A Spectrum Allocation Scheme Between Smart Grid Communication and Neighbor Communication Networks

Article *in* IEEE Systems Journal · June 2015
DOI: 10.1109/JSYST.2015.2441637

Mohammad Fathi
University of Kurdistan

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

A Spectrum Allocation Scheme Between Smart Grid Communication and Neighbor Communication Networks

Mohammad Fathi, *Member, IEEE*

***Abstract*—One key requirement of a smart grid communication network (SGCN) is to provide wireless-enabled devices with a frequency spectrum for data transmission. This spectrum can be partially supplied from existing neighboring communication networks (NCNs) via spectrum ordering. The scope of this paper is to propose a coexistence scheme, in which NCNs declare their own price per frequency channel and allow an SGCN to make decisions on the number of channels to be ordered. Due to dynamic NCN conditions and, accordingly, time-varying channel pricing, the spectrum ordering by an SGCN over a time horizon is formulated as a stochastic optimization problem. Having decoupled the problem over time, a dynamic spectrum allocation scheme is proposed. As a result of this scheme, the required data transmission rate of an SGCN is provided statistically. Numerical results demonstrate the effectiveness of the proposed scheme from the viewpoint of the grid operational cost.**

***Index Terms*—Coexistence, optimization, smart grid communication, spectrum allocation.**

I. Introduction

The next power system generation in the form of a smart grid (SG) is aimed to provide a unified structure of distributed power sources and consumers. In comparison with the centralized and conventional model of power generation, an SG offers several advantages from the perspective of both sources and consumers [1]. The wide area monitoring and control of a power system [2], along with the intelligent decision-making requirement within the SG, necessitate a gridwide SG communication network (SGCN), through which different entities get connected. Accordingly, the SG will be integrated with communication technologies, enabling the two-way information transmission between customers and utilities [3]. This information is used to enhance the grid flexibility and reliability, and to enable the incorporation of various components such as renewable energy resources and distributed microgenerators.

Motivations and challenges behind communication technologies to be adopted by an SGCN have been reviewed in [4]–[6]. In addition to the discussion of the technical specifications of these technologies, SGCN requirements including security, reliability, scalability, and the quality of service have been also determined in these works. In comparison with wired communication technologies, wireless communication can offer an SG a greater degree of freedom for information collection, dissemination, and processing [6]. For instance, to improve the SGCN monitoring capability, the application of a wireless sensor network as a monitoring technology was introduced in [7] and [8]. Integrating renewable energy sources using wireless communication was discussed in [9]. Furthermore, Lu *et al.* [10] have addressed the fundamental question on how to design, implement, and practically integrate efficient communication infrastructures with power systems.

Several key challenges are imposed on the design of wireless communication for an SG. On one hand, a large amount of information is generated by sensors and renewable energy sources that require a heterogeneous quality of service [11]. On the other hand, there is a shortage on the limited wireless spectrum with increasing interference. As a consequence, the literature on this issue have considered a three-tiered structure for SGCN consisting of a set of home area networks (HANs), neighborhood area networks (NANs), and wide area networks (WANs) [12], [13]. A HAN consisting of home appliances provides energy efficiency management and a demand response. A NAN connects HANs through wireless-enabled devices, which are usually known as smart meters (SMs). Finally, a WAN, as the backbone network, provides the connection between NANs and the utilities.

Advanced metering infrastructure (AMI) is an important system in an SGCN [4]. This system aims at providing consumers with the knowledge of their energy usage and the capability of monitoring and control. The SMs installed within consumers' houses are basic components of the AMI. They act as gateways between HANs and NANs to gather information from consumer households and to relay information to the corresponding utilities. In contrast to conventional meters, SMs provide the network utilities with consumers' consumption information and demand profiles. This information is crucial for network operators to provide economic power dispatching and demand-side management [14]–[16].

Basically, two types of information flows exist in the AMI. The first type is from sensors and electrical appliances to SMs, and the second type is between SMs and the utility data centers. Although the first data flow can be accommodated through short-range technologies such as ZigBee, the second data flow needs broadband cellular technologies [5]. Moreover, this flow contains heterogeneous traffic such as control commands,

Manuscript received February 10, 2015; revised April 24, 2015; accepted June 1, 2015.

The author is with the Department of Electrical Engineering, Faculty of Engineering, University of Kurdistan, Sanandaj 66177-15177, Iran (e-mail: mfathi@uok.ac.ir).

Digital Object Identifier 10.1109/JSYST.2015.2441637

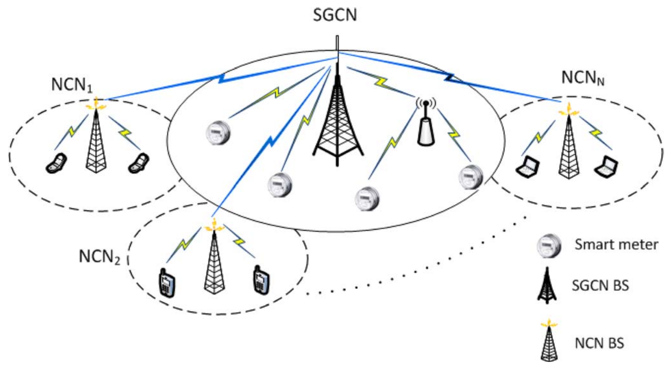

Fig. 1. Overall network model.

multimedia sensing data, and meter readings that need priority-based traffic scheduling schemes due to their quality-of-service requirements [17], [18]. As a result, SMs as transmitting nodes in a wireless SGCN need to be provided with efficient *spectrum* resources.

