An MRF Cross-layer Resource Allocation Approach with Back-pressure Features for QoS in Dynamic Social and Cognitive Communications

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***Abstract*—Future dynamic wireless and online social networks will require more agile and efficient infrastructures to support the anticipated user traffic and service requirements. In response, in this work, we propose a novel spectrum-agile resource allocation approach that combines Markov Random Field (MRF) cross-layer decisions for the allocation of resources at the lower protocol layers with Back-pressure (BP) features at the higher ones, in order to achieve the above objectives. The BP-enhanced MRF (BPeMRF) network optimization serves the purpose of improving the capacity of agile infrastructures in a low complexity manner, while espousing the recent developments in dynamic spectrum environments (cognitive radios), which are required to adapt fast according to the demands of overlaying dynamic online social networks. The obtained results exhibit the efficacy of BPeMRF regarding the above objectives and demonstrate significant promise for further improving the corresponding infrastructures.**

Keywords*—*Markov Random Fields; Back-pressure; Cognitive radio networks; Cross-layer design;

I. Introduction

Wireless technology and online social networks have experienced tremendous growth in the last decade, so that nowadays most of the Internet access takes place through smart handhelds [1]. At the same time wireless data traffic increases considerably, mainly due to the widespread proliferation of online social networks and the corresponding services/applications offered [2]. These trends are anticipated to continue, and in fact, they are expected to even drive the evolution of wireless networks in the Future Internet.

Along these lines, one of the major emerging problems is spectrum under-utilization, whereas in other cases, e.g., big social events such as conferences, sports finals, etc., traffic bottlenecks arise quickly when many users attempt to access simultaneously scarce resources, e.g., available channels, in a static/inefficient manner. The Cognitive Radio (CR) paradigm [3] has been conceived in a brain-empowered manner to address such problems, following a methodology that mimics the human behavior and by extension the evolutionary processes of physical, biological and other systems that exhibit social structure and cognition [4]. Above all, CRs can be used to alleviate problems emerging in cyber-physical systems combining wireless infrastructures and online social networks, e.g., to provide on-the-fly traffic offloading of the cellular infrastructure, thus expediting data transfers and reducing delays (LTE-advanced) in crowded locations. At the same time, the cognition-based operation of CRs, requires dynamic reconfigurations and flexible adaptations in order to support efficiently the anticipated Quality of Service (QoS) demands by the future services and applications developing in diverse wireless and online social networks.

Motivated by the aforementioned observations and emerging trends we focus on the design and analysis of spectrum-agile communications networks for the Future Internet, aiming at supporting the increased QoS requirements imposed by current and future dynamic and online social networks. More specifically, we propose a network optimization approach for CR networks, which aims at jointly determining the transmission power and channel allocation towards optimal scheduling and routing through lightweight and distributed computation. The optimization proposed by our approach is based on a Markov Random Field (MRF) [5] cross-layer formulation and the inherently distributed Gibbs sampling technique [6] enhanced with Back-pressure (BP) [7] features, with the goal of increasing capacity, avoiding interference, and essentially supporting the development of flexible spectrum-agile infrastructures for dynamic online social networks.

More specifically, the BP-enhanced MRF (BPeMRF) approach requires the minimum possible information from a centralized spectrum database and it can proceed with distributed computation in order to determine the transmission power and channel allocation through an MRF decision model. BPeMRF exploits BP features for ensuring optimal scheduling and determining routing at the higher protocol stack layers. We compare the joint mechanism with a traditional BP scheme in order to validate its efficiency and performance. The simulation results follow the lines of the theoretical results, indicating the throughput optimal performance of the BPeMRF scheme, similarly to BP, while allowing for less complex computations than BP by leveraging Gibbs sampling.

The rest of this paper is structured as follows. In Section II we explain the assumed system model, while in Section III the MRF part of BPeMRF. In Section IV, the BP features of BPeMRF are analyzed and in Section V numerical results on the operation of BPeMRF are provided. Section VI presents previous works on MRFs and BP related to BPeMRF, while Section VII concludes the paper.

II. System Model

Following the latest trends in dynamic spectrum environments, we adopt a CR database-assisted system model that

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conforms to recent approaches designed for the exploitation of the unlicensed TV whitespaces [8]. White space databases gather spectrum sensing data, provide spectrum awareness and adapt secondary user (SU) transmit profiles in order to ensure seamless primary user (PU) operation.

We consider N SUs within an unlicensed opportunistic spectrum access model of M heterogeneous channels, while each channel m is characterized by its own central frequency carrier f_m and bandwidth W_m. SUs coexist with higher priority PUs, potentially of different technologies, and communicate with a centralized entity (network controller), which is responsible for providing them specific operational parameters, i.e., channel availability list and power restrictions per channel depending on primary activity and SU location. We denote by $P_{i,m}$ the maximum permitted power at channel m at which node i can transmit without causing interference to PUs.

