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Wireless Networking of Smart Meters in Next Generation Power Systems

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***Abstract*—Smart meters in next generation power systems are used to gather power measurement data in a home with smart devices. To forward this data to utility companies, smart meters are equipped with wireless radios connected together and form a communication network, called smart grid communication network (SGCN). The aim of this paper is to provide a coexistence scheme between a SGCN of smart meters and neighboring communication networks (NCNs) for channel ordering. In this scheme, considering time-varying channel qualities and dynamic prices of channels, SGCN orders its own required channels from NCNs. Numerical results demonstrate the effectiveness of the proposed scheme from the viewpoint of SGCN operational cost.**

***Index Terms*—Smart grid Communication, frequency demand, optimization.**

I. Introduction

The next power system generation in the form of smart grid (SG) is aimed to provide a unified structure of distributed power sources and consumers. In comparison with centralized and conventional model of power generation, SG offers several advantages from the perspective of both sources and consumers [1]. Wide area monitoring and control of power system [2] along with intelligent decision making requirement within the SG necessitie a grid-wide SG communication network (SGCN), through which different entities get connected. Accordingly, SG will be integrated with communication technologies enabling 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 micro-generators.

Several key challenges are imposed on the design of wireless communication for SG. On the one hand, a large amount of information is generated by sensors and renewable energy sources that requires heterogeneous quality of service [4]. On the other hand, there is 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 home area network (HAN), neighborhood area network (NAN), and wide area network (WAN) [5], [6]. HAN consisting of home appliances provides energy efficiency management and demand response. NAN connects HANs through wireless-enabled devices, usually known as smart meters (SMs). Finally, WAN as the backbone network provides connection between NANs and the utilities.

Advanced metering infrastructure (AMI) is an important system in SGCN [7]. This system aims at providing consumers with knowledge of their energy usage and the capability of monitoring and control. SMs installed within consumers houses are basic components of 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 [8]–[10].

Basically, two types of information flows exist in AMI. The first is from sensors and electrical appliances to SMs, and the second is between SMs and the utilities data centers. While the first data flow can be accommodated through short range technologies such as ZigBee, the second one needs broadband cellular technologies [11]. Moreover, this flow contains heterogeneous traffic such as control commands, multimedia sensing data and meter readings which needs priority-based traffic scheduling schemes due to their quality of service requirements [12], [13]. As a result, SMs as transmitting nodes in a wireless SGCN need to be provided with efficient *spectrum* resources. To address this issue, cognitive radio based SGCN has been introduced in [6] and [4]. Cognitive radio refers to the potentiality that wireless systems opportunistically utilize spectrum holes in neighboring networks to mitigate spectrum deficiency.

The design objective in this paper is to provide SMs, as wireless-enabled transmitting nodes in a SGCN, with efficient frequency channels to establish a reliable communication infrastructure. In particular, we investigate the coexistence of a SGCN with a set of neighboring communication networks (NCNs) in order to be provided with required frequency channels. Considering stochastic user arrival rates in NCNs, an immediate question from SGCN side is how to order 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 [14]. The outcome of spectrum ordering could be interesting in this perspective. Therefore, we employ real-time pricing of frequency channels as a motivation for interactions between SGCN and NCNs. The objective is to minimize the