To address this issue, a cognitive-radio-based SGCN has been introduced [11], [13]. A cognitive radio refers to the potentiality that wireless systems opportunistically utilize spectrum holes in neighboring networks to mitigate spectrum deficiency. The cross-layer designs of a cognitive-radio-based SGCN to satisfy differential quality-of-service classes have been proposed in [19] and [20]. The reliability is low since SG users as secondary users should leave the spectrum upon the arrival of primary users. To provide spectrum access diversity, a joint spatial and temporal spectrum-sharing technique has been proposed in [21] to enhance spectrum-sharing opportunities to increase the communication reliability for demand response management. Finally, a hybrid spectrum access in a cognitive-radio-based SGCN to support the quality of service has been proposed in [22]. The SG operators have access to a number of leased spectrum bands, and at the same time, they are allowed to use a portion of cognitive spectrum bands opportunistically. The objective is to minimize the number of leased channels.

The design objective in this paper is to provide SMs, as wireless-enabled transmitting nodes in an SGCN, with efficient frequency channels to establish a reliable communication infrastructure. In particular, we investigate the coexistence of an SGCN with a set of neighboring communication networks (NCNs) in order to be provided with the required frequency channels. Considering the stochastic user arrival rates in NCNs, an immediate question from the SGCN side is how to order the frequency channels from NCNs to provide an aggregate data transmission rate for within SMs. Due to the cost of spectrum ordering, this issue raises the economic exploitation of channels within the grid [23]. The outcome of spectrum ordering could be interesting in this perspective. Therefore, we employ the real-time pricing of frequency channels as a motivation for the interactions between an SGCN and NCNs. The objective is to minimize the SGCN operational cost and to satisfy a required data rate in average at the same time. With the solution of this problem, an iterative stochastic algorithm is proposed to capture the randomness of the NCNs' user arrival rates and to take advantage of this randomness to perform spectrum ordering efficiently.

This paper is organized as follows. The system model and the problem formulation are presented in Section II. The problem solution and the derived algorithm are proposed in Section III. As two more proposed solutions, a linear integer formulation and a greedy algorithm are given in Sections IV and V, respectively. Numerical results are given in Section VI, and this paper is concluded in Section VII.

II. System Model

Consider a set $\mathcal{N} \triangleq \{n : n = 1, \ldots, N\}$ of NCNs interconnected through a wired or wireless backbone, as shown in Fig. 1. Each NCN can be considered a single cell in cellular networking. Within each NCN, there is a set of users served by the corresponding NCN base station (BS). Furthermore, the SMs within the area of NCNs are connected together and form a distinct SGCN that is managed and operated by power utilities. The SMs forward the household consumers' information to the corresponding BS, i.e., the SGCN BS.

The maximum number of frequency channels available at each NCN$_n$ is indicated by B_n. NCN$_n$ uses these dedicated channels to serve the users within and partly to serve the SGCN upon its request. The user arrival rate within each NCN$_n$ is assumed to be λ_n per time instant.

Consider a market of channel allocation in which NCNs supply the channel demand of the SCGN. In other words, the spectrum demand of the SGCN can be partially supplied from the frequency channel resources in NCNs. The price per channel announced by each NCN BS$_n$ is dynamic and is assumed to be a differentiable and convex function of the user arrival rate, which is denoted by $f_n(\lambda_n)$. It is reasonable that each NCN increases the price when the user arrival rate increases.

Let k_n be the number of channels to be ordered and allocated from NCN$_n$ to the SGCN. From the SGCN point of view, the channel allocation from NCNs can be considered a decision-making problem, in which the number of channels k_n purchased from each NCN$_n$ should be determined. The objective in this problem is to minimize the cost of purchased channels during a time horizon and at the same time to provide a target aggregate data rate R for the SMs in the SGCN. It is understood that this rate can satisfy the quality-of-service requirements within the SGCN during this time horizon. Here, under the assumption of time-varying user arrival rates within

NCNs, a statistical approach is developed toward the total cost minimization as

$$\min_{\mathbf{K}} \sum_{n=1}^{N} \mathbb{E}_{\lambda_n}\left[k_n f_n(\lambda_n)\right] \tag{1a}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} \mathbb{E}_{\gamma_n}\left[k_n \log_2(1+\gamma_n)\right] \geq R \tag{1b}$$

$$k_n \leq B_n \qquad \forall\, n \in \mathcal{N} \tag{1c}$$

where $\mathbf{K} = \{k_n\}_{n\in\mathcal{N}}$ is the vector of optimization variables. γ_n is the SNR achieved within the SGCN over the spectrum portion purchased from NCN_n. It is observed in (1b) that this parameter can be interpreted as the quality of NCN_n channels to be used within the SGCN. Moreover, $\mathbb{E}_{\lambda_n}$ and $\mathbb{E}_{\gamma_n}$ denote the expectation with respect to λ_n and γ_n, respectively. In this problem, parameters $\Gamma = \{\gamma_n\}_{n\in\mathcal{N}}$ and $\Lambda = \{\lambda_n\}_{n\in\mathcal{N}}$ are assumed as random variables varying over time but without any assumption on their probability density functions. Constraint (1b) satisfies the required data transmission rate within the SGCN in average, and constraint (1c) restricts k_n to the maximum available channels at each NCN.

Problem (1) is linear integer programming and can be solved using software packages, albeit it is NP-hard with exponential complexity. However, this requires the availability of $\Gamma = \{\gamma_n\}_{n\in\mathcal{N}}$ and $\Lambda = \{\lambda_n\}_{n\in\mathcal{N}}$ *a priori* for the whole time in the scope of the problem. This knowledge is not always available. Alternatively, we are interested in progressively solving this problem over time, when each γ_n and λ_n is realized at each time instant t, to come up with a dynamic spectrum ordering scheme in the sequel section.

