Sharing of Backup Power Supply of Co-located Multi-Operator Sites in Wireless Networks

Minh N. H. Nguyen, Chuan Pham, Nguyen H. Tran and Choong Seon Hong
Department of Computer Science and Engineering, Kyung Hee University
Email: {minhnhn, pchuan, nguyenth, cshong}@khu.ac.kr

Abstract: Installation of backup power supply plays an important role in maintaining communication services which helps saving billions of dollars as well as human lives during natural disasters. However, being costlier than public power, it increases the capital expense of the base stations. While downsizing the backup power source, it can significantly downgrade the quality of services due to insufficient power supplies. In case of co-location of multiple mobile network operators at a single base station, sharing backup power sources among the operators is a possible economical solution to reduce the delay of traffic flows and enhance power usage. In this paper, we have used Nash Bargaining solution and decentralized convex optimization over operators to determine the optimal user association distribution so that we can get maximum improvement in the delay performance of each operator while fairly sharing the backup power.

1. Introduction

In these days, the mobile service demand and mobile network capacity keeps increasing to serve more and more devices and users. For this strongly dependency, service availability of mobile communication becomes crucial for the success of all mobile network operators. However, there are many factors can affect to this requirement (e.g., aging power infrastructure, natural disasters) power outages often happen and making it extremely challenging to keep communication services availability. Even in developed economies such as the United States, communication service outages are also proliferating [1].

As a promising backup power supply for many systems, fuel cells have been profound to improve technical performance, reliability and reduce environmental issues. In mobile communication system, a typical site with one base station (BS) can reduce the CO_2 emission 34.4 tones per years using a hydrogen fuel cell compared to gas and diesel generator [2]. Moreover, fuel cell is highly robust in rugged areas and has a much lower maintenance cost than batteries. Accordingly, fuel cell is emerging as one of the most popular options for many applications including BS backup power. However, the backup power options are all very expensive. Therefore, backup power sharing between operators can be simply implemented with almost no changes to the co-located site, where many wireless operators already shared the tower infrastructure and physically co-locate their BSs. Since most mobile towers are owned and leased by third party mobile tower companies, co-located BSs has a strong presence in the United States [3]. Consequently, as an infrastructure sharing, backup power sharing among multiple wireless operators can be easily deployed and viewed as an integral element of infrastructure sharing [3]. In addition, downsizing the backup power supply and sharing the backup power among the operators at a multi-operator site can be economical and energy efficient, enhancing the communications service continuity and surviving power outages.

In this paper, we study the under-explored problem - fairness of backup power sharing in multi-operator cellular towers where wireless operators can associate their own traffic loads (i.e., route their power demand) to different towers in a fair manner. Towards this end, we adopt Nash Bargaining theory, which is designed for a cooperative game that helps participants can take part in a cooperation and guarantee the fairness and Pareto optimal solutions [4]. Intuitively, operators can make an agreement to maintain the service by using shared backup power in a collaborative manner if they attain greater utility than non-cooperating. Our proposed cooperative strategy helps operators improve the delay performance compared to no sharing approach in which the operators use their own individual backup power alone.

2. System Model

We apply the infrastructure-based wireless communication networks model from [5] to the co-located multi-operator sites. Mobile users in the region $\mathcal{L} \in \mathbb{R}^2$ is served by a set $\mathcal{G}$ of operators. Rather than the individual deployment, each operator i has a BS set $\mathcal{H}_i$, which is located at different sites.

At any location $x \in \mathcal{L}$, the traffic flows follow an inhomogeneous Poisson point process with arrival rate per unit area $\lambda(x)$. For simplicity, the arrival traffics can be modeled as user flows (i.e., data requests) with random sizes following independent distribution with mean $1/\mu(x)$. Then the traffic load density at the location x is defined as $\gamma(x) = \lambda(x)/\mu(x)$ in [5]. Following the literature [5], we consider the path loss model to capture the average channel quality between user locations and BSs. At location x, the transmission rate served by BS j of operator i is denoted by $c_{ij}(x)$ which follows Shannon capacity as in [5].

