Dynamic Control and Resource Allocation in Wireless-Infrastructured Distributed Cellular Networks with OFDMA

Lei You[†‡] Ping Wu[†] Mei Song[‡] Junde Song[‡] Yong Zhang[‡]
[†]Signals & Systems, Dept. of Engineering Sciences, Uppsala University, Uppsala, Sweden
[‡]PCN&CAD Certer, Beijing University of Posts and Telecommunications, Beijing, P.R. China
youlei.feng@gmail.com Ping.Wu@angstrom.uu.se {songm, jdsong, zhangyong}@bupt.edu.cn

***Abstract*—In this paper, we consider joint optimization of end-to-end data transmission and resource allocation for Wireless-Infrastructured Distributed Cellular Networks (WIDCNs), where each base station (BS) in a cell is connected with its neighboring BSs via wireless links, and a mobile station (MS) can access one or multiple adjacent BSs simultaneously through time-varying OFDMA channels. The communications between a source MS and a destination MS are carried out with the help of BSs in the multi-hop, distributed manner. To achieve the joint optimization for such WIDCNs, a Stochastic Network Utility Maximization (SNUM) problem is formulated under the constraints of OFDMA sub-channel allocation on time-varying access links (both uplink and downlink), as well as routing and scheduling on forwarding links among BSs. By decomposing the corresponding dual problem, transforming it into a stochastic convex optimization problem and solving it by quasi-gradient method, we obtain distributed dynamic control algorithms for end-to-end data transmission. The algorithm can adapt to the OFMDA channel variation and converges asymptotically to the optimal solution. We also develop a distributed algorithm for OFDMA sub-channel allocation and link coordination between BSs. The simulation results show that the data rates of the flows can converge to optimal solution approximately, queues of the network is stable under the proposed distributed dynamic algorithm, and the multi-receiver scheme outperforms the single-receiver scheme due to diversity.**

Keyword*—*Wireless-Infrastructure Distributed Cellular Networks; stochastic optimization; distributed dynamic control

I. INTRODUCTION

In the existing cellular networks the base stations (BSs) are connected via wires. Deployment of such networks will become difficult and expensive in complicated geographical and disaster areas. In this case, connection of BSs via wireless links will make deployment fast, coverage flexible and cost low. Communications over such wireless infrastructured networks are conducted in the multi-hop and distributed manner. In this paper, we investigate such cellular networks which have Wireless-connected Base Station (WBS) with OFDMA technology, called Wireless-Infrastructured Distributed Cellular Network (WIDCN). Due to the limited wireless resource, providing services with high quality any time and anywhere is challenging.

Joint design of different functions in different layers, e.g., congestion control, routing, MAC and resource scheduling, can significantly improve the performance of networks [1]. Optimization of an overall network is often formulated as a network utility maximization (NUM) problem. This can be classified into two categories: static network optimization and stochastic network optimization.

For static network optimization, it is assumed that the states of the network (e.g., topology and channels), and the converged rates of data flows are invariant with time, and that there is no packet loss. The problem is often analyzed under deterministic fluid model. The solutions of such an optimization problem in the form of network utility function converge to a single optimal value [2] [3]. Decomposition technique has been proved to be a useful method to obtain the optimal value in a distributed way. An excellent survey on theory, architecture and the NUM problem and different decomposition techniques is given in [1].

For stochastic network optimization, the dynamic and variance of the networks (due to channel fading, user mobility, or link failure etc.) are considered. Adaptive queue and Lyapunov optimization technique have been developed in [4] [5] to design dynamic control algorithm for congestion control, routing and resource scheduling. A greedy primal-dual algorithm for stochastic network optimization was proposed in [6]. In [7] an ad hoc network with time-varying links is considered and the algorithms for the NUM problem are proposed based on the dual decomposition method for state network optimization.

