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Management of cognitive radio ad hoc networks using a congestion-based metric

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SUMMARY

In this paper, we propose a new network management protocol to address the unique challenges of managing cognitive radio ad hoc networks that have distributed, multihop architectures with dynamic spectrum availability. We focus on performance management for these networks, and address the problem of network congestion for secondary users, because of its significant impact on data throughput. Specifically, we define a performance metric, the average congestion level of the network, and derive it analytically as a function of the primary users' activities and the secondary users' strategy. For practical implementation, we further propose a cluster-based management architecture that utilizes a designated central manager and cluster heads that function as distributed managers. The cluster heads collect information from multiple layers of the protocol stack using new MIB (management information base) variables to capture the characteristics of cognitive radio ad hoc networks, such as the location-dependent spectrum availability. The objective of the management action is to utilize a network-level view of the congestion situation in the network by directing the secondary users to select the highest-quality links available and avoid congested clusters. This hierarchical networkmanagement design allows us to take advantage of its scalability to achieve near-real-time management. Numerical results demonstrate the effectiveness of the proposed scheme. Copyright © 2013 John Wiley & Sons, Ltd.

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1. INTRODUCTION

With the increased use of radio-frequency devices competing for scarce spectrum resources, the US Federal Communications Commission (FCC) has indicated in a 2002 report that portions of the spectrum are significantly underutilized [1]. The spectrum shortage and the inefficient usage of spectrum has encouraged the development of cognitive radio (CR), which is a context-aware intelligent radio capable of autonomous reconfiguration by learning and adapting to the spectrum environment [2,3]. The emergence of bandwidth demand for a host of wireless devices has motivated new spectrum allocation policies, which allow unlicensed secondary users (SU) to access the radio spectrum when it is not occupied by licensed primary users (PU). The intent is that this cognitive radio approach will improve spectrum utilization in wireless communications systems. Since the unlicensed or lower-priority SUs employing CR must limit any interference to the PUs, the SUs must only transmit in the spectrum holes left available by the PUs, where a spectrum hole is a frequency band assigned to a primary user that is not being used at a particular time and geographic location [3].

CR networks may be composed of single-hop networks, such as the fixed point to multipoint type as described by the IEEE 802.22 specification. They may also include multihop links, without a central base station, and these networks are called cognitive radio ad hoc networks (CRAHNs).They are characterized by dynamically changing network topology and spectrum availability. The major functions

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of CRAHNs are described by Akyildiz *et al*. [4], including spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility.

In this paper, we propose a framework for intelligent network management that was introduced in our preliminary work [5], called Cognitive Network Management Protocol (CNMP), which will focus initially on network performance management of the SU nodes.

It has been observed that network congestion is a dominant factor in dropped packets in mobile ad hoc networks (MANET) [6]. Additionally, because the SU nodes must opportunistically access the spectrum only when PU nodes are idle, network congestion is increased more due to the intermittent availability of bandwidth. Therefore, enhancing data throughput for both primary and secondary radio users depends largely on avoiding and reducing network congestion. To address this problem, we propose a metric to assess the congestion between SU nodes that is based on cross-layer information from those nodes and the observation of the transmission activity of the PU nodes.

1.1. Network management architectures

Network management architectures for wireless networks are broadly defined as three basic types [7]. Centralized network management uses a single manager station to gather information from all of the managed nodes and controls the network. While centralized management allows a global view of the network to make management decisions, there are several drawbacks. The central manager is a single point of failure if the manager is incapacitated and no backup manager is in place. The amount of management traffic from all of the network nodes in a wireless multihop network may be prohibitive in a CRenvironment to provide meaningful management functions in a timely manner.

Distributed network management uses multiple managers who each manage a subnetwork of nodes. This decreases the amount of network management overhead and per manager computation compared to the centralized approach. In this architecture, the managers communicate peer to peer, with no central manager, and can provide higher reliability with more networked information among the manager peers.

Hierarchical network management uses intermediate managers, each having their own management domain, to distribute management tasks. This architecture uses a central manager and the intermediate managers communicate up or down the hierarchy. There is no direct communication between intermediate managers. However, depending on the needs of the management system, any of these architectures can be used in combination.

While the development of CR hardware and software of has been the subject of much research, comprehensive network management of CR networks is not well addressed. CR networks may be implemented as single-hop networks, where network can be managed by central base stations, such as the scheme described by the IEEE 802.22 Wireless Regional Area Networks (WRAN) specification [8]. In the 802.22 specification, the network management system (NMS) receives information from the managed nodes, such as base stations (BSs) and customer premise equipment (CPE), which collect and store the managed objects in a WRAN Interface management information base (MIB) (e.g. wranIfMib) and device MIB (e.g. wranDevMib) using the Simple Network Management Protocol (SNMP).

While the 802.22 network configuration uses BS and CPE devices in a cognitive implementation, the operation of those networks is controlled primarily by the BSs and therefore are dissimilar to the independent spectrum-sensing and channel acquisition operation of CRAHNs. Thus the management of CRAHNs [9] is inherently different, which we address with a clustered architecture-based management system in this work.

CRAHNs require management of distributed CR nodes and can be implemented with a management system based on a clustered architecture similar to the Ad Hoc Network Management protocol (ANMP) [7] model. An example is shown in Figure 1, where the architecture is comprised of a hierarchical three-layer system which includes a central network manager, cluster head nodes and managed CR nodes. The network manager node has knowledge of the entire network by exchanging management information with cluster heads CH $_1$, CH $_2$, CH $_3$ and CH $_4$. These cluster heads communicate management information with the CR nodes in their respective clusters. The managed nodes use SNMP, which includes a modified MIB, cnmpMIB, which specifically addresses the management information needed for CRAHNs.

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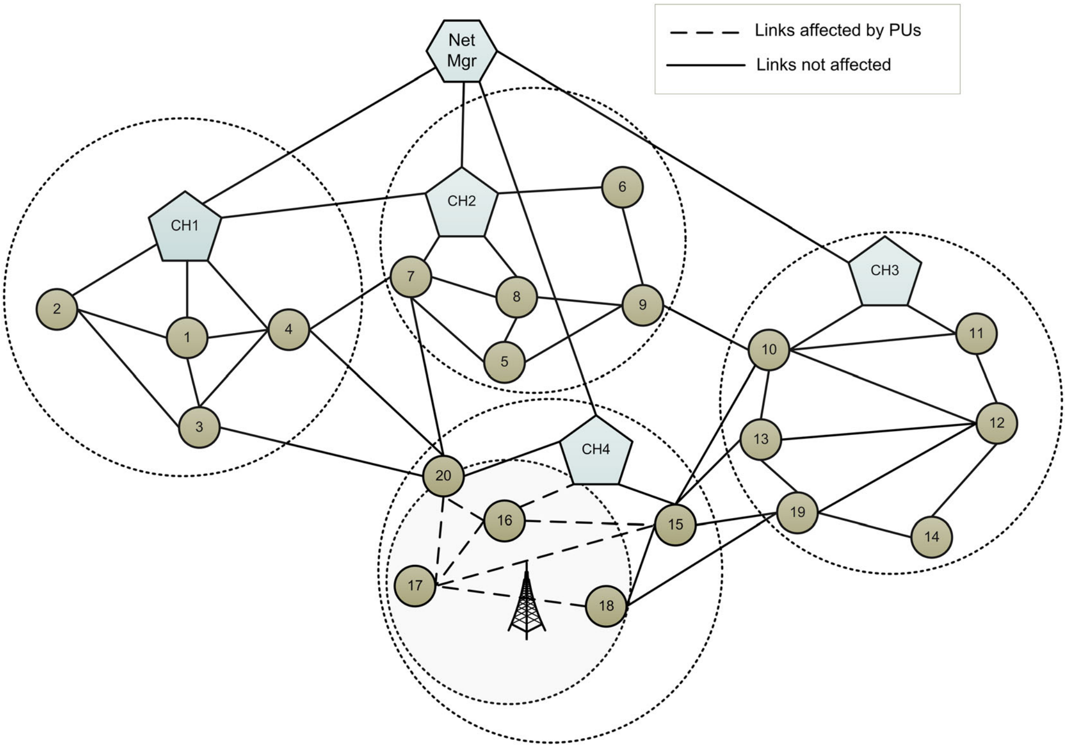

Figure 1. Clustered architecture for cognitive radio network management system

As an example of a management scenario from Figure 1, consider the case where most traffic from cluster 1 to cluster 3 traverses through cluster 4. However, if the primary user PU becomes active and occupies a substantial number of channels, many linksin cluster 4 may become unavailable to the CR network and the network manager should advise the cluster heads to redirect traffic from cluster 1 to cluster 3 traversing through cluster 2. CR networks that are sharing spectrum with very active PU networks may have to frequently move their communication data to new channels (spectrum handover) or through a different geographical area to avoid interference with the PUs. Thus we propose an autonomous management system by distributed management network nodes in near-real time that capitalizes on the capabilities of the CR nodes to perform basic functions such as spectrum sensing [10,11] and channel acquisition [9] in order to optimize overall network throughput.

1.2. Outline of work

In this paper, we focus on the performance management aspect of CNMP. Specifically, the congestion management issue is examined and the overall flow is shown in Figure 2. We consider a CRAHN of SUs overlaid on a PU system that senses spectrum holes to provide transmission opportunities. The SU network with assigned nodes monitors the average PU ON and OFF activity in addition to spectrum sensing done by the remaining SU nodes. This PU information, together with the SU sensing, transmission and idle times, are used to determine the steady-state probability of channel availability.

