Radio Resource Management for QoS Guarantees in Cyber-Physical Systems

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Abstract—The recent deployment of Cyber-Physical Systems (CPS) has emerged as a promising approach to provide extensive interaction between computational and physical worlds. For a large-scale distributed CPS comprising of numerous machines, sharing radio resource efficiently with the existing wireless networks while maintaining sufficient quality of service (QoS) for machine-to-machine (M2M) communications becomes an essential and challenging requirement. By clustering CPS machines as a swarm with the cluster head managing radio resources inside the swarm, spectrum sharing among numerous machines can be achieved in a distributed and scalable fashion. Specifically, we apply the recent innovation, cognitive radio, and a special mode in cognitive radio, interweave coexistence, to leverage machines to collect radio resource usage information for autonomous and interference-free radio resource management in the CPS. To reduce the communication overheads of channel sensing feedbacking from machines, we apply compressive sensing to construct a spectrum map indicating the radio resource availability on any given locations within the CPS coverage. Such spectrum map resource management (SMRM) only utilizes a small portion of machines to perform channel sensing but enables distributed cluster-based spectrum sharing in an efficient way. Through the concept of effective capacity, the SMRM controls available resources to guarantee the QoS for communications of CPS. By evaluating the performance of the proposed SMRM in the most promising realization of CPS based on LTE-Advanced machine-type communications coexisting with LTE-Advanced Macrocells to utilize identical spectrum, the simulation results show effective QoS guarantees of CPS by SMRM in the realistic environments.

Index Terms—Cyber-physical systems (CPS), cognitive radio (CR), spectrum map, compressive sensing, machine-to-machine (M2M) communication, quality of service (QoS), effective capacity, radio resource management.

1 Introduction

There is an increasing concern for integrating real-world physical activities and the cyber-world of computations and communications to design efficient Cyber-Physical Systems (CPS) [1]. These systems consist of networks of embedded computations and communications machines which monitor and control the physical entities via sensors and actuators on electrical power grids, transportation vehicles and traffic roads, robotic systems, healthcare and medical machines, environmental control and smart buildings. To bridges cyber and physical worlds, CPS must operate in a reliable, safe, secure, and real-time fashion [2].

The major characteristic of CPS is that there can be an extremely large number of machines involved in the system operation. To provide ubiquitous communications among such a large amount of machines without additional cyber-infrastructure deployment costs, connecting all these machines by leveraging cellular communication systems turns out to be an effective and efficient solution. As a result, a promising realization of CPS can be the machine-type communication (MTC) in Long Term Evolution-Advanced (LTE-Advanced) [3], [4], [5]. Although all machines could be connected via cyber-infrastructure of LTE-Advanced, it does not suggest a successful realization of CPS. To ensure the effective operation of CPS, the reliable information delivery of physical events is essential, especially in the most challenging and variant environments of wireless links. In other words, the quality-of-service (QoS) guaranteed wireless networking among machines is essential for many cases [6], [7].

Furthermore, to preserve the precious spectrum resources, communications/connections among machines desirably exploit spectrum of the existing radio networks (such as LTE-Advanced [3], [8]), and thus the appearance of numerous machines induces catastrophic impacts on the existing radio network. Although, in LTE-Advanced, a base station (BS) is designed to be able to simultaneously deal with accesses of machines and human [9], it is desirable to separate managements of machine-to-machine (M2M) communications and human-to-human (H2H) communications to different BSs to significantly reduce the burden of each BS. As a result, a BS dealing with M2M communications is referred as a CPS-BS (and forms a CPS-cell). On the other hand, a BS dealing with H2H communications is referred as a Macro-BS (and forms a Macrocell). To control the interference between CPS-cells and existing Macrocells, a centralized resource management is not feasible due to an unacceptable complexity of the radio resource allocation. As a result, how to distributively share the limited radio resources according to the QoS demand of machines without inducing harmful

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Manuscript received 23 Sept. 2001; revised 3 May 2012; accepted 4 May 2012; published online 16 May 2012.
Recommended for acceptance by S. Papavassiliou, N. Kato, Y. Liu, C.-Z. Xu, and X. Wang.
For information on obtaining reprints of this article, please send e-mail to: tpds@computer.org, and reference IEEECS Log Number TPDSSI-2011-09-0697.
Digital Object Identifier no. 10.1109/TPDS.2012.151.

interference so that numerous machines could underlay with the existing radio network emerges as a primary challenge.

To tackle this challenge, the cognitive radio (CR) technology enabling a station to cognize and adapt to communications environments so as to achieve the optimum overall network performance [10], [11] is considerably noted. Under the design constraint of simplicity without imposing additional complexities on current radio network protocols and operations, the CR technology is well suited for CPS communications. Under this framework, if each machine performs periodical channel sensing to identify the radio resources usage of existing Macrocells and only utilizing radio resources identified as unoccupied by existing Macrocells, interference can thus be mitigated. However, under this framework, all machines in the CPS-cell shall perform channel sensing and report sensing results to the CPS-BS. This leads to an enormous amount of feedback data, which makes the concept of CR infeasible to be directly applied to CPS-cells.

To achieve autonomous interference mitigation by leveraging the CR technology in the CPS-cell, the key is to reduce the amount of feedback. One effective solution is to significantly reduce the number of machines required to perform channel sensing. Specifically, only a small number of machines in the CPS-cell (instead of all machines) devote to perform channel sensing and report sensing results, while interference levels of all machines can be obtained. In addition, when numerous machines directly execute monitoring or control subprocess in CPS simultaneously, a considerable amount of information is funneled toward the same destination and utilize common resources. Even with the aid of CR, the available radio resource might not be sufficient and the regional hot spots might be spawn. The resulting large delays and wasteful packet drops violate QoS requirements [12]. When the density of machines grow, rudimentary coordination in the form of resource management becomes essential.

For the above two goals, 1) it is proposed to group machines into clusters in the *swarm* and the monitor/control information is collected/distributed by an elected *data aggregator, DA* (i.e., cluster head), then DA transmits aggregated traffic to the cloud via CPS-BS. In addition, 2) a powerful technology known as the *compressive sensing* (CS) [13] widely applied to the signal compression and restoration is particularly noted, by which the ordinary sparse signal is sampled with a sampling rate far lower than the Shannon/Nyquist sampling rate, while the signal can still be recovered with a high probability. By leveraging the compressive sensing, DAs and a portion of machines (instead of all machines) are required to perform channel sensing and report sensing results to the CPS-BS, and interference levels at any given swarms/locations within the coverage of the CPS-cells can be constructed, which is particularly referred as the *spectrum map*. As a result, the amount of channel information feedback is significantly reduced and the CR technology can be applied to CPS-cells for autonomous interference mitigation.

