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Abstract: Cognitive radio networks (CRNs) benefit from several features, such as decision-making, spectrum-awareness and reconfigurability over heterogeneous channels. After a link failure due to the appearance of primary users or if the channel quality becomes unacceptable, these features enable CRNs to perform a spectrum migration to a new channel to recover the transmission. In this paper, we propose a general hierarchical recovery model in which the heterogeneous channels are classified based on their parameters into distinct sets. Instead of performing a flat channel search over all channels, the CRN first selects a channel set and then performs a spectrum migration over the selected set to complete the channel search. The focus of this research is the decision procedure for selecting the best channel set to perform the recovery mechanism based on the CRNs current state and its knowledge concerning the different channel parameters. A general dynamic decision model is proposed to find the optimal solution to this problem. Additionally, we present three decision-making heuristic algorithms. Numerical and simulation results are provided to illustrate the significant benefits of the optimal and heuristic decision algorithms for channel recovery over heterogeneous channels.

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1 Introduction

To solve the problem of spectrum scarcity and usage inefficiency, the idea of using vacant portions of the spectrum licensed to a primary network to deploy a secondary network was proposed previously [1]. Cognitive radio (CR) technology [2] was selected as the best candidate for implementation of this concept because of its spectrum-awareness and reconfigurability abilities. The opportunistic use of the spectrum by CR networks (CRNs) implies that a channel should be vacated by the CRs when the primary licensees return to the channel or if the channel quality becomes unacceptable. The event of CRs vacating a channel can be modeled as a failure [3], and when such a failure occurs, the CRs must spend a certain amount of time, called the *recovery time*, sensing the different channels, making a decision, and performing a spectrum handover to re-establish their communication on a new vacant channel. Similar to any failure recovery approach, the objective is to switch to the best possible channel within the shortest period of time.

In the literature, the focus has mostly been on flat recovery models in which the CR user makes a selection from a set of channels. Thus, the recovery algorithm objective generally has been to find the first available channel that is free of primary users. For example, in [4], different search schemes over a flat structured channel set are investigated. In [5–9], the authors propose algorithms to determine the recovery sensing orders for CRNs. They also discuss the trade-offs between stopping the recovery and using the channel found in comparison to continuing the recovery to try to find a better channel. Several recovery schemes embedded in medium access (MAC) protocols have also been proposed for homogeneous channels [10, 11]. In [12], the authors proposed channel selection schemes considering only the heterogeneity of channel availability without any hierarchy.

However, due to their frequency and transmission bandwidth agility, CRs can be reconfigured to use heterogeneous channels with different parameters, such as the availability, recovery time and transmission rate. This is particularly important with the advent of heterogeneous wireless networks [13]. Following a failure event, CRs must perform the recovery mechanism over these heterogeneous channels and must not limit themselves to homogeneous channels similar to the one that was originally in use in order to fully take advantage of their abilities. However, the CRs are faced with a trade-off with respect to performing a recovery mechanism over heterogeneous channels given that some channels may provide higher quality but are less available and require a longer recovery period, whereas other channels may remain available for a longer duration but their transmission rate can be lower. For example, a CRN could use unlicensed wideband channels, which are susceptible to both the appearance of primary users and contention with other CRNs, while obtaining access to a bank of narrowband licensed backup channels, which are more reliable. Thus, the objective of this paper is to propose a decision procedure for the link recovery of CRNs operating over heterogeneous channels.

To tackle this problem, we introduce a general hierarchical model for channel recovery in CRNs where the available channels are classified into multiple sets based on their characteristics, such as availability and service capacity. To perform the recovery, the CRN first selects a channel set (type) and then performs a channel migration in the selected set to search for an available channel. The focus of this paper is on the first part of the hierarchical channel handover, that is, selecting the appropriate channel set. Recovery in the selected set can be any of the proposed schemes in the literature for flat channel handover [4]. We model the channel set selection problem as an optimization and decision-making problem in which the objective is to minimize the average total transmission time of a flow of packets. The decision may be made packet by packet (packet model) even if the current operating channel is still available, or only when the operating channel becomes unavailable (flow model). In the latter case, the CR node continues using the same channel. In this paper, this problem is optimally solved using dynamic programming. Decision-making heuristic algorithms are also proposed to efficiently solve this problem, and the numerical results are provided to illustrate their benefits.

Note that even if the CR node is equipped with wideband sensing capabilities, a hierarchical channel recovery is indispensable because of the wide frequency range over which a CR network may operate. Consider a CR network which operates on both TV channels (6MHz channels in 470–806 MHz) and ISM IEEE 802.11a bands (20MHz in 5.18–5.825 GHz), and frequencies in between such as 2.4GHz ISM band or recently released channels in 3.5GHz. It is thus unrealistic to assume that the CR node can sense the whole range of 400MHz to 5.8GHz at the same time. Further, the number of users is not necessarily always large enough to implement a cooperative sensing model which covers the whole range. However, when a channel set was selected, wideband or cooperative sensing may help the CR node to find sooner an available channel.

The main contribution of this paper is therefore to propose a recovery procedure for heterogeneous CR networks and to frame the procedure as an optimization and decision-making problem within a novel hierarchical channel recovery model. To the best of our knowledge, this approach to recovery in CRNs has never been discussed before.

The remainder of the paper is organized as follows. In Section 2, the hierarchical channel recovery model and all parameters related to the model are presented. Section 3 provides the dynamic programming equations for the different decision models. In Section 4, three heuristic algorithms for the decision-making problem are proposed. We discuss the numerical and simulation results in Section 5, and finally, Section 6 concludes the paper with several remarks on future research directions.

2 Hierarchical Recovery Model

In this section, we propose a novel hierarchical recovery model for cognitive radios that can perform the recovery procedure over heterogeneous channels with dissimilar characteristics due to their frequency and bandwidth agility. As illustrated in Figure 1, we assume that I channel sets are available for recovery, and in each set, the channel characteristics and statistics are similar. For example, each set could belong to a different licensee or network, such as TV channels, ISM bands, or telephony networks. Further, in the same group of channels of a licensee or a network, only the channels with similar characteristics should be regrouped in the same set.

Each set i consists of N_i channels and is characterized by multiple parameters, A_i, U_i, B_i, R_i, and S_i, as listed in Table 1. Note that A_i, U_i, B_i, R_i, and S_i are all random variables (RV's) denoting the availability periods, unavailability periods, service rate, recovery periods, and blocking periods, respectively, of the channels in set i. The distribution of these random variables (which we denote by F_Z and f_Z, which represent the cumulative distribution function (CDF) and probability density function (PDF), respectively, of any random variable Z) is the same for all channels in one set.

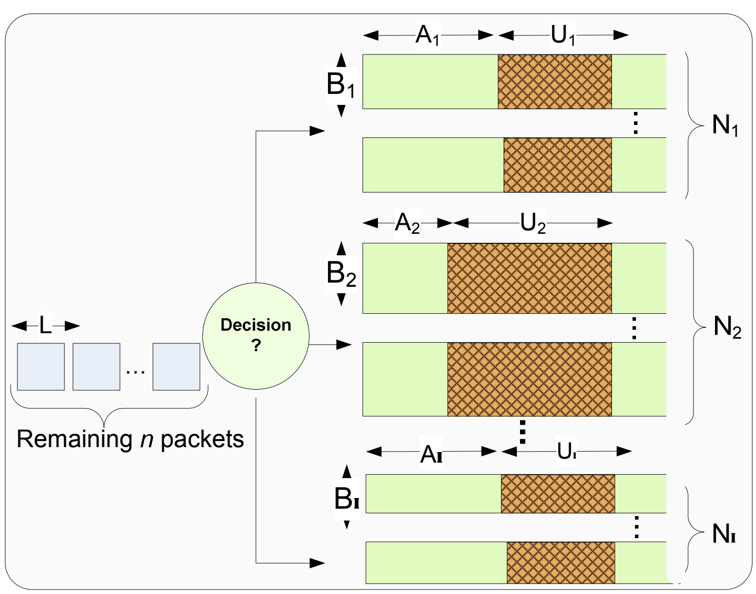

Figure 1: General decision model for a channel hierarchy in cognitive radio networks. L is the packet length. Other parameters are introduced in Table 1.

Table 1: Channel set parameters.