In addition, we go one step ahead by optimizing the performance of secondary network, while conforming to regulation limitations. This will reinforce the improvement of soft QoS demands imposed by the overlaying online social networks. In this direction, we suppose that each SU i is capable of selecting channel m and performing power control under the constraints of $P_{i,m}$. We assume that the range of permitted power is discretized into L levels, i.e., $a_P^{(i)} \in \{a_{P_1}, \cdots, a_{P_L}\}$ where $a_P^{(i)}$ denotes a percentage value (e.g., $a_{P_1} = 0\%$, $a_{P_L} = 100\%$) of the maximum permitted power $P_{i,m}$. Thus, using a simplified path loss model and denoting by P_R^{thr} the SU receiver sensitivity threshold as determined by hardware specifications, the transmission range $R_{T_i}^m$ of node i over channel m can be estimated as:

$$R_{T_i}^m = d_0 \Big[\frac{a_P^{(i)} P_{i,m} G_t G_r}{P_R^{thr}} \cdot \Big(\frac{c_0}{4\pi d_0 f_m} \Big)^2 \Big]^{\frac{1}{\eta}} \tag{1}$$

where c_0 represents the speed of light, d_0 the Line-of-Sight (LOS) reference distance and η the path-loss exponent. The antenna gains of the transmitter and receiver are denoted by G_t and G_r, respectively, both assumed to be equal to unity.

Packet collisions at a SU receiver can occur whenever two or more packets are received at the same time. However, we assume that overlapping transmissions in the secondary network are possible due to the capture effect. More precisely, in case of two concurrent SU transmissions, a SU can still receive a packet without collision if the signal-to-interference ratio at the receiver is high enough for successfully decoding the ongoing transmission. Therefore, in our analysis we adopt the capture threshold model [9], by which SU i can successfully transmit to j over channel m if

$$a_P^{(i)} \cdot P_{i,m} \cdot G_{i,j}^{(m)} \geq P_R^{thr} \quad \text{and} \quad \frac{a_P^{(i)} \cdot P_{i,m} \cdot G_{i,j}^{(m)}}{a_P^{(i')} \cdot P_{i',m} \cdot G_{i',j}^{(m)}} \geq C_p^{thr} \quad \forall i' \neq i$$

where C_p^{thr} denotes the capture threshold above which the interference from any potential transmitter i' can be ignored (not strong enough to create a collision). $G_{i,j}^{(m)}$ stands for the channel gain of link (i,j) at channel m, i.e., $G_{i,j}^{(m)} = G_t \cdot G_r \cdot \left(\frac{c}{4\pi d_0 f_m}\right)^2 \cdot \left(\frac{d_0}{d_{ij}}\right)^\eta$, where d_{ij} is the Euclidean distance between SUs i and j.

Regarding the SU traffic, we consider the existence of a finite number of commodities representing either flows, i.e., SU source-destination pairs, or destinations, within a time-slotted network operation. At each time slot t new data are generated and transmission decisions are made towards delivering all packets to their proper destinations. Specifically, the packets generated exogenously (e.g., application layer of an online social network) are assumed to arrive at each SU i with rate λ_i^c, where $\lambda_i^c \neq 0$ only if i is a source of packets for commodity c. Hence, the instantaneous number of packets arriving at source node i at time t for commodity c is equal to $A_i^c(t)$, where $\mathbb{E}[A_i^c(t)] = \lambda_i^c$. The arrival rates are considered upper bounded, i.e., $\lambda_i^c(t) \leq \lambda_{\max},\ \forall\ i, c$. Furthermore, we denote the communication traffic in number of packets of every secondary link $s = (i,j)$ at time t by $\mu_{i,j}(t)$ as upper bounded by $\mu_{i,j}(t) \leq \mu_{i,j}^{\max} = \max_m \left\{ \left\lfloor \frac{W_m}{Pkt_s} \cdot \log_2 \left(1 + SNR_s\right) \right\rfloor \right\}$, where Pkt_s is the packet size and $SNR_s = \frac{P_{i,m} \cdot G_{i,j}^{(m)}}{N_0 + N_P}$. N_0 denotes the background noise, while N_P stands for the total additive interference/noise caused by the underlying primary system. Similarly, $\mu_{i,j}^c(t)$ stands for the communication traffic over site $s = (i,j)$ regarding only commodity c. The packets for commodity c that have arrived at SU i, but have not yet been forwarded, are stored in a commodity-specific queue at node i, denoted by Q_i^c, with state $Q_i^c(t)$ at time slot t.