The *system load density* [5] is denoted by $\beta_{ij}(x) = \frac{\gamma_i(x)}{c_{ij}(x)}$, which defines the fraction of active transmission time required to deliver the traffic load $\gamma_i(x)$ of operator i from BS j to location x. The user associated routing probability vector for each operator i is denoted by $\boldsymbol{p}_i(x) = \{p_{ij}(x)\}$ for all $x \in \mathcal{L}$, and $j \in \mathcal{H}_i$.

Definition 1 (Feasibility): The set $\mathcal{F}_i$ of feasible BS *loads* (or *utilization*) of the operator *i*, i.e. $\boldsymbol{\rho}_i = \{\rho_{ij}\}$ for all $j \in \mathcal{H}_i$ as

$$\mathcal{F}_i = \{\rho_i | \rho_{ij} = \int_{\mathcal{L}} \beta_{ij}(x) p_{ij}(x) dx, \\ 0 \le \rho_{ij} \le 1-\epsilon,\ 0 \le p_{ij}(x) \le 1, \\ \sum_{j\in\mathcal{H}_i} p_{ij}(x) = 1, \forall j \in \mathcal{H}_i, \forall x \in \mathcal{L}\},$$

where ϵ is an arbitrarily small positive constant. This set was proved to be convex [5].

A. Flow-Level Cost Model

In this work, we adopt the flow-level dynamic systems [5], which considers data requests (i.e., flows and file transfers) that are initiated randomly and leave the system after serving. Based on the queueing analysis [5] for the M/GI/1 multi-class processor sharing system, the expected total number of flows of the operator *i* is calculated by $L_i = \sum_{j\in\mathcal{H}_i} \rho_{ij}/(1-\rho_{ij})$. Since minimizing the expected total number of flows is equivalent to minimize the average delay according to Little Law. The cost function for flow level performance is defined as

$$\phi(\rho_i) = \sum_{j\in\mathcal{H}_i} L_i + 1 = \sum_{j\in\mathcal{H}_i} 1/(1-\rho_{ij}). \quad (1)$$

B. Base Station Power Model

According to [6], the BS power consumption increases with the BS utilization and there are two kinds of power consumptions: fixed power consumption and the power consumption that are proportional to BSs utilization. Thus, the total power consumption of a BS is given by

$$\psi_{ij}(\rho_{ij}) = (1-m_{ij})\rho_{ij}Q_{ij} + m_{ij}Q_{ij}, \quad (2)$$

where $m_{ij} \in [0,1]$ is a portion of the fixed power consumption of the BS and Q_{ij} is the maximum BS's operational power when it is fully utilized, i.e., $\rho = 1$.

3. Backup Power Sharing

A. Problem Formulation

Each operator minimizes flow-level cost function (1), which is convex function. Independently optimizing user association with their own backup power would be trivial if the operators had no cooperation. The cost of operator *i*, denoted by $\hat{\phi}_i$, is determined by solving the following No Backup Power Sharing (**NBPS**) problem

$$\textbf{min}.\quad \phi(\rho_i)$$
$$\textbf{subject to}.\quad \psi_{ij}(\rho_{ij}) \le B_{ij},\ \rho_{ij} \in \mathcal{F}_i, \qquad \forall j \in \mathcal{H}_i,$$

Based on the optimal user association probability vector, MTs should be associated with their corresponding BSs to minimize the flow-level cost faced by operator *i* at every site under the limitation of the BS's maximum operational power. Therefore, downsizing the maximum operational power decreases the number of MTs that can be associated with their closest BSs.

We apply Nash Bargaining Solution (NBS) for the backup power fair sharing that guarantees an outcome which is not only Pareto-efficient, but also proportional fair [4]. If NBS cannot produce better delay performance, the operator performance is still at least that of the solution of the **NBPS**, which represents the disagreement point. Especially, if the NBS exists, it is unique, and satisfies the four axioms, i.e. *Pareto efficien*cy, s*ymmetry*, *independence of affine transformations*, and *independence of irrelevant alternatives* [4]. The NBS can be achieved by solving the following Backup Power Fair Sharing **(BPFS)** problem

$$\textbf{max}.\quad \prod_{i\in\mathcal{G}} [\hat{\phi}_i - \phi(\rho_i)]$$
$$\textbf{subject to}.\quad \sum_{i\in\mathcal{G}} \psi_{ij}(\rho_{ij}) \le \sum_{i\in\mathcal{G}} B_{ij}, \forall j \in \mathcal{H}_i, \quad (3)$$
$$\phi(\rho_i) \le \hat{\phi}_i, \forall i \in \mathcal{G}, \quad (4)$$
$$\rho_{ij} \in \mathcal{F}_i,\ \forall i,j. \quad (5)$$

