Improving Spectrum Efficiency via In-Network Computations in Cognitive Radio Sensor Networks

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***Abstract*—To alleviate the spectrum shortage for sensor networks with tremendous sensors, cognitive radio technology enabling multi-hop opportunistic networking and concurrent transmissions overlaying the primary system suggests an attractive facilitation of large-scale wireless sensor networks (WSNs) and machine-to-machine communications. However, subsequent significant end-to-end delay in large WSN can prohibit practical applications. Leveraging the nature of traffic in sensor networks, we develop in-network computation to reduce requisite transmissions and to accommodate more concurrent transmissions under a given spectrum. Specifically, distributed source coding and broadcasting in wireless communication are exploited to build the computational framework and the achievable network capacity is examined. Furthermore, a greedy networking algorithm is adopted to justify significant improvement on end-to-end delay and further *statistical QoS guarantee*, while yielding considerable system throughput gain for practical deployment of WSNs. Performance evaluations confirm that we successfully demonstrate communication efficiency from in-network computations and facilitate a new paradigm for spectrum efficient cognitive radio networks, which shall be applicable in general multi-hop wireless networks and spectrum-sharing WSNs.**

***Index Terms*—In-network computation, distributed source coding, cognitive radio, QoS guarantees, wireless sensor networks, ad hoc networks, machine-to-machine communications.**

I. Introduction

Wireless sensor networks (WSNs) [1]–[6] have attracted tremendous attention for their mission-driven development and deployment. For a large-scale WSN comprising lots of sensors, providing an efficient spectrum sharing with existing wireless networks is surely a trend. As facing the increasing spectrum demand of wireless services and devices [7], cognitive radio technology [8] is widely employed to enhance spectrum utilization [9]. Specifically, exploiting WSNs for smart grid applications [10], spectrum-aware technique is recognized as a promising solution to enable reliable and low-cost remote monitoring for smart grids. To fully exploit this technology especially for large WSNs [10]–[13], more concurrent transmission opportunities within given spectrum are desired to realize spatial reuse of spectrum. In addition, maintaining reliable data transportation on top of numerous opportunistic links in cognitive (radio) multi-hop sensor networks becomes an essential requirement to bring the spectrum efficiency into reality. However, as indicated by [14], there exists an significant end-to-end delay for greater network diameter in large cognitive machine networks and prevents practical applications. Thus, it becomes a great challenge to support an effective end-to-end quality-of-service (QoS) guarantee with regards of reliable communications in cognitive radio sensor networks (CSNs), while such likely technology is applicable for machine-to-machine communications, cyber-physical systems [15], and spectrum-sharing WSNs.

To achieve efficient spectrum management for cognitive radios, it is often done via forming the allocation optimization problems [16]–[18], such as spectrum or resource block allocation, user-based station assignment, and so on. Regarding multi-channel cognitive radio networks, time-spectrum blocks are allocated [16] by constructing the subset of the good assignments and therefore obtain the suboptimal from given assignments. A CSMA-based multi-channel MAC protocol is proposed by [17] that optimizes the throughput performance for co-existing multiple systems. A distributed multi-channel MAC protocol is further proposed by [18] for energy-efficient communication in multi-hop cognitive radio networks. Above efforts only focus on the efficient allocation of primary systems' (PSs') spectrum holes. However, an innovative view for spectrum efficiency (i.e. throughput per bandwidth) is to look at the reduction of transmitted data without information loss by possible computations, as transmission opportunities are scarce within given spectrum. This approach equivalently enhances the spectrum efficiency with the same transmitted information. Specifically, we are motivated to compute the minimization of total traffic among nodes in cognitive multi-hop sensor networks, equivalent to the enhancement of throughput per bandwidth namely spectrum efficiency. This is actually an ingenious tradeoff between communication efficiency and computation, as a new paradigm of in-network computations and the scope of this paper.

Utilizing in-network aggregation (or computation) techniques [6] for overall spectrum efficiency (i.e. the throughput supported by per bandwidth usage), it is necessary for nodes to perform computations on data rather than to simply originate and forward data (i.e. without data computations for conventional existing scheme) and a cross-layer design is suggested for optimal performance. We examine the correlation among transmitted contents by the source sensor and exploit distributed source coding (DSC) [19] by linear codes [20] to seek for the traffic reduction. Through distributed computation for the minimum required transmissions of the destination's loss-

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less decoding, more transmission opportunities are obtained for cognitive sensors' usages.

Inspiring from network flow perspective of random network coding [21], we first derive the upper and lower capacity bounds in graph-theoretic max-flow under the computation framework and obtain the limits for further designated mechanisms. Furthermore, to leverage the computation impacts on the network-level, we adopt the greedy networking to assemble each node's computation capability into the whole system's behavior. With greedy determination of nodes to execute DSC and opportunistic assignment of flows among paths, the networking achieves the minimum aggregated path delay(s) for end-to-end transmission. Such algorithm contributes the most in the distributed computing functionality with satisfied performance, which makes it well suit for next-generation wireless systems. In addition, regarding the provision of QoS guarantee for the system throughput in real applications, we employ statistical QoS guarantee to overcome opportunistic links and time-vary fading [22]. It is a practical and reasonable solution for real-time services, which suffer from time-varying fading. By analytical derivations with Markov inequality and Chernoff's bound, two types of QoS guarantees are proposed and the system throughput within guaranteed delay is consequently obtained. We summarize our methodology as follows:

1) To bring traffic reduction by employing DSC via linear code schemes.
2) To derive the graph-theoretic max-flow bounds to present theoretical limits.
3) To propose greedy networking exploiting each node's computation ability at link-level and assembles into good network-level gain.
4) To develop two proposed QoS guarantees that exhibit remarkable spectrum efficiency enhancement.

Simulation results show that our design outperforms existing schemes with 10 dB throughput gain or so. Beyond sophisticated link-level algorithms, our proposed approach resorts to network-level gain via distributed computations and creates a new research frontier in spectrum sharing (or cognitive radio) WSNs, with great potential in large wireless networks such as machine-to-machine communications and ad hoc networks.

The rest of paper is organized as follows. The background for our study is in Section II and system model is presented in Section III. In-network computation is examined in Section IV. Under this computation framework, achievable network capacity is studied in Section V. Greedy networking algorithm is proposed in Section VI and QoS guarantees are proposed in Section VII. Performance evaluations are in Section VIII and this paper is concluded in Section IX.

II. Background

Many excellent works [23]–[26] have been extensively studied for WSNs of different purposes but primarily for the efficiency of processing data under special purposes. In [23], a survey of data gathering (collection) is provided for WSNs with mobile elements. In [24], a comprehensive study is given for distributed detection and data fusion for wireless sensors. Aiming at assisted living and residential monitoring [25], context-aware protocols are presented for in-network processing. In [26], a data aggregation scheme is proposed via adaptive compression for WSNs. In light of large wireless networks, a novel technology known as in-network computation was proposed to process data before reaching final destination in large WSNs [1], [3]. In [2], a probably approximately correct normalized histogram is computed with lower energy costs via in-network computations. Exercising on DSC [19], a lot of application specific techniques exist. [4] achieves energy savings by directed diffusion for wireless sensor networking. For parallel relay wire-tap network, [27] studies the information-theoretic secrecy problem and derives the secrecy capacities for the deterministic diamond and parallel Gaussian diamond networks. [5] further presents data fusion to improve the coverage of WSNs.

In addition, another sort of in-network computation [6], [28]–[30] adopt context analysis for context-aware computing. In [6], a sort of practical realization of context computing is examined. To achieve energy-efficient, ubiquitous wireless connectivity, [28] provides a context-based network estimation that exploits context information such as time, history, and device motion. Moreover, to enable context-aware applications, [29] proposes a novel approach for localization in wireless ad hoc networks, advancing the conventional trilateration-based methods. [30] presents a resource-optimized, quality-assured context mediation framework for sensor networks, leading to an optimal estimation of context states. However, these excellent explorations do not thoroughly consider traffic flow together with designated mechanisms and thus overlook realistic routing algorithms. In this paper, inspired by Giridhar and Kumar's pioneer efforts [1], [3] in wireless networks, we aim to bring the merits of data computation into networking and QoS guarantees upon opportunistic links, to exchange computation complexity for system throughput in cognitive sensor networks per given spectrum under the general scenario.

III. System Model

Considering spectrum efficiency with multiple cognitive radio sensors overlaying PSs, we first examine the network topology for CSNs and study opportunistic links from cognitive radio's access schemes. Then, we provide the traffic model. Note that, in the rest of paper, we denote CRs for cognitive radio sensors to ease readability. Important notations in this paper are summarized in Table I.