It is noteworthy that the proposed model (1) has the feasibility to be used in cognitive-radio-based infrastructures. Suppose that NCNs and the SGCN are considered primary and secondary networks, respectively. In this case, the required rate R of the SGCN in (1b) can be partially supplied from both the licensed and unlicensed channels of NCNs. To utilize unlicensed channels, the SGCN first performs spectrum sensing and accordingly detects the idle spectrum holes of NCNs to be used for data transmission, albeit without any price. The achieved rate on this spectrum is then computed. Let this be indicated by $\hat{R}$. To determine the number of licensed spectra purchased from NCNs, the SGCN subtracts $\hat{R}$ from the target rate R. In other words, it replaces R by $R - \hat{R}$ in (1b).

III. Dynamic Spectrum Ordering

The most significant challenge in the solution of problem (1) is due to the integer optimization variables and coupling expectations. The solution would be straightforward if we use integer relaxation to temporarily consider k_n as continuous variables and then to decouple the aggregate rate constraint. This motivates the incorporation of (1b) into the objective function and forms a Lagrangian function as

$$L(\mathbf{K},\mu) \triangleq \sum_{n=1}^{N} \mathbb{E}_{\lambda_n}[k_n f_n(\lambda_n)] - \mu\left(\sum_{n=1}^{N} \mathbb{E}_{\gamma_n}[k_n \log_2(1+\gamma_n)] - R\right) \tag{2}$$

where $\mu \geq 0$ is the Lagrange multiplier. Optimizing with respect to primal variable $\mathbf{K}$ yields the following dual function:

$$D(\mu) \triangleq \inf_{\mathbf{K}} \left\{L(\mathbf{K},\mu) \mid k_n \leq B_n\right\} \tag{3}$$

which provides a lower bound on the optimal solution of (1) for every feasible variable μ [24]. Hence, the tightest lower bound is obtained by the dual problem as follows:

$$\max_{\mu\geq 0} \quad D(\mu). \tag{4}$$

Prior to solving the problem in the dual domain, $D(\mu)$ in (3) needs to be evaluated. Hence, $L(\mathbf{K},\mu)$ is rewritten as

$$L(\mathbf{K},\mu) = \sum_{n=1}^{N} k_n \left(\mathbb{E}_{\lambda_n}[f_n(\lambda_n)] - \mu \mathbb{E}_{\gamma_n}[\log_2(1+\gamma_n)]\right) + \mu R. \tag{5}$$

Due to the decomposable form of $L(\mathbf{K},\mu)$, we can take advantage of the dual decomposition to decouple (3) into subproblems across NCNs as

$$\min_{k_n} k_n \left(\mathbb{E}_{\lambda_n}[f_n(\lambda_n)] - \mu \mathbb{E}_{\gamma_n}[\log_2(1+\gamma_n)]\right) \tag{6a}$$

$$\text{s.t.} \quad k_n \leq B_n \tag{6b}$$

for all $n \in \mathcal{N}$. These subproblems are convex and can be solved using the iterative subgradient method [25] by the SGCN if it has the knowledge of $f_n(\lambda_n)$ and γ_n for all NCNs. Considering each subproblem n at time instant t, with the given $k_n(t)$ and Lagrange multiplier $\mu(t)$, the value of $k_n(t)$ can be updated using the subgradient method as

$$k_n(t+1) = \left[k_n(t) - \alpha\left(\mathbb{E}_{\lambda_n}[f_n(\lambda_n)] - \mu \mathbb{E}_{\gamma_n}[\log_2(1+\gamma_n)]\right)\right]_0^{B_n} \tag{7}$$

where $[x]_0^{B_n} = \min\{B_n, \max\{0, x\}\}$. Moreover, $(\mathbb{E}_{\lambda_n}[f_n(\lambda_n)] - \mu \mathbb{E}_{\gamma_n}[\log_2(1+\gamma_n)])$ is the subgradient of (6a) with respect to k_n, and α is the step size.

Having obtained $k_n(t)$ for all n and, accordingly, $D(\mu)$ in (3), it is time to solve dual problem (4). Due to its convexity, it can be similarly solved using the iterative subgradient method. Beginning with an initial $\mu(0)$, given $\mu(t)$ at time t, it can be updated as

$$\mu(t+1) = \left[\mu(t) - \alpha\left(\sum_{n=1}^{N} \mathbb{E}_{\gamma_n}[k_n(t)\log_2(1+\gamma_n)] - R\right)\right]^{+} \tag{8}$$

where $[x]^+ = \max(0, x)$. Inspecting (6), Lagrange multiplier $\mu(t)$ can be interpreted as the marginal benefit of the SGCN from transmitting a unit of data at time instant t.

Gradient iterations (7) and (8) are efficient in finding the optimal solution. The key knowledge we need in these equations is the probability density functions of every λ_n and γ_n, only with which we can evaluate the expected values $\mathbb{E}_{\lambda_n}$ and $\mathbb{E}_{\gamma_n}$, respectively. The assumption of the known probability density functions of λ_n and γ_n may be reasonable for theoretic studies. However, the importance of practical spectrum allocation schemes motivates the optimal strategy by *learning* the parameter time variations on the fly. Interestingly, stochastic gradient iterations can be developed to solve (7) and (8) without the probability density functions of λ_n and γ_n. To this end, consider dropping $\mathbb{E}_{\lambda_n}$ and $\mathbb{E}_{\gamma_n}$ from (7) and (8) to devise online iterations for *dynamic* decisions based on the per-instant realizations of $\lambda_n(t)$ and $\gamma_n(t)$, respectively, as

$$\hat{k}_n(t+1)=\left[\hat{k}_n(t)-\alpha\left(f_n\left(\lambda_n(t)\right)-\hat{\mu}(t)\log_2\left(1+\gamma_n(t)\right)\right)\right]_0^{B_n} \tag{9}$$

$$\hat{\mu}(t+1)=\left[\hat{\mu}(t)-\alpha\left(\sum_{n=1}^{N}\left(\hat{k}_n(t)\log_2\left(1+\gamma_n(t)\right)\right)-R\right)\right]^+ \tag{10}$$

where hats are to stress that these iterations are stochastic estimates of those in (7) and (8), respectively. Provided that the user arrival rate and SNR of all NCNs are stationary and ergodic, stochastic gradient iterations (7) and (8), and ensemble gradient iterations (9) and (10) produce a pair of primary and averaged systems [26]. The convergence of such stochastic gradient iterations can be established statistically, provided that α is small enough. Such a proof for a typical problem is provided in the Appendix.