The channel availability is then estimated based on a threshold probability and is used in the assessment of the probability of successful channel contention for each active SU link. Together with the probability of packet error, the probability of successful transmission per link is used to determine the probability of packet drop (PPD). We then compare the PPD to a congestion threshold to determine whether the link is considered congested. In our hierarchical cluster scheme, the average congestionof the links in each cluster is calculated. Additionally, the overall cluster congestion is determined by comparing the average congestion to a cluster-level congestion threshold value. The average link congestion and the overall cluster congestion are then reported to the CR network manager, which can be used to influence adaptive routing or other management tasks.

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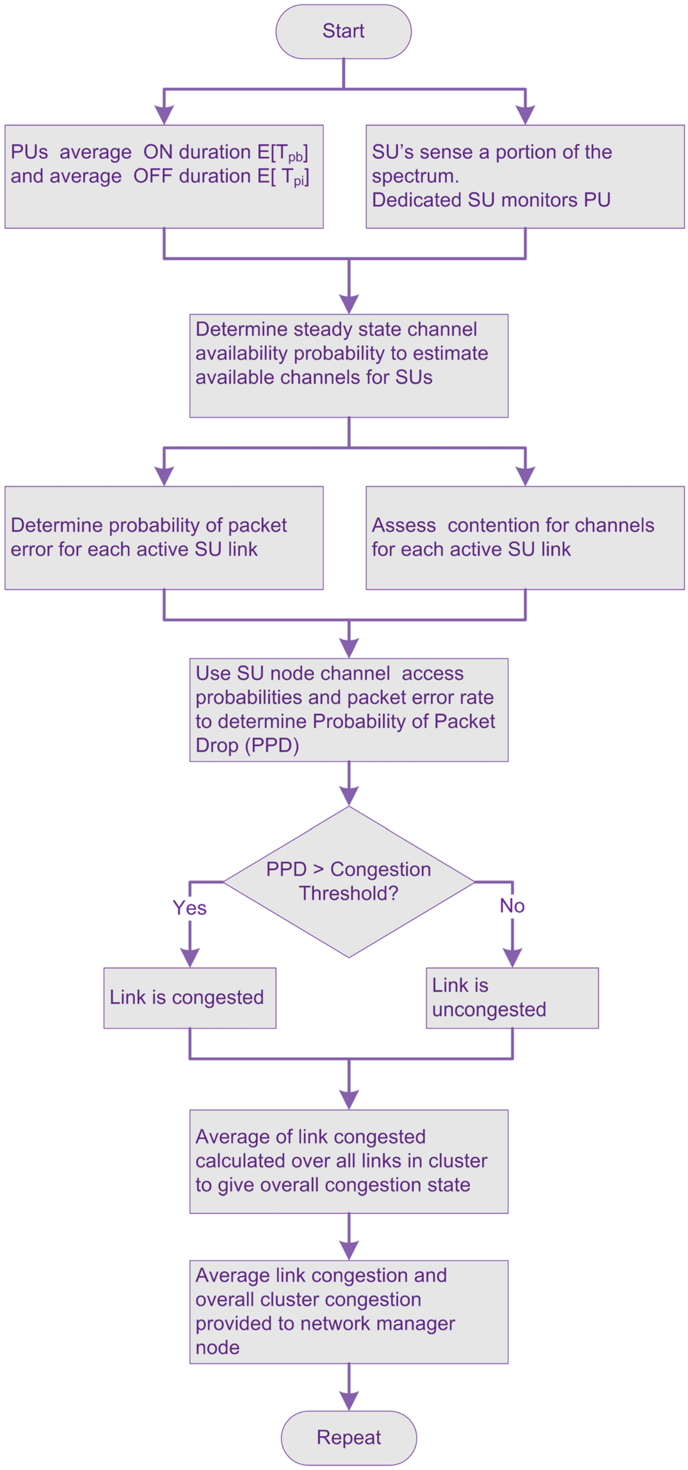

Figure 2. Overview of congestion metric development

This paper is organized as follows. Section 2 provides a review of the related studies. Section 3 discusses the problem formulation and the proposed network congestion indicator. The proposed procedure for acquiring the management data is given in Section 4 and our numerical results are reviewed in Section 5. Finally, we provide our conclusions and future research plan in Section 6.

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2. RELATED WORK

2.1. Comparison with classic network management

We start by providing an overview of the inherent differences between managing traditional networks and CRAHNs [5]. Traditional network management of wireline networks is divided into five areas: performance management, fault management, security management, configuration management and accounting management [12]. These areas as applied to telecommunications can begenerally described using the Bellcore-GR2869 Generic Requirements for Operations Based on the Telecommunications Management Network (TMN) Architecture [13] and the ITU-T Recommendation M-3400 TMN Management Functions [14]. In Table 1 we contrast the traditional functions to those required by CRAHNs. Managing a CRAHN poses a unique set of problems which include the availability and stability of channels in the wireless CRAHN environment, and in particular the potential channel interruptions due to PU activities.

1. *Performance management*. This involves measurement of network performance, with metrics such as overall throughput, packet loss and delay. Baseline performance levels are then established, based on acquired data, and performance thresholds are set for various monitored parameters. Network tuning is accomplished by throttling network devices as required to maintain network throughput [12]. In a CRAHN, performance management also should consider the ‘exploit vs. explore’ tradeoff, which applies to the amount of time the SUs sense the spectrum. Longer sensing time possibly finds more available bandwidth but leaves less time for data transmission. Spending less time sensing allows more time to transmit data, but possibly using a smaller bandwidth. The optimization of this parameter is considered by Kim and Shin [15] and leads to the acquisition of additional or better-performing channels to meet quality-of-service (QoS) objectives.
2. *Fault management*. This includes identifying, isolating and potentially correcting abnormal conditions that adversely affect services in the network [16]. Deciding which faults to manage will be influenced by the scope of control desired over the network, which affects the amount of data gathered from network devices and also by the size of the network [12]. The sub-areas of fault management include detecting alarms, localizing faults, performing diagnostic tests and fault correction. Fault management in a CRAHN environment can be very complex, due to dynamically changing spectrum availability, which can cause severe difficulties in performing fault identification and isolation. Communication alarms that include loss of signal or frames must take into account the resumption of communication in an alternative channel if there is spectrum handover of the communication flow due to PU interruption.
3. *Security management*. This ensures that network users are authenticated and authorized by controlling network access points. It also prevents unauthorized users from spoofing the

Table 1. Traditional versus cognitive radio network management system functions

Network management component	Wired traditional network	Wireless cognitive radio ad hoc network
Performance management	Monitor performance and throttle resources	Proactive and reactive performance control with dynamic bandwidth allocation
Fault management	Identify, isolate and clear faults	Manage highly variable link quality, channel acquisition after PU interruption
Security management	Control network access, Protect against intrusion, tampering, spoofing	Control network access and routing, mobility handling. Protect against intrusion, tampering, spoofing
Configuration management	Setup equipment configuration, update software versions	Update network for nodes that move, power-off or die, spectrum sensing and utilization
Accounting management	Track resource utilization, allocate resources per service-level agreements	Accounting/billing used with performance management for QoS agreement

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network or tampering with network operation [12]. CRAHNs, in addition to these traditional security functions, must handle spectrum congestion—where attacks may be waged by malicious jammer nodes to occupy all channels in a geographic area [17]. This denies channel availability to SU users, who sense that itis PU activity, and affects both transmitting and receiving CR nodes.

4. *Configuration management*. This traditionally involves locating and setting up the parameters and versions of network devices for operation. Additionally, it includes network planning and engineering, installation, service planning, provisioning and control [13]. However, in CRAHNs, nodes may be mobile, or may power off intentionally to save power, or die from battery discharge. Also, during PU or malicious node activity, there may be no channels available to reach some of the CR nodes, effectively altering the topology of the network. In a hierarchical CR network model, methods for cluster head selection and managed node affiliation that can be applied to configure a CR network are discussed by Chen *et al*. [7].
5. *Accounting management*. This monitors the network usage of users and groups and provides the measurement method for compliance to a service-level agreement. The management system also keeps records of the usage metrics for charging andbilling. Managing a QoS agreement on a CRAHN is more complex than using traditional management because the service is not solely dependent on the CR network, but also on the activity of the PU network, which can hamper throughput or completely interrupt service. This provides a potential application of accounting management to track quantities such as bandwidth usage, average throughput and spectrum handovers due to PU activity, as spectrum markets and brokering systems are developed. Markets based on primary to secondary users and also between secondary users, as discussed in work by Xu [18], will require accounting management.

2.2. *Comparison with related network management protocols*

While the literature describes various approaches to managing CR networks, we should distinguish between network management and radio resource or spectrum management. There has been significant research for spectrum management, such as those discussed in the survey done by Akyldiz *et al*. [19]. However, these studies do not provide solutions for a comprehensive network management system.

The Ad Hoc Network Management Protocol [7] is fully compatible with SNMP and has created a set of MIBs that are more germane to wireless than wireline networks, such as power usage, agent information and topology maintenance groups of information records. ANMP also uses a clustering concept to simplify management of the network by reducing management messaging overhead. However, ANMP was intended for fixed spectrum access and the network management message overhead was not dependent on spectrum availability. We note that for CR networks, in addition to grouping CR nodes by geolocation or number of hops proximity to each other, we must also take into account that they should also be clustered by a set of common potentially available channels.

Policy-based management was initially proposed as an approach to automate the management of large-scale networks and distributed systems. However, the conventional policy-based management systems cannot be directly applied to CR networks [20].