To provide QoS guarantees while fully exploiting the radio resource in the swarm, we adopt the concept of *effective capacity* [14], which is a link-layer channel model specifying the maximum constant arrival rate that the system can support while satisfying the given QoS requirement. We consequently propose the spectrum map-based resource management (SMRM) for CPS-cells to construct the spectrum map. By analytically deriving the effective capacity of the SMRM, a systematic procedure for radio resource allocation of the CPS-cell is further proposed, thus enabling a successful realization of CPS.

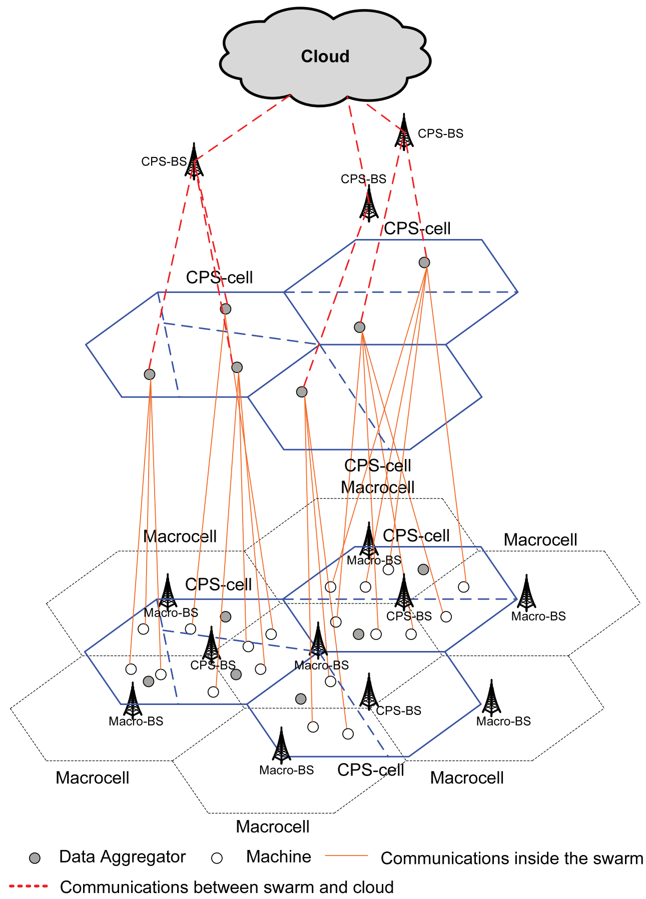

Fig. 1. The CPS architecture based on LTE-Advanced machine-type communications that coexists with LTE-Advanced Macrocells.

The remainder of this paper is structured as follows. After elaborating the system model and related backgrounds in Section 2, the SMRM for the CPS-cell is proposed in Section 3, and the control of sensing period and resource blocks (RBs) allocation to achieve QoS guarantees are provided in Section 4. The performance of the proposed SMRM is evaluated in Section 5 and this paper is concluded in Section 6.

2 System Model and Related Backgrounds

We consider the radio resources management problem with multiple CPS-cells overlaying Macrocells, as shown in Fig. 1. A CPS-cell is composed of a CPS-BS, V machines and S DAs. A Macrocell is composed of a Macro-BS and multiple user equipments (UEs). In LTE-Advanced, all CPS-cells and Macrocells adopt orthogonal frequency division multiple access (OFDMA) and share all available spectrum. Considering that all CPS-cells and Macrocells belong to the same wireless technology (e.g., LTE-Advanced), the subframe structure of the Macrocell and CPS-cells are identical and boundaries of frames of CPS-cells align to that of Macrocells.

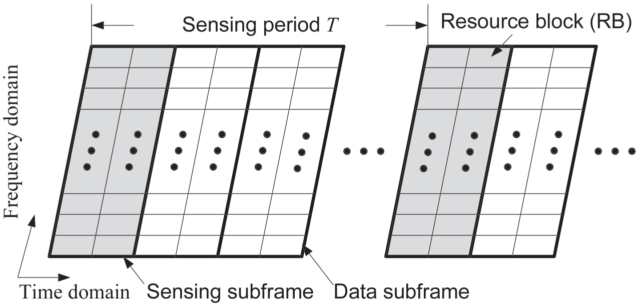

Fig. 2. The subframe structure of CPS. In the SMRM, a subframe is referred as a "sensing subframe" if the subframe is allocated for performing channel sensing; otherwise, a subframe is referred as a "data subframe."

Radio resources are allocated in the unit of "resource block" as shown in Fig. 2. Denote the number of RBs in each subframe as M, and these RBs are indexed by $m = 1, \ldots, M$.

2.1 Power Control Considerations

In the CPS-cell, power control is used to combat the channel fading and we choose to adopt the *truncated channel inversion* [15], by which the signal to interference and noise power ratio (SINR) on each RB can be maintained at a required value, so that all RBs in a subframe can carry the same number of bits [15]. As a result, there is no difference in selecting different RBs. This setting simplifies the problem of RBs allocation. In this paper, we say that an RB without suffering interference if this RB is unoccupied by Macrocells.

2.2 Compressive Sensing

Based on the revelation that a small collection of a sparse signal contains enough information for reconstruction, Compressive Sensing [13], [16], [17] shows high promise for distributed scheme. CS is a new paradigm to perform sampling and compression simultaneously thus significantly reduce the sampling rate. Traditional approaches acquire the entire signal and process it to exact the information. CS acquires only a small number of linear measurements that preserve the structure of the signal, and the signal is then reconstructed from these measurements using an optimization process. Specifically, CS uses the measuring matrix $\mathbf{A}$ to measure the signal $\mathbf{x}$ and acquire the measurements $\mathbf{y}$: $\mathbf{y}_{R\times 1} = \mathbf{A}_{R\times N}\mathbf{x}_{N\times 1}$, where the dimension $R \ll N$. To reconstruct $\mathbf{x}$ from $\mathbf{y}$, there are two necessary conditions to satisfy:

1. Sparsity of signal $\mathbf{x}$: the N-dimensional vector signal $\mathbf{x}$ is K-sparse, that is, there are only $K \ll N$ elements in $\mathbf{x}$ that are nonzero. When $\mathbf{x}$ is binary, $\mathbf{x}$ is K-sparse if there are only $K \ll N$ elements in $\mathbf{x}$ that are nonzero, or there are only $K \ll N$ elements in $\mathbf{x}$ that are zero.
2. Restricted isometry property (RIP) of measurement matrix $\mathbf{A}$: for any K-sparse signal $\mathbf{x}$, the $R \times N$ matrix $\mathbf{A}$ has the property that

$$\|\mathbf{x}\|_2(1-\delta) \leq \|\mathbf{A}\mathbf{x}\|_2 \leq \|\mathbf{x}\|_2(1+\delta), \tag{1}$$

where $0 \leq \delta \leq 1$.