In this paper, we consider joint optimization of end-to-end data transmission control and distributed resource allocation for WIDCN with time-varying OFDMA channels on access links. It is a problem of stochastic network optimization. To develop a distributed algorithm for such joint optimization, we solve the problem by dual decomposition in its dual domain. We deduce the dynamic control algorithm by transforming dual problem into a stochastic optimization problem and solving it using stochastic quasi-gradient method [8]. A similar method was used in [9], in which the authors developed a centralized algorithm for joint link scheduling and power control in time-varying multi-hop network, but did not consider end-to-end data transmission control and distributed implementation of the algorithm.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. WIDCN Model

The WIDCN we consider here is shown in Fig.1. Its

1530-2016/09 $26.00 © 2009 IEEE
DOI 10.1109/ICPPW.2009.20

architecture is similar to the traditional cellular networks except that BSs are connected by wireless links and thus called wireless BSs (WBSs). A mobile station (MS) can access one or multiple adjacent WBSs simultaneously through time-varying OFDMA channels. There is no control node to centrally coordinate resource allocation. Thus the network considered here is totally distributed. It can be an individual network to cover a certain area and provide high quality services for some special purposes which need fast deployment and low cost. It also can be connected to the exterior networks (existing cellular networks, Internet) through gateways.

Each WBS is assumed to have two different radio interfaces operating over independent frequencies. One radio interface is used for WBS-to-WBS communication to form *forwarding links*, the other is used for uplink and downlink communication between WBSs and MSs to form uplink and downlink *access links*. The frame structures for both access links and forwarding links are showed in Fig. 2. An access frame is divided into an uplink and a downlink sub-frame, respectively, and each sub-frame includes several OFDMA sub-channels that can be used by different WBS-MS pairs in the same sub-frame. We assume that the lengths of uplink and downlink access sub-frames are the same, and each has half of the entire access frame. The lengths of the access frame and the frame for forwarding links are the same.

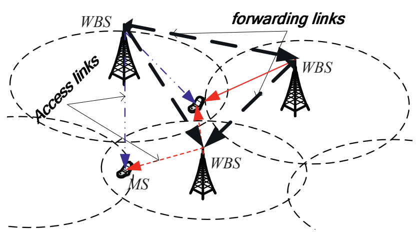

Fig 1. Architecture of Wireless Infrastructured Distributed Cellular Network (WIDCN).

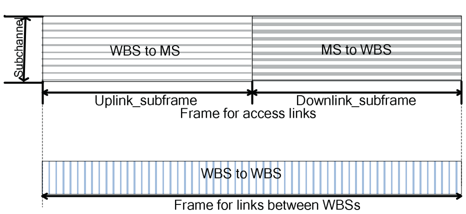

Fig 2. Frame structure for access and forwarding links

We assume that a MS can communicate with one WBS or with several adjacent WBSs simultaneously by using different OFDMA sub-channels when the MS is located near the boundary of several cells so as to gain multiple receiver diversity (called multi-receiver scheme). To avoid interference, one-hop neighboring WBSs can not use the same OFDMA sub-channel on their access links at the same sub-frame, and thus they need to allocate OFDMA sub-channels in a distributed way. OFDMA channels are time-varying due to slow mobility of MSs and varying environment. Every WBS is assumed to have six neighbors due to stationary cellular structure, and have six directional antennas installed, each of which faces its adjacent WBS. We further assume that the forwarding links are stationary with fixed link rates, but operate in half-duplex mode. With these reasonable assumptions, the scheduling of links among WBSs becomes simpler and just needs the coordination between WBSs on both ends of an individual link.

B. Optimization Problem for End-to-end Data Transmission

We consider a WIDCN with B WBSs, labeled $\{1,...,b,\ \ ...,B\}$ and M MSs, labeled $\{1,...,m,...,M\}$. Let C_b represent the set of MSs that can be connected to WBS b, and D_m represent the set of WBSs which MS m can connect to. Assume the number of OFDMA sub-channels (labeled $\{1, \ldots, n, \ldots, N\}$) is N.

The bit rate of an end-to-end service flow from source MS m to destination MS d is denoted $x_m^d, m \neq d$. The utility function associated with each service flow is $U_m^d(x_m^d)$. $U(\bullet)$ is assumed to be a strictly concave, and differentiable function. Utility function represents the satisfaction of corresponding service flow with bit rate x_m^d [1].

Assuming that access channels are time-invariant within each frame, then the time-varying OFDMA sub-channels on the access link can be modeled as a stationary process $\{s(t), t>0\}$ with finite state space S and having an independent and identical distribution (i.i.d.) $\{d(s), s \in S\}$. In each state s, let $Ru_{m,b,n}(s)$ be the bit rate on sub-channel n between source MS m and BS b ($m \in C_b$ and $b \in D_m$).