A. *Network Topology*

A multi-hop cognitive sensor network consists of a source CR (denoted as node n_S), a destination CR (denoted as n_D), and several relay CRs (denoted as n_Rs) that can help relay packet flows from n_S to n_D. We assume that there are totally n relay CRs. In order to avoid the interference to PSs, links in networks are available under idle duration of PSs that dynamic spectrum access can effectively fetch such transmission opportunities, after effective spectrum sensing [31]. Link available period results in random network topology even all nodes being static. We assume that the n_S, the n_D, and the n_Rs are mobile but stationary during each unit time interval (i.e. the network topology varies per unit time). Figure 1

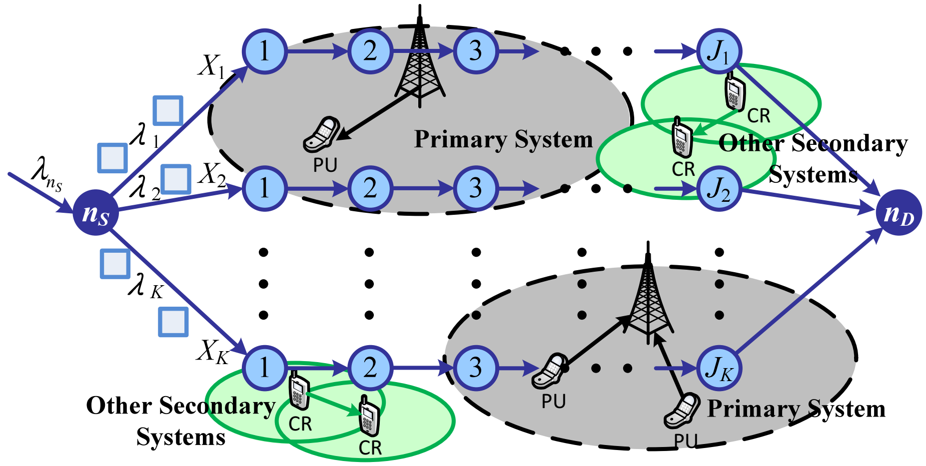

Fig. 1. Network topology for CSNs.

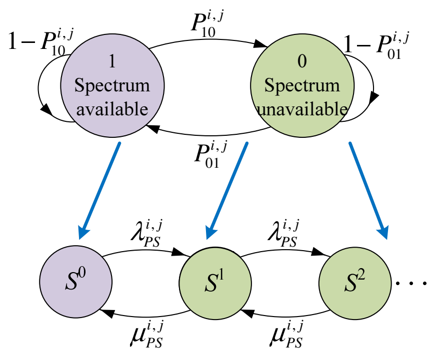

Fig. 2. State transition diagram for j-th link of i-th opportunistic path.

shows a stationary topology during unit time interval. It is supposed that there are K possibly disjointed opportunistic paths between n_S and n_D. The set of these paths is denoted as $P = \{p_1, p_2, ..., p_K\}$, where the i-th opportunistic path p_i consists of $J_i{+}1$ links, for $i = 1, 2, ..., K$. Also, the set of links in such paths is labeled by $\iota = \{J_1 + 1, J_2 + 1, ..., J_K + 1\}$. n_S transmits a set of data $X_1, X_2, ...X_K$ over these K paths. The values of the data are drawn from some joint distribution and can be either continuous or discrete.

B. Opportunistic Link Model

To avoid generating destructive interference, CR links are mandated to exploit temporary spectrum holes for data transmission [31]. The spectrum for CR's transmissions is temporarily occupied or unoccupied by PSs. This transmission opportunity on a CR link can be mathematically modeled as a two-state discrete-time Markov chain with the available state "1" (the PS does not occupy the link) and the unavailable state "0" (the PS occupies the link) [32]. The state transition diagram of the j-th opportunistic link of the i-th path is shown in Figure 2. We could formulate the available probability of this link as $\sigma_i^j = P_{01}^{i,j}/(P_{01}^{i,j} + P_{10}^{i,j})$. Furthermore, to accommodate wireless fading effects and interference models among secondary transmissions, we model each attempt to transmit a packet over the j-th link of the i-th path as a Bernoulli process with a successful transmission rate $\nu_{CR,i}^j$. Specifically, concerning a successful transmitted packet at a time, $\nu_{CR,i}^j$ can be recognized as the probability for the received signal-to-interference-noise ratio $SINR_r$ higher than the threshold κ. As for multi-path fading environment, received signal may suffer from Rayleigh fading and

$$\begin{aligned}\nu_{CR,i}^j =& \mathbf{Pr}\{\frac{\omega(d/d_0)^{-\alpha}P_s}{N_0+I} > \kappa\}\\ =& \exp\left(-\frac{\kappa N_0 d^\alpha}{\Omega P_s d_0^\alpha}\right)\mathbf{E}_I\left[\exp\left(-\frac{\kappa I d^\alpha}{\Omega P_s d_0^\alpha}\right)\right], \quad (1)\end{aligned}$$

where P_s is transmitted signal power, N_0 is noise spectral density, I is the interference received by CR receiver,d_0 is a reference distance for antenna far field, d is the distance between transmitter and receiver, α is the path-loss exponent, and Ω is the second moment of Rayleigh distribution ω. Regarding different interference models [33], [34] (i.e. protocol model with one primary interference or n interferences as well as physical model), I could be explicitly expressed by the channel gain of interfered nodes to CR receiver. For example, with one primary interference and its channel gain H and distance d' to CR receiver,

$$\nu_{CR,i}^j = \exp\left(-\frac{\kappa N_0 d^\alpha}{\Omega P_s d_0^\alpha}\right)\frac{\Omega H P_s d^{-\alpha}}{\Omega H P_s d^{-\alpha} + \kappa P_s d'^{-\alpha}}. \quad (2)$$

Similarly, $\nu_{PS,i}^j$ accounts for the wireless fading and interference of PS around such the link.

C. Traffic Model

Packet data session with variable packet size is considered. For the j-th opportunistic link of the i-th path, Poisson packet arrival with rate $\lambda_{CR,i}^j$ is chosen, since it suits for the aggregate traffic of a large number of similar and independent packet transmissions [35]. To serve packets with variable size, exponential distribution with $\mu_{CR,i}^j$ is chosen due to its memoryless character. Thus, employing first come first served (FCFS) policy, we model opportunistic link as $M/M/1/\infty/FCFS$ queue [36]. Meanwhile, PS's spectrum usage is also modeled as $M/M/1/\infty/FCFS$ queue with continuous-time Markov chain of queue size as in Figure 2, where S^k denotes that there are k packets in PS's traffic queue. $\lambda_{PS,i}^j$ and $\mu_{PS,i}^j$ denote

TABLE I
IMPORTANT NOTATIONS UTILIZED IN THIS PAPER

Notations	***Descriptions***
K	Number of opportunistic paths
$P = \{p_1, p_2, ..., p_K\}$	The set of disjointed paths
J_i	Number of links for p_i
σ_i^j	The available probability of j-th link of i-th opportunistic path
n	Number of relay CRs
$\nu_{PS,i}^j$ and $\nu_{CR,i}^j$	Successful transmission rates for PSs and CRs of j-th link in i-th path
$\Delta_{CR,i}^j$	Transmitted packet size of j-th link in i-th path for CRs' traffic
N_{PS} and N_{CR}	Encoding symbols at a time for PSs and CRs
B_{PS} and B_{CR}	Packets per block for PSs and CRs
$C_{PS,i}^j$ and $C_{CR,i}^j$	Capacities of j-th link in i-th path for PSs' and CRs' traffic
l_i^j	Expected capacity of j-th link in i-th path for CRs' traffic
γ_i^j	Expected capacity under linear codes (i.e. $\gamma_i^j = N_{CR} l_i^j$)
$\mu_{PS,i}^j$ and $\mu_{CR,i}^j$	Packet service rates of j-th link in i-th path for PSs and CRs
λ_{n_S}	Packet arrival rate from CR's source (i.e. n_S)
$\lambda_{\mathbf{CR}} = [\lambda_{CR,1} \cdots \lambda_{CR,K}]^T$	Arrival rate to total K paths
$\mathbf{a} = [a_1 \cdots a_K]^T$	Traffic assignment vector regarding packet arrival rate
$\mu_{CR,i}^{greedy,j}$	Packet service rates of CRs under greedy networking algorithm
W	End-to-end delay for CRs' packets
D_{max}	Requisite bound of end-to-end delay
τ	Degree of QoS guatantees
$\mathbf{Z} = (Z_1, ..., Z_K)$	Vector of transmitted information form CR's source
$\mathbf{X} = (X_1, ..., X_K)$	Quantized information vector with respect to $\mathbf{Z}$
$H(X)$	Entropy of $\mathbf{X}$
$h(\mathbf{Z})$	Differential entropy of $\mathbf{Z}$
$R(X_i)$	Feasible rate of X_i
$H(X_i \mid X_{i^c})$	Conditional entropy of X_i
T	Number of jointly ergodic processes for PSs' DSC

for PS's Poisson packet arrival and service rates upon the link. Concerning wireless channel fading as in Section III-B, $\mu_{CR,i}^j$ and $\mu_{PS,i}^j$ become $\nu_{CR,i}^j \mu_{CR,i}^j$ and $\nu_{PS,i}^j \mu_{PS,i}^j$ by the formulation of geometric sum of exponential distributions. The available probability of opportunistic link is also recognized as another Bernoulli trail and is obtained from PS's transmission as

$$\sigma_i^j = \frac{\nu_{PS,i}^j \mu_{PS,i}^j - \lambda_{PS,i}^j}{\nu_{PS,i}^j \mu_{PS,i}^j}. \quad (3)$$