B. Decentralized Solution Method

Since solving the **BPFS** problem by a centralized controller requires traffic load information of all operators, the decentralized approach based on the dual decomposition optimization method [7] can protect each operator's private traffic information. The non-concave **BPFS** problem is transformed into an equivalent concave problem with a separable objective $\sum_{i\in\mathcal{G}} \ln[\hat{\phi}_i - \phi(\rho_i)]$.

The partial Lagrangian of **BPFS** problem is derived as follows

$$\sum_{i\in\mathcal{G}} \ln[\hat{\phi}_i - \phi(\rho_i)] - \sum_{j\in\mathcal{H}_i} \lambda_j \sum_{i\in\mathcal{G}} (\psi_{ij}(\rho_{ij}) - B_{ij}). \ (6)$$

In this approach, at each iteration *k*, operator *i* receives the dual variable λ which considered as the backup power sharing price. Then it iteratively solves the subproblem

$$\textbf{max}.\quad \ln[\hat{\phi}_i - \phi(\rho_i)] - \sum_{j\in\mathcal{H}_i} \lambda_j (\psi_{ij}(\rho_{ij}) - B_{ij})$$
$$\textbf{subject to}.\quad \rho_{ij} \in \mathcal{F}_i, \qquad \forall j \in \mathcal{H}_i.$$

After solving the subproblem, each operator will send its BS load $\rho_{ij}(k)$ to the aggregators at co-located sites. Then the aggregator at each site *j* will update dual variables as follows

$$\lambda_j(k+1) = [\lambda_j(k) + \alpha \sum_{i\in\mathcal{G}} \psi_{ij}(\rho_{ij}(k)) - B_{ij})]^+. \quad (7)$$

Since the problem is concave, and the objective function is differentiable, a small enough constant step size α can ensure the convergence to the optimal solution [7].

C. Case Studies

As an example scenario, we consider co-located operators at five sites. These sites are located in a 1 × 1 km^2 region, which is divided into 100 unit squares. The location *x* of data requests is determined at the bottom left corner of each unit area. According to the communication model of urban macrocells with the simulation parameters in the WiMAX evaluation methodology document [8], we use the used COST 231 path loss model. The backup power capacity at the multi-operator sites is downsized to 388W per operator while the maximum BS operational power is 865W [6].

Figure 1 shows the convergence of BS loads of the decentralized approach compared with the optimal solution of the centralized approach (i.e., optimization solver). As a result of the sharing advantage, compared with no sharing, the sharing approach increases the expected number of flows and reduces average delay by 4.6% in Figure 2.

Figure 3 illustrates the user association distribution of the central BS3, the read area, and coverage of other BSs belong to Operator 1. We generate heavy traffic loads near BS2 and

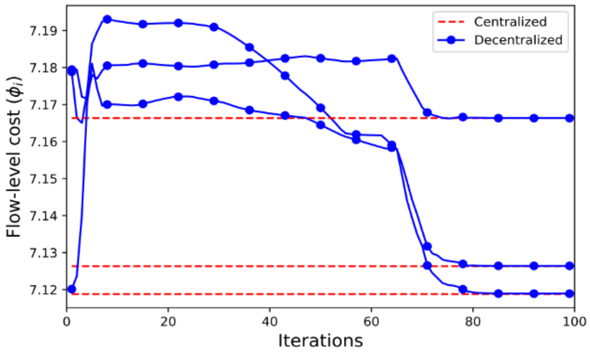


Fig. 1: Flow-level cost convergence of each operator.