Given the solution of subproblems (6) at the SGCN, we are now in position to propose a dynamic spectrum allocation (DSA) scheme formally stated in Algorithm 1. This scheme, which is run by the SGCN BS, is based on the iterative updates of the optimization variables in (9) and (10). At the beginning of each iteration t, the SGCN BS estimates $\gamma_n(t)$ for all NCNs in step 3, assuming that the SNR remains constant while the allocation is being decided. At the same time, all NCNs forward their own price functions $f_n(\lambda_n)$ to the SGCN BS in step 4. This is the only information required to be sent to the SGCN BS through the high-capacity links that interconnect the BSs, resulting in a low signaling overhead of the DSA. Then, at every iteration, the SGCN BS solves spectrum subproblems (6) to determine the number of channels to be allocated from NCNs in steps 5 and 6. Note that round$(\cdot)$ is the nearest integer function to return an integer number of channels. Finally, in step 7, at the end of each iteration, the SGCN BS notifies the NCNs' BSs of the spectrum allocation decisions.

Algorithm 1 DSA algorithm at the SGCN BS

1: Initialization: $\hat{\mu}(0)=\mu_{\text{init}}, \hat{\lambda}_n(0)=\lambda_{\text{init}} \forall\, n\in\mathcal{N}, t=0$.
2: **while** $t \leq T$ **do**
3: estimate $\gamma_n(t)$ for all NCNs.
4: receive price functions $f_n(\lambda_n(t))$ from NCNs.
5: update $\hat{k}_n(t)$ and $\hat{\mu}(t)$ using (9) and (10).
6: set the number of ordered channels from NCN n to round$(\hat{k}_n(t))$.
7: notify every NCN of the number of ordered channels.
8: $t=t+1$.
9: **end while**

As in any iterative implementation, a concern is raised on the computational complexity. The DSA takes advantage of the dual decomposition to overcome the exponential complexity of (1). By decoupling the problem into subproblems over NCNs, the complexity becomes linear in the number of NCNs. Therefore, the overall complexity over T iterations becomes $O(NT)$ that is reasonable for online implementations. Moreover, in SG communication, household SMs are immobile, and accordingly, the coherence time of the shared frequency channels is high enough to not be affected by the time delay of running the DSA at each time instant t.

IV. LIP Formulation

In the derived iterative manner of the DSA algorithm, at each time instant t, the SGCN BS is provided with the instantaneous values of $f_n(\lambda_n(t))$ and $\gamma_n(t)$ for all n. With these values in hand, we are motivated to formulate the decision making at each time instant t as a deterministic linear integer problem (LIP) in

$$\min_{\{k_n(t)\}_{n\in\mathcal{N}}} \sum_{n=1}^{N} k_n(t) f_n\left(\lambda_n(t)\right) \tag{11a}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} k_n(t)\log_2\left(1+\gamma_n(t)\right) \geq R \tag{11b}$$

$$k_n(t) \leq B_n \qquad \forall\, n\in\mathcal{N}. \tag{11c}$$

In comparison with (1), this problem has been decoupled over the time and can be solved by off-the-shelf solvers. Although the resulting problem is still NP-hard, there exist several techniques, e.g., branch-and-cut techniques, and software packages that can efficiently find the optimal solution by frequently avoiding an exhaustive search. In this paper, the optimal solution of the LIP is achieved by calling the GNU linear programming kit [27]. This solution can be used as a benchmark for comparison with the proposed DSA algorithm.

V. Greedy Algorithm

In addition to the LIP formulation, an alternative but suboptimal approach to channel allocation is to simply use channels from NCNs with low announced prices. In this approach, which is called the greedy algorithm, the SGCN BS chooses NCNs with the minimum announced prices and tries to supply its own required rate from these NCNs. The complexity of this algorithm is less than that of the DSA algorithm. However, the performance is certainly degrading as the greedy algorithm does not take channel qualities into account for channel allocation.

This algorithm is formally described in Algorithm 2. After some required initializations in step 1, the SGCN BS chooses the NCN n^* with the minimum price in step 3, and in step 4, it determines the number of required channels $k_{n^*}(t)$ to supply its own demand rate R_{temp}. In the case of requiring a larger rate, i.e., $R_{\text{temp}} > 0$, in the next loop iteration, the next NCN with the minimum price is chosen to supply the rest of the required rate. This process continues until the satisfaction of aggregate rate R.

Note that $\lfloor\cdot\rfloor$ and $\setminus$ are used as the floor and set minus operations, respectively.

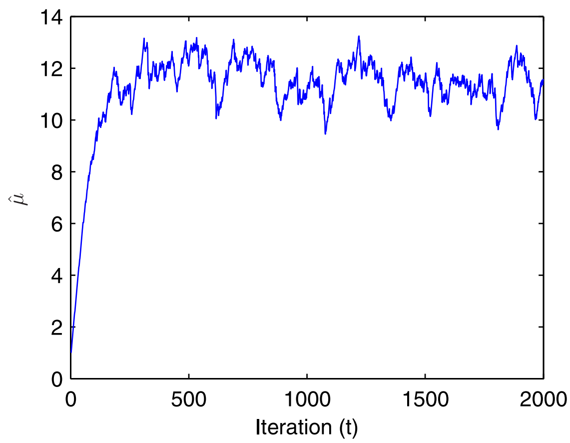

Fig. 2. Statistical convergence of the Lagrange multiplier.