In summary, for the j-th opportunistic link of the i-th path, we have $M/M/1/\infty/FCFS$ queue model with packet arrival rate $\lambda_{CR,i}^j$ and service rate $\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j$.

IV. In-Network Computation

Although the correlation structure of source's transmitted data [3], [6] has been initially explored in WSN, it has never been studied to achieve spectrum efficiency in CSNs. We therefore develop in-network computation to eliminate the redundancy of transmitted data via distributed source coding (DSC) as another way to enhance spectrum efficiency. Specifically, as shown in Figure 3, CR's available transmission opportunities without the computations serve as the benchmark. When CRs employ in-network computations for their multi-hop relay traffic, they compress forwarded information and more concurrent transmissions are granted. Furthermore, if PSs also conduct such computations for their efficient transmissions, less PS's required traffic allows much more CR's concurrent transmissions and greatly facilitates CR's end-to-end networking. Note that, as the maximum information capacity is fixed for given bandwidth, in-network computations provides a better way for spectrum usage and thus enhances spectral efficiency (i.e. network effective throughput per bandwidth). In other words, in-network computations equivalently increase the available capacity for data transmissions among cognitive radio sensors given the spectrum bandwidth (or maximum information capacity).

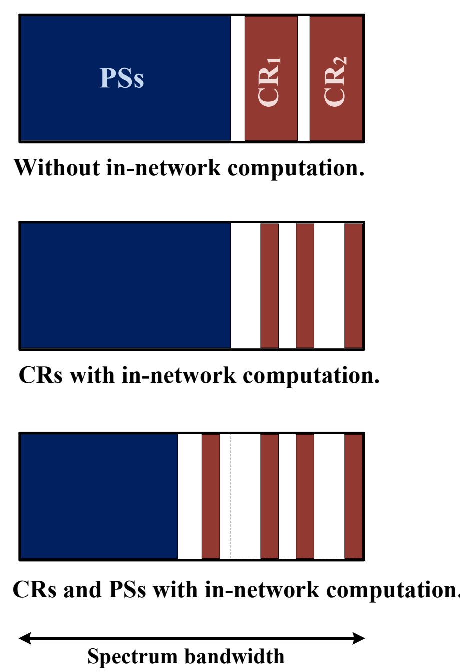

Fig. 3. PSs' and CRs' spectrum using behavior for the adoption of in-network computations.

A. Distributed Source Coding

As shown by Figure 3, there are three scenarios for PSs' and CRs' spectrum using when adopting in-network computations. For the first case, i.e. no in-network computations or conventional methodology, redundant transmissions adopted by CRs bring less CRs to operate concurrently with the existed PSs. Furthermore, for the second case, i.e. CRs with computations, more concurrent transmission opportunities are available for more CRs operating with PSs. For the last case, i.e. CRs and PSs with in-network computations, plenty of transmission opportunities are available for tremendous CRs with PSs and thus provide great spectrum efficiency for CSNs. Note that, in the last scenario, PSs might also employ computations for energy efficiency due to spectrum efficiency. Specifically, as in-network computations minimize total traffic load via compressions, spectral efficiency (i.e. network throughput per bandwidth) enhances accordingly. Furthermore, such enhancement of spectral efficiency could be recognized as better energy efficiency, as less relays are required to operate now for successful end-to-end data transportation and subsequently total communication energy saving.

Suggested by [6], the topology of multiple chain paths in Figure 1 is suitable for the scenario of hybrid in-network aggregations that allow the combination of tree-based and multi-path schemes. We assume the information X_1 to X_K are discrete and memoryless and their values are drawn i.i.d. from a joint distribution $p(x_1, ..., x_K)$ with the respective rate $R(\cdot)$ and entropy $H(\cdot)$ functions defined in Table I. In particular, as in Figure 1, such information is sent with rates $R(X_1)$ to $R(X_K)$ by n_S independently along K cooperative paths. While n_Rs do not generate new information, n_S must transmit enough information upon the network to n_D so that n_D can recover the original information losslessly. From Slepian and Wolf's work [19], distributed compression of correlated sources is as efficient as their compression when the sources can communicate with each other. It implies that by examining the correlation between transmitted data, the Slepian-Wolf range is given by $\Re = \{(R(X_1), ..., R(X_K)) : \forall 1 \leq i \leq K, R(X_i) \geq H(X_i|X_{i^c})\}$. Thus, to achieve this region with the set of K paths, there should be a n_R in each chain path to take charge of compressing data. Similarly, PSs can also adopt DSC. For the j-th opportunistic link of the i-th path, we assume the information transmitted by PSs' traffic is Y_i^j. With the computations operating, the feasible rate for Y_i^j is given by $R(Y_i^j) \geq H(Y_i^j|Y_{i^c}^j)$. In the following, linear codes [20] are adopted as it approaches Slepian-Wolf bounds arbitrarily closely.

B. Linear Codes

The transmission schemes of linear codes are based on block-wise coding. Assume n_S encodes N_{CR} symbols at a time, the j-th opportunistic link of the i-th path with capacity $C_{CR,i}^j$ bits/sec can transmit $\lfloor N_{CR} C_{CR} \rfloor$ bps per block. Then, the service rate is given by $\mu_{CR,i}^j = \lfloor N_{CR} C_{CR,i}^j \rfloor / \Delta_{CR,i}^j$ where $\Delta_{CR,i}^j$ denotes for transmitted packet size of the link. Furthermore, with B_{CR} packets per block, $\Delta_{CR,i}^j = \lfloor N_{CR} R(X_i) \rfloor / B_{CR}$. Thus, $\mu_{CR,i}^j$ becomes $B_{CR} \lfloor N_{CR} C_{CR,i}^j \rfloor / \lfloor N_{CR} R(X_i) \rfloor$. To simplify the presentation, we assume that all $C_{CR,i}^j$ and $R(X_i)$ are rational and the block length N_{CR} is large enough so that $N_{CR} C_{CR,i}^j$ and $N_{CR} R(X_i)$ are integral. From Section IV-A,

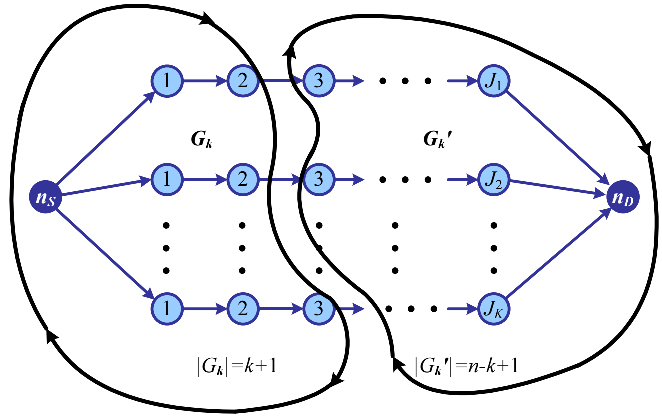

Fig. 4. There are $\prod_{i=1}^{K}(J_i+1)$ cuts for which $|G_k| = k+1$ and $|G_k'| = n-k+1$. The figure shows one such cut that partitions the network into a bipartite graph.

$$\mu_{CR,i}^j = \frac{B_{CR} C_{CR,i}^j}{H(X_i)} \text{ without DSC; } \frac{B_{CR} C_{CR,i}^j}{H(X_i|X_{i^c})} \text{ with DSC.}$$

Moreover, PSs might also employ DSC for their in-network computation. Therefore, with the similar approach as CRs, for the PSs around the j-th opportunistic link of the i-th path,

$$\mu_{PS,i}^j = \frac{B_{PS} C_{PS,i}^j}{H(Y_i^j)} \text{ without DSC; } \frac{B_{PS} C_{PS,i}^j}{H(Y_i^j|Y_{i^c}^j)} \text{ with DSC.}$$

V. Graph-Theoretic Max-Flow Capacity Bounds

To propose a preferable networking algorithm, the theoretic limit on network capacity is crucial. Considering the topology of chain paths, we appeal random network coding to the graph-theoretic max-flow capacity [37]. In the following, we derive the capacity bound for a transmission cut first, and then goes to the lower and upper capacity bounds for the network. Some related notations are summarized in Table I.