III. MRF Formulation for Secondary Networks

Constrained by the underlying limitations posed by primary activity, SUs make adaptations and continuously take decisions which unavoidably influence neighboring SUs. In this manner, a knock-on effect is generated by which local decisions give rise to long-range adaptations and essentially can contribute to the overall secondary network performance. This behavior unveils spatial dependencies along with a generalized Markov property that motivate our following Markov Random Field (MRF) centered analysis and formulation.

Based on the maximum transmission range of each SU i, $R_{T_i}^{(max)}$, which can be estimated by Eq. (1), we define by $\mathcal{K}$ the set of all possible directed secondary links, with cardinality K. Each link $s = (i,j) \in \mathcal{K}$ is mapped to an MRF site s and represents a communication link with transmitter node i and receiver node j. MRFs describe a probabilistic measure in a family of spatially dependent random variables X_s which are associated with a finite number of MRF sites $s \in S$, where $S \doteq \mathcal{K}$ in our case. Every random variable X_s takes values x_s, also referred to as states, from a finite space Λ, whereas the combination of states of all MRF sites describes a configuration $\omega = \{(x_1, \ldots, x_s, \ldots, x_n) : x_s \in \Lambda, s \in S\}$ that corresponds to one of all possible states of the whole system. In the same manner for our formulation, the state of a secondary link $s = (i,j)$ is expressed by the 2-tuple $\langle m, a_P \rangle_s$ with state space size equal to $M \times L$. It represents the selected channel m and the real power (after power control) of the transmitter i as the percentage of the maximum permitted power $P_{i,m}$. Thus, for example if site $s = (i,j)$ has state $\langle 1, 50\% \rangle$, it means that the corresponding link is active and node i transmits to node j at channel 1 (namely, at frequency carrier f_1 and channel bandwidth W_1) with transmission power equal to $0.5 \times P_{i,1}$.

The main property of MRFs is that the state of each site depends only on a local set of neighbors and is expressed by the following conditional probabilities (also called local characteristics),

$$\mathbb{P}(X_s = x_s \mid X_r = x_r, r \neq s) = \mathbb{P}(X_s = x_s \mid X_r = x_r, r \in \mathcal{G}_s) \tag{2}$$

where $\mathcal{G}_s$ stands for the MRF neighborhood of each site s and satisfies the conditions: $\forall s \in S$, $s \notin \mathcal{G}_s$ and $r \in \mathcal{G}_s$ if and only if $s \in \mathcal{G}_r$. In our case, we define a neighborhood system $\mathcal{G} = \{\mathcal{G}_s\}_{s\in\mathcal{K}}$ such that two sites (secondary links) s and s' are MRF neighbors if and only if their concurrent operation is possible to affect the network performance in terms of packet collisions. Thus, the MRF neighborhood of s is defined as:

$$\mathcal{G}_s = \left\{ \begin{array}{c} s' = \{i', j'\} : \qquad s' \neq s \text{ and} \\ \left(\begin{array}{c} i = i' \text{ or } i = j' \text{ or } i' = j \text{ or } j = j' \\ \text{or} \\ \min\limits_{m \,:\, P_{i,m}\cdot G^{(m)}_{i,j} \geq P^{thr}_R} \left(\dfrac{P_{i,m}\cdot G^{(m)}_{i,j}}{P_{i',m}\cdot G^{(m)}_{i',j}} \right) < C^{thr}_p \\ \text{or} \\ \min\limits_{m \,:\, P_{i',m}\cdot G^{(m)}_{i',j'} \geq P^{thr}_R} \left(\dfrac{P_{i',m}\cdot G^{(m)}_{i',j'}}{P_{i,m}\cdot G^{(m)}_{i,j'}} \right) < C^{thr}_p \end{array} \right) \end{array} \right\} \tag{3}$$

Any random field with property (2) on a neighborhood system $\mathcal{G}$ can be also represented as a Gibbs field of the form

$$\mathbb{P}(X = \omega) = \frac{1}{Z} e^{-\frac{U(\omega)}{T}} \tag{4}$$

with a suitable choice of energy function $U(\omega)$ that can be further decomposed into the contributions of smaller subsets of S, $V_C(\omega)$, also called potential functions. $Z := \sum_{\omega\in\Omega} e^{-\frac{U(\omega)}{T}}$ denotes the partition function and T a system parameter, also referred to as temperature. In this work, we leverage the class of pairwise, nearest-neighbor potentials and decompose the system energy into neighbor pair potentials, i.e., $V_C = 0$ if C is not a clique or $|C| > 2$, as follows

$$U(\omega) = \sum_{s\in S} V^{(1)}_{\{s\}}(x_s) + \sum_{\{s,s'\}\in(S\times S), s'\in\mathcal{G}_s} V^{(2)}_{\{s,s'\}}(x_s, x_{s'}) \tag{5}$$