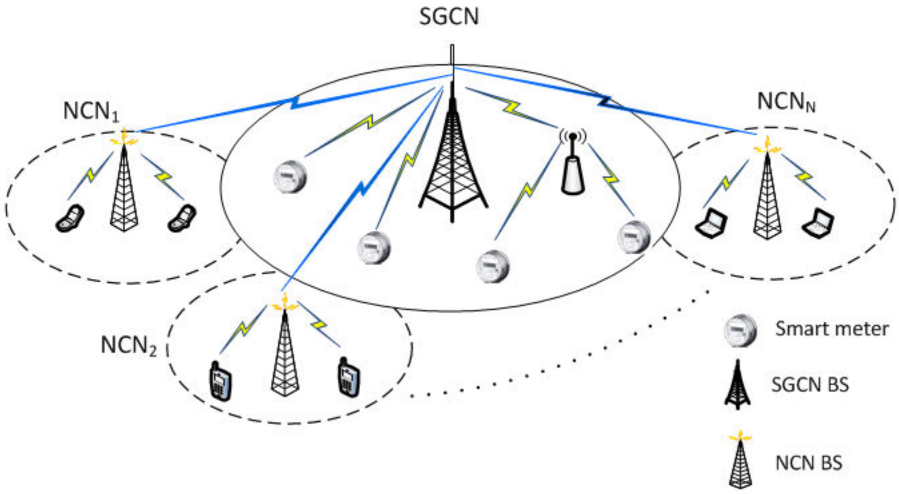

Fig. 1. Overall network model

SGCN operational cost and at the same time to satisfy a required data rate in average. With the solution of this problem, an iterative stochastic algorithm is proposed to capture the randomness of NCNs user arrival rates and to take advantage of this randomness to perform spectrum ordering efficiently.

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

II. System Model

Assume a SGCN along with 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 as a single cell in cellular networking. Within SGCN, there is a set of SMs forwarding consumers' information to the corresponding base station (BS), i.e., SGCN BS. Furthermore, within each NCN, there is a set of users served by the corresponding NCN BS. The maximum number of frequency channels available at each NCN_n is indicated by B_n. NCN_n uses this dedicated channels to serve the users within, and partly to serve SGCN upon its request. 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 channel demand of SCGN. In other words, the spectrum demand of SGCN can be supplied partially from 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 user arrival rate, denoted by $f_n(\lambda_n)$. It is reasonable that each NCN increases the price when user arrival rate increases.

Let k_n be the number of channels to be ordered and allocated from NCN_n to SGCN. From the SGCN point of view, channel allocation from NCNs can be considered as 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 SMs in SGCN. It is understood that this rate can satisfy the quality of service requirements within SGCN during this time horizon. Here, under the assumption of time-varying user arrival rates within NCNs, a statistical approach is developed towards 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 signal-to-noise ratio achieved within SGCN over the spectrum portion purchased from NCN_n. It is observed from (1b) that this parameter can be interpreted as the quality of NCN_n channels to be used within 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 the time, but without any assumption on their probability density functions. Constraint (1b) satisfies the required data transmission rate within 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.

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 consider k_n's as continuous variables temporarily and then to decouple the aggregate rate constraint. This motivates the incorporation of (1b) into the objective function and form a Lagrangian function as

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

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

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

which provides a lower bound on the optimal solution of (1) for every feasible variable μ [15]. Hence, the tightest lower bound is obtained by the dual problem

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

Prior to solve the problem in the dual domain, it is needed to evaluate $D(\mu)$ in (3). Hence, $L(\mathbf{K},\mu)$ is rewritten as

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

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

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

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

for all $n \in \mathcal{N}$. These subproblems are convex and can be solved using iterative subgradient method [16] by 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 given $k_n(t)$ and lagrange multiplier $\mu(t)$, the value of $k_n(t)$ can be updated using subgradient method as

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

where $[x]_0^{B_n} = \min\{B_n, \max\{0,x\}\}$. Moreover, $\left(\mathbb{E}_{\lambda_n}\left[f_n(\lambda_n)\right] - \mu\mathbb{E}_{\gamma_n}\left[\log_2(1+\gamma_n)\right]\right)$ is the subgradient of (6a) with respect to k_n and α is 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 similarly be solved using iterative subgradient method. Beginning with an initial $\mu(0)$, given $\mu(t)$ at time t, it can be updated as

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

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

Given the solution of subproblems (6) at SGCN, we are now in position to propose a dynamic spectrum allocation (DSA) scheme formally stated in Algorithm 1. This scheme, run by SGCN BS, is based on the iterative updates of optimization variables in (7) and (8). At the beginning of each iteration t, SGCN BS estimates $\gamma_n(t)$ for all NCNs in step 3, assuming that signal-to-noise ratio remains constant while the allocation is being decided. At the same time, all NCNs forward their own price functions $f_n(\lambda_n)$ to SGCN BS in step 4. This is the only information required to be sent to SGCN BS through the high-capacity links that interconnect BSs, resulting in a low signalling overhead of 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 5-6. Note that round(.) is the nearest integer function to return an integer number of channels. Finally, in step 7, at the end of each iteration, SGCN BS notifies NCNs BSs of the spectrum allocation decisions.