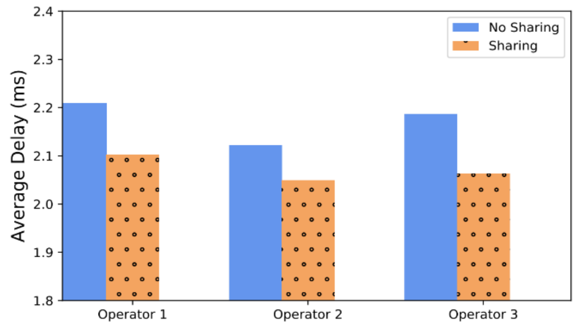
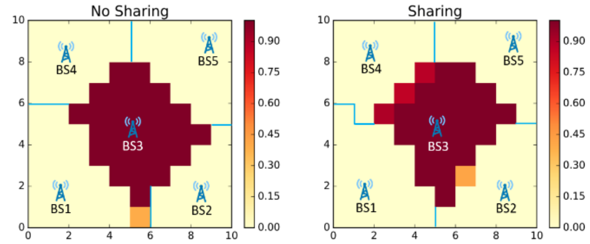


Fig. 2: Average flow delay of each operator.

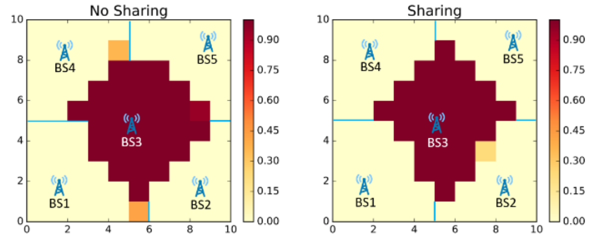
BS4. The orange squares shows that the traffic flows in that area can be probabilistically associated with multiple BSs. Since user flows try to associate with the closer BSs rather than the farther ones due to path loss effect, when the backup power capacity of BS3 is set to 388 W, the BS2 and BS4 have smaller coverage than other BSs, as illustrated in Figure 3a. However, with power sharing, there are more MTs being able to associate with their closest BS. In consequence, BS2 and BS4 coverage become larger with the sharing backup power approach. Figure 3b illustrates the user association distribution of the BS3 and the coverage of the other BSs of Operator 1 when backup power capacity is increased to 500 W. The higher power capacity allows the central BS to cover a larger region in both sharing and no sharing schemes.

4. Conclusion

In this paper, we investigate an under-explored problem of backup power sharing for co-location BSs to improve the network performance and service availability during power outages. The fairness of sharing backup power supply among the operators at multi-operator sites is tackled by using Nash Bargaining solution. Then decentralized algorithm is proposed for backup power sharing. Simulation results show that the backup power fair sharing guarantees better delay reduction than that of no sharing approach.



(a) Backup power capacity of BS3 is 388 W,



(b) Backup power capacity of BS3 is 500 W,

Fig. 3: User association distribution of the BS3 of Operator 1.

Acknowledgment

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) (NRF-2017R1A2A2A05000995). *Dr. CS Hong is the corresponding author.

References:

[1] "Blackout tracker united states annual report 2015," vol. EATON, Tech. Rep., pp. 1–73, 2015.
[2] M. Crouch, "Fuel cell systems for base stations: Deep dive study," *GSMA Report*, 2012.
[3] "Mobile infrastructure sharing," vol. GSM Company, Tech. Rep., 2012.
[4] M. J. Osborne and A. Rubinstein, "Bargaining and markets," 1990.
[5] H. Kim, G. De Veciana, X. Yang, and M. Venkatachalam, "Distributed alpha-optimal user association and cell load balancing in wireless networks," *IEEE/ACM Transactions on Networking*, vol. 20, no. 1, pp. 177–190, 2012.
[6] K. Son, H. Kim, Y. Yi, and B. Krishnamachari, "Base station operation and user association mechanisms for energy-delay tradeoffs in green cellular networks," *IEEE journal on selected areas in communications*, vol. 29, no. 8, pp. 1525–1536, 2011.
[7] S. Boyd, L. Xiao, A. Mutapcic, and J. Mattingley, "Notes on decomposition methods," *Notes for EE364B, Stanford University*, pp. 1–36, 2007.
[8] R. Srinivasan, J. Zhuang, L. Jalloul, R. Novak, and J. Park, "Ieee 802.16m evaluation methodology document (emd)," *IEEE 802.16 Broadband Wireless Access Working Group*, 2008.