Aiming at uniquely specifying our MRF formulation, we design the corresponding singleton $V^{(1)}_{\{s\}}$ and doubleton potentials $V^{(2)}_{\{s,s'\}}$ towards capturing via the energy function the different contributions of system configurations ω in the secondary network capacity, as well as the cost of potential packet collisions. Thus, the singleton potential for each link $s = (i, j)$ with state $x_s = \langle m, a_P\rangle_s$ is expressed by

$$V^{(1)}_{\{s\}}(x_s) = \begin{cases} \delta_1 > 0, & \text{if } 0 < a^{(s)}_P \cdot P_{i,m} \cdot G^{(m)}_{i,j} < P^{thr}_R \\ -\lambda_1 \cdot \frac{W_m}{C_{max}} \cdot \log_2\left(1 + \frac{a^{(s)}_P \cdot P_{i,m} \cdot G^{(m)}_{i,j}}{N_0 + N_P}\right), & \text{otherwise.} \end{cases} \tag{6}$$

In the above formation, each state of an MRF site (secondary link) contributes to the system energy according to the maximum possible link capacity that could offer, whereas δ_1 represents a penalty for useless links activations, i.e., incapable of successfully delivering packets. C_{max} denotes the maximum link capacity in the secondary network and serves for normalization purposes. Similarly, doubleton potential $V^{(2)}_{\{s,s'\}}$ is designed to capture the interaction between secondary communication links, e.g., link s with state $x_s = \langle m, a_P\rangle_s = \{m, a^{(s)}_P\}$ and link s' with $x_{s'} = \langle m, a_P\rangle_{s'} = \{m', a^{(s')}_P\}$, as follows

$$V^{(2)}_{\{s,s'\}}(x_s, x_{s'}) = \begin{cases} \lambda_2 \cdot \delta_2 > 0, & \text{if “collisionCondition” = 1} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

δ_2 is a large positive constant value that penalizes collisions between two active secondary links by increasing the system energy. The “collisionCondition” describes the possible scenarios/configurations between s and s' that can lead to packet collision and is expressed by

$$\left(\begin{array}{c} a^{(s)}_P \neq 0 \text{ and } a^{(s')}_P \neq 0 \text{ and} \\ \left(i = i' \text{ or } i = j' \text{ or } i' = j \text{ or } j = j' \right) \end{array} \right) \text{ OR}$$

$$m = m' \text{ and}$$
$$\left(\begin{array}{c} P^{thr}_R \leq \left[a^{(s)}_P \cdot P_{i,m} \cdot G^{(m)}_{i,j}\right] < C^{thr}_p \cdot \left[a^{(s')}_P \cdot P_{i',m} \cdot G^{(m)}_{i',j}\right] \\ \text{or} \\ P^{thr}_R \leq \left[a^{(s')}_P \cdot P_{i',m} \cdot G^{(m)}_{i',j'}\right] < C^{thr}_p \cdot \left[a^{(s)}_P \cdot P_{i,m} \cdot G^{(m)}_{i,j'}\right] \end{array} \right)$$

It is noted that λ_1 and λ_2 represent non-negative parameters to control the strength of potentials' contributions.

The above MRF formulation of the secondary network facilitates the estimation of optimal solutions by taking advantage of powerful MRF energy minimization techniques (mostly derived from the field of image processing) in an otherwise difficult to be solved problem. Given that the space of possible configurations can be very large, MRF formulation can leverage algorithms for the computation of global optimum solutions relying on repeated computation of local characteristics (Eq. (2)). As a result, by finding configurations (i.e., specifying channel allocations and power control at each secondary link) with minimum MRF system energy, we are able to both maximize the offered capacity per link and provide to SUs an efficient scheduling scheme avoiding collisions and hence, improving the overall secondary network performance.

In this work, we investigate optimal configurations with minimum MRF energy based on a stochastic relaxation methodology, namely Gibbs sampling [6]. The key idea behind Gibbs sampling is that following a visiting scheme each currently visited MRF site, s, updates its own state according to the local conditional probability distribution

$$\begin{aligned} &\mathbb{P}(X_s = x_s \mid X_r = x_r, r \neq s) = \\ &= Z_s^{-1} \cdot \exp\left(-\frac{1}{T(sweepID)} \cdot \sum_{C: s\in C} V_C(\omega^{x_s})\right) \end{aligned} \tag{8}$$

where $Z_s = \sum_{x_s\in\Lambda} \exp\left(-\frac{1}{T(sweepID)} \cdot \sum_{C:s\in C} V_C(\omega^{x_s})\right)$. $T(sweepID)$ represents an annealing schedule with decreasing rate of temperature T for each sweep that denotes the time interval within which all sites have updated their states. ω^{x_s} stands for the configuration which has value x_s at site s and agrees with ω everywhere else. It has been theoretically proven in [6] that by applying Gibbs sampling with a suitable logarithmic annealing, the system converges to minimum energy configurations.