A. Transmission Cut

Since we model opportunistic links as $M/M/1/\infty/FCFS$ queues in Section III-C, for the j-th link of the i-th path, the capacity of the link $C_{CR,i}^j$ (bits/sec) is a Poisson r.v. with $\mathbf{E}[C_{CR,i}^j] = l_i^j$. Furthermore, under linear codes scheme, $C_{CR,i}^j$ becomes a Poisson r.v. with $\gamma_i^j = N_{CR} l_i^j$ from Section IV-B. Regarding chain topology, we assume $\gamma_i^1 = ... = \gamma_i^{J_i+1} = \gamma_i$ for $1 \leq i \leq K$ (i.e. for the i-th path, all link capacities are independent and identically Poisson distributed $C_{CR,i}$ as $C_{CR,i} \geq 0$ with mean γ_i).

Lemma 1: Let $C_k = \sum_{i=1}^{K} C_{CR,i}$ be the capacity of a cut in chain topology as shown in Figure 4. The cut is defined by partitioning the $n+2$ nodes into a bipartite graph with a group G_k ($|G_k| = k+1$) such that $n_S \in G_k$ and the complementary group G_k' ($|G_k'| = n-k+1$) such that $n_D \in G_k'$. If $0 < \epsilon < 1$, then $\mathbf{Pr}\{C_k \leq (1-\epsilon)\mathbf{E}[C_k]\} \leq \exp\{[-\epsilon - (1-\epsilon)\ln(1-\epsilon)] \sum_{i=1}^{K} \gamma_i\}$.

Proof: Since $C_{CR,i}$ is Poisson distributed with γ_i for $1 \leq i \leq K$, for a cut $C_k = \sum_{i=1}^{K} C_{CR,i}$, it is Poisson distributed with $\sum_{i=1}^{K} \gamma_i$. Let $\theta \geq 0$, then

$$\begin{aligned}
&\mathbf{Pr}\{C_k \leq (1-\epsilon)\mathbf{E}[C_k]\} \\
&= \mathbf{Pr}\{e^{-\theta C_k} \geq e^{-\theta(1-\epsilon)\mathbf{E}[C_k]}\} \leq \min_{\theta \geq 0} \frac{\mathbf{E}[e^{-\theta C_k}]}{\mathbf{E}[e^{-\theta(1-\epsilon)\mathbf{E}[C_k]}]} \\
&= \min_{\theta \geq 0} \exp\{\theta(1-\epsilon)\mathbf{E}[C_k]\}\mathbf{E}[e^{-\theta C_k}] \\
&= \min_{\theta \geq 0} \exp\{[\theta(1-\epsilon) + (e^{-\theta} - 1)] \sum_{i=1}^{K} \gamma_i\}.
\end{aligned}$$

The inequality of minimum function is from Chernoff's bound. By differentiation with θ, we get the minimum value $-\epsilon-(1-\epsilon)\ln(1-\epsilon)$ when θ equals to $\ln[1/(1-\epsilon)]$ and end the proof. ■

B. Lower and Upper Capacity Bounds for CSNs

Based on *Lemma 1*, we can obtain a corollary that bounds the probability that any cut in the graph falls below $(1-\epsilon)$ times its mean value.

Corollary 1: Let C_k be as defined in *Lemma 1* and define A_k to be the event $\{C_k \leq (1-\epsilon)\mathbf{E}[C_k]\}$. Then, $\mathbf{Pr}\{\bigcup_k A_k\} \leq \exp\{\ln[\prod_{i=1}^{K}(J_i+1)] + [-\epsilon - (1-\epsilon)\ln(1-\epsilon)] \sum_{i=1}^{K} \gamma_i\}$.

Proof: Please see Appendix A. ■

Now we bear the relation between the minimum cut C_{min} and C_0 via $\mathbf{E}[C_k]$. That is, we upper-bound the probability that a random instance of the chain graph has a minimum cut $\leq (1-\epsilon)\mathbf{E}[C_0]$. $\mathbf{E}[C_0]$ is the expected value of the total flow to n_S's nearest neighbors (i.e. all of the first node in each chain path).

Theorem 1: Consider the model specified for opportunistic links as $M/M/1/\infty/FCFS$ queues in Section III-C and with the definition of cuts by *Lemma 1* for chain topology shown in Figure 4. If $0 < \epsilon < 1$, then with the probability at least $1 - \exp\{\ln[\prod_{i=1}^{K}(J_i+1)] + [-\epsilon - (1-\epsilon)\ln(1-\epsilon)] \sum_{i=1}^{K} \gamma_i\}$, the network coding capacity $C_{n_S,n_D}^{NC} > (1-\epsilon)\mathbf{E}[C_0]$.

Proof: Please see Appendix B. ■

Theorem 2: Consider the model specified for opportunistic links as $M/M/1/\infty/FCFS$ queues in Section III-C and with the definition of cuts by *Lemma 1* for chain topology shown in Figure 4. If $0 < \epsilon < 1$, then with the probability at least $1 - \exp\{[\epsilon - (1+\epsilon)\ln(1+\epsilon)] \sum_{i=1}^{K} \gamma_i\}$, the network coding capacity $C_{n_S,n_D}^{NC} \leq (1+\epsilon)\mathbf{E}[C_0]$.

Proof: Please see Appendix C. ■

Under in-network computation framework in Section IV, *Theorem 1* and *2* provide achievable capacity bounds and serve as the benchmark for QoS guaranteed throughput as considered in Section VII.

VI. Greedy Networking Algorithm

To bring the merit of in-network computations into network-level (i.e. for end-to-end transmissions), we assemble each individual nodes and links via routing algorithm. Proposed greedy networking aims to provide optimal performance by guiding the flows to draw possibly greatest advantage from computations. It achieves the minimum aggregated path delay(s) by exploiting optimal compression for data reduction. In the following, the end-to-end delay is first examined.

A. End-to-end Delay Analysis

As considering the end-to-end delay of data transportation, a common and widely adopted definition is the minimum path delay among all possible paths. According to Figure 1, for n_S's incoming Poisson traffic with λ_{n_S}, n_S splits the traffic and sends Poisson arrival with rate $\lambda_{CR,i}^1$ to the i path. That is, with K disjoint paths between n_S and n_D, $\sum_{i=1}^{K} \lambda_{CR,i}^1 = \lambda_{n_S}$. Note that, for the i-th path, there are $J_i + 1$ opportunistic links while each is modeled as a $M/M/1/\infty/FCFS$ queue from Section III-C. Also note that, when concerning link delay, we focus on the transmission delay and queueing delay in a node. Although the processing delay might come from in-network computations, this term is relatively negligible from Moore's law [38] for exponentially fast processing abilities. The propagation delay is also not a concern for fair evaluation of algorithms. Given $\lambda_{CR,i}$ as the arrival rate to the i-th path, the time to transmit a packet through such path D_i is obtained as follows. With the queue model for the j-th link of the i-th path, average waiting time for the service is $W_q = \lambda_{CR,i}/[\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j (\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j - \lambda_{CR,i})]$. The packet delay is then given as $1/\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j + W_q = 1/(\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j - \lambda_{CR,i})$. Furthermore, from the Burke's Theory [36], the arrival rate of the $j+1$-th link is the same with the j-th link and both equal to the arrival rate of the i-th path (i.e. $\lambda_{CR,i}^j = \lambda_{CR,i}^{j+1} = \lambda_{CR,i}$). By accumulating $J_i + 1$ link delay for the i-th paths, $D_i = \sum_{j=1}^{J_i+1} 1/(\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j - \lambda_{CR,i})$. Thus, the end-to-end delay W (i.e. the required time for the destination to receive the source's data from one of K possible paths) is $\min(D_1, ..., D_K) = \min_{1 \leq i \leq K} \sum_{j=1}^{J_i+1} 1/(\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^j - \lambda_{CR,i})$.