Clearly, the unique network management needs of CRAHNs demand a new approach. To address this problem, our contribution builds on the concepts reviewed and includes the following:

1. The CR network is implemented as a hierarchical cluster with a network manager, cluster heads (distributed managers) and managed nodes.
2. The manager uses average network congestion indicator as one of its tools to manage the CR network nodes.
3. The proposed average network congestion indicator is derived as a function of PUs' activities and SUs' strategy, which is based on a two-state Markov model, and in turn provides grounds for setting control parameters for SUs to relieve networkcongestion if needed.
4. Thirteen new MIB variables are introduced to facilitate calculation of the new management metric.

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Several network management and performance metrics for CR networks are shown in Table 2, where we observe that the existing metrics in the literature do not directly address network congestion based on PU activity as interference to SU channel access. However, the new metrics presented in this paper will address the need for congestion awareness.

3. PROBLEM FORMULATION AND THE PROPOSED NETWORK CONGESTION INDICATOR

Given the uncertainty of spectrum availability for CRAHNs as we have discussed above, we now propose a model from which we will develop our network management platform. Initially, we determine the probability of packet drop, which is a key indicator for network congestion that the network manager can use to influence the overall routing behavior determined by the cluster heads and managed nodes.

In order to model the channel usage patterns of primary users, various approaches have been proposed in the literature, such as the hidden Markov model (HMM) [23], and multivariate time series [24], to learn the primary user characteristics and predict the future occupancy of channels. For practical implementation considerations, a binary scheme (empty or occupied) can be used to reduce the complexity and storage requirements. It is also noted in Geirhofer *et al.* [25,26], based on real-world measurement data, that the statistical model of a primary user's behavior should be kept simple enough to be able to design optimal higher-order protocols. On the other hand, the model would be useless if the primary user's behavior could not bepredicted well. In order to strike a balance between complexity and effectiveness, in this work we have used a Markov model of PU's activities, adjusted by the SU's perceptions. This is very important since the channel availability the SU perceived would be what actually matters in terms of actions taken by the SU. The periodic spectrum sensing/data transmission based MAC layer model is the de facto choice for CR networks, and it is also general enough to cover most of the proposed MAC structures proposed in the literature [27]. As a result, the model used in this work represents realistic implementations of real-world CR ad hoc networks.

In this paper, we assume that there exists a radio network consisting of a set of Z licensed primary users, $\mathcal{Z} = \{1, \dots, Z\}$ and a set of S unlicensed secondary users, $\mathcal{S} = \{1, \dots, S\}$ employing CR devices. To simplify the metric development, we assume that both the PU and SU devices are stationary but randomly distributed. The CR nodes are connected via a set of L links, $\mathcal{L} = \{l_{jk} | j \in \mathcal{S}, k \in \mathcal{S}\}$, where each link is defined by the nodes on either end of the link. The set of channels used is $\mathcal{C} = \{1, \dots, C\}$, where C is the total number of channels in the system. Each link, l_{jk}, uses a subset of available channels obtained by spectrum sensing. As various source and destination nodes communicate across the network, they will establish a setof F data flows, $\mathcal{F} = \{1, \dots, F\}$, to occupy some or all of the available channel bandwidth on the links. We define the total flow across a given link as the set of individual flows traversing the link, $\mathcal{F}_{jk} = \{f_{jk} | f \in \mathcal{F}, j \in \mathcal{F}, k \in \mathcal{S}\}$. Similarly, the set of channels in use on a particular link, l_{jk}, is specified by $\mathcal{C}_{jk} = \{c_{jk} | c \in \mathcal{C}, j \in \mathcal{S}, k \in \mathcal{S}\}$. For the specific set of channels that are used by the total flow $\mathcal{F}_{jk}$ on link l_{jk}, we define the set $\mathcal{C}_{jk}^{\mathcal{F}} \subset \mathcal{C}_{jk}$.

Table 2. Comparative network management and performance metrics and explanations

Metric	Explanation
Signalling load	Number of bytes required for signalling as an indicator of the amount of management traffic [21]
Spectrum utilization	Sum of network throughput or goodput, network available time, and throughput of secondary (CR) system [22]
Power efficiency	Measure of active time and battery efficiency [22]
Communication cost	Communication cost for end users [22]
Link reliability	Link reliability with respect to bit error rate (BER), frame error rate (FER) and packet drop ratio (PDR) [22]
Average packet delay	Average amount of delay experienced by primary network due to secondary (CR) network [22]
Application QoS	Voice quality measured by mean opinion score (MOS), video quality measured by media delivery index (MDI), distortion and peak signal-to-noise ratio (PSNR) [22]

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Each channel, $c \in \mathcal{C}$, will have a data rate of b_c. The aggregate data rate of a link can then be expressed as

$$\beta_{jk}^{\mathcal{C}} = \sum_{c \in \mathcal{C}_{jk}} b_c \tag{1}$$

and the data rate of the flow per link as

$$\beta_{jk}^{\mathcal{F}} = \sum_{c \in \mathcal{C}_{jk}^{\mathcal{F}}} b_c \tag{2}$$

3.1. Primary user activity model

It is assumed that the PU's activity follows a Markov model, where the ON or OFF intervals of each PU are completely independent and determine the availability of the channels for the SUs in the interference range of any PU. We assume that the ON and OFF durations are exponentially distributed. We will consider the channel availability as perceived by the SUs, given that their spectrum sensing may include some probability of error. Referring to Figure 3, let T_{st}^c be a random variable representing the time duration that the SU transmits in channel $c \in \mathcal{C}$, after sensing that the channel is idle. We also let T_{si}^c be a random variable representing the time duration that the SU is idle in channel c after sensing that the channel is busy. Since the SU may not always sense the channel state accurately, P_{ef}^c represents the probability of false alarm, and P_{em}^c is the probability of missed detection. With respect to the PU, the duration of the busy period from a PU transmission onchannel c is T_{pb}^c, and the complimentary idle period duration for the PU on the channel is T_{pi}^c. The SU will attempt to acquire the channel, c, for the overall time duration of interest, T_{sd}.

As discussed by Kim and Shin [15], we define channel utilization, u^c, as the fraction of the total time duration of interest in which channel c is in the busy state as

$$u^c = \frac{E\left[T_{pb}^c\right]}{E\left[T_{pb}^c\right] + E\left[T_{pi}^c\right]} \tag{3}$$

Additionally, we define the average number of arrivals of a channel going into a busy state as

$$\lambda_b = \frac{1}{E\left[T_{pb}^c\right]} \tag{4}$$

and the average number of arrivals of a channel going into an idle state as

$$\lambda_i = \frac{1}{E\left[T_{pi}^c\right]} \tag{5}$$

which then allows the channel utilization, u^c, to be expressed as

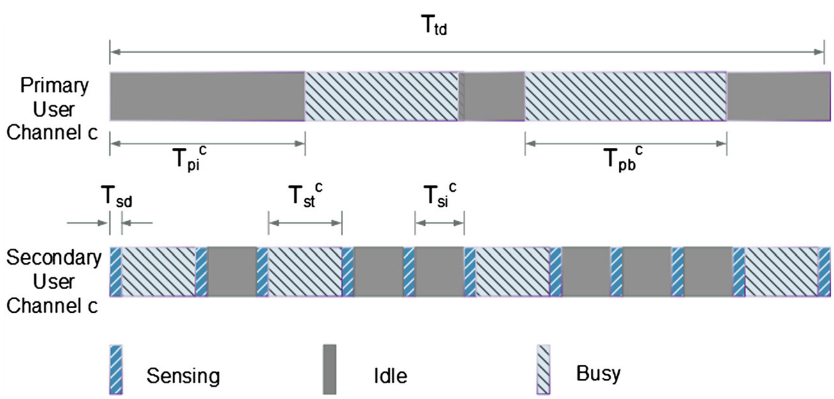

Figure 3. Time durations for channel access

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$$u^c = \frac{\lambda_i}{\lambda_i + \lambda_b} \tag{6}$$

Referring to Figure 4, as noted earlier, we model the state of the channel activity as a Markov process to determine the transition probabilities of the channel states. The transition probability of changing from the idle state, S_{idle}, to the busy state S_{busy}, at any time instant, t, is shown by Kim and Shin [15] as

$$P^c_{ib}(t) = u^c - u^c e^{-(\lambda_i+\lambda_b)t} \tag{7}$$

and from the busy state to idle state as

$$P^c_{bi}(t) = (1 - u^c) - (1 - u^c)e^{-(\lambda_i+\lambda_b)t} \tag{8}$$

The probability of the idle state transitioning back to itself is given by

$$P^c_{ii}(t) = (1 - u^c) + u^c e^{-(\lambda_i+\lambda_b)t} \tag{9}$$

and similarly the probability of the busy state transitioning to itself is

$$P^c_{bb}(t) = u^c + (1 - u^c)e^{-(\lambda_i+\lambda_b)t} \tag{10}$$

These equations represent the *actual* channel state transition probabilities based on the activity of the PUs. To reduce the complexity of our numerical results, we will consider the network state at a specific value of t, thus allowing the actual transition probabilities to be treated as static quantities.

Since the secondary user nodes may not always correctly sense channel availability, we note that the *perceived* transition probabilities must account for the probability of missed PU activity or false alarm for the time interval under consideration. There are four cases to consider regarding the correct or incorrect sensing of the channel:

1. The SU correctly senses the channel and transmits.
2. The SU incorrectly senses the channel and transmits.
3. The SU correctly senses that channel and is idle.
4. The SU incorrectly senses the channel and is idle.