IV. Potential Function via Back-pressure

In this section, we revisit the design of the potential functions (Section III) targeting at introducing throughput optimality in the MRF energy minimization problem. Towards this direction, we adapt the main idea of the throughput optimal back-pressure algorithm [7] which performs routing and link scheduling based on the congestion gradients (queue backlogs) computed on every connection. Specifically, BP chooses for transmission at each time slot, a maximal independent set of links (non-interfering links) that achieves the maximum sum of queue backlogs. At each time slot t, after the computation of the communication traffic variables, $\mu^c_{i,j}(t),\ \forall\ s = (i, j),\ c$ (Section II), according to the chosen schedule, each SU i

renews its queue for commodity c following the renewal relation:

$$Q_i^c(t+1) \leq \max\{Q_i^c(t)+A_i^c(t)-\sum_j \mu_{i,j}^c(t), 0\}+\sum_j \mu_{j,i}^c(t). \quad (9)$$

Throughput optimality is tied with the strong stability of queues. A queue, Q_i^c, is strongly stable if $\limsup_{t->\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} E(Q_i^c(\tau)) < \infty$ [10]. If all the queues of the network are strongly stable, then the whole network is strongly stable. The capacity region, $\mathcal{C}$, of the network is defined as the set of source rates $\lambda_i^c,\ \forall\ i,c$, for which there exists a control algorithm that can stabilize the network [11]. Any algorithm that can support every source rate inside $\mathcal{C}$ while maintaining stability is called throughput optimal [11].

Aiming to leverage the throughput optimality of the BP algorithmic design, we modify the singleton and doubleton potential functions in Eq. (6), (7) by replacing the constant homogeneous parameters $\lambda_1,\ \lambda_2$ correspondingly, with the heterogeneous, time-varying queue backlogs defined on each corresponding site of the MRF graph. In this case, the following proposition holds.

Proposition 1: Let us define the parameters $\lambda_1,\ \lambda_2$ in MRF singleton and doubleton potentials correspondingly (Eqs. (6), (7)) separately for each site $s = (i,j)$, as $\lambda_1 = \max\{\max_c\{\frac{Q_i^{(c)}-Q_j^{(c)}}{Q_{max}}\},0\}$ and $\lambda_2 = \max\{\max_c\{\frac{Q_i^{(c)}-Q_j^{(c)}}{Q_{max}}\},1\}$. Q_{max} represents a global constant normalization factor. Then, the proposed BPeMRF is throughput optimal, i.e., it stabilizes the queues, assuming that the arrival rates on the SUs lie inside the capacity region $\mathcal{C}$.

Proof: The MRF energy minimization problem becomes:

$$\min_X \sum_{s\in S} V_{\{s\}}^{(1)}(x_s) + \sum_{s\in S}\sum_{s'\in\mathcal{G}_s} V_{\{s,s'\}}^{(2)}(x_s,x_{s'})$$

Since δ_1 and δ_2 are large positive values, the corresponding configurations that activate such penalties cannot be part of the minimum energy solution. Let us denote with Γ the set of configurations $X = \{X_s, s \in S\}$ adding cost equal to δ_1 or δ_2 in the total MRF energy based on Eqs. (6), (7). Then, the search space of the optimal solution can be restricted by rewriting our initial minimization problem as:

$$\min_X \sum_{\{i,j\}\in S}\left[-\lambda_1\cdot W_m\cdot\log_2\left(1+\frac{a_P^{(s)}\cdot P(i,m)\cdot G_{i,j}^{(m)}}{N_0+N_P}\right)\right]$$
$$\text{subject to} \quad X \notin \Gamma$$

Since the constraints expressed by Γ guarantee interference avoidance between two active secondary links (based on capture threshold model), the experienced SNR of an active link s is equal to $SNR_s = \frac{a_P^{(s)}\cdot P_{i,m}\cdot G_{i,j}^{(m)}}{N_0+N_P}$. Since $\mu_{i,j}(t) = \frac{W_m}{Pkt_s}\cdot\log_2\Big(1+SNR_s\Big)$ is the communication traffic over site $s = (i,j)$ at t given the chosen channel m and the power level $a_P^{(s)}$ (Section II) and by defining that $\mu_{i,j}(t) = 0$ for all $\{i,j\}$ node pairs with distance greater than their maximum communication range (i.e., $d_{i,j} > R_{T_i}^{(max)}$), it is rewritten as

$$\min_X \sum_i\sum_j \left[-\lambda_1\cdot\mu_{i,j}(t)\right], \text{ subject to } \quad X\notin\Gamma$$