B. Greedy Networking Algorithm

The algorithm aims to obtain the minimum end-to-end delay and consists two steps to fulfill this purpose: greedy computation and opportunistic scheduling. First, the algorithm greedily determines the nodes to dominant in-network computations. Instead of equally partitioning traffic load, such algorithm employs opportunistic scheduling and assigns the flows with regard to relay qualities of all possible paths. Note that, while we distribute the source's data into K opportunistic paths for relaying, the destination is able to decode the information only when it receives the data from K paths. A more suitable objective function for proposed opportunistic scheduling becomes minimizing the aggregated path delay(s). Moreover, minimizing such metric enables the assignment of large traffic loads to the opportunistic paths with good relaying conditions (i.e. the abilities of fast packet transmissions) while small portions to the paths with bad conditions. This's the reason for the so-called "opportunistic" scheduling as the algorithm opportunistically assigns traffic load with respect to corresponding path delay(s).

From Section IV, there is one node for each opportunistic path to dominate in-network computation for maximizing the link service rates. Considering the greedy computation for the i-th opportunistic path, the favored node j should compress the data as early as possible. That is, $\arg\min_j D_i(j)$ gives the first

Algorithm 1 Greedy Networking

Greedy computation phase:
Source greedily decides nodes for computations.
Obtain $\mu_{CR,i}^{greedy,j}$ for all links by equation (4).
Opportunistic scheduling phase:
Collect PSs' traffic characteristics to solve (4).
Obtain $\mathbf{a}^{\mathbf{greedy}}$ for further flow assignment.
Networking phase:
Source makes node list for computations and sets up a timer.
while (1) **do**
  Source randomly mixes packets in a single batch by random network coding [21].
  Source assigns flows to K paths acc. to $\mathbf{a}^{\mathbf{greedy}}$ with the list.
  if *Destination* doesn't receive the packet **then**
    for every received packet relay node z **do**
      Decodes and saves new information.
      if relay node z is in the list **then**
        z employs linear codes [20] for DSC.
      end if
      z sends the packet to its forwarder(s).
      if *Destination* receives the packet **then**
        break
      end if
    end for
  else
    break
  end if
end while
Destination sends ACK;
Source moves to next batch once it receives ACK or a timeout happens.

node of the path. From the chain topology, j is to be the first node in the path and it is the same for $i = 1, ..., K$. Therefore, the service rates of all opportunistic links are settled. That is, $\mu_{CR,i}^{greedy,j} = B_{CR} C_{CR,i}^{j} / H(X_i|X_{i^c})$ for $1 \leq j \leq J_i + 1$ and $1 \leq i \leq K$.

Next, while n_S exercises K opportunistic paths for relaying, it assigns its packet arrival with $\lambda_{CR,i}$ to the i-th path, for $1 \leq i \leq K$. That is, with $\boldsymbol{\lambda}_{\mathbf{CR}} = [\lambda_{CR,1} \cdots \lambda_{CR,K}]^T$, traffic assignment vector $\mathbf{a} = [a_1 \cdots a_K]^T$, and $\sum_{i=1}^{K} a_i = 1$, $\boldsymbol{\lambda}_{\mathbf{CR}} = \mathbf{a}\lambda_{n_S}$. As mentioned, the opportunistic scheduling aims to minimizes the aggregated path delay(s) for n_S's traffic assignment. The scheduling assigns traffic loads according to path relaying capabilities and avoids any arbitrarily large path delay(s). The opportunistic scheduling can be formulated as a delay-minimizing problem with respect to $\mathbf{a}$. The optimization problem is obtained as

$$\begin{array}{ll} \text{Minimize} & \sum_{i=1}^{K} D_i(\boldsymbol{\lambda}_{\mathbf{CR}}) \\ \text{Subject to} & \mathbf{1}^T \mathbf{a} = 1, \quad \mathbf{a} \succ \mathbf{0}. \end{array} \tag{4}$$

Therefore, $W^{greedy} = \min(D_1^{greedy}, ..., D_K^{greedy})$ is obtained with $\mathbf{a}^{\mathbf{greedy}} = [a_1^{greedy} \cdots a_K^{greedy}]^T$.

In **Algorithm 1**, after greedy computation and opportunistic phases, the source (i.e. n_S) randomly mixes packets in a single batch with linear combinations and exercises K cooperative paths for relaying as in Figure 1 by random network coding [21]. n_S keeps a timer to indicate the specific batch is totally loss without any chance for the destination (i.e. n_D) to successfully decode batch of data. The period of timer might correspond to historical transmission behavior and current cooperative relay conditions (i.e. available relay paths). From the structure of these diverse paths, each CR relay operates the packet for different purposes of applications and transmits a new coded packet to next forwarder along the path. n_D continuously verifies whether it gets the batch of packets, determines the acknowledgement (ACK) transmission. Once there is a timeout or received ACK message, n_S moves to next batch for successive transmissions. Note that, while ACK might be lost when transmitting back to n_S, the source would not stop forwarding the specific batch of data before it receives ACK or timeout happens. n_D will keep sending ACK as it collects all batch of data for the specific batch. To help destination be aware of the size of batches, the source and destination might have a consensus for such information during signaling session before data transmissions session. Thus, the error recovery mechanism is built and embedded in proposed greedy networking. Also note that, while the period of timer highly dominates the performance for batch transmissions, too short period brings successive failures of end-to-end communications and thus seriously deteriorates the qualities of applications.

The importance of proposed networking is that any prior knowledge of network topology or the assumption of end-to-end routing information is not required at each node, which significantly reduces the communication overhead of control signaling. Specifically, for the considered diverse path structure, each relay path simply transmits a new coed packet to the destination. Such coded packet is generated by randomly combing the source's data via randomly generated coefficients. The destination is then able to obtain the original data once receiving enough coded packets from paths. It implies that there is no need to maintain available paths real-time even though they might change over block transmissions of linear codes. Thus, the mechanism of random network coding enables the proposed algorithm to provide successful data transportation without the need of global networking information for each single node and without maintaining the path information.

VII. Statistical QoS Guaranteed Throughput

To fully understand the trade of computation complexity for spectrum efficiency, we examine statistical QoS guarantees for end-to-end throughput. Statistical (end-to-end) delay guarantee is first studied with underlaid greedy networking. Based on this guarantee and requisite bounded delay of user's traffic, the guaranteed throughput is then obtained from two proposed propositions.

A. Statistical QoS Guarantees

Real-time services care end-to-end delay and requisite bounded delay. From the impact of time-varying fading, it has been proven that providing *deterministic* QoS guarantees (i.e. the probability of delay requirement violation is zero) over the Rayleigh fading channels is impossible [39]. A practical and reasonable solution is to provide *statistical* guarantees (i.e. the probability that the packet violates its delay constraint is bounded) in QoS control as $\mathbf{Pr}\{W \geq D_{max}\} \leq \tau$, where W is end-to-end delay, D_{max} is requisite bound, and τ characterizes the degree of guarantees. By statistical inequalities or bounds,

$$\mathbf{Pr}\{W \geq D_{max}\} \leq f(W, D_{max}). \tag{5}$$

Formulating the f function for designated routing, we thus get the end-to-end throughput with statistical delay guarantees as the maximum available load to n_S that satisfies the constraint:

$$f(W, D_{max}) \leq \tau. \tag{6}$$

B. QoS Guaranteed Throughput in CSNs

To obtain system throughput with guaranteed delay, we formulate f function in equation (5) by both Markov inequality and Chernoff's bound to get the desired throughput with equation (6).

Proposition 1: For all K opportunistic paths in cognitive sensor networks (i.e. $1 \leq i \leq K$), denote δ_i equals to $\min_j(\sigma_i^j \nu_{CR,i}^j \; \mu_{CR,i}^{greedy,j}) - a_i^{greedy}\lambda_{n_S}$. The type-I statistical QoS guarantee exploits Markov inequality to obtain the guaranteed throughput with the greedy networking as

$$\text{Type I:} \quad \prod_{i=1}^{K} \frac{J_i + 1}{\delta_i} \leq \tau D_{max}^{K}. \tag{7}$$

Proof: From equation (5), the statistical delay guarantee for greedy networking is

$$\begin{aligned}
&\mathbf{Pr}\{W^{greedy} \geq D_{max}\} \\
&= \mathbf{Pr}\{\min(D_1^{greedy}, ..., D_K^{greedy}) \geq D_{max}\} \\
&= \prod_{i=1}^{K} \mathbf{Pr}\{D_i^{greedy} \geq D_{max}\} \leq \prod_{i=1}^{K} \frac{\mathbf{E}[D_i^{greedy}]}{D_{max}}
\end{aligned}$$

where the derivations are from disjoint paths of the network topology and from Markov inequality. Furthermore, with the queueing analysis in Section VI-A, we have $\mathbf{Pr}\{W^{greedy} \geq D_{max}\} \leq \prod_{i=1}^{K} 1/D_{max} \sum_{j=1}^{J_i+1} 1/(\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^{greedy,j} - a_i^{greedy}\lambda_{n_S}) \leq \prod_{i=1}^{K}(J_i+1)/D_{max}\delta_i$. Therefore, by equation (6), the throughput by type-I guarantee is obtained and ends the proof. ■

We further exploit tighter Chernoff's bound in type-II statistical QoS guarantee as follows.