Par.	Description	A function of
N_i	Number of channels	–
A_i	RV of availability period length	–
X_i	RV of remaining time availability period	A
U_i	RV of unavailability period length	–
γ_i	Channel availability indicator	$= \frac{\bar{A}_i}{\bar{A}_i+\bar{U}_i}$
B_i	Service rate	Fading, BW, regulation
R_i	Recovery period	N_i, A_i, U_i, Algorithm
S_i	Blocking period	N_i, A_i, U_i, Algorithm
P_i^b	Blocking Probability	N_i, A_i, U_i, Algorithm
P_i^f	Packet-based failure probability	$=\Pr(X_i < \frac{L}{B_i})$
n	Remaining packets (n^0: flow size)	–
q_i^f	Flow-based failure probability	$=\Pr(X_i < \frac{nL}{B_i})$

2.1 System Model

Assume that the CR user has detected that its operating channel in set i is not available anymore, requiring that the channel be vacated. At this time, the user can wait for the channel to become available again (in which case, the recovery time is U_i), or the user can start a recovery procedure to find a new vacant channel. A flat recovery procedure, directly searching over all channels, could be used. However, in this paper, we propose taking advantage of the fact that the heterogeneous channels can be grouped in sets of channels with similar characteristics to perform a more efficient hierarchical recovery. In this recovery model, a decision should first be made concerning the next channel set intended for use. If the selected channel set is j, the CR user first aligns the radio to set j with a switching timing cost equal to W_{ij} to reconfigure the radio. Then, a recovery timing cost equal to R_j is imposed to find an acceptable channel from within set j. A blocking period S_i can also be incurred if no channel is found. The service rate of the selected channel is equal to B_j. In the packet by packet decision (packet model), if the time to the next unavailability on the selected channel, called X_j, is larger than $\frac{L}{B_j}$ where L is the packet length, the next packet can be successfully transmitted. Otherwise, the packet will experience a failure, and the user should perform a new recovery procedure. Similarly for a flow with n packets (flow model), if X_j is larger than $\frac{nL}{B_j}$, the flow can be entirely transmitted; otherwise, a new recovery procedure should be repeated at the time of failure to transmit the remaining packets in the flow. Generally, the decision points can include the time at which the operating channel is no longer available while a packet awaits transmission or the time after the successful or unsuccessful transmission of each packet. We discuss both cases below.

In addition to the use of a traditional radio for signaling and controlling purposes, we also assume that the CR users are equipped with only one CR transceiver, which can be used either for data communication or channel sensing purposes. Note that the control radio cannot be used for out-of-band sensing during the transmission because it should remain aligned to the control channel at all times.

2.2 Channel Availability

From the perspective of the CRN, the main cause of channel unavailability is the appearance of primary users. However, channel unavailability can also be due to other causes, such as excessive interference, shadowing, deep fading, and traffic congestion [3]. As illustrated in Figure 2a, the A_i and U_i random periods form alternating renewal processes [14] for the channels.

As illustrated in Figure 2b, after a recovery time of length R_i, the user transmits for a random length X_i over the selected channel of type i until it experiences a failure (flow model), as determined by the sensing result of the current operating channel. A new channel is then selected, using the procedure previously described, to transmit the remaining packets. This procedure repeats for each failure occurrence. The

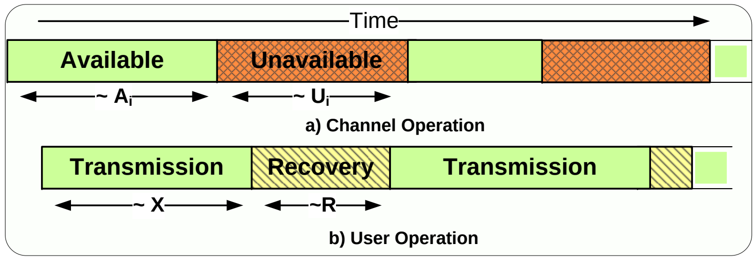

Figure 2: **a)** Alternating renewal processes of channel type i operation: availability and unavailability. **b)** Alternating processes of a CR user: transmission and recovery.

operation of the user is thus modeled with alternating processes in which the user consecutively alternates between recovery and transmission. Note that to decrease the complexity of the proposed decision making models, we assume that channel availability periods are exponentially distributed. With this assumption, there is no need to keep the time spent so far on a channel as a state variable.

It is also important to note that, as illustrated in Figure 3, X_i is a random variable representing the length of the remaining available period of the selected channel of type i, which, in general, is different from A_i. X_i is also known as the *operating period* over a channel of type i or as the recurrence time in the context of alternating renewal theory [14]. That is, when the user senses that a channel is available and starts using it, the user does not know how long this channel has been available. Thus, it is common to assume uniform access to the channel during an availability period. With this assumption, one can find the distribution of X_i based on A_i as follows [14]:

$$f_{X_i}(t) = \frac{1 - F_{A_i}(t)}{\bar{A}_i}, \tag{1}$$

where $\bar{A}_i$ is the expected value of A_i. Let us also find the Laplace–Stieltjes transform (LST) of f_{X_i}, which can be written as:

$$X_i(S) = \mathcal{L}[(f_{X_i}(t)] = \frac{1 - A_i(S)}{S\bar{A}_i} \tag{2}$$

where $A_i(S)$ is the LST of A_i. It will be used in Section 4.3.

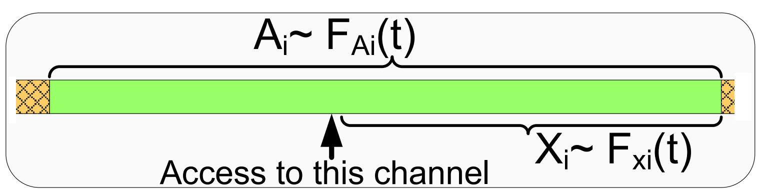

Figure 3: The operating period of a user over a found channel is the remaining part of the channel availability period, until the channel becomes unavailable.

2.3 Service Rate

B_i is the service rate of the channel set i and is a function of several parameters, such as the bandwidth of the channels in the set, the regulation policy (allowed protocols, modulation and coding schemes, maximum transmitted power, etc.) for that set, the frequency range of the channels (e.g., the channels center frequency has an impact on the large scale attenuation) and other environmental effects (impact of mobility, small scale fading, diversity, etc.). The aforementioned parameters together define the distribution of the service capacity of one set. The transmission time of a packet of length L over a link with a service rate B_i is equal to $\frac{L}{B_i}$ units of time. The unit of time can be assumed to be any appropriate unit, and all timing parameters are represented in this unit of time.

2.4 Recovery and Blocking

R_i and S_i represent the duration of the recovery and blocking periods, respectively, and depend on the channel parameters and the recovery algorithm. The recovery time is the period required to sense the channels in a set and to select a new channel for transmission, given that a channel has been found. The blocking time is the period required to determine that no channel is available in this channel set, at which point the transmission is blocked.

For example, to illustrate the concepts of recovery and blocking periods, let us assume a random channel search (it is a common assumption that when a set is selected, the channels are sensed in a random order) and memoryless channels. The availability state of a channel in each instant of time can be modeled with a binary random variable $\gamma_i = \frac{\bar{A}_i}{\bar{A}_i+\bar{U}_i}$. The distribution of the recovery time, conditioned upon finding an available channel, is therefore given by:

$$Pr(R_i = k\tau_i) = \frac{\gamma_i(1-\gamma_i)^{k-1}}{1-(1-\gamma_i)^{N_i}} \quad k \leq N_i \tag{3}$$

τ_i it the search time spent for each channel of set i, which includes the sensing time, the time to perform channel probing, and the negotiation time to start using this channel or to sense another channel. τ_i therefore depends on both the bandwidth of the channels in each set and the regulatory policies. The latter represents the accuracy required to execute sensing, which is dictated by the regulatory bodies. That is, we may have two different sets with similar bandwidth, but with different sensing time τ_i because in one of the sets, each channel should be sensed longer to have a lower probability of miss-detection. The blocking time is the time necessary to search all channels and is thus $S_i = N_i\tau_i$, and the probability of blocking P_i^b is equal to:

$$P_i^b = (1-\gamma_i)^{N_i}. \tag{4}$$

It should be noted that, in general, R_i, S_i and P_i^b depend on the channel set to which the operating channel that was in use before the last failure belongs. For example, if the last operating channel was in set j, then the CR network knowledge concerning the channel set $i \neq j$ is less than that for channel set $i = j$. That is, when the last operating channel set is also j, the CR network may have knowledge about the status of one channel from set j (the current operating channel), and then only $N_j - 1$ channels must be verified. However, when the CR switches to a new channel set, it generally has no knowledge regarding the status of the channels. Similarly, the blocking time will be less for channel set $i = j$ because one channel does not need to be sensed, and similarly, the blocking time P_i^b will be larger for channel set $i = j$ because the CRN knows that at least one channel is not available. Historical and centralized knowledge concerning the channel sets can also affect the distribution of R_i, S_i and P_i^b.