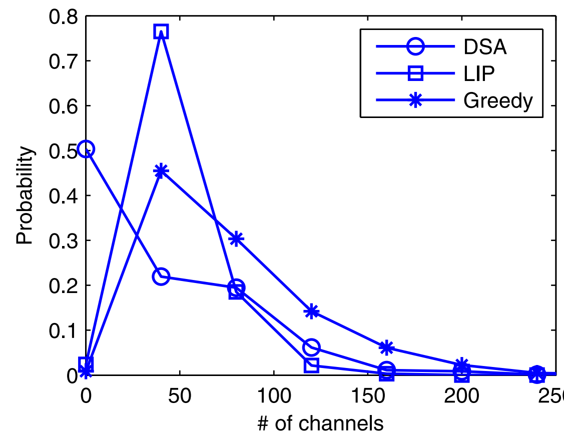

Fig. 3. Probability density function of the total allocated channels per time instant.

Algorithm 2 Greedy algorithm at time instant t

Initialization: $R_{\text{temp}} = R$, $\mathcal{N}_{\text{temp}} = \mathcal{N}$, $k_n(t) = 0\, \forall\, n \in \mathcal{N}$.
while $R_{\text{temp}} > 0$ **do**
  $n^* = \arg\min_{n \in \mathcal{N}_{\text{temp}}} f_n(\lambda_n(t))$.
  $k_{n^*}(t) = \min(\lfloor R_{\text{temp}} / \log_2(1 + \gamma_{n^*}(t)) \rfloor, B_{n^*})$.
  $R_{\text{temp}} = R_{\text{temp}} - k_{n^*}(t) \log_2(1 + \gamma_{n^*}(t))$.
  $\mathcal{N}_{\text{temp}} = \mathcal{N}_{\text{temp}} \setminus n^*$.
end while

VI. Numerical Results

To evaluate the performance of the DSA algorithm in comparison with the LIP and the greedy algorithm, first, consider $N = 6$ NCNs with arrival rates followed by a Poisson random variable with a mean of five users per time instant for all NCNs, i.e., a homogeneous network. The price function is assumed to be $f_n(\lambda_n) = \lambda_n^2 + \lambda_n + 1$ for all n. Moreover, within each NCN, there are $B_n = 64$ channels to be partly used by internal users and the SGCN. From the SGCN point of view, these channels are assumed to be flat Rayleigh fading channels, where their SNR is assumed to follow an exponential random variable with a mean of 0 dB. The required rate of the SGCN is assumed to be $R = 50$ b/s/Hz. With this setup, the DSA, LIP, and Greedy algorithms are run for 2000 realizations of user arrival rates and SNRs.

Prior to the performance comparison between the aforementioned schemes, it is interesting to investigate the statistical convergence in the DSA algorithm, which is discussed in the Appendix. Toward this, the Lagrange multiplier $\hat{\mu}$ over the iterations in (10), with initial value $\hat{\mu}(0) = 0$ and step size $\alpha = 0.002$, is shown in Fig. 2. As observed, it achieves statistical convergence after some transient iterations. In other words, long-term variations occur around a statistical mean. These variations over time are due to the randomness of user arrival rates and SNRs.

Due to the random nature of user arrival rates and channel qualities, the number of channels allocated from NCNs is time varying. To illustrate the effectiveness of the DSA scheme, the probability density function of the total number of required channels allocated to the SGCN per time instant during the time horizon of a length of 2000 instants is shown in Fig. 3. As a key observation, there is no channel allocated to the SGCN by the DSA in mostly 50% of time instants in the time horizon. Indeed, the DSA postpones providing the required rate R to time instants when the price and channel qualities are good enough for channel ordering. It takes advantage of the price and the SNR dynamics over time to determine the number of demand channels from NCNs. In particular, the SGCN prefers to order a higher number of channels and accordingly to provide a higher data rate when the situation is desired, i.e., a low price and a high SNR. On the other hand, it does not prefer to order channels when the situation is not desired. In other words, the DSA algorithm takes advantage of the *time diversity* over the time horizon to minimize the cost. However, this is not the case for the LIP and greedy algorithms. These schemes need to satisfy the required data rate per time instant. As a consequence, they have channels allocated to the SGCN during the whole time horizon. There is no time instant with zero required channels. They approximately need 50 channels per time instant. This is a key point in the performance comparison of these algorithms, which is to be considered in the sequel.

As another observation in Fig. 3, the probability of ordering a large (small) number of channels in the LIP is lower (higher) than that of the greedy algorithm. This is due to the ability of the LIP to provide the SGCN with optimal channels at each time instant.

Following the aforementioned observations, the average number of channels allocated from individual NCNs and the corresponding average cost are shown in Figs. 4 and 5, respectively. In all schemes, the number of allocated channels and, accordingly, the cost from individual NCNs are mostly the same due to their equal average arrival rates and channel qualities. Based on the discussion in Fig. 3, the DSA scheme takes advantage of the time diversity over the time horizon and allocates the smallest average number of channels to the SGCN in Fig. 4. Accordingly, it burdens the lowest cost to the SGCN in Fig. 5. Moreover, the number of allocated channels and the cost of the LIP are smaller than those of the Greedy algorithm, as expected.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

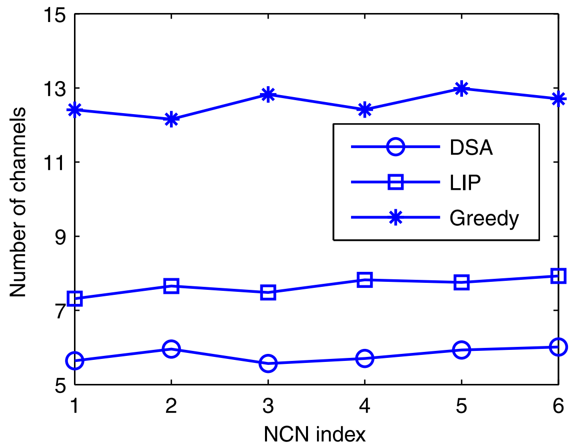

Fig. 4. Homogeneous network: Average number of allocated channels.