Proposition 2: For all K opportunistic paths in cognitive sensor networks (i.e. $1 \leq i \leq K$), denote δ_i equals to $\min_j(\sigma_i^j \nu_{CR,i}^j \; \mu_{CR,i}^{greedy,j}) - a_i^{greedy}\lambda_{n_S}$. The type-II statistical QoS guarantee exploits Chernoff's bound to obtain the guaranteed throughput with the greedy networking as

$$\text{Type II:} \quad \begin{aligned} &\textstyle\prod_{i=1}^{K}(\frac{\delta_i D_{max}}{J_i+1})^{J_i+1} \\ &\leq \tau \exp\{\textstyle\sum_{i=1}^{K}[\delta_i D_{max} - (J_i+1)]\}. \end{aligned} \tag{8}$$

Proof: With $\varphi_X(s)$ denotes for the moment generating function of X, $\mathbf{Pr}\{W^{greedy} \geq D_{max}\} \leq \prod_{i=1}^{K} \min_{s\geq 0} e^{-sD_{max}} \varphi_{D_i^{greedy}}(s)$ where the inequality equation is from Chernoff's bound. Furthermore, from the queueing analysis in Section VI-A, we obtain

$$\begin{aligned}
&\mathbf{Pr}\{W^{greedy} \geq D_{max}\} \\
&\leq \prod_{i=1}^{K} \min_{s\geq 0} e^{-sD_{max}} \prod_{j=1}^{J_i+1} \frac{\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^{greedy,j} - a_i^{greedy}\lambda_{n_S}}{\sigma_i^j \nu_{CR,i}^j \mu_{CR,i}^{greedy,j} - a_i^{greedy}\lambda_{n_S} - s} \\
&\leq \prod_{i=1}^{K} \min_{s\geq 0} e^{-sD_{max}} (\frac{\delta_i}{\delta_i - s})^{J_i+1} \\
&= \exp\{\sum_{i=1}^{K}[(J_i+1) - \delta_i D_{max}]\} \prod_{i=1}^{K} (\frac{\delta_i D_{max}}{J_i+1})^{J_i+1}.
\end{aligned}$$

The minimum value occurs when s equals to $\delta_i - (J_i + 1)/D_{max}$ Therefore, from equation (6), the throughput by type-II guarantee is obtained and ends the proof. ■

We statistically guarantee QoS of traffic in cognitive sensor networks and obtain guaranteed throughput. Through such concept, *Proposition 1* and *2* both provide system throughput by different manners with same guaranteed delay. Type-I guarantee is easier to implement as it concerns the expected value of path delay. However, for tighter statistical bound in *Proposition 2*, type-II guarantee brings more throughput than type-I as demonstrated in the following section.

VIII. Performance Evaluation

We employ the greedy networking as an integrated algorithm of computation and communication and evaluate its superiority over the existing solutions (i.e. the purely networking without the computations). All simulation parameters and values are listed in TABLE II. To validate the greedy networking, the Poisson network topology [40] is established and employed opportunistic links for relay are those having successful transmission rate greater than 0.6. Furthermore, as the successful transmission rates highly depend on the distance between transmitter and receiver, there should be a certain threshold for the distance to make successful link transmissions. That is, we should only consider the successful transmission rates within a certain range, where the lower bound of range comes from the threshold of distance. Thus, we set this range as [0.6, 1] for both primary and secondary systems with simplicity in our simulation setting. Further considering link capacities, we set the mean value for both systems around [750, 850] in order to matching the practical setting of environments. Simulation results certify that the proposed solution successfully realizes in-network computation for spectrum efficiency from remarkable end-to-end throughput enhancement with guaranteed delay. In the following, We first study the capacity bounds and then establish the computation framework for evaluating our greedy networking and statistical QoS guarantees.

A. Lower and Upper Capacity Bounds

To present network capacity via random network coding, we first generate a histogram of the n_S-n_D minimum cuts in Figure 5. With about 4000 rounds of fixed parameter setting in TABLE II, Figure 5 shows the possible limits for achievable throughput via network coding, serving as the benchmark for designs of routing algorithms. In Figure 6, the capacities, as

TABLE II
SIMULATION PARAMETERS AND VALUES FOR PERFORMANCE EVALUATIONS

Parameters	***Values***	***Parameters***	***Values***
Area for PPP [40]	$1000 \times 1000m^2$	n	1000
K	10	$\nu^j_{PS,i}$ and $\nu^j_{CR,i}$	[0.6, 1)
N_{PS}	2	N_{CR}	4
B_{PS} and B_{CR}	10	T	12
$C^j_{PS,i}$ and $C^j_{CR,i}$	Poisson distribution with mean [750, 850] (bps)		

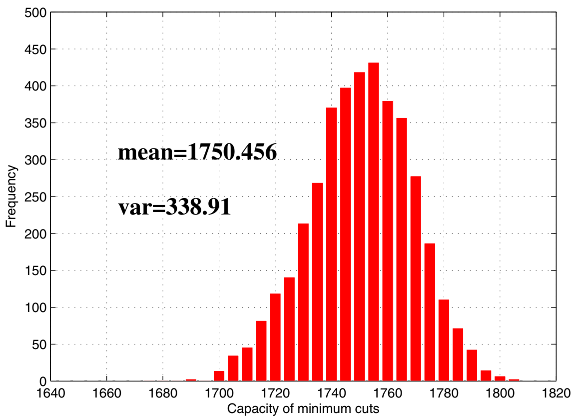

Fig. 5. Histogram of n_S-n_D minimum cuts for Poisson CSNs.

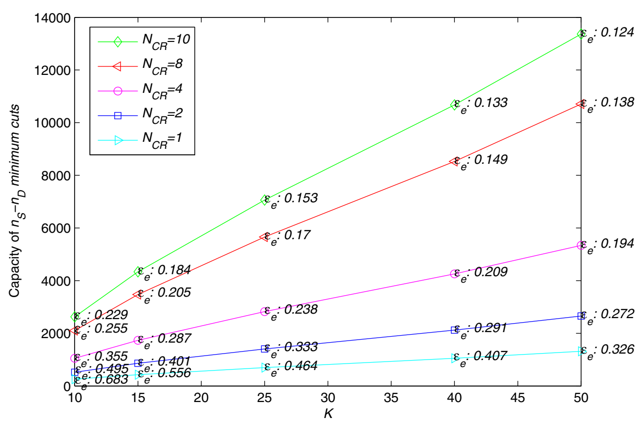

Fig. 6. Network coding capacities and error ranges of network coding with respect to K paths and N_{CR} block-wise coding.

well as the error ranges from lower and upper bounds, are further investigated under different amounts of opportunistic paths (i.e. K) and block-wise coding (i.e. N_{CR}). For each specific realization of network topology and linear codes, the error range accumulates the distance from the true value to the upper and lower bounds, as at least 90% confidence interval that true value lies between two bounds. While increasing K and N_{CR}, error range decreases and these bounds present accurate indications for true values of network capacity. Thus, above results not only reveal the theoretical limits regarding system throughput, but also indicate the practicability of network coding upon cognitive sensor networks.

Algorithm 2 Computation Framework

Establish the p.d.f. of observations in equation (9).
for $1 \le i \le K$ **do**
  Construct $H(\mathbf{X})$ and $H(X_i|X_{i^c})$.
  for $1 \le j \le J_i + 1$ **do**
    Construct PSs' $H(\mathbf{Y})$ and $H(Y_k|Y_{k^c})$ for the j-th opportunistic link of the i path.
    Obtain $\mu^j_{PS,i}$ by equation (4).
    Compute σ^j_i from equation (3).
  end for
end for
Obtain $\mu^j_{CR,i}$ for all links by equation (4).