Finally, other recovery algorithms can also be addressed because the only change will be the distribution of the recovery time. For example, if we assume that sensing is not executed perfectly or that the user does not select the first sensed available channel, hoping to find a better channel, then the recovery time distribution changes and usually becomes very complicated. However, in such a case, the decision-making model remains valid. Further, we cannot represent the recovery time or the channel service capacity by closed-form relations and known distributions; thus, we must numerically approximate (for example via simulations) the recovery time distribution. The approximated distribution is then used in the numerical/simulation experiments to solve the model.

3 Optimal Decision-Making

In this section, we propose a dynamic programming (DP) model to optimally select the channel set in the first stage of the hierarchical recovery model described in the previous section. We discuss the DP model and provide the Bellman equation for different cases of the hierarchical recovery model. In the models presented in this paper, the objective is to optimize an expectation value function ($\mathbb{E}[\cdot]$). However, for applications in which the variance (e.g., the transmission time jitter) is more important, the $\mathbb{E}[\cdot]$ value function can be replaced by a weighted function of the expected value and variance, i.e., $\omega_1\mathbb{E}[\cdot] + \omega_2 Var[\cdot]$.

We first consider the DP model of a backlogged flow with n^0 initial packets in the queue intended for transmission. In this case, we want to minimize the total transmission cost of the flow, where the cost is proportional to the total transmission time of the flow, including the recovery and blocking periods. In packet by packet decision, a channel set selection is performed after each attempted packet transmission, regardless of whether it was successful, unsuccessful due to channel failure, or blocked because there was no available channel in the selected set.

We then extend this model to the case in which a new channel set selection is only made after experiencing a failure during the flow transmission or if blocking occurred in the recovery procedure. That is, the CR user continues using the same channel until the channel becomes unavailable. In this case, and without loss of generality, the short in-band sensing times before each packet transmission are neglected, and we assume that the user can quickly detect the unavailability of the channel.

For both cases, we then modify the model to consider a packet arrival process. The DP thus becomes an infinite horizon problem in which we want to minimize the transmission cost per stage.

3.1 Backlogged Flow with Packet Decision

The objective in this case is to minimize the total transmission time of a flow with n^0 initial packets. In this model, we assume that, after transmitting each packet, the CRN releases the channel and performs a recovery (a decision). Therefore, the decision is made packet-by-packet and if a failure or blocking event occurs. The value function $V(n,i)$ is the expected minimum transmission cost of the remaining n packets in the flow when the current channel set is i and the user follows the optimal decisions. The Bellman equation for this DP problem can be written as follows:

$$V(n,i) = \min_u \Bigg\{ \mathbb{E}\Bigg[\left(1-P_u^b\right) \left((W_{iu}+R_u) + P_u^f \left(X_u^* + V(n,u)\right) + \left(1-P_u^f\right) \left(\frac{L}{B_u} + V(n-1,u) \right) \right) + P_u^b \left((W_{iu}+S_u) + V(n,u) \right) \Bigg] \Bigg\}. \quad (5)$$

The first term of the Bellman equation is the timing cost when a channel is found. It consists of the recovery overhead and the time necessary to transmit the remaining packets. In the case of an interruption during the packet transmission, the same number of packets remains for transmission in the next stage. In contrast, in the case of a successful packet transmission, one less packet remains to be transmitted in the next stage. The second term is the timing overhead in case of a blocking event in addition to the time required to transmit the same number of packets in the next stage.

The state variables are n and i, which are the number of remaining packets of the flow to be transmitted and the current channel set that is used before the decision, respectively. u is the decision variable, representing the new channel set to be selected. We have $u \in \{1,\ldots,I\}$. The stages of the DP model are defined as any time that a new decision is made, which occurs after each attempted packet transmission. The nature of the problem is of an infinite horizon, where there are terminal states after which the on-going cost is zero [15] (i.e., $v(n=0,.)=0$). The stopping condition is $V(0,u)=0$ ($\forall u$).

The DP model parameters B_u, R_u, S_u and P_b^u are described in the previous section. The other model parameters are defined as follows:

- W_{ij}: The switching time to align the radio and to reconfigure the system parameters from channel set i to channel set j. Note that $W_{ii}=0$.
- P_u^f: The probability of the occurrence of a failure during the transmission of a packet when using channel set u. Because we assumed that the remaining availability period of the channel is modeled with parameter X_u, we have $P_u^f = Pr(X_u < \frac{L}{B_u})$. B_u itself is a random variable. To simplify the model, for this case, we assume that the availability periods are exponentially distributed. Therefore, after the successful transmission of a packet, the remaining time has the same distribution. Otherwise, the time spent on one channel should also be kept as a state variable, which increases the model complexity.

- X_u^*: The time until a failure, conditioned on the fact that such a failure happens. That is, $X_u^* = X_u|(\text{failure}) = X_u|(X_u < \frac{L}{B_u})$.

3.2 Backlogged Flow with Failure Decision

We now modify the previous DP model for the case in which the user continues *using the same channel* when it is available. That is, a decision is made only when the user experiences an unsuccessful packet transmission because the channel has become unavailable or a blocking event has occurred. In the previous model, the next state was definite (either one packet or no packet is transmitted), whereas in this model, the next state depends on the number of packets transmitted and is thus random. The number of packets transmitted is itself a function of how long the channel has been available (X_i) and the service rate B_i. The Bellman equation for this DP model is:

$$V(n,i) = \min_u \Bigg\{ \mathbb{E}\Bigg[\left(1 - P_u^b\right) \Bigg((W_{iu} + R_u) + q_u^f \left(X_u^* + V(n - n_u, u)\right) + \left(1 - q_u^f\right) \frac{nL}{B_u} \Bigg) + P_u^b\big((W_{iu} + S_u) + V(n,u)\big) \Bigg] \Bigg\}, \quad (6)$$

where $X_u^* = X_u|(X_u < \frac{nL}{B_u})$ and $n_u = \lfloor \frac{B_u X_u^*}{L} \rfloor$ is the number of packets transmitted over the selected channel of type u during the operating period X_u^*. q_u^f is the probability that a failure occurs before the end of the transmission of all remaining packets, which is given by:

$$q_u^f = Pr\left(X_u < \frac{nL}{B_u}\right). \quad (7)$$

For several real-time applications, although the total transmission time is minimized, the occurrence of multiple failures can severely decrease the subjective quality of service due to increased jitter and packet losses at the application layer. One approach to reduce the number of failures is to increase the recovery overhead penalty. Thus, we propose to modify the previous DP model to include the number of failures detailed thus far as a state variable, d. The modified Bellman equation is then:

$$V(n,d,i) = \min_u \Bigg\{ \mathbb{E}\Bigg[\left(1 - P_u^b\right) \Bigg(F_c(W_{iu}, R_u, d) + q_u^f \left(X_u^* + V(n - n_u, d+1, u)\right) + \left(1 - q_u^f\right) \frac{nL}{B_u} \Bigg) + P_u^b\big(F_c(W_{iu}, S_u, d) + V(n,d,u)\big) \Bigg] \Bigg\}, \quad (8)$$

where $F_C(\cdot,\cdot,d)$ is a penalty function that depends on the number of failures having occurred thus far. For example, the following function, which linearly increases the cost as a function of d, could be used:

$$F_c(w,r,d) = w + r + (d-1)\eta(w+r), \quad (9)$$

where η is selected based on the significance of the interruption. As this modified model is only applicable to the case of backlogged flow with failure decision, it will not be used in the rest of the paper, to keep consistency with other cases.