We can define the percentage of the total duration that the SU senses the channel and transmits as

$$\alpha_{st} = \frac{T_{sd} + T_{st}}{T_{td}} \tag{11}$$

and the percentage of the total duration that the SU senses the channel and is idle as

$$\alpha_{si} = \frac{T_{sd} + T_{si}}{T_{td}} \tag{12}$$

Then the perceived transition probability by the SU of the channel moving from the idle state to the busy state uses case 1 and case 2 as

$$\gamma^c_{ib} = P^c_{ib} P^c_{ef} \left[\alpha_{si} - \alpha_{st} + \frac{\alpha_{st}}{P^c_{ef}} \right] \tag{13}$$

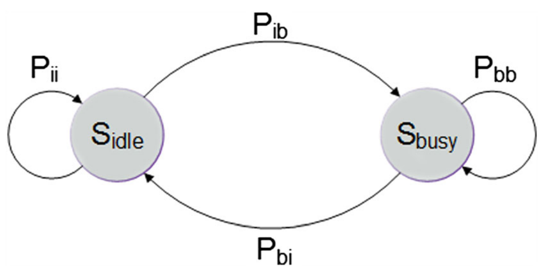

Figure 4. Two-state Markov channel diagram

and conversely the perceived transition probability of the channel going from the busy state to the idle state uses case 3 and case 4 as

$$\gamma_{bi}^{c} = P_{bi}^{c} P_{em}^{c} \left[\alpha_{st} - \alpha_{si} + \frac{\alpha_{si}}{P_{em}^{c}} \right] \tag{14}$$

To complete the set of perceived transition probabilities, we see that the self-returning transition probabilities are

$$\gamma_{ii}^{c} = 1 - \gamma_{ib}^{c} \tag{15}$$

and

$$\gamma_{bb}^{c} = 1 - \gamma_{bi}^{c} \tag{16}$$

From these transition probabilities, we can determine that the perceived steady state probability that channel c is in the idle state is

$$\pi_{i}^{c} = \frac{1}{1 + \frac{\gamma_{ib}^{c}}{\gamma_{bi}^{c}}} \tag{17}$$

which can be represented as a function of the component probabilities and time duration intervals as shown in equation (18):

$$\pi_{i}^{c} = 1 / \left\{ 1 + \left[\frac{P_{ib}^{c} P_{ef}^{c} \left(\alpha_{si} - \alpha_{st} + \frac{\alpha_{st}}{P_{ef}^{c}} \right)}{P_{bi}^{c} P_{em}^{c} \left(\alpha_{st} - \alpha_{si} + \frac{\alpha_{si}}{P_{em}^{c}} \right)} \right] \right\} \tag{18}$$

3.2. Derivation of the proposed metric

We will model the state of the network as either *congested* or *uncongested*. It is also assumed that the SU network will be managed for near-optimum throughput over time by a network manager SU node. Given the low latency requirements of delay-sensitive applications such as video or other multimedia data, the network manager concept here does not attempt to precisely control all SU nodes in each PU observation period. The time required for node-to-manager communication could beprohibitive for such applications, as pointed out by Shiang and van der Schaar [28]. Instead, the network manager operates based on the average congestion of all the links, by instructing the cluster heads (distributed managers).

In order to determine the channels perceived by the SUs as available, we use the perceived channel idle probability, π_i^c, as the probability of success in a binomial model. Here the random variable, ρ_{jk}, represents the number of available channels on link l_{jk}, and x represents a number of channels that we use in the binomial model to evaluate the probability. We test the probability for a specific number of channels against a threshold, Θ, to provide a levelof confidence for the estimated channel availability.

To accomplish this, we find x^*, such that

$$x^* = \operatorname{argmax}\{x\}, \text{subject to} \left\{ 1 - P\left[\rho_{jk} \leq x \right] \right\} > \Theta \tag{19}$$

We solve the inequality by evaluating the expression with a range of values for x, $(0 \leq x \leq C)$, until the criteria are satisfied. The total number of channels perceived by the transmitting and receiving nodes on link l_{jk} as being available can be set to the number of channels meeting the probability threshold:

$$C_{jk} = x^* \tag{20}$$

This number of available channels provides the cardinality of the set of channels that are used by the SUs on link l_{jk}, which we defined earlier as $\mathcal{C}_{jk}$.

In our study, we assume that all of the channels used by each PU are contiguous and have the same ON and OFF durations. Hence we can use the same probability, π_i^c, for each channel and treat the probability of finding a specific number of channels as a binomial distribution. In this case, we define a success as the channel being idle with probability π_i^c, or a failure otherwise. We then consider the representation of the probability in equation (19) as

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$$P\left[\rho_{jk} > x\right] = 1 - \sum_{\delta=0}^{x} \binom{C}{\delta} \left(\pi_i^c\right)^{\delta} \left(1 - \pi_i^c\right)^{C-\delta} \tag{21}$$

where δ represents the number of channels in each trial and C is the total number of channels in the network.

The system model bases its metric of congestion on the probability of packet drop (PPD) since the packets of incoming and outgoing queues on the CRs may be dropped in anticipation of filling, as in random early detection (RED) [29], or when the queues have already filled to capacity.

Referencing Figure 5, the unidirectional flow load $\mathcal{F}_{jk}$ on link l_{jk} is defined as the flow from the transmitter of link l_{jk}, (T_j), to the receiver of link l_{jk}, (R_k). The transmitting node on link l_{jk} has a coverage range, Γ_j^T, which contains a subset of the SUs that are within that area. Similarly, the receiving node on link l_{jk} has a sensitivity range, Γ_k^R, which contains the subset of SUs whose transmissions reach node R_k.

In order to calculate PPD, without loss of generality, we use a carrier-sensing multiple access (CSMA) media access control (MAC) scheme. We assume that all flows from a particular node may be accommodated by the use of orthogonal frequency division multiplexing (OFDM), with adaptive and selective allocation of OFDM subcarriers such that any subset of channels, $c \in \mathcal{C}$, may be transmitted simultaneously. Here, we note that OFDM is well suited for CR because it is agile in selecting and allocating subcarriers dynamically and it facilitates decoding at the receiving end of each subcarrier [30]. In multi-user OFDM systems, the subcarrier allocation to users can be done adaptively as well. By using OFDM, any subset of channels is a group of OFDM subcarriers, which can be allocated to a certain traffic flow. It is also shown that simultaneous transmission on a set of OFDM subcarriers is feasible [30].

We then calculate the probability that the transmitting node, T_j, of link l_{jk} is able to obtain the bandwidth required, $\beta_{jk}^{\mathcal{F}}$, that is shared with other neighboring nodes, for transmitting the total flow, $\mathcal{F}_{jk}$. That probability is

$$P_{TX}^{jk} = \prod_{R_n \in \Gamma_j^T} \left(1 - \frac{\beta_{jk}^{mn}}{\beta_{jk}^{\mathcal{C}}}\right) + \left(1 - \prod_{R_n \in \Gamma_j^T} \left(1 - \frac{\beta_{jk}^{mn}}{\beta_{jk}^{\mathcal{C}}}\right)\right) \frac{\beta_{jk}^{\mathcal{F}}}{\left(\sum_{R_n \in \Gamma_j^T} \beta_{jk}^{mn}\right) + \beta_{jk}^{f} \mathcal{F}} \tag{22}$$

Here, Γ_j^T is the interference range of T_j, and R_n is a receiver of link l_{mn}, ($l_{mn} \neq l_{jk}$), that is within the interference range of T_j. $\beta_{jk}^{\mathcal{C}}$ is the data rate on link l_{jk} that uses the channels in $\mathcal{C}_{jk}$. The channels used by the flow on link l_{mn} for its data rate that are contained in the set of channels, $\mathcal{C}_{jk}$, in use on link l_{jk}, are represented by the data rate

$$\beta_{jk}^{mn} = \sum_{c \in \left(\mathcal{C}_{mn}^{\mathcal{F}} \cap \mathcal{C}_{jk}\right)} b_c \tag{23}$$

In other words, we implicitly assume that nodes first perform frequency division multiple access (FDMA) (first term in equation (22)), then, if not possible to accommodate all flows by FDMA, determine the probability of winning the contention between competing nodes for channel access (second term in equation (22)).

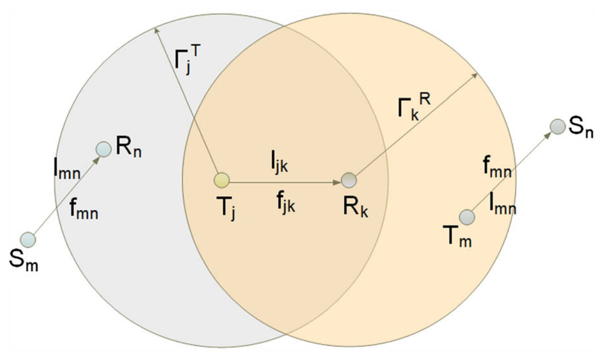

Figure 5. Secondary User node and link configuration

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Similarly, we calculate the probability that the receiving node, R_k, of link l_{jk} is able to obtain the bandwidth needed for receiving the flow from T_j that is shared with other neighboring nodes as

$$P_{RX}^{jk} = \prod_{T_m \in \Gamma_k^R} \left(1 - \frac{\beta_{jk}^{mn}}{\beta_{jk}^{C}}\right) + \left(1 - \prod_{T_m \in \Gamma_k^R} \left(1 - \frac{\beta_{jk}^{mn}}{\beta_{jk}^{C}}\right)\right) \frac{\beta_{jk}^{\mathcal{F}}}{\left(\sum_{T_m \in \Gamma_k^R} \beta_{jk}^{mn}\right) + \beta_{jk}^{f}\mathcal{F}} \tag{24}$$

where T_m is the transmitter of link l_{mn}.

Again, we implicitly assume that nodes first perform FDMA (first term in equation (24)). Then, if it is not possible to accommodate all flows by FDMA, the node competes for channel access with other neighboring nodes (second term in equation (24)).