Algorithm 1 DSA algorithm at 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 $k_n(t)$ and $\mu(t)$ using (7)–(8).
6: set the number of ordered channels from NCN n to round($k_n(t)$).
7: notify every NCN of the number of ordered channels.
8: $t = t + 1$.
9: **end while**

IV. Linear Integer Problem Formulation

In the derived iterative manner of DSA algorithm, at each time instant t, the SGCN BS is provided with 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

$$\min_{\{k_n(t)\}_{n\in\mathcal{N}}}\ \sum_{n=1}^{N} k_n(t) f_n(\lambda_n(t)) \tag{9a}$$

$$\text{s.t.}\quad \sum_{n=1}^{N} k_n(t)\log_2(1+\gamma_n(t)) \geq R \tag{9b}$$

$$k_n(t) \leq B_n \qquad \forall n \in \mathcal{N}. \tag{9c}$$

In comparison with (1), this problem has been decoupled over the time and can be solved by off-the-shelf solvers. Even though the resulting problem is still NP-hard, there exist several techniques, for example, branch-and-cut, and software packages that can find the optimal solution efficiently, by

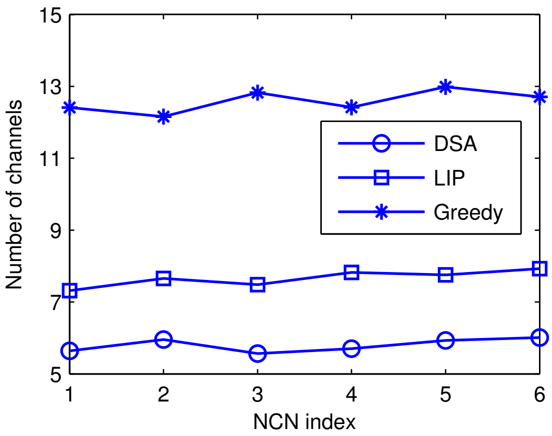

Fig. 2. Homogeneous network: average number of allocated channels

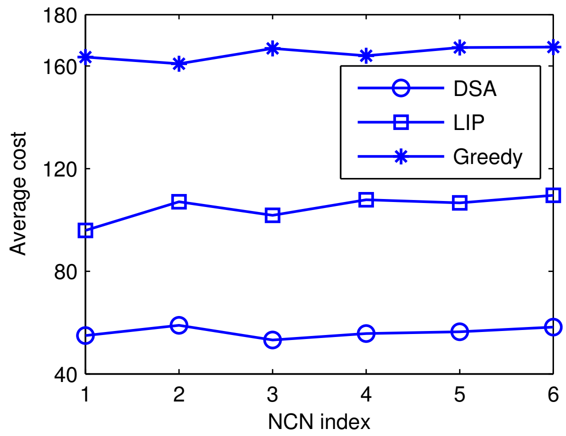

Fig. 3. Homogeneous network: average cost

frequently avoiding the exhaustive search. In this paper, the optimal solution of LIP is achieved calling the GNU linear programming kit (GLPK) [17]. This solution can be used as a benchmark for comparison with the proposed DSA algorithm.

V. Greedy Algorithm

In addition to LIP formulation, we are also interested in a greedy algorithm to make decisions at each time instant t, as a lower bound solution. Towards this, SGCN BS chooses NCNs with the minimum announced prices and tries to supply its own required rate from these NCNs. This algorithm is formally described in Algorithm 2. After some required initializations in step 1, SGCN BS chooses NCC 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 case of requiring more rate, i.e. $R_{temp} > 0$, in the next loop iteration, the next NCN with the minimum price is chosen to supply the rest required rate. This process continues until the satisfaction of aggregate rate R.
Note that $\lfloor . \rfloor$ and $\setminus$ are used as floor and set minus operations, respectively.