3.3 Packet Arrival Process

Next, we modify the previous DP models to include a random packet arrival process. In this case, a function of the total transmission time cannot be used as a cost function. Instead, we propose to use a cost function $g(n)$ that depends on the state variable n (the number of packets in the queue). For example, $g(n)$ could be a function modeling the expected system time of the last packet in the queue. Without loss of generality, it is assumed that the cost $g(n)$ is incurred at the beginning of the stage. The Bellman equation for the case in which the decision is made after each attempted packet transmission is given by:

$$\theta^* + v(n,i) = \min_u \Big\{ g(n) + \mathbb{E}\Big[\big(1-P_u^b\big)\cdot \Big(P_u^f v\big(n+\Lambda(W_{iu}+R_u+X_u^*),u\big) + (1-P_u^f)v\Big(n+\Lambda\Big(W_{iu}+R_u+\frac{L}{B_u}\Big)-1,u\Big)\Big) + P_u^b v\big(n+\Lambda(W_{iu}+S_u),u\big)\Big]\Big\}, \quad (10)$$

where $\Lambda(\Delta t)$ is the number of packet arrivals during a period Δt and $X_u^* = X_u|(X_u < \frac{L}{B_u})$. The problem is modeled as an infinite horizon problem, and we are looking for the optimal average cost per stage θ^*, which is independent of the state. $v(n,i)$ is proportional to the minimum total cost incurred to reach the state $(0,.)$ (any state with $n=0$) from the state (n,i). Naturally, we have $v(0,i)=0,\ \forall i$. Thus, it is assumed that the queue is stable such that the probability of having an empty system is larger than zero.

For the case in which the decisions are made only when a failure occurs, the Bellman equation can be given by:

$$\theta^* + v(n,i) = \min_u \Big\{ g(n) + \mathbb{E}\Big[\big(1-P_u^b\big)\cdot \Big(q_u^f v\Big(n-n_u+\Lambda(W_{iu}+R_u+X_u^*),u\Big) + (1-q_u^f)v\Big(\Lambda\Big(W_{iu}+R_u+\frac{nL}{B_u}\Big),u\Big)\Big) + P_u^b v\Big(n+\Lambda(W_{iu}+S_u),u\Big)\Big]\Big\}, \quad (11)$$

where $X_u^* = X_u|(X_u < \frac{nL}{B_u})$.

4 Heuristic Decision-Making

The dynamic programming model described in the previous section is capable of executing the optimal decision regarding the channel set selection; however, the model suffers from several known weaknesses, such as complexity, high running time and the high dimensionality required for all possible states and events (e.g., number of arrivals). The DP models are not therefore realistic for any real implementation. Thus, in this section, we propose three heuristics for the problem of set selection for a backlogged flow with the failure decision described in Section 3.2). We then discuss how those heuristics can be adapted to the other cases. Each heuristic requires different knowledge concerning the parameters (e.g., the average values or the distribution) and has different complexity and performance.

Generally, the recovery time can be a function of the distribution of the channels' availability and unavailability periods, which implies that the two random variables R_i and X_i are not always independent. For simplicity, in the heuristic algorithms, we assume that the variables are independent, and the recovery is assumed to be only a function of $\bar{A}$ and $\bar{U}$ (stationary processes). The impact of their dependence is discussed in the conclusion. Further, to simplify the inclusion of blocking events in the heuristics, we assume that the channel states are memoryless, which effectively means that a user will keep looking for channels in the same set until an available channel is found. The number of searches in the selected channel set i before finding a channel is thus a geometric random variable with parameter $1-P_i^b$. Finally, to simplify the heuristic description, we neglect the switching time (W_{ij}) in some of the proposed schemes to be able to represent the decision independently of the current channel set. However, it can be easily integrated by only considering W_{ij} when the current channel set and the next channel set are different.

4.1 Average-based Decision-making

In this first heuristic, the decisions are entirely made using the average values of the different parameters. This scheme is thus particularly suitable for cases in which the exact distributions are not known. The core concept behind this heuristic is to compare n with the average number of packets that can be transmitted over an operating instance of each channel type. Thus, let us define $\bar{n}_j$ as the expected value of n_j (the random number of packets transmitted over a type-j channel during a period X_j):

$$\bar{n}_j = \lfloor E[\frac{X_j B_j}{L}] \rfloor \approx E[\frac{X_j B_j}{L}] = \frac{\bar{X}_j \bar{B}_j}{L}. \quad (12)$$

due to assuming that B_j and X_j are independent. Note that because $\frac{L}{B_j}$ can be assumed to be small, we neglected the impact of the interrupted packet transmission and dropped the floor operation for this heuristic scheme.

To simplify the heuristic presentation, we first describe it for two channel sets (the extension to an arbitrary number of sets is explained at the end of the section). As illustrated in Figure 4, as a function of time, the number of remaining packets decreases, and three cases can be defined: when n is larger than both $\bar{n}_1$ and $\bar{n}_2$, when n is between $\bar{n}_1$ and $\bar{n}_2$ and when n is smaller than both $\bar{n}_1$ and $\bar{n}_2$. The pseudo-code of the average-based decision-making heuristic is given in Algorithm 1. For clarity of presentation, each section of the algorithm refers to one of the three zones in Figure 4.

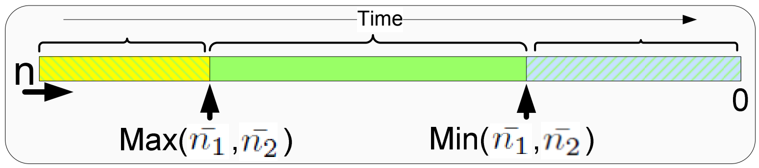

Figure 4: The boundary values for the remaining number of packets in the average-based decision making scheme.

When n is larger than both $\bar{n}_1$ and $\bar{n}_2$, the user, on average, will experience a failure before it finishes transmitting all remaining packets in just one operating instance. Thus, we compare the time to the next decision (i.e., the next failure), $\frac{P_j^b}{1-P_j^b}\bar{S}_j + \bar{R}_j + \bar{X}_j$, of both channel types. Assuming that this time is larger for type 1 channels, then if a type 2 channel is selected, the user experiences a failure sooner on a type 2 channel. Next, we compare the number of packets that would have been transmitted on a type 2 channel until its next failure with the number of packets that could have been transmitted during the same time on a type 1 channel. If the number of packets is larger, it means that the correct decision is to select a type 2 channel; otherwise, selecting a channel of type 1 would have been the correct decision.

When n is smaller than $\bar{n}_1$ or $\bar{n}_2$ (i.e., for set i) and larger than the other one, we can assume that before the next failure, all remaining packets can be transmitted over a channel of type i. Therefore, the transmission time of the remaining packets is used as a metric in decision-making instead of the number of packets transmitted before the next failure. Without loss of generality, assume that $\bar{n}_1 < n < \bar{n}_2$. Then, if the total transmission time of all remaining packets over the type 2 channel is shorter than the time to the next failure over a type 1 channel, the type 2 channel should be selected. Otherwise, we again compare the number of packets transmitted until the next failure over the type 1 channel with the packets that would have been transmitted in the same time over a type 2 channel. The number that is higher gives the heuristic channel set selection decision.

Finally, in the third zone, when n is smaller than both $\bar{n}_1$ and $\bar{n}_2$, the transmission time of all remaining packets is compared. The channel set with the shortest transmission time is selected.

It is straightforward to extend this heuristic to a multi-set scenario. The $\bar{n}_i$'s, $i = 1, \ldots, I$, are first sorted. Then, $I + 1$ zones are defined, and in each zone, we follow a similar approach as explained for the two-set case. That is, the time to the next decision point and the total transmission time are used as the comparison metric for the channel sets for which n is larger than $\bar{n}_i$ and for the channel sets for which n is less than $\bar{n}_i$, respectively.