Then, given $\mathbf{A}$ and $\mathbf{y}$, l_1 minimization problem with $R \geq cKlog(N/K)$ is able to recover $\mathbf{x}$ by

$$\mathbf{x}^* = \text{argmin}\|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{A}\mathbf{x} \tag{2}$$

2.3 Preliminary of Statistical QoS Guarantees

The real-time services typically require bounded delays. Due to the impact of time-varying fading channels, it had been shown that providing *deterministic* QoS guarantees (that is, the probability that the transmission delay violates the delay requirement is zero) over the Rayleigh fading channel is impossible [14]. As a result, a practical solution turns out to provide the *statistical* QoS guarantees (i.e., the probability that the transmissions delay violates the delay requirement is bounded by a required value). For this purpose, the *large deviation theory* [14] provides that, for stationary arrival and service processes under sufficient conditions, the probability that the buffer length B exceeds a certain threshold B' decays exponentially fast as the threshold B' increases. That is,

$$\Pr\{B > B'\} \approx e^{-\theta B'}, \tag{3}$$

where θ is a positive constant called *QoS exponent*. When delay is the main QoS metric of interests, an expression similar to (3) is given by

$$\Pr\{\text{delay} > d_{max}\} \approx e^{-\theta\delta d_{max}}, \tag{4}$$

where d_{max} is the delay bound and δ is jointly determined by the arrival process and the service process. From (4), it can be observed that a small θ implies that the system can only support a *loose* QoS requirement, while a large θ means that a *strength* QoS requirement can be supported.

To provide statistical delay guarantees, the effective bandwidth and the effective capacity serve significant foundations. The effective bandwidth [14], denoted by $\mathrm{E_B}(\theta)$, specifies the *maximum constant service rate needed by the given arrival process subject to a given* θ. On the other hand, the effective capacity, denoted by $\mathrm{E_C}(\theta)$, is the duality of the effective bandwidth, which specifies the *maximum constant arrival rate that can be supported by the system subject to a given* θ [14]. If θ^* can be found as the solution of $\mathrm{E_B}(\theta^*) = \mathrm{E_C}(\theta^*)$, δ can be obtained by [18] as

$$\delta = \mathrm{E_B}(\theta^*) = \mathrm{E_C}(\theta^*). \tag{5}$$

Consequently, the system can achieve the statistical guarantee

$$\Pr\{\text{delay} > d_{max}\} \approx e^{-\theta^*\delta d_{max}}. \tag{6}$$

The effective capacity can be formally defined by [14]

$$\mathrm{E_C}(\theta) \triangleq -\frac{\Lambda_c(-\theta)}{\theta} = -\lim_{t\to\infty}\frac{1}{\theta t}\log\Big(\mathbb{E}\Big[e^{-\theta\sum_{i=1}^{t}R[i]}\Big]\Big), \tag{7}$$

where $\mathbb{E}[\cdot]$ denotes taking the mean value, $\sum_{i=1}^{t}R[i]$ is the partial sum of the discrete-time stationary and ergodic service process $\{R[i], i = 1, 2, \ldots\}$ and

$$\Lambda_c(\theta) = \lim_{t\to\infty}\left(\frac{1}{t}\right)\log\Big(\mathbb{E}\Big[e^{\theta\sum_{i=1}^{t}R[i]}\Big]\Big) \tag{8}$$

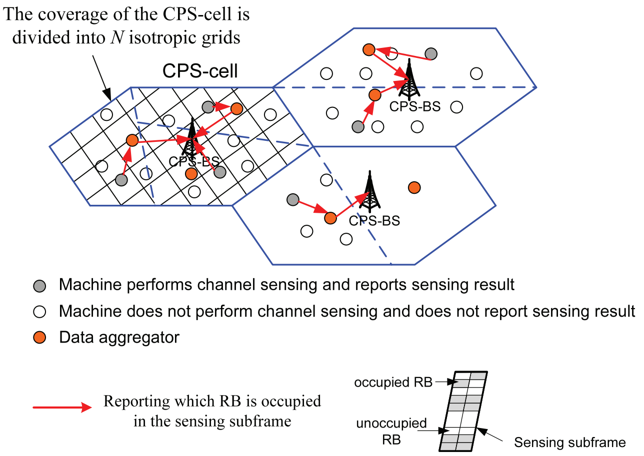

Fig. 3. The compressive sensing is applied to construct the spectrum map of the CPS-cell by channel sensing results of a portion of machines. The coverage of the CPS-cell is divided into N isotropic "grids."

is a convex function differentiable for all real θ. To achieve the statistical delay guarantees, approaches to derive the effective bandwidth of real-time streams had been widely discussed (e.g., the effective bandwidth of the voice traffic can be obtained by the method proposed in [19]). However, the effective capacity depends on the system design. We therefore shall derive the effective capacity of the proposed SMRM.

3 The SMRM for the CPS-Cell

To mitigate interference, the CPS-BS shall avoid allocating occupied RBs (by Macrocells) to DAs (and thus machines in the swarm). As a result, the key idea of interference mitigation is that all machines shall autonomously estimate the RBs usage of the Macrocell and report the sensing result (that is, identifying which RB is occupied by the Macrocell in a subframe at any given locations, i.e., the spectrum map). However, this approach is infeasible due to potentially unacceptable amount of uplink reporting data. As a result, the number of machines required to perform channel sensing shall be significantly reduced. To resolve this issue, we shall adopt the compressive sensing for the spectrum map construction. For this goal, the coverage of the CPS-cell is divided into N isotropic "grids" indexed by $n = 1, \ldots, N$, as shown in Fig. 3. With the facilitation of the spectrum map, interference can be mitigated by only allocating unoccupied RBs to machines. Such an SMRM is proposed in Algorithm 1 as follows.