Algorithm 2 Greedy algorithm at time instant t

1: Initialization: $R_{temp} = R, \quad \mathcal{N}_{temp} = \mathcal{N}, \quad k_n(t) = 0 \quad \forall n \in \mathcal{N}$.
2: **while** $R_{temp} > 0$ **do**
3: $\quad n^* = \arg \min\limits_{n \in \mathcal{N}_{temp}} f_n(\lambda_n(t))$.
4: $\quad k_{n^*}(t) = \min \left(\lfloor \frac{R_{temp}}{\log_2(1+\gamma_{n^*}(t))} \rfloor, B_{n^*} \right)$.
5: $\quad R_{temp} = R_{temp} - k_{n^*}(t) \log_2(1 + \gamma_{n^*}(t))$.
6: $\quad \mathcal{N}_{temp} = \mathcal{N}_{temp} \setminus n^*$.
7: **end while**

VI. Numerical Results

To evaluate the performance of DSA in comparison with LIP and Greedy algorithm, first, consider $N = 6$ NCNs with arrival rates followed by a Poisson random variable with mean 5 users per time instant for all NCNs, i.e., homogeneous network. Price function is assumed to be $f_n(\lambda_n) = \lambda_n^2 + \lambda_n + 1$ for all n. Moreover, within each NCN, there is $B_n = 64$ channels to be used partly by internal users and SGCN. From the SGCN point of view, these channels are assumed to be Rayleigh fading, where their signal-to-noise ratio is assumed to follow an exponential random variable with mean 0 dB. Required rate of SGCN is assumed to be $R = 50$ bps/Hz. With this set up, DSA, LIP and Greedy algorithms are run for 2000 realizations of user arrival rates and signal-to-noise ratios.

The average number of channels allocated from different NCNs and the corresponding average cost are shown in Fig. 2 and Fig. 3, respectively. In all schemes, the number of allocated channels and accordingly the cost from different NCNs are mostly the same due to their equal average arrival rates and channel qualities. DSA takes advantage of time diversity over the time horizon and allocates the smallest average number of channels to SGCN in Fig. 2. Accordingly, it burdens the lowest cost to SGCN in Fig. 3. Moreover, the number of allocated channels and the cost of LIP is smaller than Greedy algorithm, as expected.

Economically, increasing the number of producers causes cost reduction as a consequence of diversity. To verify this fact, in an homogeneous network set up, we vary the number of NCNs and investigate the impact of this variation on the average cost. It is noteworthy that the required rate is assumed to be the same for all instances, i.e., $R = 50$ bps/Hz. The average cost versus the number of NCNs is shown in Fig. 4. As shown, cost reduces in all schemes by increasing the number of NCNs. Indeed, all schemes take advantage of 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 lower cost. Moreover, due to the time diversity, DSA achieves the lowest cost in all instances, as expected.

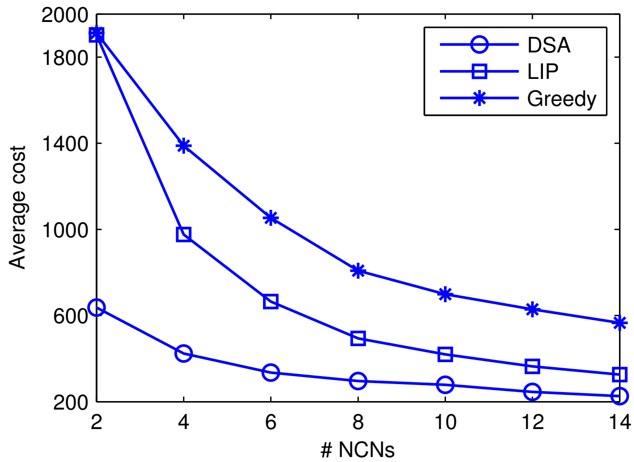

Fig. 4. Average cost versus the number of NCNs

VII. Conclusion

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

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