We define an uplink and a downlink sub-channel allocation policy, *namely*, $qu = \{qu_{m,b,n}^d, m \in C_b\}$, and $qd = \{qd_{d,b,n}, d \in C_b\}$, respectively, where $qu_{m,b,n}^d$ and $qd_{d,b,n}$ are binary indicators. $qu_{m,b,n}^d = 1$ ($qd_{d,b,n} = 1$) denotes that sub-channel n is allocated on uplink (downlink) between MS m (MS d) and BS b for the transmission of flow x_m^d (the data destined to d). Let $Qu(s)$ and $Qd(s)$ denote the sets of feasible uplink and downlink sub-channel allocation policies, respectively, in state s. Let $\phi(s,qu)$ and $\phi(s,qd)$ denote the probabilities of policies qu and qd being chosen in the state s, respectively, and $\phi(s,qu) \geq 0$, $\phi(s,qd) \geq 0$, $\sum_{qu \in Qu(s)} \phi(s,qu) = 1$ and $\sum_{qd \in Qd(s)} \phi(s,qd) = 1$. The average (mean) feasible uplink bit rate between MS m and BS b for flow x_m^d is

$$E(Ru_{m,b}^d) = \sum_{s \in S} d(s) \sum_{qu \in Qu(s)} \phi(s,qu) (\sum_n Ru_{m,b,n}(s) qu_{m,b,n}^d) \qquad (1)$$

and the average (mean) feasible downlink bit rate between BS b and MS d is

$$E(Ru_{d,b}) = \sum_{s \in S} d(s) \sum_{qd \in Qd(s)} \phi(s,qd) (\sum_n Ru_{d,b,n}(s) qd_{d,b,n}) \qquad (2)$$

Thus, for all the probabilities, $\phi(s,qu)$ and $\phi(s,qd)$, the sets of $E(Ru_{m,b}^d)$ and $E(Ru_{d,b})$ are all convex.

For the forwarding link, let $r_{i,j}^d$ be the amount of capacity allocated to the flow destined to d on the link between WBS i to WBS j. We assume the capacity of forwarding links is identical and invariable. Let Γ be the capacity of a link between two neighboring WBSs.

Objective and constraints of the problem for end-to-end data transmission:

1) Our objective is to maximize the sum of utility of all the flows in the network, namely,

$$\text{Maximize} \quad \sum_{\substack{m,d \\ m \neq d}} U_m^d(x_m^d) \qquad \mathbf{P1}$$

subject to the following constraints:

2) access constraints in source MSs

$$x_m^d \le (1/2) \sum_{b \in D_m} E(Ru_{m,b}^d) \quad \text{for} \quad \forall m, d, m \neq d \tag{3}$$

3) forward constraints in BS b for the flows whose destination is $d \notin C_b$

$$(1/2) \sum_{m \in C_b} E(Ru_{m,b}^d) \le \sum_i r_{b,i}^d - \sum_i r_{i,b}^d \quad \text{for} \quad \forall b, d \text{ and } d \notin C_b \tag{4}$$

4) forward constraints in BS b for the flows whose destination is $d \in C_b$

$$(1/2) \sum_{m \in C_b} E(Ru_{m,b}^d) \le (1/2) E(Ru_{d,b}) - \sum_i r_{i,b}^d$$
$$\text{for} \quad \forall b, d \text{ and } d \in C_b \tag{5}$$

5) and forwarding link capacity constraints

$$\sum_{d, d \notin C_i} r_{i,j}^d + \sum_{d, d \notin C_j} r_{j,i}^d \le \Gamma \quad \text{for} \quad \forall \text{ forwarding link } (i, j). \tag{6}$$

The factor 1/2 in (3), (4) and (5) is due to the assumption of lengths of uplink and downlink access sub-frames are the same. From the above assumptions and analysis in this section, we can easily know **P1** poses a convex NUM problem with linear (stochastic) constraints and a concave objective function [10]. Efficient interior-point methods (e.g., primal-dual interior-point methods) [10] can be used to solve the problem. But these methods require the knowledge of channel state distribution, all the feasible sub-channel allocation policies and computation in some central node. But a more attractive approach to the problem is the dual decomposition [1] [2] [3] [7] which results in a solution to enable distributed implementation. To tackle time-varying OFDMA channel, stochastic optimization method [8] [9] can be used to deduce solution without the need to know channel state distribution so long as the channel has an i.i.d.