Algorithm 1. SMRM

1: The CPS-BS periodically allocates subframes for machines to perform channel sensing to identify which RB is occupied. The sensing period is T subframes and each channel sensing persists for one subframe (Fig. 2). A subframe is referred as a "sensing subframe" if the subframe is allocated for performing channel sensing; otherwise, the subframe is referred as a "data subframe". All machines and DAs can not perform data transmissions/receptions within a sensing subframe.

2: Within a sensing subframe, each machine performs channel sensing with probability q to measure the *received interference power* on each RB.

3: **if** the *received interference power* on an RB exceeds a certain threshold **then**

4: this RB is identified as being occupied; otherwise, the RB is unoccupied. The machine reports the sensing result to the DA and thus the CPS-BS.

5: The CPS-BS constructs the spectrum map based on the channel sensing report (the method to construct the spectrum map will be elaborated later)

6: In subsequent data subframes, the CPS-BS only allocates unoccupied RBs sensed in the sensing subframe to machines.

7: The CPS-BS also extracts following parameters from the result of reports: (i) the traffic load of existing Macrocells, (ii) the RBs allocation correlation probability of existing Macrocells, and (iii) the fraction of correlated RBs allocation of existing Macrocells, which are detailed later.

By the proposed SMRM, only Vq machines in expectation shall perform channel sensing and report the sensing result. Since $Vq \leq V$, the number of machines required to perform channel sensing can be reduced. Furthermore, since the *received interference power* had been adopted by 3GPP LTE-Advanced as a mandatory sensing quantity and corresponding sensing results report procedures had also been defined by LTE-Advanced [20], the proposed SMRM can be applied to CPS-cell without any hardware modifications and additional signaling overheads. In LTE-Advanced, DAs can be deployed by the system operator (for example, relay stations [20] in LTE-Advanced can be very powerful DAs) and the swarm can be constructed by DAs. In the following, we devote to the spectrum map construction in Step 3 of Algorithm 1 by the compressive sensing.

3.1 Compressive Sensing for the Spectrum Map Construction

Denote $\boldsymbol{\Psi} = [\psi_1 \psi_2 \ldots \psi_N]^{\mathrm{T}}$ as the true RBs occupation of Macrocells, where ψ_n indicates M RBs occupations of existing Macrocells in a sensing subframe on the nth grid. Upon receiving feedback from DAs, the compressive sensing is obtained by multiplying a sampling matrix on the true RBs occupation of Macrocells $\boldsymbol{\Psi}$,

$$\mathbf{y} = \mathbb{A}\boldsymbol{\Psi} + \varepsilon, \tag{9}$$

where $\mathbb{A}$ is a $R \times N$ matrix with each element taking "1" with probability $q\frac{V_n}{V}$, and taking "0" with probability $1 - q\frac{V_n}{V}$, where V_n is the number of machines within the nth grid. The spectrum map can be constructed by searching the minimum l_1 norm of $\boldsymbol{\Psi}$,

$$\boldsymbol{\Psi}^* = \arg\min \|\boldsymbol{\Psi}\|_1 s.t. \|\mathbb{A}\boldsymbol{\Psi} - \mathbf{y}\|_2 \leq \epsilon, \tag{10}$$

by applying the *second order corn programming* [21] if $R = O(K \log \frac{NM}{K})$, where l_p norm of $\boldsymbol{\Psi}$ is

$$\|\boldsymbol{\Psi}\|_p := \left(\sum_{n=1}^{N} |\psi_n|^p \right)^{1/p},$$

K is the sparsity of $\mathbb{A}$, $\epsilon = \|\Phi\varepsilon\|_2$ and Φ is a random basis.

To successfully construct the spectrum map by the compressive sensing with an acceptable quality, it is suggested that two conditions shall be considered [13]: 1) $\mathbf{\Psi}$ shall be sparse. 2) The selection of $\mathbb{A}$ shall satisfy the *restricted isometry property*. Since, in typical situation in the urban environment, most RBs in a subframe could be occupied by Macrocells, Ψ is typically sparse. From [22], [23], although it is suggested that the RIP can be achieved if each machine senses the channel the i.i.d. and symmetry Bernoulli random variable, in Section 5, we will show that the spectrum map can be constructed with an acceptable quality when each machine senses the channel with probability q of the Bernoulli random variable.

3.2 More Considerations on the SMRM

By applying the SMRM, if the existing allocations of RBs change very frequently among subframes, there could be estimation errors of RBs usage. Therefore, a small sensing period T can decrease the estimation error and thus interference. However, since channel sensing is an overhead, a small T implies that more radio resource (more sensing subframes) are used for channel sensing. As a result, there is a tradeoff between sensing period T and interference. A good tradeoff shall provide QoS guarantees for machines while fully utilizing the radio resource. To achieve this goal, the CPS BS should appropriately control T and the RBs allocation. For this purpose, the CPS-BS needs more information about the characteristics of RBs allocations of existing users. That is, RBs are allocated in a high or in a low correlation manner among subframes. To capture these characteristics, the CPS-BS is proposed to extract following parameters from channel sensing in Step 5 of the SMRM.

Definition 1. *Let $M_{\rm Macro}$ be the number of RBs occupied by Macrocells in a subframe, the traffic load of Macrocells, ρ, is defined as $\rho \triangleq M_{\rm Macro}/M$.*

Definition 2. *When an RB is occupied by Macrocells in a subframe, the (aggregated) RB allocation correlation probability of Macrocells, η, is the probability that Macrocells will still occupy this RB in the subsequent subframe.*

Definition 3. *Let M_η be the number of RBs with nonzero η in a subframe, the fraction of correlated RBs allocation of Macrocells, φ, is defined as $\varphi \triangleq M_\eta/\rho M$.*

To obtain these parameters, machines still only need to sense the received interference power on each RB, by which machines can identify the traffic load of the Macrocell, ρ. By further performing the time-domain correlation of channel sensing results [24], [25], η and φ can be obtained. η and φ capture the correlation of the RBs allocation among subframes in Macrocells. If both η and φ are large, it implies that Macrocells allocate RBs in a high correlation manner among subframes. By obtaining these parameters in Step 5 of Algorithm 1, a systematic procedure is proposed in next section to control T and RBs allocation for QoS guarantees.