The probability that the transmission is not successful on link l_{jk} in a single time period can then be calculated as

$$P_{fail}^{jk} = 1 - \left(1 - P_e^{jk}\right)^N P_{TX} P_{RX} \tag{25}$$

where P_e^{jk} is the probability of bit error at the PHY layer on link l_{jk} and N is the total number of bits in the packet. We assume that all packets are of uniform length.

The probability of packet drop D_{jk} for each flow on link l_{jk} can then be determined by using the maximum number of retransmissions, q, such that

$$D_{jk} = \left(P_{fail}^{jk}\right)^{q+1} \tag{26}$$

We may now define a congestion indicator, I_{jk}, for the unidirectional link l_{jk} as

$$I_{jk} = \begin{cases} 1 & \text{if } D_{jk} > v \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

otherwise v is a predefined congestion threshold that may be based on a QoS target.

Since there are L links in the system, we define the overall system state as *congested* or *uncongested*, per the average of the link congestion indicator value, $\bar{I}$:

$$\bar{I} = \frac{\sum_{j=1}^{L} \sum_{k=1}^{L} I_{jk}}{L} \tag{28}$$

which is used to calculate the system state, S:

$$S = \begin{cases} 1 & \bar{I} \geq \tau \\ 0 & \text{otherwise} \end{cases} \tag{29}$$

where $S = 1$ corresponds to the network being congested and $S = 0$ is the uncongested case. The threshold percentage value for congestion is τ.

4. MANAGEMENT PROCEDURE

This section describes how the parameters are received from the network nodes, processed and transmitted back to the nodes, as required. We assume that there is a common control channel (CCC) that is out of band for the primary users and can be used freely by the SUs for management communication. A CCC in CR networks facilitates a variety of operations, from transmitter–receiver handshake, neighbor discovery, channel access negotiation, topology change and routing information updates, to cooperation among CR users [4]. The CCC design in CRnetworks is originated from the medium access control (MAC) in multichannel wireless networks. Although the concept of CCC is not new, the CCC design in CR networks faces two new challenges: PU activity and spectrum heterogeneity [31]. A thorough review of CCC design in CR networks is given in a CCC survey paper by Lo [31]. For instance, adaptive multiple rendezvous control channel (AMRCC) based on frequency hopping [32] can be used by dynamically adapting the hopping sequences to the detectedPU activity. We also assume that the SUs are synchronized

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such that a short quiet period for sensing is reserved. Initially, the PUs may be active on a number of contiguous channels in the set of $\mathcal{C}$ channels.

Referring to Figures A.1–A.3 in the Appendix for a more detailed description of the management process, we see that the management procedure begins with observation of the PUs' activity on the network channels by the regular SUs and one or more dedicated SUs or sensors. The reason for the dedicated units is to have uninterrupted monitoring of the PU busy and idle behavior for a complete SU time duration interval, T_{td}. However, to preserve node power, the network manager may choose to assign a different SU node for the next PU monitoring period, based on the amount of transmit and receive activity and remaining battery life. The monitoring SU collects and calculates information about the chosen PU monitored, including the new cnmpMIB variables cnmpPuMonitorTime, cnmpPuOnTime and cnmpPuOffTime. Descriptions of these variables are listed in Table 3.

Once these variables have been recorded, the monitoring SU may send a trap to its cluster head (CH) to inform the CH that the PU variables are available. This is an implementation of trap-directed polling [16], which provides timely notification that PU data are ready for processing, such that the cluster head can choose to poll the SU for data when it is ready to do so. This minimizes unnecessary polling and decreases network management channel congestion.

Simultaneously, the normal communicating SU nodes will perform spectrum sensing and determine whether channels are available for SU transmission. The SUs will calculate and populate the cnmpMIB with the variables, cnmpSuSensingTime, cnmpSuTransmitTime and cnmpSuIdleTime, based on the most recent transmission, idle time and sensing activity, respectively. Since the cnmpMIB is fully compatible with SNMPv3, an SMNP 'get' command can be issued by the cluster head node to gather the values of these elements via the SNMP management agents in the SU nodes. This information is used by the cluster head to calculate the average number of arrivals of transitions of a channel going into a busy or idle state, λ_b or λ_i, respectively. It also calculates the channel utilization, u^c, and actual transition probabilities of the channel state to idle or busy, P^c_{ib}, P^c_{bi}, P^c_{ii}, and P^c_{bb}, as described earlier. Further, the cluster head calculates the probability of false alarm, P^c_{ef}, the probability of missed detection, P^c_{em}, and the channel state transition probabilities as *perceived* by the SU nodes, γ^c_{ib}, γ^c_{bi}, γ^c_{ii} and γ^c_{bb}. These transition probabilities provide the basis to calculate the perceived steady-state probability, π^c_i, that channel c is in the idle state.

Table 3. Cognitive network management protocol MIB

MIB	MIB variable	MIB variable description
cnmpMIB(1)	cnmpNumChannelsAvailable (1)	'Number of channels available on the node interface'
	cnmpChannelIndicesAvailable (2)	'Indices of channels available on the node interface'
	cnmpNumFlowsAvailable (3)	'Number of flows available on the node interface'
	cnmpFlowIndicesAvailable (4)	'Indices of the flows available on the node interface'
	cnmpSuSensingTime (5)	'Time duration in seconds used by the node for spectrum sensing'
	cnmpSuTransmitTime (6)	'Time duration in seconds used by the node for a transmission sequence of packets'
	cnmpSuIdleTime (7)	'Time duration in seconds used by the node during which no packets are transmitted'
	cnmpPuOnTime (8)	'Time duration in seconds used by the primary user for a transmission sequence of packets'
	cnmpPuOffTime (9)	'Time duration in seconds used by the primary user during which no packets are transmitted'
	cnmpPuMonitorTime (10)	'Time period duration in seconds used by the secondary user node to monitor the activity of the primary user'
	cnmpAvgLinkCongestionInd (11)	'Value of the average link congestion metric for one or more secondary user nodes. The value range is continuous from zero to one, with zero being uncongested, and one being highly congested'
	cnmpSysCongestionState (12)	'Value of the system congestion state for one or more secondary user nodes. The value range is either zero, being uncongested, or one, being highly congested'

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The cluster head then queries the SU nodes in its cluster for the cnmpMIB variables, cnmpNumChannelsAvailable and cnmpChannelIndicesAvailable, from which it calculates the probability, P_{jk}, that each SU will meet or exceed a particular channel availability per the threshold, Θ.

We have also developed a process to increase the spectrum channel awareness of the SUs by treating the sensed channels over a geographic area as an image-processing problem. The method used is total variation inpainting and the result of the process is an estimate of the complete channel availability over a geographic region [33]. The accuracy of the inpainting algorithm in determining the idle or busy state of the channels is proportional to the amount of correctly sensed data from the SUs. The inpainting error rate then can be a factor in the estimation of the error probabilities, P^c_{ef} and P^c_{em}.

Flow per link information is also queried from each SU node by the cluster head using the SNMP 'get' command for the cnmpMIB variables, cnmpNumFlowsAvailable and cnmpFlowIndicesAvailable. Additionally, standard MIB II variables are queried by the cluster head to calculate the probability of packet drop at the SU. Those variables are ifInUcastPkts, ifInNUcastPkts, ifInDiscards, ifInErrors and ifInUnknownProtos.

The cluster head assigns a value of one to the link congestion indicator variable if the packet drop probability is greater than the assigned threshold, v. Otherwise the value for the particular link is set to zero. Each SU link in the cluster is assigned a congestion value and the average of all of the congestion values is calculated and stored in the cnmpMIB variable, cnmpAvgLinkCongestionInd. This average value is then compared to a cluster congestion threshold value, τ, and the cnmpMIB variable cnmpSysCongestionState is assigned the value one if the average congestion indicator value exceeds τ. Otherwise, cnmpSysCongestionState is set to zero.

The values of cnmpAvgLinkCongestionInd and cnmpSysCongestionState are then available for query by the Network Manager to determine coarsely whether the overall cluster is considered to be congested or, more finely, how much average link congestion is present. This can be used to influence the routing protocol to select a less congested path from source to destination, if possible. Congestion adaptive routing protocols have been proposed by Tran and Raghavendra [34] and Kumaran and Sankaranarayanan [35], which could possibly be adapted to use this metric as a predictive factor in the routing determination. Here, we see that a key contribution of this metric is that it provides a probabilistic estimate of network congestion taking into account the dynamic spectrum characteristics of a cognitive radio network using a combination of standard SNMP MIB II and custom cnmpMIB variables.

5. NUMERICAL RESULTS

The numerical study examines how capturing the information to determine the system congestion state can be used to influence the network behavior towards greater throughput by avoiding congested links where possible. The model for the study was developed using MATLAB for numerical computation. We consider a square area defined by 500×500 m in which we randomly place a number of PUs and a number of SUs. For our results, we have used one, two or five PUs and 18 SUs over the area. A table of important study parameters is included in Table 4. The node locations and coverage areas for the PUs and cluster heads are shown in Figure 6. The PUs are active on the available channels per a Poisson distribution. The interrupt range of each primary user is defined by the distance within which the channels used by the primary user are not available and in this case is set to 150 m.

The number of channels used by the primary users is contiguous, but the number of channels and the starting channel are random, unless otherwise noted, such that the PUs do not interfere with each other on the same channels. To simplify the interaction of the effect of the PUs on the SUs, we used the sum of the log distance path loss from each PU to each SU in the calculation of the probability of packet error. As an example case, we consider the bit error rate (BER), for binary phase shift keying (BPSK) and an additive white Gaussian noise (AWGN) channel for a particular packet that can be expressed as

$$P_e = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \tag{30}$$

Calculations were performed using this BER model [36].