4.2 Utility-based (Myopic) Decision-making

For the second heuristic, we simplify the DP model by using a myopic approach in which the CR network selects the channel set that maximizes the next stage throughput without considering the impact of future decisions. Thus, for the channel sets $i = 1, \ldots, I$, we define the one-stage average throughput utility function $Z_i(n)$, which is given by the average of the ratio of the number of packets that can be transmitted over the

Algorithm 1 The pseudo-code for the average-based decision-making scheme.

if $n >= Max(\bar{n}_1, \bar{n}_2)$ **then**
  if $\frac{P_1^b}{1-P_1^b}\bar{S}_1 + \bar{R}_1 + \bar{X}_1 > \frac{P_2^b}{1-P_2^b}\bar{S}_2 + \bar{R}_2 + \bar{X}_2$ **then**
    if $\bar{X}_2\bar{B}_2 > \left(\frac{P_2^b}{1-P_2^b}S_2 + \bar{R}_2 + \bar{X}_2 - \frac{P_1^b}{1-P_1^b}\bar{S}_1 - \bar{R}_1\right)\bar{B}_1$ **then**
      Select channel set 2;
    else
      Select channel set 1;
    end if
  else
    if $\bar{X}_1\bar{B}_1 > \left(\frac{P_1^b}{1-P_1^b}S_1 + \bar{R}_1 + \bar{X}_1 - \frac{P_2^b}{1-P_2^b}\bar{S}_2 - \bar{R}_2\right)\bar{B}_2$ **then**
      Select channel set 1;
    else
      Select channel set 2;
    end if
  end if
else if $Min(\bar{n}_1, \bar{n}_2) < n < Max(\bar{n}_1, \bar{n}_2)$ **then**
  i=Index of Max ; j=Index of Min
  if $\frac{P_i^b}{1-P_i^b}\bar{S}_i + \bar{R}_i + \frac{nL}{\bar{B}_i} < \frac{P_j^b}{1-P_j^b}\bar{S}_j + \bar{R}_j + \bar{X}_j$ **then**
    Select channel set i;
  else
    if $\bar{X}_j\bar{B}_j > \left(\frac{P_j^b}{1-P_j^b}S_j + \bar{R}_j + \bar{X}_j - \frac{P_i^b}{1-P_i^b}\bar{S}_i - \bar{R}_i\right)\bar{B}_i$ **then**
      Select channel set j;
    else
      Select channel set i;
    end if
  end if
else
  $\%n <= Min(\bar{n}_1, \bar{n}_2)\%$
  if $\frac{P_1^b}{1-P_1^b}\bar{S}_1 + \bar{R}_1 + \frac{nL}{\bar{B}_1} < \frac{P_2^b}{1-P_2^b}\bar{S}_2 + \bar{R}_2 + \frac{nL}{\bar{B}_2}$ **then**
    Select channel set 1;
  else
    Select channel set 2;
  end if
end if

time spent for transmission:

$$Z_i(n) = \mathbb{E}\left[q_i^f(n)\frac{(1-P_i^b)(\lfloor\frac{B_iX_i^*}{L}\rfloor)}{(R_i + X_i^*)} + (1-q_i^f(n))\frac{(1-P_i^b)n}{\left(R_i + \frac{nL}{B_i}\right)}\right], \tag{13}$$

where $q_i^f(n)$ is the probability that all remaining n packets cannot be transmitted in the incoming operating period over a channel of type i, which can be given by:

$$q_i^f(n) = Pr\left(X_i < \frac{nL}{B_i}\right) = F_{X_i}\left(\frac{nL}{B_i}\right). \tag{14}$$

In (13), we make the same assumption as for the average-based heuristic: if all the remaining packets can be transmitted before a new failure, the time spent for transmission is the real transmission time in addition to the recovery time. Otherwise, it is the average conditional operating time in addition to the recovery time. The decision is to select the set with the maximum Z_i.

For the myopic heuristic, knowledge of the CDF of X_i is required to find $q_i^f(n)$. Because R_i and B_i are also random variables, their distributions are required to compute (13) and (14). If their distributions are unknown, we can replace them by their average values in the equations, yielding an approximation.

4.3 Threshold-based Analytical Decision

For this heuristic, we propose an approach that compares, for each channel set i, the average total transmission time of all remaining packets given that a channel of this set is always used (i.e., the system always performs the recovery over the same channel set) until the end of the flow transmission. For our problem, this results in $I-1$ threshold values against which n is simply compared at each decision point to select the channel set. We now use the renewal theory results to find the average total transmission time for each channel set.

Suppose that the recursive function always recalls the same channel type, for example, i. We can then write the total transmission time of the *remaining* n packets as

$$\begin{aligned} D_i(n) &\le R_{i,1}^t + X_{i,1} + R_{i,2}^t + X_{i,2} + \ldots + R_{i,K_i}^t + X_{i,K_i} \\ &= \frac{nL}{B_i} + R_{i,1}^t + R_{i,2}^t + \ldots + R_{i,K_i}^t, \end{aligned} \tag{15}$$

where $R_{i,j}^t$ and $X_{i,j}$ represent the j-th independent and identical instances of R_i^t and X_i, respectively (i.e., the j-th recovery period and operating period). The inequality exists because in the last operating period, the transmission of the remaining packets may finish before the end of the channel availability period. The unknown in the total transmission time is K_i, which is the number of times that the function recalls itself until transmitting all n packets. K_i is equivalent to the number of failures where, for each failure, the same decision is executed.

R_i^t is the total recovery time, including the blocking period. That is, when the channel recovery is performed over set i, the user may be blocked after verifying all channels (after S_i). Based on the memoryless channel assumption, the user continues searching over the same set (restarts the recovery) until finding an available channel. Thus, the total recovery time is as follows

$$R_i^t = CS_i + R_i, \tag{16}$$

where the distribution of C is:

$$Pr(C=c) = (1-P_i^b)(P_i^b)^c, \ (c \ge 0). \tag{17}$$

We define the random variables $Y_i = X_i B_i$, $Y_{i,l}$ as the l^{th} instance of Y_i (l^{th} operating period), and $H_{i,g} = \sum_{l=1}^{g} Y_{i,l}$. K_i is then the smallest value of k such that

$$H_{i,k} \ge nL. \tag{18}$$

That is, the total time over K_i operating periods of a type i channel should be greater than the total time required to transmit all packets. From [14, Chap. 3], we can find the average of K_i as:

$$\bar{K}_i - 1 = m_i(nL) = \sum_{g=1}^{\infty} F_{H_{i,g}}(nL) \tag{19}$$

where $F_{H_{i,g}}$ is the CDF of the random variable $H_{i,g}$ and $m_i(t)$ is the mean renewal function for the operating period over a channel of type i [14]. Note that we need to subtract 1 on the left side because the mean renewal function does not take into account the first operating period before the first renewal. To find $m_i(nL)$, we apply differentiation and the LST on both sides of the equality to obtain:

$$S\mathcal{L}[m_i(t)] = \sum_{g=1}^{\infty} \sum_{m=1}^{g} Y_{i,m}(S). \tag{20}$$

Using the fact that the distributions of X_i and B_i are assumed to be identical and independent for all periods and because $|Y_i(S)| < 1$, we obtain:

$$\mathcal{L}[m_i(t)] = \frac{1}{S}\sum_{g=1}^{\infty}[Y_i(S)]^g = \frac{Y_i(S)}{S\,(1 - Y_i(S))}$$
$$= \frac{X_i(S) \circledast B_i(S)}{S\,(1 - X_i(S) \circledast B_i(S))}. \tag{21}$$

Using (2), we can find $m(t)$ and thereby derive $\bar{K}_i$. The average total transmission time can then be given by:

$$E[D_i(n)] = \mathbb{E}\left[\frac{nL}{B_i} + \bar{K}_i \bar{R}_i^t\right], \tag{22}$$

where it is assumed that all recovery times are identical and independent and that they are also independent of the number of renewals. For our problem, the latter is equivalent to assuming that when the user decides and starts the recovery over a channel set, it continues to search and does not leave the selected set until it finds a channel in this set (which is the assumption).

To make a decision, the heuristic compares the $E[D_i(n)]$ value for the different channel sets and selects the channel set with the lowest value. This is equivalent to finding $I - 1$ threshold values for the number of packets such that when n reaches a threshold value, the selected channel set is changed after a failure; otherwise, the same type of channel is consecutively selected.

For applications in which the delay jitter is more important, the decision function can be a weighted sum of the mean and the higher moments of the total transmission time; for example, $w_1 E[D_i(n)] + w_2 Var[D_i(n)]$, where the variance can be found again from the renewal theory results [14].

4.4 Heuristics for Other Models

The three proposed heuristics can be extended to the models with packet-by-packet decision making and with an arrival process. When we have a backlogged traffic with packet-based decisions, the average-based scheme selects the channel set with the shortest average transmission time of one packet given that, on average, one packet can be transmitted in an operating period (i.e., $\frac{L}{B_i} \leq \bar{X}_i$). Because the number of remaining packets is not involved in the decision rule (we only consider the transmission of a single packet), the decision does not change during the entire flow transmission.

For the myopic heuristic, the utility function (13) for the backlogged traffic with packet-based decisions can be given by:

$$Z_i = (1 - P_i^f)\mathbb{E}\left[\frac{(1 - P_i^b)}{(R_i + \frac{L}{B_i})}\right], \tag{23}$$

where the numerator represents the transmission of one packet, and the denominator is the time spent for transmission. Note that in this model, if the transmission is not successful (failure), no packet is transmitted. Again, the decision is independent of the number of packets and remains the same for the entire flow.