3.3 The Impact of the SMRM to Macrocells

According to the state-of-the-art operation of LTE-Advanced [20], the Macro-BS is able to coordinate each UE to estimate the channel quality of RBs and only allocate RBs with an acceptable channel quality to the UE. As a result, when an RB is sensed as not being occupied by Macrocells and this RB is utilized by the CPS-cell, such an RB is with a poor quality to Macrocells and Macrocells avoid utilizing such an RB. Such an operation is known as the "interweave" coexistence between CPS-cells and Macrocells [26]. However, it does not suggest that there is no interfere between Macrocells and CPS-cells under the interweave coexistence. Due the channel quality variation, Macrocells may change the RBs allocation in each subframe. As we will see later, when Macrocells change the RBs allocation very frequently (i.e., η and φ are of small values), interference between Macrocells and CPS-cells turns to severe. By estimating η and φ, in the next section, the control of T and RBs allocation is optimized for CPS-cells under any cases of η, φ, and ρ.

4 The Control of T and the RBs Allocation

The ultimate goal of the control of T and the RBs allocation is to provide QoS guarantees while achieving an efficient radio resource allocation. From (5) and (6), it is known that the effective capacity facilitate us to achieve this goal. In the following, we derive the effective capacity of the SMRM.

4.1 Effective Capacity of the SMRM

By obtaining parameters in Step 5 of Algorithm 1, we start the derivation of the effective capacity of the SMRM in the following by temporarily assuming that the RB utilized by the CPS-cell suffers no interference. Considering that all RBs carry the same number of bits (say b bits) in a subframe, based on (7), the effective capacity of a machine utilizing one RB without suffering interference is given by

$$\mathrm{E}_{\mathrm{C}}^{1}(\theta) = -\lim_{t\to\infty}\frac{1}{\theta t}\log\Big(\mathbb{E}\Big[e^{-\theta\sum_{i=1}^{t}R[i]}\Big]\Big). \tag{11}$$

For the block fading channel wherein the service process $\{R[i], i = 1, 2, \ldots\}$ is uncorrelated, (11) can be rewritten as

$$\mathrm{E}_{\mathrm{C}}^{1}(\theta) = -\frac{1}{\theta}\log\left(e^{-\theta R[i]}\right). \tag{12}$$

Since each RB carries b bits, $R[i] = b$ for all i. We therefore obtain

$$\mathrm{E}_{\mathrm{C}}^{1}(\theta) = -\frac{1}{\theta}\log\left(e^{-b\theta}\right) = b. \tag{13}$$

To generalize (13), the effective capacity of the SMRM utilizing l RBs with potential interference due to the estimation error on the RBs usage of the existing users is given by following theorem.

Theorem 1. *Considering that the SMRM is applied to the CPS-cell, the effective capacity per subframe of a machine that utilizes l RBs in each data subframe is given by*

$$\mathrm{E}_{\mathrm{C}}^{l}(\theta) = l\varpi^{l}\mathrm{E}_{\mathrm{C}}^{1}\big(l\varpi^{l}\theta\big), \tag{14}$$

where

$$\varpi^{l} = \frac{T-1}{T} \cdot\left(1 - \frac{\sum_{g=0}^{\min(l,(1-\eta\varphi)\rho M)} g\mathrm{C}_{g}^{l}\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}}{l\cdot \mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}}\right) \tag{15}$$

and $\mathrm{C}_{b}^{a} \triangleq \frac{a!}{b!(a-b)!}$.

Proof. Due to the potential estimation error on the BRs usage of Macrocells, we need to derive the probability that there are g RBs suffering interference among l RBs utilized by the machine in the data subframe. For this purpose, we can divide RBs occupied by the Macrocells into two classes: 1) There are $\eta\varphi\rho M$ RBs whose allocations are the same in each subframe. 2) There are $(1-\eta\varphi)\rho M$ RBs whose allocations certainly change in each frame. Therefore, there are $\mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}$ possibilities of the RBs arrangement of Macrocells in each subframe. In a data subframe, the CPS-BS only allocates RBs sensed as unoccupied in the sensing subframe to the machine. Therefore, there are $\mathrm{C}_g^l\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}$ possibilities that there are g RBs suffering interference among l RBs utilized by the CPS-cell. Therefore, the probability that there are g RBs suffering interference among l RBs utilized by the CPS-cell in the data subframe is

$$\frac{\mathrm{C}_g^l\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}}{\mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}}.$$

Since the maximum value of g is

$$\min(l,(1-\eta\varphi)\rho M),$$

the expected value of g is

$$\sum_{g=0}^{\min(l,(1-\eta\varphi)\rho M)} g\frac{\mathrm{C}_g^l\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}}{\mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}}.$$

Therefore, among l RBs utilized by the CPS-cell, the expected number of RBs without suffering interference in each data subframe is

$$l-\sum_{g=0}^{\min(l,(1-\eta\varphi)\rho M)} g\frac{\mathrm{C}_g^l\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}}{\mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}}.$$

Further considering the overhead of sensing subframes, we can obtain

$$l\varpi_{\mathrm{C}}^l=\frac{T-1}{T}\left(l-\sum_{g=0}^{\min(l,(1-\eta\varphi)\rho M)} g\frac{\mathrm{C}_g^l\mathrm{C}_{(1-\eta\varphi)\rho M-g}^{(1-\eta\varphi\rho)M-l}}{\mathrm{C}_{(1-\eta\varphi)\rho M}^{(1-\eta\varphi\rho)M}}\right) \quad (16)$$

as the average number of RBs without suffering interference in each subframe. By applying the results in [27], [28], the effective capacity per subframe that the machine utilizes l RBs in each data subframe without suffering interference is

$$\mathrm{E}_{\mathrm{C}}^l(\theta)=l\mathrm{E}_{\mathrm{C}}^1(l\theta). \quad (17)$$

By substituting l in (17) by $l\varpi_{\mathrm{C}}^l$ in (16), we can obtain (14) as the effective capacity per subframe of the machine that utilizes l RBs in each data subframe. □

4.2 The Control of T and the RBs Allocation

Since machines locate at different areas experience different RBs occupations from Macrocells. As a result, ρ, η, φ and thus the effective capacity of a machine may be distinct from that of each other. With the facilitation of Theorem 1, we thus can propose the control of T and the RBs allocation to achieve the statistical delay guarantees for each machine, as elaborated in the following.