B. Computation Framework

We establish the computation framework for our DSC scheme as follows and summarized in **Algorithm 2**. As in Figure 1, let the random vector of transmitted information from n_S be denoted as $\mathbf{Z} = (Z_1, ..., Z_K)$. Suggested by [41], a jointly Gaussian model was exploited. Then, the p.d.f. of observations by the first node of each opportunistic path is assumed to be

$$f_{\mathbf{Z}}(z_1, ...z_K) = \frac{1}{2\pi^{K/2}|\Sigma_{ZZ}|^{1/2}} \times \exp\{-\tfrac{1}{2}(\mathbf{z}-\mu_{\mathbf{z}})^T \Sigma_{ZZ}^{-1}(\mathbf{z}-\mu_{\mathbf{z}})\} \quad (9)$$

where Σ_{ZZ} is the covariance of the observations. We assume a correlation model where $\Sigma_{ZZ}(i,i) = \delta^2$ and $\Sigma_{ZZ}(i,j) = \delta^2 \exp(-cd^{\beta}_{ij})$ when $i \neq j$. c and β are positive constants and d_{ij} is the distance between node i and j. It is further assumed that the samples are quantized independently at all first nodes with the same quantization step Φ that is sufficiently small. Under these conditions, the quantized random vector $\mathbf{X} = (X_1, ..., X_K)$ is $H(\mathbf{X}) \approx h(\mathbf{Z}) - K\log\Phi$ as shown in [42] where $H(X)$ represents the entropy of $\mathbf{X}$ and $h(\mathbf{Z}) = 1/2\log(2\pi e)^K|\Sigma_{ZZ}|$ represents the differential entropy of $\mathbf{Z}$. The conditional entropy is

$$H(X_i|X_{i^c}) \approx \frac{1}{2}\log\left[(2\pi e)^{K-|i^c|}\frac{|\Sigma_{ZZ}|}{|\Sigma_{Z_{i^c}Z_{i^c}}|}\right] - (K-|i^c|)\log\Phi. \quad (10)$$

Such conditional entropies are from Slepian-Wolf region by sensors' DSC as mentioned in Section IV-A. Similarly, PSs might also employ DSC for their traffic. Specifically, for PSs around the j-th opportunistic link of the i-th path, let the random vector of transmitted information be denoted as $\mathbf{W^j_i} = (W^j_{1,i}, ..., W^j_{T,i})$. (Omit further notations for the j-th link of the i-th path in the followed derivation.) The covariance of the jointly Gaussian model is Σ_{WW} where $\Sigma_{WW}(k,l) = \delta^2_{PS}$ and $\Sigma_{WW}(k,l) = \delta^2_{PS}\exp(-c_{PS}d^{\beta_{PS}}_{kl})$ when $k \neq l$. The quantization step Φ_{PS} is also assumed to be

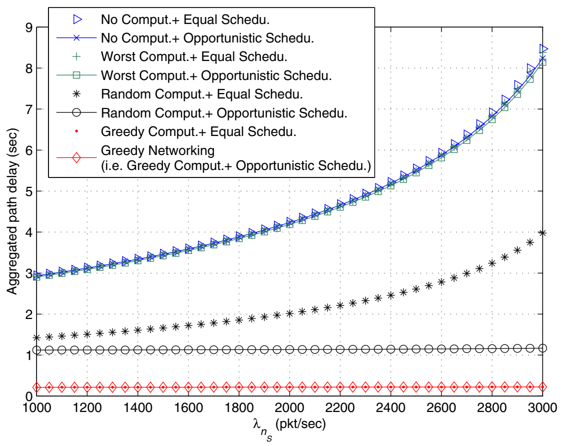

Fig. 7. Aggregated path delay with respect to traffic arrival rate λ_{n_S}. No computation types are represented for existing schemes.

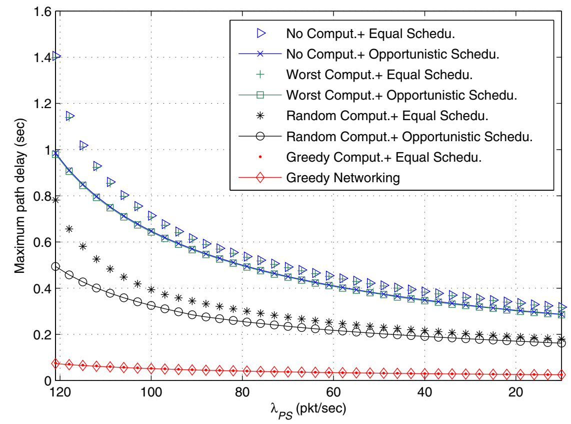

Fig. 8. Maximum path delay with respect to traffic arrival rate of all PSs.

the same and sufficiently small. Thus, the quantized random vector $\mathbf{Y} = (Y_1, ..., Y_T)$ is $H(\mathbf{Y}) \approx h(\mathbf{W}) - T \log \Phi_{PS}$ where $H(Y)$ represents the entropy of $\mathbf{Y}$ and $h(\mathbf{W}) = 1/2 \log(2\pi e)^T |\Sigma_{WW}|$ represents the differential entropy of $\mathbf{W}$. Then,

$$\begin{aligned} H(Y_k|Y_{k^c}) \quad &\approx \tfrac{1}{2}\log\left[(2\pi e)^{T-|k^c|}\frac{|\Sigma_{WW}|}{|\Sigma_{W_{k^c}W_{k^c}}|}\right] \\ &-(T-|k^c|)\log\Phi_{PS}. \end{aligned} \tag{11}$$

For the following evaluations, we choose $\delta^2 = \delta^2_{PS} = 1$, $c = c_{PS} = 1$, and $\beta = \beta_{PS} = 1$. Moreover, the quantization step size is chosen to be $\Phi = \Phi_{PS} = 0.01$.

C. Performance of the Greedy Networking

We compare greedy networking with sorts of algorithms that are from different combinations of computation and scheduling strategies. Existing schemes are those networking without concerning computations and serve as the benchmark. Worst, random, and greedy computation are those schemes who select the last, the arbitrary, and the first nodes of paths to dominate computing functionality, respectively. Moreover, n_S either equally distributes its traffic among all paths by equal scheduling or opportunistically assigns traffic for minimum aggregated delay by opportunistic scheduling. As mentioned in Section VI-B, the greedy networking employs greedy computation with opportunistic scheduling.

In Figure 7, with increasing traffic from n_S, the significant delay improvement of greedy and random computations come from eliminating redundant transmissions via data compression of DSC. There is barely different between the performance of worst computations and existing schemes due to limited transmission opportunities of compressed data in worst computations (i.e. only the last hop of every opportunistic path). Moreover, regarding random computations, Figure 7 shows the preference for opportunistic scheduling due to less delay. Considering the maximum path delay in Figure 8, the disadvantage of equal scheduling is further examined with respect to PSs' traffic. Under equal distribution of n_S's traffic, equal scheduling cannot avoid the possibility of arbitrarily large path delay(s), whereas opportunistic scheme can. On the other hand, regarding better computation ability in greedy

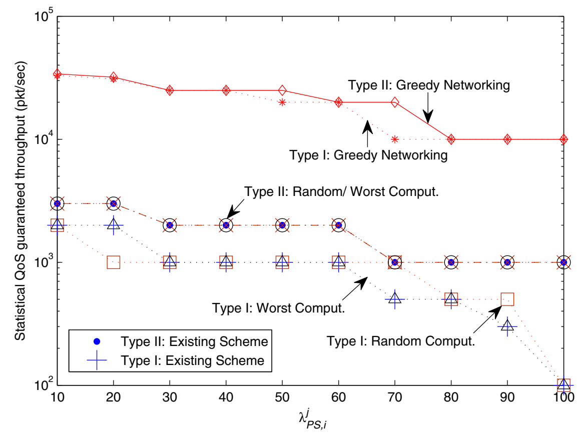

Fig. 9. End-to-end throughput with guaranteed delay (i.e. $D_{max} = 20ms$ and $\tau = 0.02$) for two types of statistical guarantees with respect to traffic arrival rate of all PSs.

computations, both figures suggest that such drawback of equal scheduling is suppressed. Greedy computations annihilate large path delay by only transmitting essential information with fewer traffic loads. Thus, with greater computation and scheduling capabilities, greedy networking works perfectly under CRs' or PSs' heavy traffic.

D. End-to-end Throughput with Guaranteed Delay

To evaluate the capability of proposed guarantees, a real-time voice transmission is considered. VoIP stream employs the well-known ON-OFF fluid model for its arrival process and the holding time in both states are exponentially distributed with mean $6.1s$ and $8.5s$, respectively. Moreover, the delay bound (i.e. D_{max}) is $20ms$. In the following, based on opportunistic scheduling, we evaluate type-I and type-II QoS guaranteed throughput for various computation approaches (i.e. no, worst, random, and greedy ones).