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Table 4. Numerical study parameters and explanations

Numerical study parameter	Explanation
Geographic area grid	500 × 500 m
PU interference range	150 m
Number of PUs	1, 2 or 5
Number of SUs	18
Total number of channels	30
Number of active PU channels	1–25
System congestion threshold, τ	50%
Packet drop rate threshold, v	5%
Probability of false alarm error, P^c_{ef}	10%
Probability of missed detection error, P^c_{em}	10%

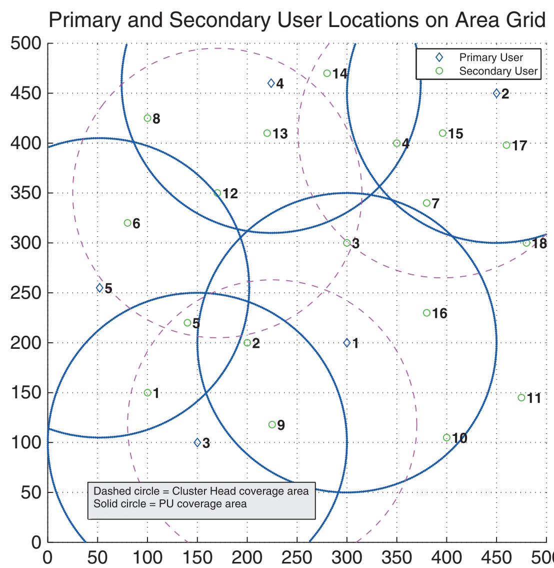

Figure 6. Distribution of PU and SU node locations with coverage areas of PUs and cluster heads on grid

We assume sensing error probability values for the probability of false alarm, P^c_{ef}, and probability of missed detection, P^c_{em}, are 10%. The system has 30 total channels and we included the ‘genie’ case, where the SUs are allowed to have full channel availability knowledge, so that the effect of the PU activity could be more directly observed on our network link graphs.

Figure 7 shows the effect of a single PU with 10 active channels on the SU network where several SU links in the PU coverage area have a packet drop rate greater than the threshold, v, of 5%, showing those links as congested, as indicated by the red dashed arrows. Note, however, that the availability of other links, such as link $l_{2,9}$ and $l_{10,16}$, is not affected by the PU, as shown by the green solid arrows. This is because the assignment of channels to the SUs are random and theremay be up to 20 additional available channels when the PU is active. Recall that the number of remaining available channels is dependent upon the busy and idle durations of the PU, together with the probability of sensing error, and the overall time duration that the SU nodes are attempting to access the channel.

Similarly, for Figures 8 and 9, we see the effects of PU activity where each PU has 10 active channels. Consolidating the data from using one, two and five PUs as shown in Figure 10, we see that increasing the number of PUs and the number of channels quickly increases the average link congestion.

The system congestion threshold, τ, is set to 50% and we see that for the case of two PUs the system state becomes congested when each uses 11 contiguous channels. When five PUs are used, the congestion threshold is exceeded at only seven channels. The threshold can be used by the

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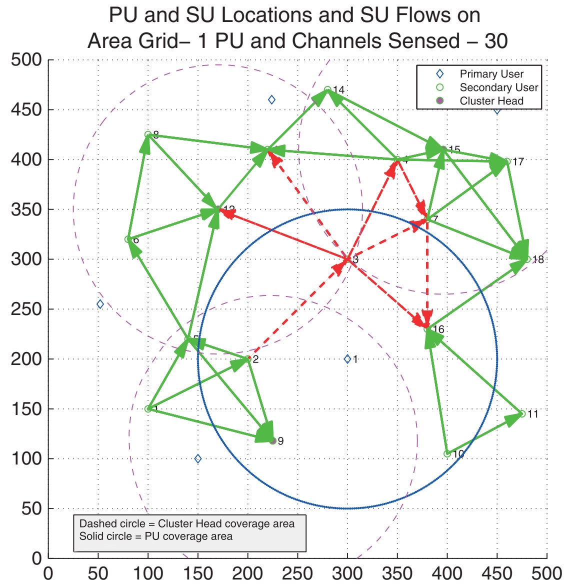

Figure 7. Effect of one PU with 10 active channels on the SU network

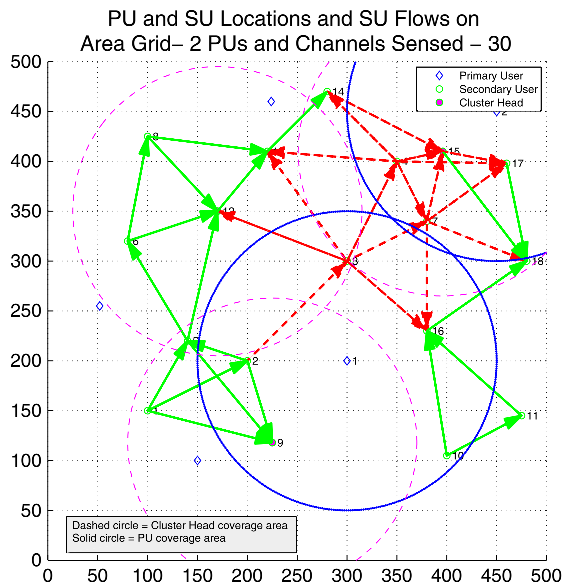

Figure 8. Effect of two PUs with 10 active channels on the SU network

network manager to trigger management action and can be arbitrarily set, based on the desired network performance. The threshold can also be set adaptively depending on changing conditions, such as differing performance criteria in response to the level of PU activity, or external factors such as time of day.

In Figure 10 we examine the effect of how the number of contiguous channels used by the PUs affects the average link congestion. In each case of one, two or five PUs, the congestion increases until adding more PU channels no longer increases the congestion. In our system, in each PU configuration, the congestion maximum remains basically constant after 15–20 channels. It does not increase further, because the total number of SU channels that have been interfered with by the PU coverage area is not further affected by additional channels used by the PUs. Hence the average congestion

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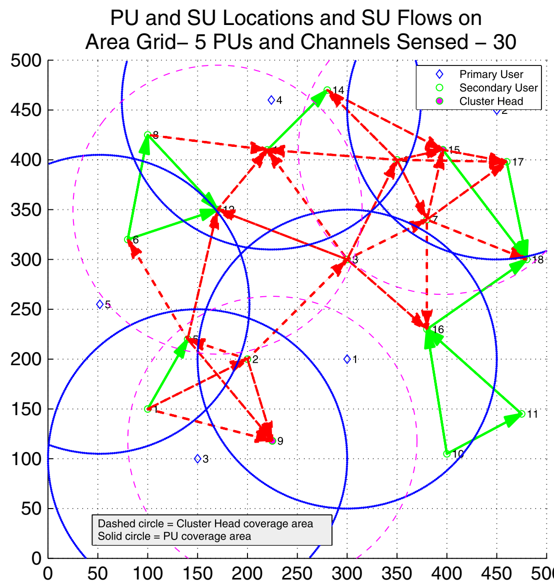

Figure 9. Effect of five PUs with 10 active channels on the SU network

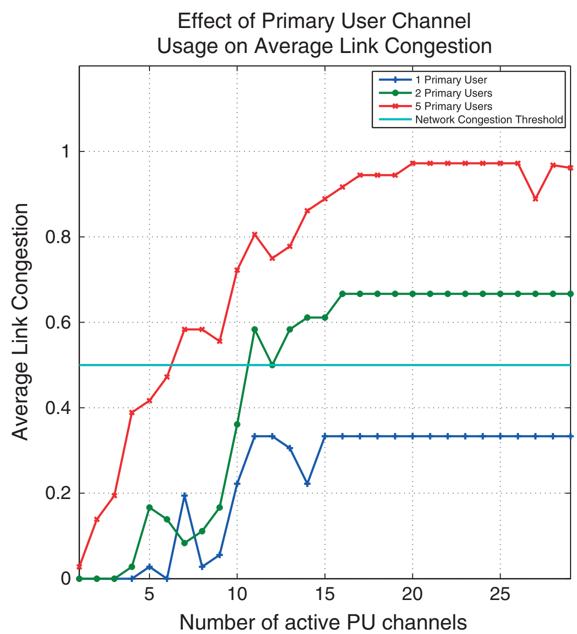

Figure 10. Effect of PU activity on average link congestion

remains relatively constant because the ratio of unaffected to affected SU channels stabilized for this spatial configuration.

Another consideration of the PU effect on the CR network is to examine the perceived number of available channels, C_{jk}, as affected by PU idle duration in Figure 11. Here we observe that, as the perceived number of channels increases with increasing PU idle duration, we see also that the increasing false alarm probability delays the recognition of possible available channels. For example, when the PU idle duration is at 45%, the lowest false alarm of 2% shows the channel increase from 12 to 13 prior to false alarm probabilities of 5% and 10%. Intuitively, we would expect this result, since a

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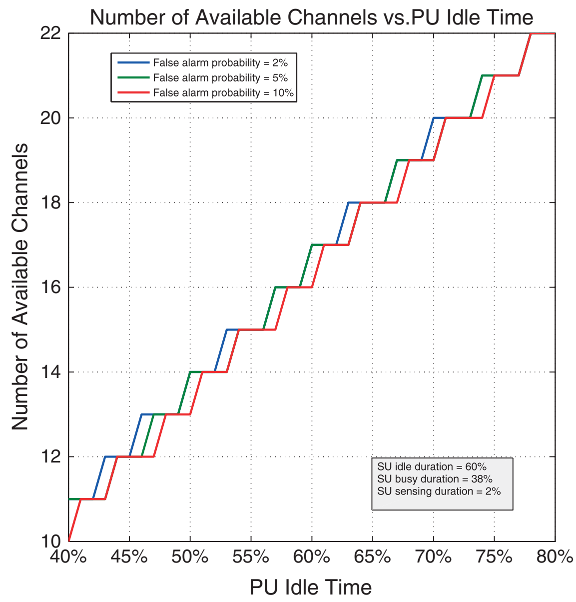

Figure 11. Effect of the PU idle time on the number of channels perceived available

lower error probability indicates more correct sensing, and therefore a more accurate perception of the channel availability for a given amountof average PU idle time per observation period.