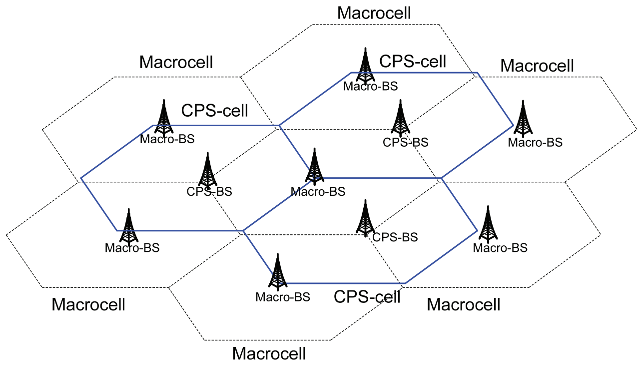

Fig. 4. Network topology for simulations. There are seven hexagonal-grid Macrocells with wrap around. Three CPS-cells are deployed at the boundary of the central Macrocell with wrap around. The interside distance of Macrocells and CPS-cells are 500 m.

Algorithm 2. The control of T and the RBs Allocation

1: The CPS-BS calculates the effective bandwidth $\mathrm{E}_{\mathrm{B}}(\theta)$ of the real-time traffic.
2: To efficiently utilize radio resource, T is initially set to a predetermined value.
3: The CPS-BS first allocates $l=1$ RB to the machine in the data subframe.
4: The CPS-BS calculates the effective capacity for the machine by (14).
5: Find the solution of θ such that

$$\mathrm{E}_{\mathrm{B}}(\theta)=\mathrm{E}_{\mathrm{C}}^l(\theta)=\delta. \quad (18)$$

6: Derive the delay violation probability by

$$\Pr\{\text{Delay}>d_{max}\}=e^{-\theta\delta d_{max}} \quad (19)$$

7: **if** $e^{-\theta\delta d_{max}}>\varepsilon$ **then**
8: l is determined by

$$\min_{1\le l\le L}\{l\}, s.t. e^{-\theta\delta d_{max}}\le\varepsilon \text{ for all machines} \quad (20)$$

L is the maximum number of RBs that can be allocated to the machine in a data subframe.
9: **if** If (20) is not satisfied **then**
10: decrease T by one and repeat Steps 4 to 10 to find the appropriate l and T such that (20) can be satisfied.

5 Performance Evaluations

Since the considered CPS is realized based on MTC in LTE-Advanced, we evaluate the performance of the proposed SMRM by adopting system parameters of LTE-Advanced [29]. The network deployment for the simulation is shown in Fig. 4, where three CPS-cells coexist with six Macrocells. Such a deployment is a typical coexistence of CPS-cells and Macrocells. CPS-cells are capable of the proposed SMRM and thus the cognitive radio technology, while the SMRM is not applied to Macrocells. Details of simulation parameters

TABLE 1
System Parameters and Assumptions for Simulations

Parameters	Values/assumptions
Carrier Frequency	2 GHz
System bandwidth	20 MHz (100 RBs per subframe)
Subframe length	1 ms
Number of subcarriers in an RB	12
Number of OFDM symbols in an RB	7
Diameter of Macrocell coverage	500m
Diameter of CPS-cell coverage	500m
Number of grids per CPS-cell	40
Number of machines per CPS-cell	200
Number of DAs per CPS-cell	10
Cells layout (as shown in Fig. 4)	Seven hexagonal-grid Macrocells with wrap-around. Three CPS-cells are deployed at the boundary of the central Macrocell with wrap-around.
DAs deployment	Uniformly distributed over each CPS-cell
Machines deployment	Uniformly distributed over each CPS-cell
DL TX power of Macrocells	46 dBm
DL TX power of CPS-cells	46 dBm
Interference threshild	-65 dBm
Modulation	QPSK
Voice/video trace file	According to [29], [32]

and assumptions are listed in Table 1. This performance evaluation is conducted by C++.

In this evaluation, the following two schemes are selected as performance comparison benchmarks for the SMRM:

- **Randomize**. Without the SMRM, the distributed interference mitigation scheme widely adopted by the state-of-the-art OFDMA systems is to randomize RBs allocation in each subframe. Such a randomized scheme is similar to concept of the interleaved RBs allocation to combat the block fading channel. This interference mitigation scheme is widely adopted when the radio resources usage of neighboring cells is totally unknown, which is a typical interference mitigation scheme when the system lacks of the cognitive radio capability.
- **Gibbs sampler**. As mentioned in Section 3.3 that the state-of-the-art Macrocells as well as CPS-cells have the capability of channel quality assessment and avoid to utilize an RB with poor channel quality (i.e., severe interference or poor channel gain). However, without a centralized coordination between Macrocells and CPS-cells and without the SMRM in CPS-cells, an RB with acceptable channel quality may be simultaneously occupied by both the Macrocell and the CPS-cell. Under this situation, such an RB is identified as with poor channel quality and both the Macrocell and the CPS-cell select other RBs with better channel quality. As a result, an appropriate RBs selection scheme is the key for such the state-of-the-art operation of Macrocells and CPS-cells without the SMRM. Recently, in [30], [31], an iterative algorithm known as the Gibbs sampler-based radio resources selection is proposed to optimize the selection of RBs. That is, each Macrocell and CPS-cell computes the temperature parameter $U = \frac{C_0}{\log_2(2+u)}$, where u is the age variable denoting the system time and C_0 is an appropriately selected constant. Next, each Macrocell computes the energy on every RB in a subframe as the summation of all interference from CPS-cells and each CPS-cell computes the energy on every RB in a subframe as the summation of all interference from Macrocells. Then, the Macrocell and the CPS-cell select an RB in a subframe according to Gibbs distribution with temperature U [30], [31]. To achieve an acceptable performance, a considerable number of iterations is required. By considering the average performance on each iteration, this scheme is adopted to show the performance of the CPS-cell without the SMRM in the interweave coexistence.

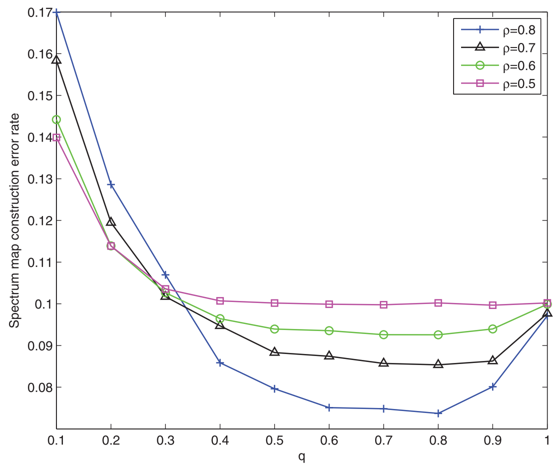

Fig. 5. Error rate of the spectrum map construction under different q.

