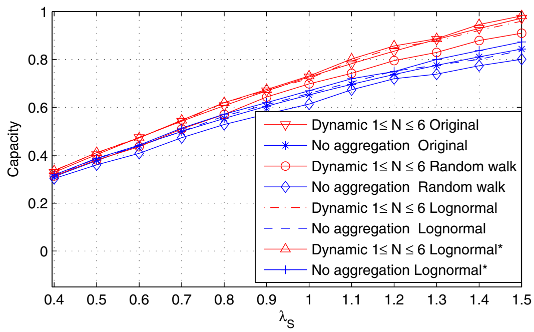


Fig. 3. System capacity as a function of λ_S when various distributions are utilized

in other strategies declines with an increasing λ_P. Comparing *No aggregation* with *Dynamic* $1 \leq N \leq 3$, SU services in the *Dynamic* strategy are dispatched more quickly than in *No aggregation* since more channels are used, even when they have similar capacity which is close to the offered load with a small λ_P. In the *Greedy* strategies, since ongoing SU services will not share channels with new coming SU services, higher average service rate is achieved than in the *Dynamic* cases.

4.2 Traffic Pattern with Various Distributions

For the results presented above, Poisson arrivals and exponential distributed service time are assumed. In real life, traffic patterns might be different from those ones, making the analytical treatment infeasible. However, the performance of these strategies can still be evaluated by simulations for various traffic types.

Figure 3 illustrates the system capacity of two example strategies, *No aggregation* and *Dynamic* $1 \leq N \leq 6$ as a function of λ_S, under two traffic models based on real-life traffic observations [10, 11]. For traffic pattern one, Poisson arrivals and log normal distributed service time for both PUs and SUs are utilized. Within this traffic type, we consider further two cases. The first case is that both the mean value and the variance of log normal distributions equal to those of the corresponding original exponential distributions, labeled as *Lognormal*. The other case, labeled as *Lognormal**, is that the variance values of log normal distributions are larger than those of the original exponential distributions, i.e., the Squared Coefficient of Variation (SCV) equals to 4.618 [11] (SCV= variance/mean^2) while the mean values are kept the same. For traffic pattern two, a random walk model for PUs [10], and a Poisson arrival and log normal distributed service time for SUs are adopted, labeled as *Random walk*, where the average time interval between events in the random walk model is 1.0683 time unit. For the log normal distribution of SU service time used in this case, we make the mean value and variance equal to that of the original exponential distribution. The results from the mathematical analysis are also plotted as a reference, labeled as *Original*, with $M = 6$, $\mu_S = 0.5$, $\lambda_P = 0.5$ and $\mu_P = 0.15601$.

From this figure, we can observe that the results under different traffic models are still quite close to the ones obtained under Poisson arrivals and exponential service time distributions. This observation indicates that although different traffic models exist, the mathematical analysis presented in this paper can be used as a good approximation for analyzing the performance of those channel aggregation strategies in CRNs.

5 Conclusions

In this paper, two channel aggregation strategies in CRNs with spectrum adaptation are proposed and investigated, and their performance is evaluated and compared through both mathematical analyses and simulations. Numerical results demonstrate that the *Dynamic* strategy with a small value of the lower bound of the number of aggregated channels can achieve higher capacity and lower blocking probability than *No aggregation* and its *Greedy* counterparts do. From an individual SU service's perspective, however, a commenced SU service in the *Greedy* strategies can enjoy a higher service rate as well as lower forced termination probability, at the cost of lower system capacity and higher blocking probability.

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