The threshold-based heuristic changes as follows. We still assume that the same channel set is used repeatedly but only for the successful transmission of one packet. The distribution of the time to transmit one packet is therefore geometric, where the parameter (the probability of success) is equal to $\Pr(\frac{L}{B_i} \geq X_i)$ when a channel is found (successful recovery). This is equivalent to the completion time of a packet in a queueing model with interruptions and service repeat discipline [16], where K_i can be found from the geometric distribution, as discussed in [16].

For the models in which a random arrival process is utilized, if we consider a linear cost function $g(n)$ for the number of packets in the queue, we can use the same heuristics for decision-making because linearity allows us to split the cost function between the number of packets that are in the queue, the number of packets that will be transmitted and the number of arrivals. Because the only difference when selecting different sets is the number of packets that can be transmitted, the previous heuristics are applicable because their goal is to maximize the number of transmitted packets. For instance, the myopic utility-based scheme of Eq. (13) can be modified to the following form to take the arrivals into account:

$$Z_i(n) = \mathbb{E}\Bigg[q_i^f(n)\Bigg(\frac{(1-P_i^b)(\lfloor\frac{B_iX_i^*}{L}\rfloor - \Delta(X_i^*))}{(R_i+X_i^*)} - \frac{(P_i^b)(\Delta(S_i))}{(S_i)}\Bigg) + \big(1-q_i^f(n)\big)\Bigg(\frac{(1-P_i^b)(n-\Delta(\frac{nL}{B_i}))}{\Big(R_i+\frac{nL}{B_i}\Big)} - \frac{(P_i^b)(\Delta(S_i))}{(S_i)}\Bigg)\Bigg]. \quad (24)$$

In other words, the number of arrivals during the time which existing packets are served are counted with a negative sign. For non-linear cost functions, the extension of the previous heuristics is not straightforward and should be investigated.

5 Numerical and Simulation Results

Considering the fact that the proposed models are similar and can be inter-converted, in this paper, we present the numerical and simulation results only for the backlogged model with the failure decision described in Section 3.2. The random channel search described in Section 2.4 has been used to find an available channel within the selected channel set. We have selected arbitrary but representative values for all parameters in the hierarchical channel recovery model, as listed in Table 2. We have repeated the experiments for several other parameter values and distributions, which are not included here due to space constraints, and we obtained similar results.

Five channel sets are assumed in which four or five channels are present. The possible service rates for each channel in all channel sets are $B_i \in \{0.5, 1, 1.5, 2\}$ Mbps, $i = 1, \ldots, 5$. However, as shown in Figure 5, the service rate distribution is different for each channel set (but is the same for all channels within a channel set). A_i and U_i $(\forall i)$ are assumed to be exponentially distributed (X_i is, therefore, also exponentially distributed as A_i), but the mean is different for the different channel sets. Note that $\bar{U}_1$ is variable and depends on $\gamma_1 = \frac{\bar{A}_1}{\bar{A}_1+\bar{U}_1}$, which is the availability of channels within channel set 1. The first decision was made at the flow transmission start, assuming that the last channel set before the start was set 1.

Value iteration [15] is used to numerically solve the proposed dynamic programming model. Considering the fact that the optimal decision only varies with n when n is close to the boundary values ($n \to 0$), we can consider only small flows (n^0 small). For n^0 large, the same decision will be optimal in the initial consecutive stages. The optimal decision was numerically found and then fed into simulation scenarios, using MATLAB, in which each experiment was repeated 400,000 times. To simplify the DP model, we also assumed that the recovery and blocking time were independent of the previous channel set.

Table 2: Numerical and Simulation Parameters.

Notation	**Description**	**Value**
I	Number of sets	5
$\vec{N}$	Number of channels	[5 5 6 4 4]
$\vec{\tau}$	Sensing time	[2 1 2 2.5 2] ms
$\vec{\bar{A}}$	Channel availability (1$^{\text{st}}$ Scen.)	[42 31 41 51 61] ms
$\vec{\bar{A}}$	Channel availability (2$^{\text{nd}}$ Scen.)	[42 35 41 44 31] ms
$\vec{\bar{U}}$	Channel unavailability	[$\bar{U}_1$ 35 41 44 31] ms
B	Service rate	[0.5 1 1.5 2] Mbps
L	Packet length	500 Bytes
W_{ij}	Switching time	1 (if $i \neq j$ Oth. 0)
n^0	Flow size	50 Packets

Set1	Set2	Set3
[0.25,0.25,0.25,0.25]	[0.2,0.3,0.4,0.1]	[0.4, 0.35, 0.15, 0.1]
Set4	**Set5**	
[0.2, 0.38, 0.22, 0.2]	[0.1, 0.47, 0.33, 0.1]	

Figure 5: The associated probabilities of the service rate of the channels (the distribution of B_i).

For comparative purposes, we included the simulation results of a CRN that performs a random channel set selection. We also simulated a CRN that uses a random flat search over all channels after a failure, which represents the baseline flat model.

Figure 6 compares the total transmission cost (time) versus γ_1 for the first scenario, where $\vec{A}$ =[42, 35, 41, 44, 31]. As expected, the scheme that selects the channel based on the DP model provides the best result. However, the myopic scheme based on the proposed utility function also exhibits a close-to-optimal performance. To illustrate the difference, let us discuss the decisions made by the different schemes when $\gamma_1 = 0.6$. The optimal decision provided by DP always selects channel set five, except for very small values of n, at which point channel set two is selected. The myopic utility-based scheme behaves similarly. In contrast, the analytical threshold-based scheme always uses channel set one, while the average-based scheme always uses channel set five, which explains the slightly worse performance of this scheme. In the second scenario, to show that the sub-optimal schemes do not necessarily provide a close-to-optimal scheme, we have changed the value of $\vec{A}$ to [42, 31, 41, 51, 61]. As illustrated in Figure 7, the DP model still provides the best result. However, in this scenario, the sub-optimal schemes provide results farther from the optimal.

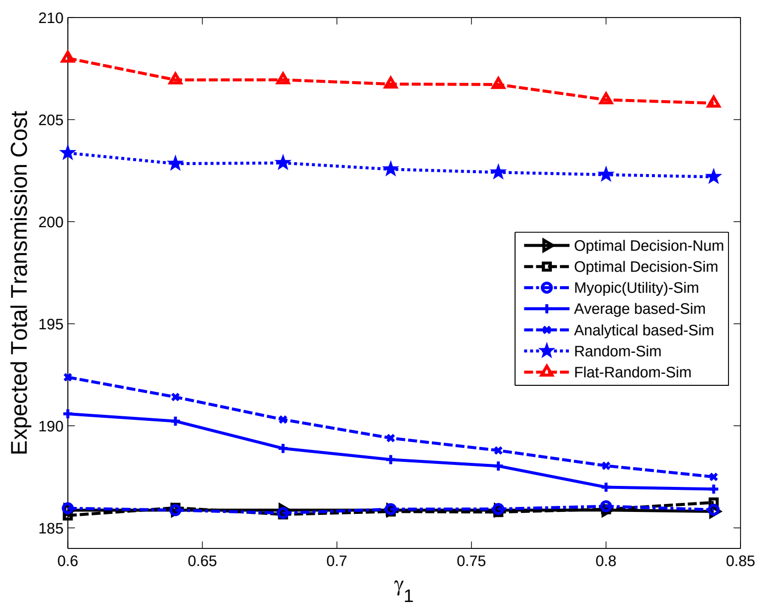

Figure 6: The total transmission cost versus the variation in γ_1 (the 1^{st} scenario).

All results show that the optimal channel set selection performs significantly better than a naive random channel set selection and a flat random search over all channels. Further, the performance degradation with the heuristics is acceptable, and the cost is still significantly lower than that of a random search, even for the average-based algorithm with limited information. The results also indicate that when the remaining number of packets to be transmitted is high such that the probability to transmit all of them in the incoming operating period is low, the channel set selection decision remains the same for consecutive decision-making points. That is, the assumption made for the proposed threshold-based scheme, which repeatedly uses the same type of channel for a range of backlogged packets, is realistic, perhaps due to the independence of the channels and, for a given channel set, the independence of the consecutive channel availability periods.