In this simulation, we shall first evaluate the performance of the spectrum map construction by compressive sensing. Fig. 6 shows the error rate of the spectrum map construction. The error rate is measured by

$$\xi = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M}\Upsilon(m,n)}{NM}, \quad (21)$$

where $\Upsilon(m,n) = 1$ if there is an error on the spectrum map construction on the mth RB in a subframe on the nth grid; otherwise, $\Upsilon(m,n) = 0$. We can observe from Fig. 5 that, when Macrocells are with a typically high traffic load ($\rho = 0.8$), there is only a 7.5 percent error (7.5 RBs are occupied by Macrocells but they are estimated as unoccupied, or 7.5 RBs are not occupied by Macrocells but they are estimated as occupied, among 100 RBs in a frame) if $q \in [0.6, 0.8]$. Please note that only 60 percent of machines are adopted for channel sensing. This result suggests the effectiveness of the SMRM on the spectrum map construction. We may particularly note that, in the compressive sensing, a large q may lead to the oversampling issue to degrade the performance.

In Macrocells, there are typically certain correlations in RBs allocations among subframes. Since the swarm suffers aggregated interference from multiple Macrocells, there are certain correlations in such aggregated interference (RBs occupations) from multiple Macrocells. Therefore, we should evaluate the performance of the swarm under different correlations of RBs allocations of Macrocells among

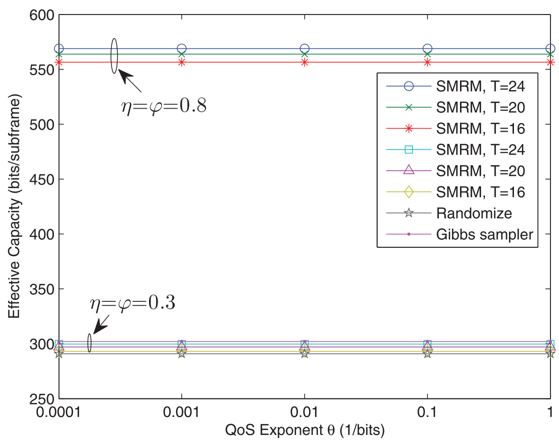

Fig. 6. Effective capacity of the CPS-cell adopting the SMRM, the randomized scheme and Gibbs sampler-based RB selection under different T ($l = 6$, $\rho = 0.8$), where the average performance of Gibbs sampler-based RBs selection on each iteration is evaluated.

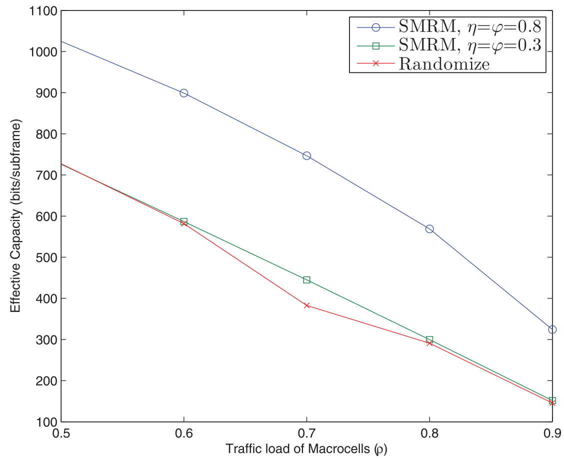

Fig. 8. Effective capacity of the machine adopting the SMRM and the randomized scheme under different traffic loads of the Macrocell ρ. ($T = 24$, $l = 6$).

subframes. In this performance evaluation, a high correlation is considered by $\eta = \varphi = 0.8$ and a low correlation is considered by $\eta = \varphi = 0.3$. In the low correlation case, when $\rho = 0.8$, there are only $\lceil 0.3 \times 0.3 \times 0.8 \times 100 \rceil = 8$ RBs that will be persistently occupied by Macrocells in each subframe. This is a very extreme case. Please note that, in Figs. 6, 7, 8, and 9 shown as follows, the error of the spectrum construction, the error on the estimation of the RBs usage of Macrocells, and the error on the estimation of η and φ are taken into the consideration of the performance evaluation.

In the SMRM, channel sensing is an overhead. In addition, there could be potential errors on the estimation of RBs occupation of Macrocells. Therefore, the first thing required to be investigated is whether it is effective to perform channel sensing to mitigate interference. It can be observed from Fig. 6 that, when T is appropriately selected, the SMRM outperforms the randomized scheme when RBs are occupied by Macrocell with a high correlation among subframes. Even in the extreme case that RBs are occupied by Macrocell with a low correlation, the performance of the SMRM is around the same level of the randomized scheme. These results support the effectiveness of channel sensing on the SMRM for the interference mitigation. Since the Gibbs sampler-based radio resources selection scheme requires a considerable number of iterations to achieve an acceptable performance, we shall evaluate the average performance of the Gibbs sampler-based radio resources selection scheme on each iteration. We can also observe that, the SMRM also outperforms the Gibbs sampler scheme when RBs are occupied by Macrocell with a high correlation among subframes. Even in the extreme case that RBs are occupied by Macrocell with a low correlation, the performance of the SMRM is around the same level of the Gibbs sampler scheme, which demonstrates the effectiveness of the proposed SMRM. Furthermore, the performance of the SMRM can be enhanced when T increases, while this performance enhancement becomes marginal when T keeps increasing. Therefore, by selecting an appropriate T (e.g., 24 subframes), the performance can be close to the optimum. Please also note that, due to the interweave coexistence between the CPS-cell and the Macrocell, when an unoccupied RB is utilized by the CPS-cell, Macrocells may not occupy such an RB. As a result, the effective capacity of CPS-cell is only affected by the sensing and estimation error

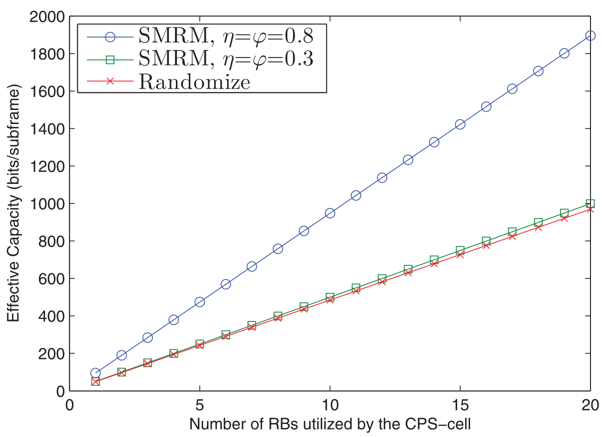

Fig. 7. Effective capacity of the machine adopting the SMRM and the randomized scheme under different l. ($T = 24$, $\rho = 0.8$).