However, in Figure 12, we see that for increasing SU idle duration the average link congestion decreases. This is due to less contention for the links by the SUs. The figure shows curves for PU idle values of 40%, 60% and 80%, which also demonstrates that increasing idle duration decreases the link congestion, whether applied to SU nodes or the PU nodes. This observation allows the use of a possible network management control action to relieve congestion by regulating SU idle duration when necessary to reduce congestion. Additionally, cross-layer control could include throttling of the data to be transmitted at the application layer.

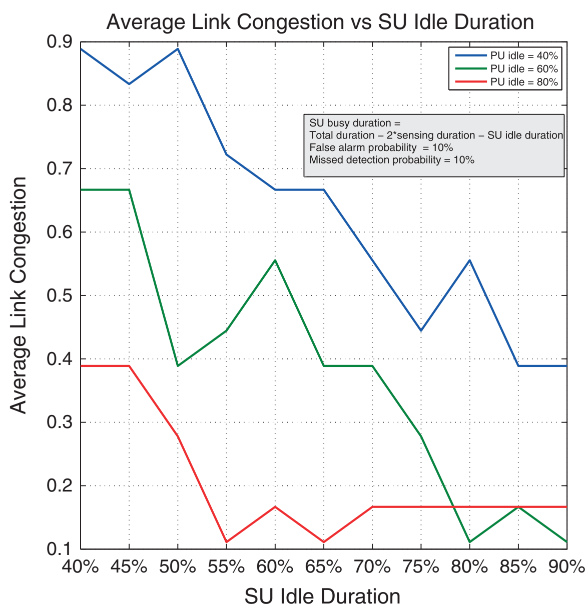

Figure 12. Effect of the SU idle duration on the average link congestion

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Figure 13 shows the effect of the total number of channels in the system on the average congestion value. Here we examine how one, two or five PUs impact the average congestion as the number of channels in the system increases from 10 to a maximum of 40 channels, and each PU can access up to 10 available channels. The figure shows that the congestion response shape is similar for each set of PUs, in that the congestion is generally not reduced below the 50% threshold until the system contains 27 or more channels. That the congestion generally reduces as the number of channels increases is intuitive, given the increased connectivity available to the SU nodes.

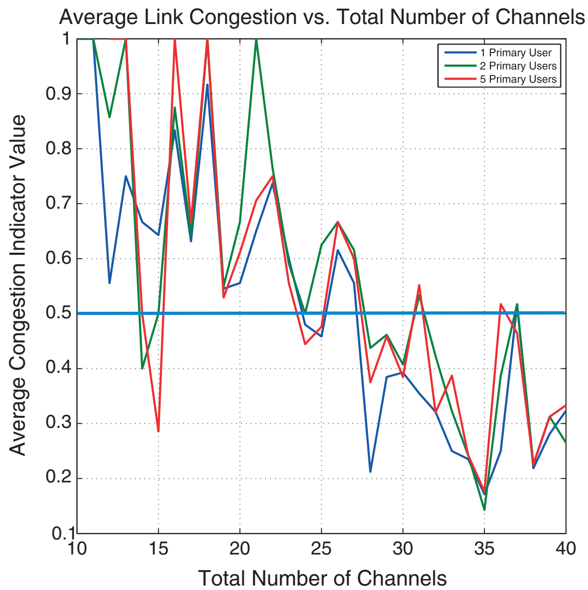

Figure 13. Effect of the total number of channels on the average link congestion

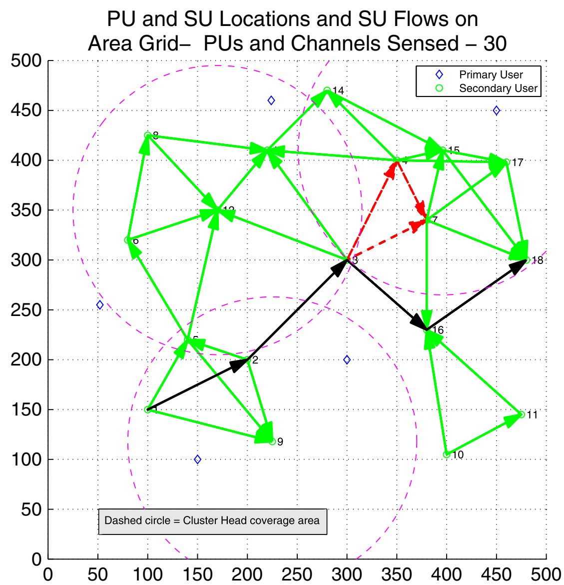

Figure 14. Example path without PU interference

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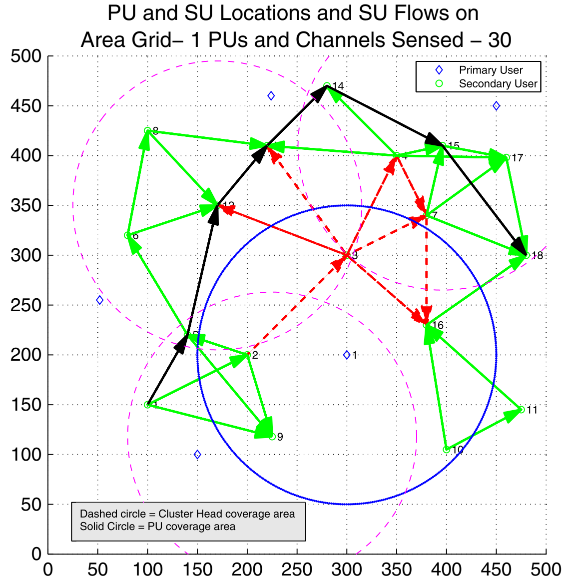

Figure 15. Example path avoiding PU interference

When the number of channels is below 25, because the available channels to SUs are usually small due to the occupancy of the channels by the PUs, the congestion will not monotonically change with the number of PUs. When a sufficient number of channels is available, the number of PUs plays a more important role in determining the average congestion of the channels for the SUs. The randomness exists in the figure because in our simulation the channels sensed by the SUs are randomly chosen, as may happen in a practical system [33], which in turn affects the success probability of the SUs acquiring the channels needed fordata transmission. This again demonstrates the major role of the perception of channel availability to the SUs, which could be a decisive factor for the performance of the SUs in the secondary network.

Considering another potential control action, we see in Figure 14 an example of a source-to-destination SU path without PU interference after applying the congestion metric to the active links. Then, as a result of the congestion information, the network manager can direct the path to be rerouted around the congestion caused by emerging PU activity to maintain similar throughput, as shown in Figure 15.

6. CONCLUSION AND FUTURE WORK

In this paper, we have investigated the need to adapt and extend the traditional network management concepts to cognitive radio ad hoc networks. We have shown that by creating a model framework to introduce new metrics that are available to a network manager with a total system view, such as the network congestion index, the network manager can influence network performance. This can be done, for instance, by directing the cluster heads (distributed managers) to avoid potentially troubled areas, and route paths with higher channel availability and throughput. This management action can reduce the interference to the primary users.

This work created probabilistic congestion metrics that are specifically intended for application to CRAHNs. These are the average link congestion indicator and overall network (or cluster) congestion indicator as components of a tool set utilized by a network manager node to manage the CR network. Thirteen new cnmpMIB variables have been created to aid in the metric calculations. The average network congestion indicator is derived as a function of PU's activities and SU's strategy per a two-

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state Markov model, and in turn provides grounds for setting control parameters for SUs to relieve network congestion if needed.

As highlighted in a recent NSF report [37], Section 4.5 states: ‘Most currently available approaches towards measurement provide coarse-grained counters such as SNMP variables, or long timescale flow-based summarizations. From an architectural standpoint, research is needed to determine what finer-grained currently-hidden information (e.g., wireless channel characteristics, MAC protocol and routing information) can be exposed to the user, to network management functions, and to others (e.g., carried in protocol headers) to help manage (e.g., diagnose and (auto-)configure) a network.’ Our proposed congestion indicator can be considered as an attempt to relate finer-grained information such as channel availability and MAC protocol to a network-level metric used by a network manager to make decisions. This work is preliminary and we intend to further investigate network control that can take advantage of the network management process.