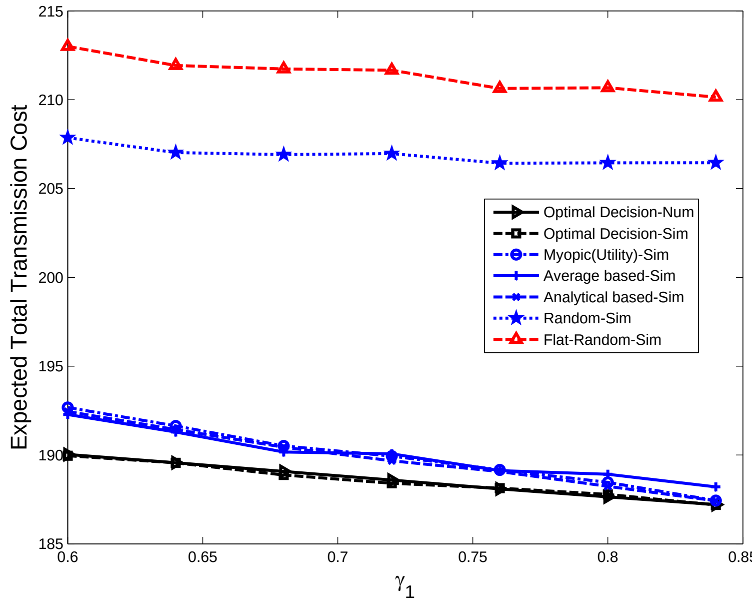

Figure 7: Total transmission cost versus the variation of γ_1 (2^{nd} scenario).

Accepting such an assumption implies that, for a new decision point in comparison to the previous one, the only change is the remaining number of packets. Therefore, for a large number of remaining packets and a long decision horizon, the same decision is valid in several consecutive decision points.

The previous results have confirmed the exactitude of the proposed DP model for a backlogged traffic and the superiority of an optimal decision versus heuristic and random decisions. In the following, we will focus on a two-set model in order to gain some insights on the behavior of the decision mechanisms versus the variation of different network parameters. A two-set model not only simplifies the analysis versus the different parameters, but it also represent a realistic scenario where a decision should be made, for instance, between using a set of low-speed high-available backup channels and a set of dynamic high-speed opportunistic channels. To be able to use closed-form and exact analytical results, we assume that the service rate of both two sets is fixed (i.e., $B_1 = b_1$ and $B_2 = b_2$).

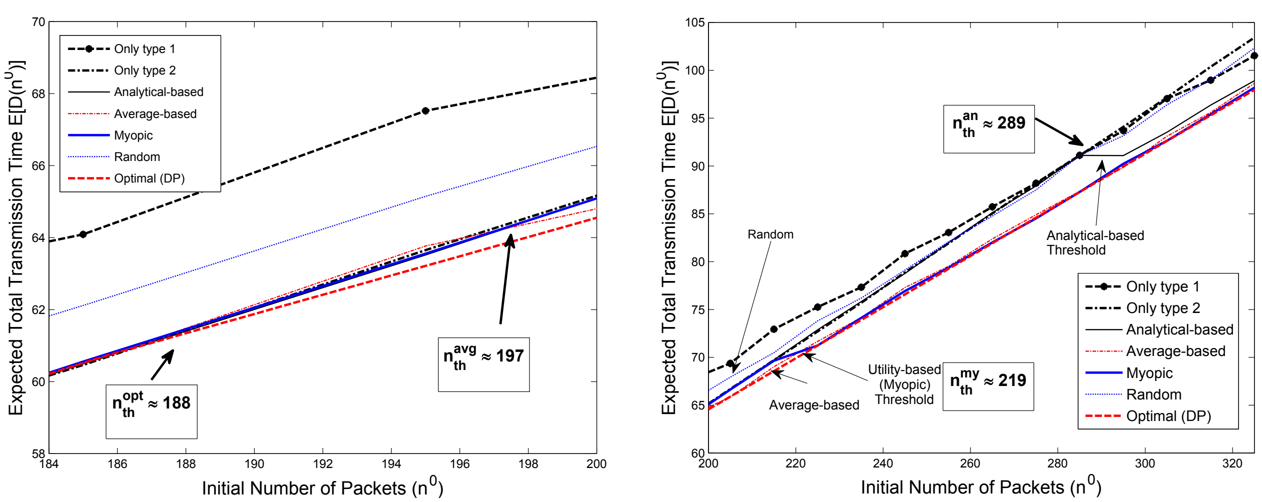

Figure 8: During the course of transmission of a flow, switching from type 1 to type 2 channels occurs at different threshold values for different schemes ($\vec{A} = [45, 60]$, $\frac{L}{b_1} = \frac{1}{5}$, $\frac{L}{b_2} = \frac{1}{3.5}$, $\vec{R} = [15, 4]$).

In Figure 8, the total transmission time as a function of the flow size length over the two-set channels is illustrated. We have selected channel set parameters such that for shorter flows channel set 2 is the best option for the entire flow transmission while for longer flows channel set 1 is the optimal decision to start with and eventually the selected set switch to channel set 2. The optimal policy for the dynamic programming model is thus a threshold policy. We want to investigate the threshold points for the DP model and proposed heuristics (naturally except the random scheme) in which the decision, in the course of transmission of a flow, is switched from channel set 1 to set 2. For this reason, the figures are magnified around the switching points.

It can be seen in the left side of Figure 8 that the DP decision switches at $n_{th}^{opt} = 188$ while the threshold value for the average-based and myopic schemes are respectively $n_{th}^{avg} = 197$ and $n_{th}^{my} = 219$. Finally, for the analytical scheme, we have $n_{th}^{an} = 289$. Therefore, all schemes except the random operate always over channel set 1 if the remaining packets to be transmitted is higher than the threshold. Then, for lower values of n, the decision schemes select channel set 2. This explains why for values of n less than the thresholds, any scheme has the same performance as always using channel set 2. However, for larger values of n, the performance is better than always using channel type 1 because some parts of the flow are transmitted over the type 2 channels.

Analytically finding the threshold value of n for the DP model is difficult. As it is expected that the threshold values of different schemes have the same trend versus the variation of different set parameters, such as the length of availability and unavailability periods and channel rate, we focus in the following on the analytical scheme since it switches exactly at the crossing point of two curves of always using type 1 and type 2 channels, which is easier to analytically derive.

Given the threshold-based analytical scheme and regarding the definition of that heuristic, the threshold value is n if $E[D_1(n)] = E[D_2(n)]$. Assuming X_i $(\forall i)$ is exponentially distributed, the threshold value n_{th}^{an} of the analytical heuristic can be found solving the following equation:

$$\begin{aligned} &\frac{n_{th}^{an} L}{b_1}\left[1+\frac{\bar{R}_1^t}{\bar{A}_1}\right]+\bar{R}_1^t = \frac{n_{th}^{an} L}{b_2}\left[1+\frac{\bar{R}_2^t}{\bar{A}_2}\right]+\bar{R}_2^t \Longrightarrow \\ &n_{th}^{an} = \frac{\bar{R}_2^t-\bar{R}_1^t}{\frac{L\left(1+\frac{\bar{R}_1^t}{\bar{A}_1}\right)}{b_1}-\frac{L\left(1+\frac{\bar{R}_2^t}{\bar{A}_2}\right)}{b_2}}. \end{aligned} \tag{25}$$

We can thus investigate how the threshold value moves when other network parameters change. For this aim, we consider in Figure 9 the example of a large set of backup channels (no blocking) with a low transmission rate but high availability, and another large set of channels with opportunistic spectrum access (OSA) with a high transmission rate but also a higher dynamism between availability and unavailability periods. The horizontal access is $E[X_2]$ (equal to $E[A_2]$), the average availability period length of the backup channels. The operating ratio of OSA channels is always fixed to $\frac{1}{3}$; i.e., $E[A_1] = 3E[R_1]$ and we vary the length of the availability and unavailability periods while maintaining this ratio. We can first observe that, as expected, the decision to select channel set 2 occurs at a larger threshold value in the number of packets to be transmitted as a function of its availability.