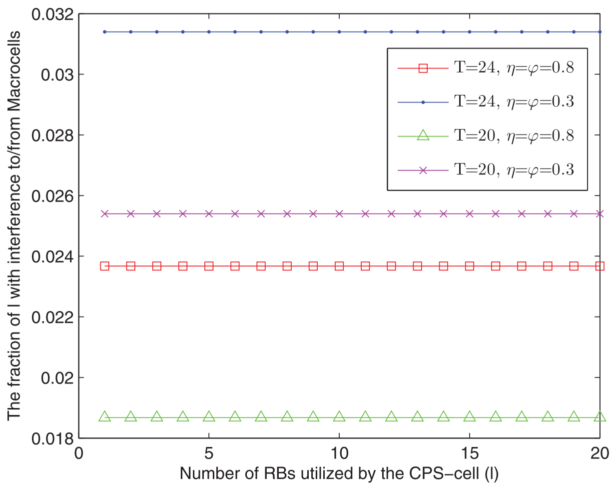

Fig. 9. The fraction of l with potential interference to/from Macrocells. ($\rho = 0.8$).

TABLE 2
Simulation Results of the Delay Bound Violation Probabilities of the VoIP ($d_{max} = 20$ ms) and the High-Quality MPEG4 Video ($d_{max} = 40$ ms) Transmissions in the Swarm ($\varepsilon = 0.02$)

Traffic	Viol. Prob. of SMRM (simul.) η=φ=0.3	Viol. Prob. of SMRM (19) η=φ=0.3	Viol. Prob. of SMRM (simul.) η=φ=0.8	Viol. Prob. of SMRM (19) η=φ=0.8	Viol. Prob. of Randomize (simul.) η=φ=0.3	Viol. Prob. of Randomize (19) η=φ=0.3	Viol. Prob. of Randomize (simul.) η=φ=0.8	Viol. Prob. of Randomize (19) η=φ=0.8
Video	0.010	0.0199	0.0066	0.015	0.0464	0.091	0.0331	0.072
VoIP	0.0012	0.003	0.0003	0.0007	0.0013	0.0031	0.0008	0.0017

of RBs usage from the Macrocell and T, which is thus independent of θ.

Next, we investigate the performance of the CPS-cell utilizing different number of RBs in Fig. 7. Please note that, when l unoccupied RBs are utilized by CPS-cell, the worst case of total error rate (jointly considering spectrum map reconstruction error and the estimation error on the RBs usage of Macrocells) can be a constant (as we will see in Fig. 9 later). Therefore, there is a constant fraction of RBs among l RBs utilized by the CPS-cell that may suffer/induce interference from/to Macrocell. As a result, the effective capacity increases linearly as l increases. Since the CPS-cell adopting the SMRM can identify unoccupied RBs to utilize, interference can be alleviated, especially when the number of RBs required by the machine increases.

In Fig. 8, the performance of the CPS-cell under different traffic load of Macrocells is investigated. It can be observed that when the traffic load of Macrocells increases, both the effective capacities of the CPS-cell adopting the SMRM and adopting the randomized scheme decrease. The reason is, when the number of RBs occupied by Macrocells increases, the probability that the CPS-cell and the Macrocell utilizing the same RB also increases. However, since the CPS-cell adopting the SMRM only utilizes the unoccupied RBs, the SMRM outperforms the randomized scheme.

Under the proposed SMRM, there could be errors on the spectrum map construction and errors on the estimation of the RBs usage of Macrocells. These errors may induce interference to/from Macrocells. Therefore, we shall evaluate whether these estimation errors induces severe impacts to Macrocells. It can be observed from Fig. 9 that, these estimation errors only induce a very limited impact to Macrocells. That is, only 2.34 and 3.13 percent among l when l RBs are utilized by the CPS-cell, for $\eta = \varphi = 0.8$ and $\eta = \varphi = 0.3$, respectively, as $T = 24$. When $T = 20$, as expected, the impact can be reduced to 1.85 and 2.54 percent among l for $\eta = \varphi = 0.8$ and $\eta = \varphi = 0.3$, respectively, due to the improvement on the estimation accuracy of η and φ. This result suggests that, by adopting the proposed SMRM, the impact induced by the CPS-cell to Macrocells is very limited.

Finally, we focus on the performance of SMRM in the realistic applications such as healthcare surveillance, traffic monitoring in transportation systems, and environment monitoring systems, where real-time VoIP and video transmissions are necessary. Table 2 shows the simulation results of the SMRM on the support of real-time VoIP [29] and high-quality MPEG4 video transmissions [32]. The arrival process of VoIP is the well-known ON-OFF fluid model. The holding times in "ON" and "OFF" states are exponentially distributed with means 6.1 and 8.5 s, respectively. The data rate of the "ON" state is 32 Kbps. The delay bound is 20 ms and the delay bound violation probability is 0.02. The delay bound of MPEG4 is 40 ms and the delay bound violation probability is 0.02. The effective bandwidth calculation of VoIP and video traffic can be found by [19], [33]. We can observe from Table 2 that the theoretical results of the delay constraint violation probabilities effectively capture the simulation results, which shows the effectiveness on adopting the effective capacity model for providing statistical QoS guarantees. Table 2 also shows the effectiveness of the SMRM on the support of the statistical delay guarantee, while the MPEG4 movie cannot be supported by the randomized scheme.

6 Conclusion

In this paper, we resolve the most critical challenge of autonomous radio resource management to provide QoS guarantees for the swarm in CPS by applying the cognitive radio technology and the distributed radio resource monitoring, which is enabled by the compressive sensing spectrum map. The propose SMRM can be applied into the realistic CPS platform underlying with LTE-Advanced networks and other possible wireless infrastructure. Performance evaluation results showed that the proposed SMRM outperforms the randomized scheme to enable a smooth real-time voice/video transmissions for healthcare surveillance applications or traffic monitoring systems over the swarm.

Acknowledgments

This research is sponsored by the National Science Council and INTEL Corp. under the contract of NSC 100-2911-I-002-001, and by the NSC under the contract of 98-2221-E-002-065-MY3.

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