Following the assumption of the proposition, by tuning the parameter λ_1 of each singleton as $\lambda_1 = \max\{\max_c\{\frac{Q_i^{(c)}-Q_j^{(c)}}{Q_{max}}\},0\}$ for each site $s = (i,j)$, the MRF minimization is transformed to the following maximization:

$$\max_X \sum_i\sum_j\left[\mu_{i,j}\cdot\max\left\{\max_c\{\frac{Q_i^{(c)}(t)-Q_j^{(c)}(t)}{Q_{\max}}\},0\right\}\right]$$
$$\text{subject to} \quad X\notin\Gamma$$

The final equivalent maximization problem is identical to the back-pressure routing/scheduling policy which is throughput optimal [7], thus concluding the proof. ■

It is important to mention that the proposed design of the potential functions allows for the routing component to be included in the BPeMRF cross-layer scheme, in an exactly similar way as in the BP algorithm, while also leading to throughput optimality regarding scheduling. More specifically, routing is introduced via the choice of the optimal commodity to be served by each site. Each link (site) $s = (i,j)$ computes its queue backlog for all commodities, $P_{ij}^c(t) = Q_i^c(t) - Q_j^c(t), \forall\ c$ and the maximum one among all commodities $P_{ij}(t) = \max\{\max_c P_{ij}^c(t), 0\}$ is inserted in the parameters $\lambda_1,\ \lambda_2$ (Proposition 1) for the decisions regarding power and channel assignments to be made (scheduling is enclosed in the power control) via the MRF energy minimization. Finally, the commodity $c^*(i,j) = arg\max_c P_{ij}^c(t)$ will be chosen for service if the site $s = (i,j)$ is scheduled to transmit (i.e., the optimization concludes to non-zero power assignment to node i). Therefore, $\mu_{i,j}^c(t) = \mu_{i,j}(t)$ if $c = c^*(i,j)$, else $\mu_{i,j}^c(t) = 0$.

On the other hand, our contribution is favorable for the back-pressure algorithm itself and its practical implementation. This is due to the fact that the optimal realization of BP requires the solution of a Maximum Weight Matching (MWM), the centralized implementation of which is NP-hard [12]. BPeMRF can be alternatively seen as the replacement of the MWM in the BP algorithm with the less complex Gibbs sampling technique which can be performed distributively on each node based on some globally provided information (spectrum database, Section II). This fact constitutes an important contribution of the BPeMRF scheme in the field of dynamic social networks where the dynamic network topology requires the repetitive NP-hard computation of the maximal independent sets of the underlying physical layer graph for the solution of the MWM. However, since the Gibbs sampler needs an infinite number of time steps to converge, its finite application will provide an approximation of the optimal MWM solution.

Based on the previous observations, in Section V we compare the performance of the BPeMRF scheme (approximation of the MWM) with the back-pressure routing and scheduling algorithm (optimal computation of the MWM). However, contrary to the BPeMRF scheme, BP in its canonical form does not perform channel selection. To tackle this issue and only for comparison reasons we proceed with the redesign of the BP algorithm as follows.

Let us define a binary function I_s, where $I_s(m,t) = 1$ if the site $s = (i,j)$ uses the channel m at time slot t, else $I_s(m,t) = 0$. Also, $\sum_m I_s(m,t) = 1$ (Section II). The communication traffic of the site $s = (i,j)$ for commodity c will be equal to $\mu_{i,j}^c(t) = \sum_m \mu_{i,j}^{c,m}(t)I_{i,j}(m,t)$, where $\mu_{i,j}^{c,m}(t)$ denotes the communication traffic for commodity c over channel m at time slot t. Also, $\mu_{i,j}^m(t) = \sum_c \mu_{i,j}^{c,m}(t)I_{i,j}(m,t)$ the total communication traffic of site $s = (i,j)$ over channel m at time t and $\mu_{i,j}(t) = \sum_m\sum_c \mu_{i,j}^{c,m}(t)I_{i,j}(m,t)$ the total communication

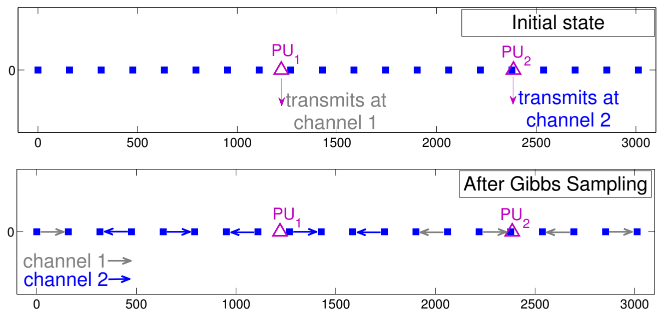

Fig. 1. Examined secondary topology (before and after Gibbs sampling).