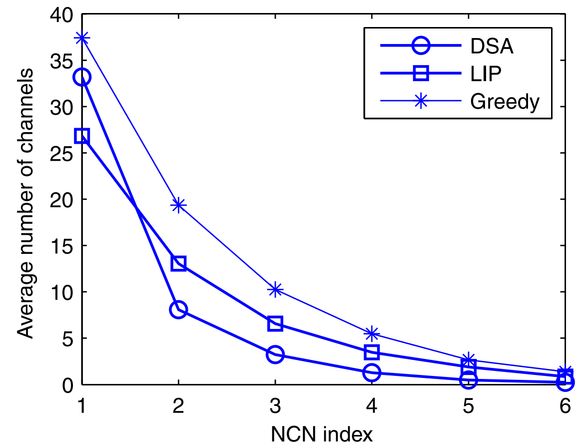

Fig. 6. Heterogeneous network: Average number of allocated channels.

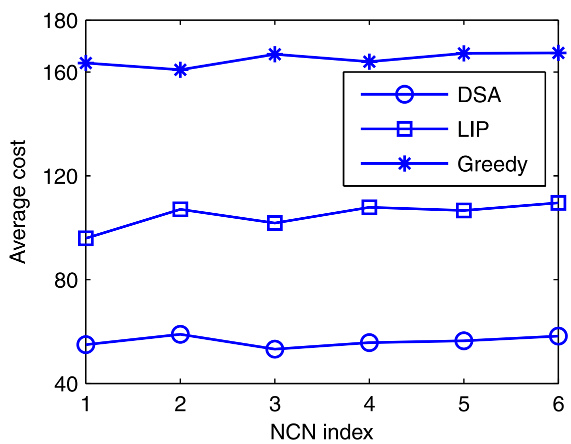

Fig. 5. Homogeneous network: Average cost.

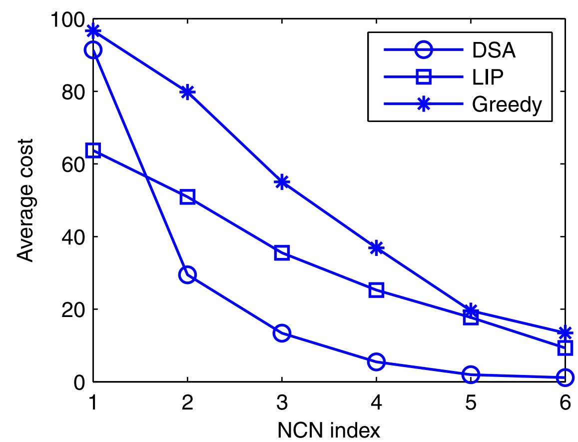

Fig. 7. Heterogeneous network: Average cost.

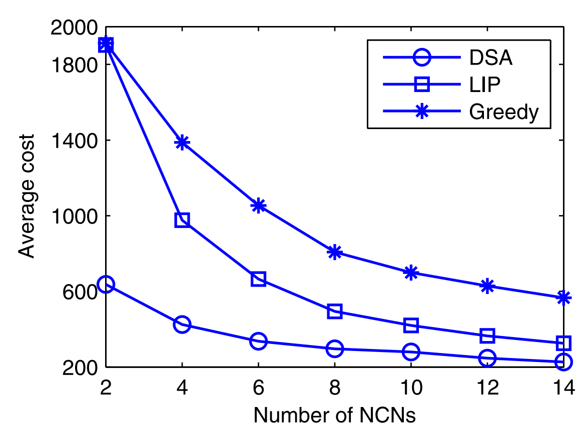

Fig. 8. Average cost versus the number of NCNs.

Now, consider $N = 6$ of NCNs but with different user arrival rates, i.e., a heterogeneous network. NCNs are enumerated from 1 to 6 with average arrival rates as $1, \ldots, 6$ users per time instant, respectively. Channel qualities are assumed to be the same for all NCNs. The setup is run for 2000 time instants with Poisson user arrival rates and exponential channel qualities. The average number of channels allocated from individual NCNs and the corresponding average cost are shown in Figs. 6 and 7, respectively. Similar to the homogeneous case, the DSA scheme achieves lower costs for all NCNs, except for the first NCN. This is the NCN with the smallest average cost. That is why it has been given more weight by the DSA scheme. Moreover, in all schemes, the number of ordered channels decreases as the average user arrival rate increases. This is due to the increasing property of price function $f_n(\lambda_n)$ with respect to λ_n and the tendency of the SGCN in all schemes to order channels from low-price NCNs.

Economically, increasing the number of producers causes cost reduction as a consequence of diversity. To verify this fact, in a homogeneous network setup, we vary the number of NCNs and investigate the impact of this variation on the average cost per time instant. It is noteworthy that the required rate is assumed to be the same for all instances, i.e., $R = 50$ b/s/Hz. The average cost versus the number of NCNs is shown in Fig. 8. As shown, the cost reduces in all schemes by increasing the number of NCNs. Indeed, all schemes take advantage of the NCN diversity to decrease the cost when the number of NCNs increases. Increasing the number of NCNs and, accordingly, the number of channels increases the probability of ordering high-quality channels. This results in ordering a lower number of channels and, consequently, a lower cost. Moreover, due to the time diversity, the DSA scheme achieves the lowest cost in all instances, as expected.