The results also reveal an interesting fact which is that for the same operating ratio, when type 1 channels are more dynamic and have short operating and recovery periods, the threshold value is smaller, meaning that the type 1 channel set remains the optimal decision for a longer range of remaining packets. Increasing the availability length is beneficial, as can be seen for the channel set 2. Therefore, we should expect that as we increase $E[X_1]$, the threshold should decrease instead of what is actually observed. However, since the operating ratio remains the same for the different curves, $E[R_1]$ also increases. Therefore, it can be concluded that the longer recovery period of type 1 channels is the reason that as the dynamic decreases (i.e., long availability and recovery periods), the decision threshold to switch to channel type 2 increases. In other words, $E[R_1]$ plays a more important role than $E[X_1]$ in threshold value determination. The other interesting insight to mention is that for small values of $E[A_2]$, an increase in $E[A_2]$ makes type 2 channels more rewarding, so the threshold value increases and a switching to type 2 channels occurs for a larger number

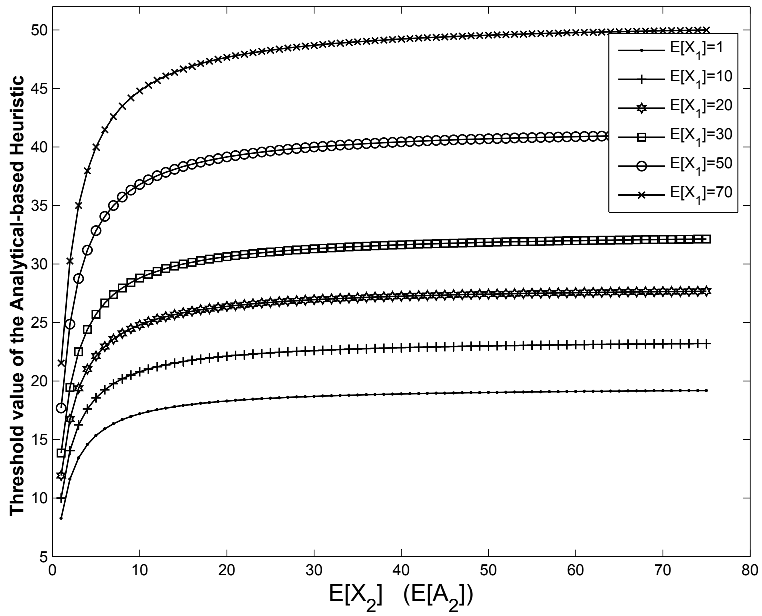

Figure 9: Threshold value (switching point) of the analytical-based heuristic versus the variation of network parameters ($\frac{L}{b_i} = [\frac{1}{5}, 1]$ and $E[R_2] = 1$).

of backlogged packets (larger n_{th}^{an}). However, for enough large values of $E[A_2]$, where type-2 channels can even be considered always available, the threshold value converge to a constant value because the channel rate is too low. That is, for a large number of backlogged packets, it will always be better to use a faster channel with unavailability periods than using an always on channel with a low rate.

We now study the two channel set model with a Poisson packet arrivals where the cost function $g(n)$ is defined as $g(n) = n$ in the DP model in Eq. (11) (decision in case of failure). Using this definition, we will have the expected system occupancy per stage. The results are illustrated in Figure 10. It can be seen that the optimal decision based on the DP model outperforms using only type 1 or type 2 channels. Regarding the threshold points in the DP model, there are two key observations. First, for the models with arrival, the optimal policy is not necessarily a single threshold policy as can be seen from Table 3. We observe two switching points for larger values of λ where channel set 2 is replaced with channel set 1, as the optimal decision, while for larger values, again channel set 2 is selected. For low values of λ, as can also be observed in Figure 10, channel set 2 is always used. The second observation is that the threshold values change with the variation of the arrival rate even if it is a traffic parameter and not a characteristic of the channel sets.

Table 3: Threshold values for Queue Occupancy (model with arrival). Parameters are the same as in Figure 10.

λ	0.05	0.1	0.15
Type-1 used	Never (Always 2)	Never	Never
λ	0.2	0.25	0.3
Type-1 used	Never	$7 < n < 15$	$6 < n < 17$
λ	0.35	0.4	0.45
Type-1 used	$5 < n < 17$	$4 < n < 16$	$4 < n < 15$

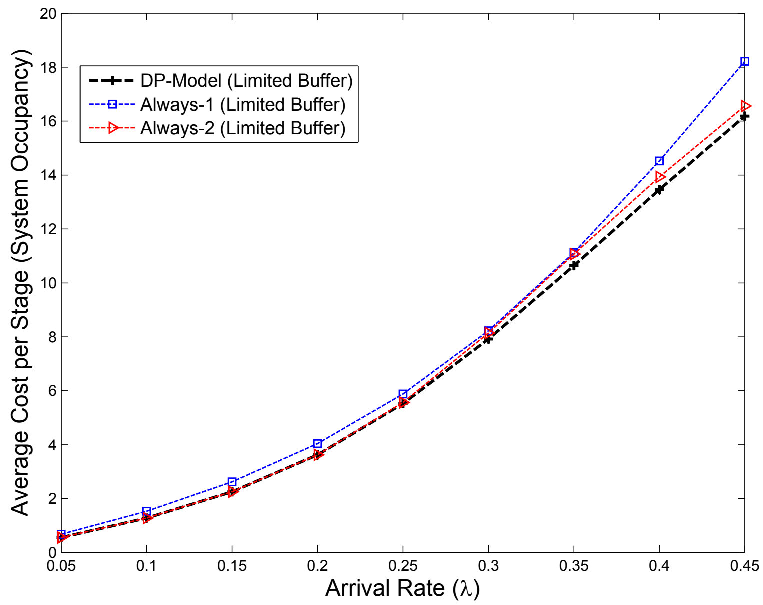

Figure 10: Average cost per stage (system occupancy) versus the variation of the arrival rate for the DP model with arrival rate and failure decisions ($\frac{L}{b} = [\frac{1}{3.6}, \frac{1}{2.4}]$, $\vec{\bar{A}} = \vec{\bar{X}} = [11, 19]$ and $\vec{\bar{R}} = [11, 9]$ for type 1 and 2 respectively. $W_{12} = W_{21} = 0$. Buffer limit is $n_{max} = 60$ packets.).

6 Conclusion and Future Work

A hierarchical channel handover and link recovery model for cognitive radio networks was proposed. Using the cognitive radio networks' capabilities of reconfigurability, decision-making, and channel sensing and switching, and given that cognitive radio networks operate over heterogeneous channel sets, we demonstrated that a decision problem exists when the CR wants to select a channel set (first tier of the recovery) to perform the second tier of the recovery over the selected set. To analyze such a decision, the DP model was used to find an optimal solution, and some heuristics were provided for both the packet-based and flow-based approaches. When the remaining number of packets of a backlogged flow is high such that the probability to transmit all of the packets before a new failure is low, the simulation results for a backlogged flow demonstrate that repeatedly using the same type of channel can be an appropriate choice because no other dependency exists between two consecutive decision points. In real scenarios, a cognitive radio network can thus take a channel set selection decision only for some threshold values of the number of remaining packets, instead of taking a decision after each channel failure or each packet transmission. This approach decreases the implementation complexity of the decision models.

In this paper, we discussed a single CR user. For multiple CR users operating in the same manner and following the proposed recovery model, more assumptions about the spectrum sharing and users' synchronization are required, which are not in the scope of this paper. With multiple users, a game theoretical analysis is unavoidable. However, assuming that all CR users are synchronized is not realistic and violates the assumption of random channel failures. On the other side, when the users are not synchronized, a CR user does not know how many users are competing with him to find a new channel. Therefore, game theoretical analysis should be provided for imperfect information where the number of players is unknown. This could be an interesting future work. Also, when the number of users which are using different channel sets is kept as a new state variable, it could be assumed that the recovery time and service time of each set is dynamic and changes in time as a function of the number of users. The multi-user scenarios can thus be addressed in theory. The proposed decision making models remain valid with only changing B_i and R_i to $B_i(m_i)$ and $R_i(m_i)$, where m_i is the current number of users operate over the channel set i. However, not only the dynamic programming models will not be tractable due to the extended state space, it is not realistic to assume that such knowledge (current number of users on each set) is available for any user in the network.

Note that in general, the existence of multiple users makes the recovery on a selected set (second tier of recovery) longer because an available channel may be taken by another CR user, and the service capacity lower because the channel may be shared with another CR user. Without keeping the number of users on each set as a state variable, the definition of R_i and B_i can be adjusted to take into account the average number of users, if, for instance, such knowledge is statistically available.

For simplicity, in this paper, we also assumed that the recovery time is independent of the channel availability. In many cases, such as random recovery schemes with a large number of channels, the use of either external spectrum servers that provide spectrum information [1] or learning-based schemes that provide a smaller decision space for recovery [8], this assumption is valid. However, a dependency can exist because when channels are less available, the probability to find an available channel decreases and, consequently, the recovery time increases. Deriving a decision procedure by considering such dependencies cannot be neglected, representing a challenging area for future research.

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