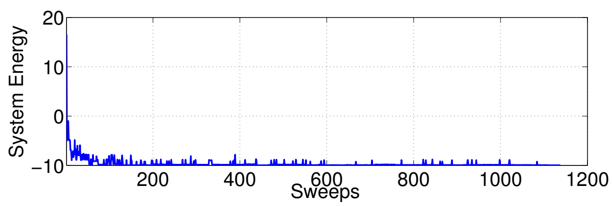

Fig. 2. Convergence to minimum energy configurations (maximum value of y-axis represents the maximum system energy as occurred at the early sweeps).

traffic over site s. Then, scheduling is decided by solving the MWM: $\max_I \sum_{(i,j)} \left\{ \sum_m \mu_{i,j}^m(t) I_{i,j}(m,t) \right\} P_{ij}(t)$, subject to interference constraints and $\sum_m I_s(m,t) = 1$, $I_s(m,t) \in \{0,1\}$. In order to solve the MWM we consider the graph of SUs where each link (i,j) is replaced by M links, each one corresponding to a channel $m \in \{1...M\}$, and denoted by (i,j,m). Then, we appropriately define the maximal independent sets (set $ID(t)$) over the interference constraints of the new graph, i.e., each site can use only one channel and half duplex communication, and the constraints of the capture model (Section II) for the links transmitting at the same channel. Let us denote with $\mu_{i,j,m}(t) = \mu_{i,j}^m(t)$ the communication traffic of link (i,j,m) and $P_{ijm}(t) = P_{ij}(t), \forall\ m$. Then according to the above, the initial MWM is equivalent to the MWM defined as $\max_{\mu \in \mathbf{ID(t)}} \sum_{(i,j,m)} \mu_{i,j,m} P_{ijm}(t)$, and therefore the latter needs to be solved. Each site $s = (i,j)$ for which $\mu_{i,j,m}(t) \neq 0$ for a channel m, serves over channel m, the commodity $c^*(i,j)$ with rate $\mu_{i,j}^m(t)$.

V. Simulation Results

In this section, we present indicative simulation results of our proposed BPeMRF operation and evaluate its performance in comparison with the traditional back-pressure methodology (namely, based on MWM solution). For the rest of the experiments, we adopt a logarithmic annealing schedule for Gibbs sampling (similar in spirit to the theoretical annealing schedule [6]), e.g., $T = \frac{2}{\ln(1+sweepID)}$, and proceed until convergence or a predefined finite number of sweeps.

To demonstrate the MRF energy minimization procedure and the underlying convergence behavior, we examine the trivial case of a line secondary topology (as shown in Fig. 1), where the distance between neighboring SUs allows communication only at their maximum transmission power and thus, optimal configurations can be easily deduced. In the examined scenario, 20 SUs coexist with 2 randomly located PUs over $M = 2$ homogeneous licensed channels, while we assume $L = 3$ available power levels and $\lambda_1 = \lambda_2 = 1$. Obviously, optimality (in terms of maximum network capacity without packet collisions) implies the activation of successive links with one vacant space. Fig. 2 illustrates the MRF energy decrease during the annealing schedule and until convergence, whereas the corresponding final configuration is depicted in Fig. 1. It is observed that convergence is achieved after approximately 1000 sweeps, while the channels are intelligently allocated to protect PUs' seamless operation. We note that in the following, if Gibbs sampling has not fully converged by 1000 sweeps, the best solution found thus far is adopted.

In order to compare the performance of the proposed BPeMRF scheme with the BP algorithm, we consider 14 SUs in a 2×7 grid network topology where each SU chooses another SU randomly as its destination node. Since BP does not perform power control we consider only two power levels ($L = 2$, Section II) for the BPeMRF and apply the redesigned BP described in Section IV over 1000 time slots. At each time slot t, each SU produces with probability 20%, $n_s = 1:12$ packets for its corresponding destination. In Figs. 3, 4, 5, the performance of the BPeMRF in terms of the achieved capacity region, delay and throughput respectively, is compared with BP. It is noted that in this series of experiments λ_1, λ_2 are tuned according to Proposition 1.