In Figure 9, with $\tau = 0.02$, more throughput is obtained for type-II guarantee, as we exploit tighter bound (i.e. Chernoff's bound) with more underlying assumption. Facing the heavy PSs' traffic loads, greedy networking for its greedy computation ability, still provides the remarkable performance as compared to other schemes. The random and worst computations

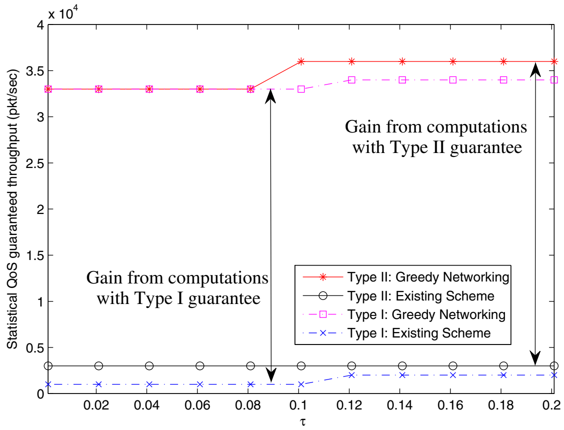

Fig. 10. End-to-end throughput gain between in-network computation (i.e. greedy networking) and existing schemes with respect to degree of QoS guarantee (i.e. τ).

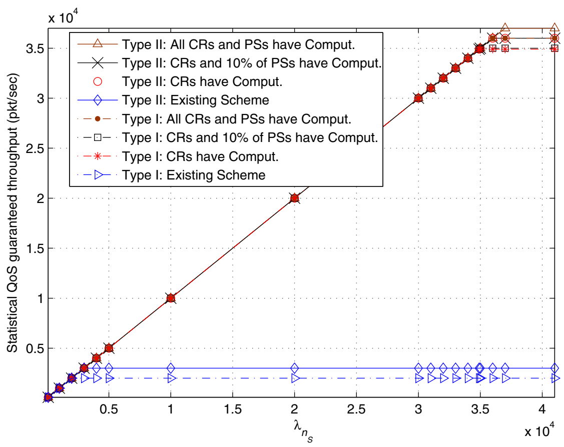

Fig. 11. End-to-end throughput with two types of guarantees for different scenarios of in-network computations between PSs and CRs with respect to traffic arrival rate λ_{n_S}.

as well as existing schemes (i.e. no computation) give much few throughput with only slight difference under these PSs' highly active areas. In addition, with respect to degree of QoS guarantee (i.e. τ), Figure 10 also exhibits the effectiveness to perform in-network computation to eliminate unnecessary transmissions. Loose τ gives more throughput and both types of guarantees present significant throughput gain as compared with existing schemes.

Finally, we investigate the attainable end-to-end throughput with respect to λ_{n_S} in Figure 11, while CRs and PSs might both exploit greedy computations. As being secondary users, CRs do not expect great compression of PSs' traffic as T sets to 12 for all PSs in TABLE II. It turns out that there are incremental enhancements among three computation scenarios (i.e. only CRs adopt computations, CRs and 10% of PSs adopt computations, and all CRs and PSs adopt computations), whose prominent throughput gains all surpass existing schemes. As a summary, above evaluations suggest a new design concept: rather than struggling improvement from sophisticated link-level algorithms, our mechanism resorts to greater network-level gain and outperforms existing schemes with about 90% delay reduction and equivalently 10 dB throughput gain. Moreover, such spectral efficiency (i.e. network throughput per bandwidth) enhancement could be translated to better energy efficiency, as less relays are required to operate for successful data transportation and thus total energy saving. That is, the great achievement of end-to-end delay improvement from proposed schemes indeed bring remarkable energy saving. Therefore, we introduce a new paradigm for reliable spectrum efficient communications regardless of PSs' heavily traffic loads and offer a novel avenue toward energy efficiency in large-scale spectrum-sharing WSNs.

IX. Conclusion

In this paper, the fundamental challenge for spectrum efficiency over large-scale WSNs is addressed by exploiting cognitive radio technology and in-network computation to explore extra available transmission opportunities for cognitive radio sensors' traffic. From the histograms of minimum cuts, achievable network capacity are first examined via random network coding. Leveraging distributed source coding, proposed greedy networking enables distributed computing functionality and provides more concurrent transmission opportunities with significant delay improvement. Furthermore, by analytically deriving packet delay under proposed networking, statistical QoS guarantees characterize the attainable throughput with guaranteed delay and successfully demonstrate communication efficiency (i.e. 10 dB throughput gain) with great practicability. Performance evaluations certify that our distributed designs enjoy great scalability for large-scale networks and we have presented a novel paradigm for spectrum efficiency, particularly crucial for spectrum sharing in large WSNs and machine-to-machine communications.

Appendix A
The Proof of Corollary 1

From *Lemma 1*, we have that $\mathbf{Pr}\{A_k\} \leq \exp\{[-\epsilon - (1-\epsilon)\ln(1-\epsilon)]\sum_{i=1}^{K}\gamma_i\}$. There are a maximum of $\prod_{i=1}^{K}(J_i+1)$ cuts in this chain graph. A union bound on all A_k's gives

$$
\begin{aligned}
&\mathbf{Pr}\{\bigcup_k A_k\} \leq \sum_{k=0}^{n}\binom{n}{k}\mathbf{Pr}\{C_k \leq (1-\epsilon)\mathbf{E}[C_k]\}\\
&= \prod_{i=1}^{K}\binom{J_i+1}{1}\exp\{[-\epsilon-(1-\epsilon)\ln(1-\epsilon)]\sum_{i=1}^{K}\gamma_i\}\\
&= \exp\{\ln[\prod_{i=1}^{K}(J_i+1)] + [-\epsilon-(1-\epsilon)\ln(1-\epsilon)]\sum_{i=1}^{K}\gamma_i\}.
\end{aligned}
$$

Appendix B
The Proof of Theorem 1

Let $\hat{A}_k$ to be the event $\{C_k \leq (1-\epsilon)\mathbf{E}[C_0]\}$ and A_k to be the event $\{C_k \leq (1-\epsilon)\mathbf{E}[C_k]\}$. Recall that $\mathbf{E}[C_0] = \mathbf{E}[C_k] =$

$\sum_{i=1}^{K}\gamma_i$ for $k \geq 0$. So $\mathbf{Pr}\{\hat{A}_k\} = \mathbf{Pr}\{A_k\}$. Thus,

$$\begin{aligned}
&\mathbf{Pr}\{C_{n_S,n_D}^{NC} \leq (1-\epsilon)\mathbf{E}[C_0]\} = \mathbf{Pr}\{\bigcup_k \hat{A}_k\} = \mathbf{Pr}\{\bigcup_k A_k\} \\
&\leq \exp\{\ln[\prod_{i=1}^{K}(J_i+1)] + [-\epsilon-(1-\epsilon)\ln(1-\epsilon)]\sum_{i=1}^{K}\gamma_i\} \\
&\Rightarrow \mathbf{Pr}\{C_{n_S,n_D}^{NC} > (1-\epsilon)\mathbf{E}[C_0]\} \\
&\geq 1-\exp\{\ln[\prod_{i=1}^{K}(J_i+1)] + [-\epsilon-(1-\epsilon)\ln(1-\epsilon)]\sum_{i=1}^{K}\gamma_i\}.
\end{aligned}$$

Appendix C
The Proof of Theorem 2

To show the upper bound on $\mathbf{Pr}\{C_{n_S,n_D}^{NC} \geq (1+\epsilon)\mathbf{E}[C_0]\}$, it is sufficient to consider the cut separating n_S from all the other nodes. Let $\theta \geq 0$, then

$$\begin{aligned}
&\mathbf{Pr}\{C_{n_S,n_D}^{NC} \geq (1+\epsilon)\mathbf{E}[C_0]\} \\
&\leq \mathbf{Pr}\{\sum_{i=1}^{K} C_{Si} \geq (1+\epsilon)\mathbf{E}[C_0]\} \leq \min_{\theta\geq 0}\frac{\mathbf{E}[e^{\theta\sum_{i=1}^{K}C_{Si}}]}{e^{\theta(1+\epsilon)\mathbf{E}[C_0]}} \\
&= \min_{\theta\geq 0}\exp\{[e^{\theta}-1-\theta(1+\epsilon)]\sum_{i=1}^{K}\gamma_i\} \\
&= \exp\{[\epsilon-(1+\epsilon)\ln(1+\epsilon)]\sum_{i=1}^{K}\gamma_i\}
\end{aligned}$$

where the inequality of minimum function is from Chernoff's bound. By differentiation with θ, we get the minimum value $\epsilon-(1+\epsilon)\ln(1+\epsilon)$ when θ equals to $\ln(1+\epsilon)$ and proof the bound.

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