VII. Conclusion

The conclusion of this paper is twofold. The first is on the NCN diversity. Increasing the number of NCNs and, accordingly, the number of available frequency channels increases the probability of ordering channels with high SNRs. This results in a lower number of channels for the required rate satisfaction and, as a consequence, a gain in the cost reduction for all schemes. The second is on the time diversity. By allowing the DSA scheme to provide the required rate in average over the time horizon, it achieves the opportunity to take advantage of both the price and the SNR dynamics over time to adapt the number of purchased channels. Indeed, the lower (higher) the price per channel in a time instant, the higher (lower) the number of purchased channels. The LIP and the greedy algorithm are out of this gain, as they need to provide the required rate at every time instant.

Appendix
Convergence of Stochastic Iteration

Without loss of generality, consider the following problem:

$$\min_x \ \mathbb{E}_r \left[f(x, r) \right] \tag{12}$$

where r is a random variable, and $f(x,r)$ is a convex function in x. To find the optimal solution x^* and the optimal value $p^* = \mathbb{E}_r[f(x^*, r)]$, the following gradient iteration is used:

$$x(t+1) = x(t) - \alpha g(t) \tag{13}$$

where α is the step size, and $g(t)$ is the gradient of $f(\cdot)$ with respect to $x(t)$, i.e., $g(t) \triangleq \nabla f_x(x(t), r(t))$. Taking the *norm-2* of $(x(t+1) - x^*)$, we derive

$$\begin{aligned} \|x(t+1) - x^*\|^2 &= \|x(t) - \alpha g(t) - x^*\|^2 \\ &= \|x(t) - x^*\|^2 - 2\alpha g(t)\left(x(t) - x^*\right) \\ &\quad + \alpha^2 \|g(t)\|^2 . \end{aligned} \tag{14}$$

Due to the convexity of $f(x(t), r(t))$ in $x(t)$, the following inequality holds [25]:

$$f\left(x^*, r(t)\right) \geq f\left(x(t), r(t)\right) + g(t)\left(x^* - x(t)\right). \tag{15}$$

Applying this inequality to (14), it is written as

$$\begin{aligned} \|x(t+1) - x^*\|^2 &\leq \|x(t) - x^*\|^2 \\ &\quad - 2\alpha \left\{ f\left(x(t), r(t)\right) - f\left(x^*, r(t)\right) \right\} + \alpha^2 \|g(t)\|^2 . \end{aligned} \tag{16}$$

Taking a similar recursive approach from $x(t)$ to $x(0)$ as an initial value, we derive

$$\begin{aligned} \|x(t+1) - x^*\|^2 &\leq \|x(0) - x^*\|^2 + \alpha^2 \sum_{i=0}^{t} \|g(i)\|^2 \\ &\quad - 2\alpha \sum_{i=0}^{t} \left\{ f\left(x(i), r(i)\right) - f\left(x^*, r(i)\right) \right\}. \end{aligned} \tag{17}$$

Since the left-hand side is always nonnegative, then we have

$$\begin{aligned} &2\alpha \sum_{i=0}^{t} \left\{ f\left(x(i), r(i)\right) - f\left(x^*, r(i)\right) \right\} \\ &\qquad \leq \|x(0) - x^*\|^2 + \alpha^2 \sum_{i=0}^{t} \|g(i)\|^2 . \end{aligned} \tag{18}$$

Now, consider the following two assumptions.

1) $\|g(i)\| \leq G$ for all i.
2) $\|x(0) - x^*\|^2 \leq R^2$.

With reference to the system model in Section II, these assumptions are reasonable and can be provided in the model. Dividing both sides of (18) by $2\alpha t$, it is concluded that

$$\frac{1}{t} \sum_{i=0}^{t} \left\{ f\left(x(i), r(i)\right) - f(x^*, r(i)) \right\} \leq \frac{R^2}{2\alpha t} + \frac{\alpha^2 t G^2}{2\alpha t}. \tag{19}$$

If $t \to \infty$, by the law of large numbers, we have

$$\overline{f(x, r)} - p^* \leq \frac{\alpha}{2} G^2 \tag{20}$$

where $\overline{f(x,r)} = (1/t)\sum_{i=0}^{t} f(x(i), r(i))$, and $p^* = \mathbb{E}_r[f(x^*, r)] = (1/t)\sum_{i=0}^{t} f(x^*, r(i))$.

Since $f(\cdot)$ is a convex function, by Jensen's inequality [24], we have $\overline{f(x,r)} \geq f(\bar{x}, r)$, and consequently, we have

$$f(\bar{x}, r) - p^* \leq \frac{\alpha}{2} G^2. \tag{21}$$

Choosing step size α to be small enough, we conclude that gradient iteration (13) converges statistically. In other words, as t goes to infinity, the solution derived from gradient iteration (13), i.e., $f(\bar{x}, r)$, converges to the optimal value p^*.

Acknowledgment

The author would like to thank Prof. H. Bevrani of the Department of Electrical Engineering, Faculty of Engineering, University of Kurdistan, Sanandaj, Iran, for his invaluable comments on the verification of the proposed communication approach in the domain of smart grids.