Throughput (Fig. 5) is expressed as the fraction of the number of packets that reached the destination divided by those sent by the source for each flow, and then the average over all flows is taken. Delay (Fig. 4) is computed as the mean time difference between the packet production by the source and its arrival to the destination for each flow, while also averaged over all flows. According to the definition of the capacity region as the set of source rates for which the sum of queue lengths remains finite (Section IV), Fig. 3 provides an intuition of the set of admissible source rates, as those rates before the sum of queue lengths starts to rapidly increase (i.e., approximately up to source rate 8). From Fig. 3, it can be observed that BPeMRF and the throughput optimal BP demonstrate very similar behavior with respect to capacity

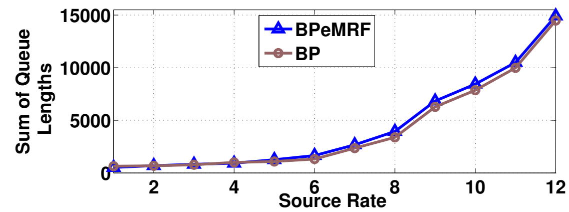

Fig. 3. Sum of queue lengths (packets that have not reached their destination) by the end of the simulation.

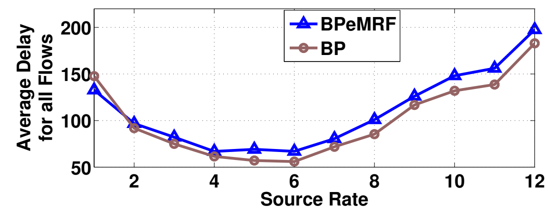

Fig. 4. Average end-to-end delay for all flows (source-destination pairs).

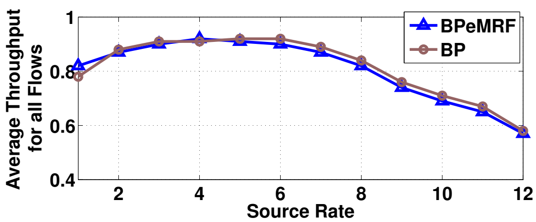

Fig. 5. Average throughput for all flows given as the fraction of the packets reached the destination divided by those produced by the source.

region which is in accordance with the theoretical results (Proposition 1), although BPeMRF runs for a finite number of steps which implies non-perfect convergence. Therefore, BPeMRF is suitable for application in dynamic social networks as it allows for efficient spectrum reuse and throughput optimal cross-layer network control while avoiding the hard solution of the MWM. Figs. 4 and 5, further reinforce the performance equivalence between BPeMRF and BP, since the induced throughput and delay values for both schemes are very close.

VI. Related Work

Dynamic social networks and cognitive communications have come to the forefront the last decade towards serving the emerging needs and providing flexible communication. In response to National Regulatory Authorities (NRAs) about immature CR technology for purely ad-hoc operations, regulation bodies have already acted towards allowing viable infrastructure-based CRNs assisted by centralized spectrum databases, e.g., [8]. In this direction, our work conforms to this initial centralized framework and aims at further improving SU operation by introducing an MRF cross-layered resource allocation approach. MRF formulation serves for modeling spatial dependencies and, along with Gibbs sampling, has attracted the attention of diverse research fields due to the inherent capability for addressing a class of problems with large space of possible configurations. Gibbs sampling accompanied by MRFs has been initially proposed for image restoration in [6] and has recently employed on resource allocation problems in wireless networks [13]–[15]. In this paper, we focus on leveraging MRF structure and Gibbs sampling combined with back-pressure features such that throughput optimal joint scheduling and routing is efficiently achieved through channel allocation and power control in the secondary network.

The traditional back-pressure scheduling/routing algorithm [7], achieves throughput optimality based on the solution of an NP-hard centralized MWM problem [12], with complexity depending on the number of maximal independent sets of the network graph. Several suboptimal schemes have been developed to approximate the solution of the MWM [12]. Greedy Maximal Scheduling (GMS) is an alternative to MWM that maintains performance close to optimal, and can be replaced equivalently by Local GMS which uses only local information [12]. Also, [11] presents a broad category of alternative approaches based on randomized schedulers allowing for imperfections and relaxations on their operation. Introducing imperfections allows for the development of low-complexity (e.g., polynomial) and distributed schedulers for general interference model. Contrary to the above works approximating MWM, our approach achieves throughput optimality with low-complexity and local information exchange, by avoiding solving MWM and relying on a converged Gibbs sampler to obtain the optimal schedule at each time slot.

VII. Conclusion

In this paper, we presented a BP-enhanced MRF (BPeMRF) approach for joint assignment of transmission power/channel, optimal scheduling and routing. We have demonstrated BPeMRF's efficacy in cognitive radio infrastructures and discussed its potentials as a cross-layer approach for providing and improving QoS in various dynamic and online social network infrastructures. Future work will further exploit the reconfiguration and adaptation capabilities of BPeMRF in more dynamic and stochastic environments, even closer to the real field of online social network cyber-physical systems.

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