APPENDIX

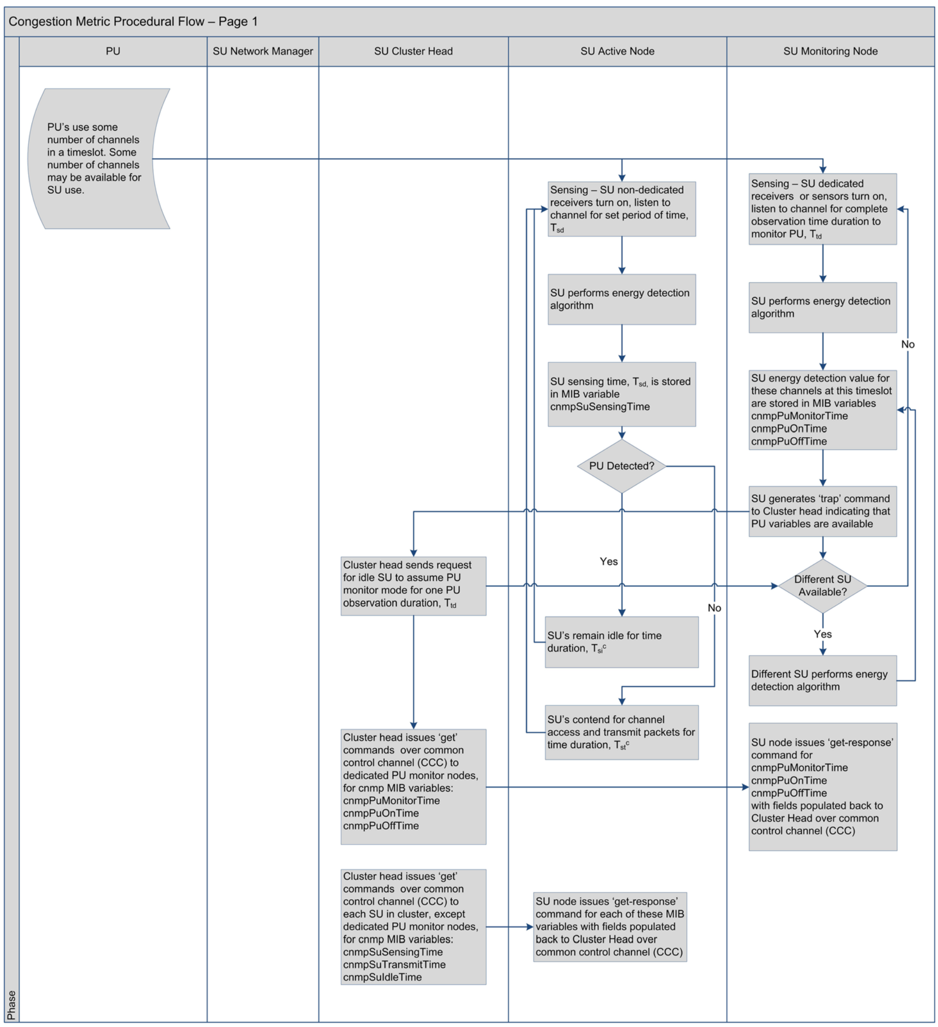

Figure A.1. Management procedure flowchart: page 1

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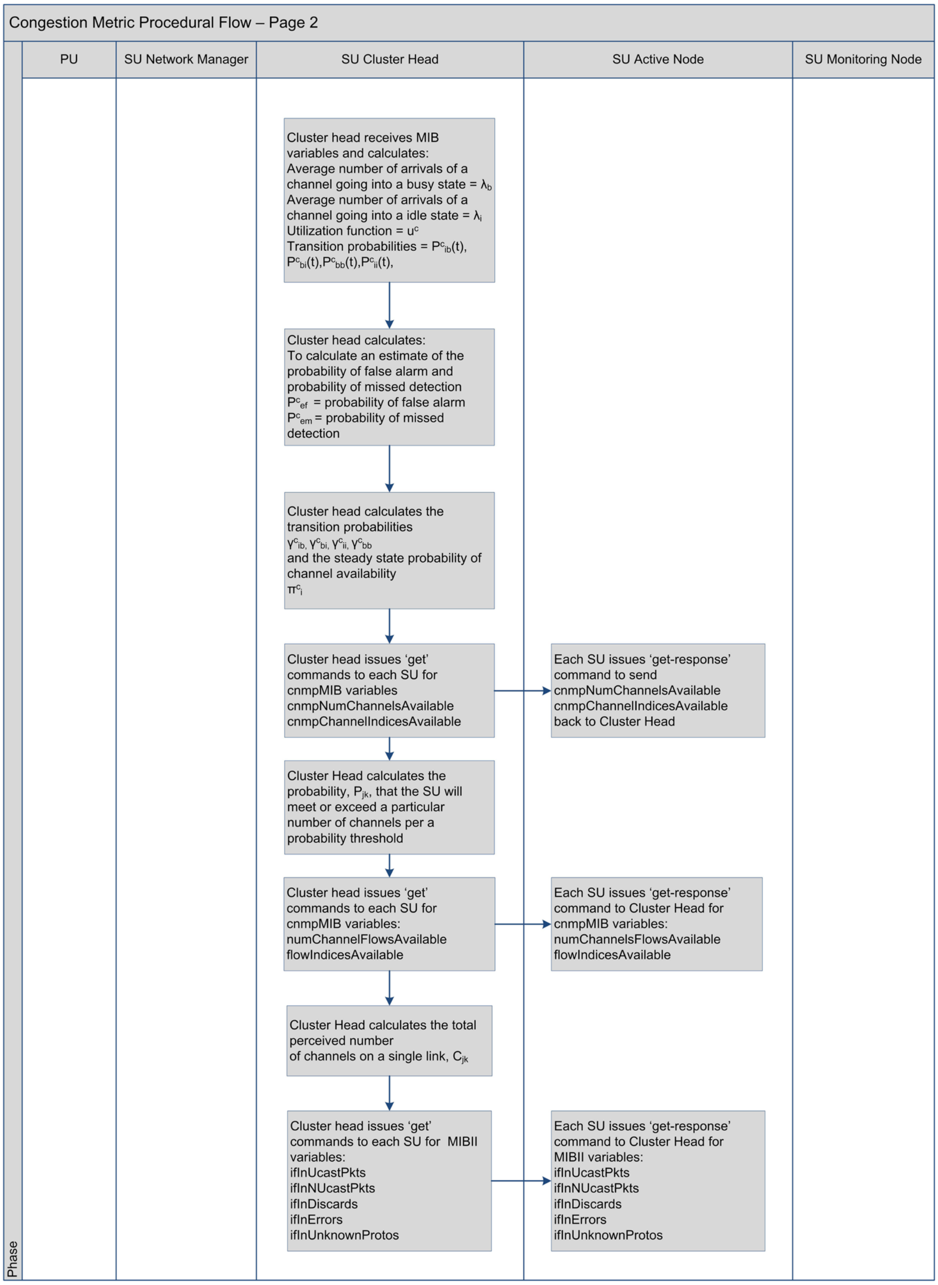

Figure A.2. Management procedure flowchart: page 2

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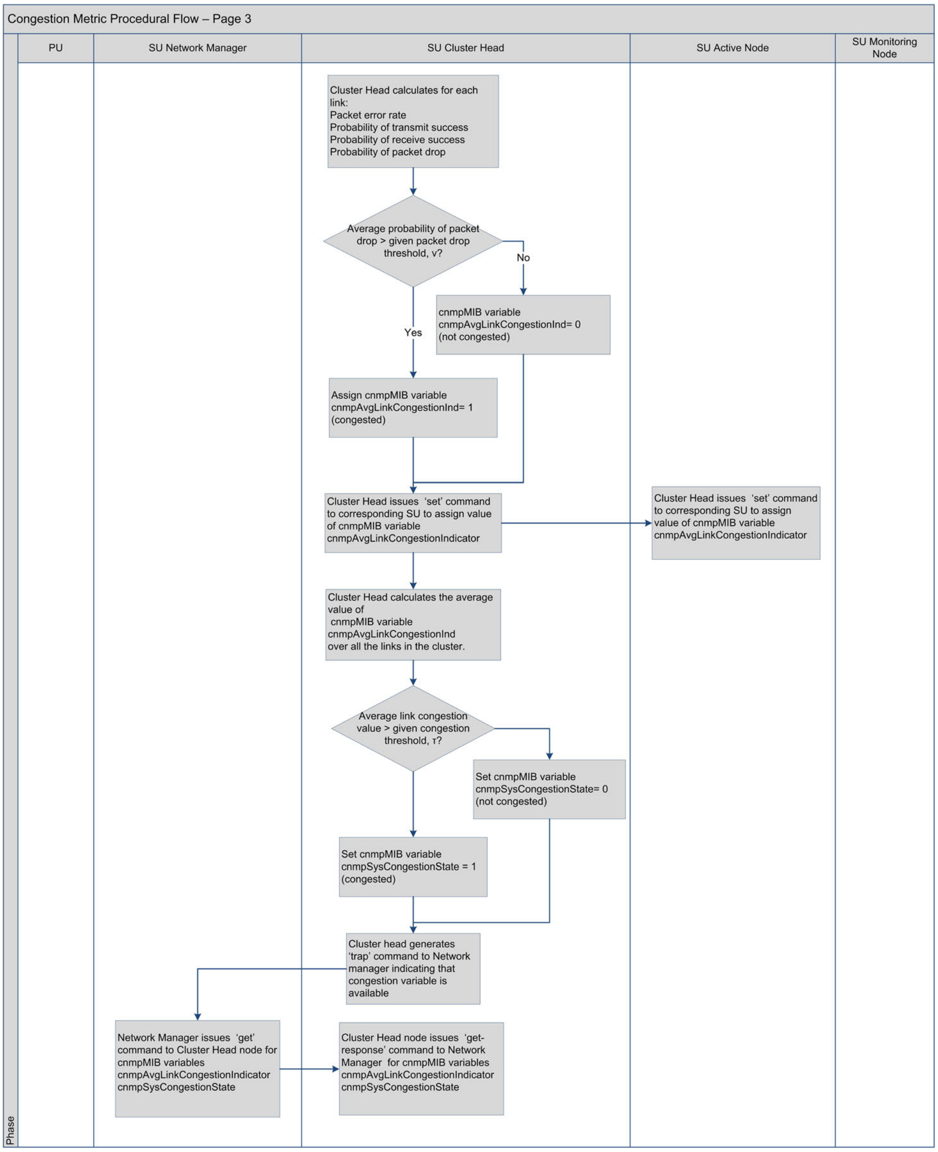

Figure A.3. Management procedure flowchart: page 3

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