References

[1] H. Jiayi, J. Chuanwen, and X. Rong, "A review on distributed energy resources and microgrid," *Renew. Sustainable Energy Rev.*, vol. 12, no. 9, pp. 2472–2483, Dec. 2008.
[2] H. Bevrani, M. Watanabe, and Y. Mitani, *Power System Monitoring and Control*. Piscataway, NJ, USA: IEEE-Wiley Press, 2014.
[3] D. M. Laverty, D. J. Morrow, R. Best, and P. A. Crossley, "Telecommunications for smart grid: Backhaul solutions for the distribution network," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, 2010, pp. 1–6.
[4] Y. Yan, Y. Qian, H. Sharif, and D. Tipper, "A survey on smart grid communication infrastructures: Motivations, requirements and challenges," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 5–20, 1st Quart. 2013.
[5] V. Gungor *et al.*, "Smart grid technologies: Communication technologies and standards," *IEEE Trans. Ind. Informat.*, vol. 7, no. 4, pp. 529–539, Nov. 2011.
[6] R. Ma, H.-H. Chen, Y.-R. Huang, and W. Meng, "Smart grid communication: Its challenges and opportunities," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 36–46, Mar. 2013.

[7] V. Gungor, B. Lu, and G. Hancke, "Opportunities and challenges of wireless sensor networks in smart grid," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3557–3564, Oct. 2010.
[8] M. Erol-Kantarci, B. Lu, and H. T. Mouftah, "Wireless multimedia sensor and actor networks for the next-generation power grid," *Ad Hoc Netw.*, vol. 9, no. 4, pp. 542–551, Jun. 2011.
[9] F. Yu, P. Zhang, W. Xiao, and P. Choudhury, "Communication systems for grid integration of renewable energy resources," *IEEE Netw.*, vol. 25, no. 5, pp. 22–29, Sep. 2011.
[10] X. Lu, W. Wang, and J. Ma, "An empirical study of communication infrastructures towards the smart grid: Design, implementation, and evaluation," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 170–183, Mar. 2013.
[11] H. Wang, Y. Qian, and H. Sharif, "Multimedia communications over cognitive radio networks for smart grid applications," *IEEE Wireless Commun.*, vol. 20, no. 4, pp. 125–132, Aug. 2013.
[12] Q.-D. Ho, Y. Gao, and T. Le-Ngoc, "Challenges and research opportunities in wireless communication networks for smart grid," *IEEE Wireless Commun.*, vol. 20, no. 3, pp. 89–95, Jun. 2013.
[13] R. Yu *et al.*, "Cognitive radio based hierarchical communications infrastructure for smart grid," *IEEE Netw.*, vol. 25, no. 5, pp. 6–14, Sep. 2011.
[14] H. Liang, B. J. Choi, A. Abdrabou, W. Zhuang, and X. Shen, "Decentralized economic dispatch in microgrids via heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 6, pp. 1061–1074, Jul. 2012.
[15] M. Fathi, and H. Bevrani, "Statistical cooperative power dispatching in interconnected microgrids," *IEEE Trans. Sustainable Energy*, vol. 4, no. 3, pp. 586–593, Jul. 2013.
[16] D. Niyato, P. Wang, and E. Hossain, "Reliability analysis and redundancy design of smart grid wireless communications system for demand side management," *IEEE Wireless Commun.*, vol. 19, no. 3, pp. 38–46, Jun. 2012.
[17] J. Huang, H. Wang, Y. Qian, and C. Wang, "Priority-based traffic scheduling and utility optimization for cognitive radio communication infrastructure-based smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 78–86, Mar. 2013.
[18] H. Gharavi and C. Xu, "Traffic scheduling technique for smart grid advanced metering applications," *IEEE Trans. Commun.*, vol. 60, no. 6, pp. 1646–1658, Jun. 2012.
[19] G. Shah, V. Gungor, and O. Akan, "A cross-layer design for QoS support in cognitive radio sensor networks for smart grid applications," in *Proc. IEEE ICC*, Jun. 2012, pp. 1378–1382.
[20] R. Yu, W. Zhong, S. Xie, Y. Zhang, and Y. Zhang, "QoS differential scheduling in cognitive-radio-based smart grid networks: An adaptive dynamic programming approach," *IEEE Trans. Neural Netw. Learn. Syst.*, to be published.
[21] Q. Li, Z. Feng, W. Li, T. A. Gulliver, and P. Zhang, "Joint spatial and temporal spectrum sharing for demand response management in cognitive radio enabled smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1993–2001, Jul. 2014.
[22] R. Yu, C. Zhang, X. Zhang, L. Zhou, and K. Yang, "Hybrid spectrum access in cognitive-radio-based smart-grid communications systems," *IEEE Syst. J.*, vol. 8, no. 2, pp. 577–587, Jun. 2014.
[23] H. Allcott, "Real time pricing and electricity markets," in *Group*, Cambridge, MA, USA: Harvard Univ. Press, 2009, pp. 1–77.
[24] S. Boyd, and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
[25] D. Berteskas, *Nonlinear Programming*. Boston, MA, USA: Athena Scientific, 1999.
[26] V. Solo, and X. Kong, *Adaptive Signal Processing Algorithms: Stability and Performance*. Upper Saddle River, NJ, USA: Prentice-Hall, 1995.
[27] "GNU Linear Programming kit," version 4.45. [Online]. Available: http://www.gnu.org/software/glpk

Mohammad Fathi (M'10) received the M.Sc. and Ph.D. degrees in electrical engineering from the Amirkabir University of Technology, Tehran, Iran, in 2003 and 2010, respectively.

From 2003 to 2006, he was a Lecturer with the Department of Electrical Engineering, University of Kurdistan, Faculty of Engineering, Sanandaj, Iran, where he is currently working as an Assistant Professor. From February 2010 to November 2010, he conducted part of his Ph.D. research work in the Communications and Networking Theory Laboratory, Royal Institute of Technology, Stockholm, Sweden. His current research interests include power scheduling, smart grid communications and control, network resource allocation, and optimization.