III. Solution by Dual Decomposition and Stochastic Optimization

Since **P1** is convex, strong duality holds. Thus, it can be approached by solving its dual problem which has a desirable property of decomposition in protocol layering to enable real-time and distributed implementation [1]. In this section we consider time-varying channel state, and we transform the dual problem into a stochastic optimization problem and solve it using stochastic quasi-gradient method. The algorithm in this case only depends on the channel state of the current frame, but it can obtain asymptotic global optimal solution. This solution serves as a basis for our development of a distributed dynamic control algorithm, which is presented in detail in the next section.

A. Dual Problem

We introduce Lagrange multipliers, λ_m^d and λ_b^d $\forall m, b, d, m \neq d$, to relax the corresponding constraints in (3), (4) and (5). Let λ be the vector of all the Lagrange multipliers and $X, r, E(Ru), E(Rd)$ denote the vectors of variables $x_m^d, r_{i,j}^d$, $E(Ru_{m,b}^d)$ and $E(Ru_{d,b})$, respectively. We have a dual function

$$\begin{aligned}
&D(\lambda; X, r, E(Ru), E(Rd)) \\
&= \max_{\sum_d r_{i,j}^d + \sum_d r_{j,i}^d \le \Gamma} \{ \sum_{m,d} U_m^d(x_m^d) + \sum_{\substack{m,d \\ m \neq d}} \lambda_m^d ((1/2) \sum_{b \in D_m} E(Ru_{m,b}^d) - x_m^d) \\
&+ \sum_{\substack{d,b \\ d \notin MS_b}} \lambda_b^d (\sum_i r_{b,i}^d - \sum_i r_{i,b}^d - (1/2) \sum_{m \in C_b} E(Ru_{m,b}^d)) \\
&+ \sum_{\substack{d,b \\ d \in C_b}} \lambda_b^d ((1/2) E(Ru_{d,b}) - \sum_i r_{i,b}^d - (1/2) \sum_{m \in C_b} E(Ru_{m,b}^d)) \}
\end{aligned} \tag{7}$$

which turns the primal problem **P1** to the following dual problem

$$\text{Minimize} \quad D(\lambda) \qquad \mathbf{P2}$$
$$\text{Subject to} \quad \lambda \ge 0$$

B. Transforming Dual Problem into a Stochastic Convex Optimization Problem

Considering (1) and (2), the dual function (7) can be reformulated in the following form:

$$\begin{aligned}
&D(\lambda; X, r, E(Ru), E(Rd)) \\
&= \sum_{\substack{m,d \\ m \neq d}} D_{1,m}^d(\lambda) + \sum_{s \in S} d(s) [D_2(s, \lambda) + D_3(s, \lambda)] + D_4(\lambda) \\
&= \sum_{\substack{m,d \\ m \neq d}} D_{1,m}^d(\lambda) + E[D_2(s, \lambda) + D_3(s, \lambda)] + D_4(\lambda) \\
&= E[D_2(s, \lambda) + D_3(s, \lambda) + \sum_{\substack{m,d \\ m \neq d}} D_{1,m}^d(\lambda) + D_4(\lambda)]
\end{aligned}$$

where

$$D_{1,m}^d(\lambda) = \max_X [U_m^d(x_m^d) - \lambda_m^d x_m^d] \tag{8}$$

$$D_2(s, \lambda) = \max_{qu, \phi(s,qu)} \sum_{qu \in Qu(s)} \phi(s, qu) \sum_b \sum_{\substack{(m,d) \\ m \in C_b,}} [\lambda_m^d - \lambda_b^d] (\sum_n Ru_{m,b,n}(s) qu_{m,b,n}^d) \tag{9}$$

$$D_3(s, \lambda) = \max_{qd, \phi(s,qd)} \sum_{qd \in Qd(s)} \phi(s, qd) \sum_{\substack{d,b,n \\ d \in C_b}} \lambda_b^d (\sum_n Ru_{d,b,n}(s) qd_{d,b,n}) \tag{10}$$

$$D_4(\lambda) = \max_{\sum_d r_{i,j}^d(t) \le \Gamma} \sum_{i,j} \sum_{d, d \notin Ci,} [\lambda_i^d - \lambda_j^d] r_{i,j}^d \tag{11}$$

There may be multiple policies to maximize (9) and (10) in each state s. To obtain maximum in (9) and (10), we can select optimal policies, qu^* and qd^*, from the following sets, respectively,

$$Qu^*(s) = \arg \max_{qu \in Qu(s)} \sum_b \sum_{\substack{(m,d) \\ m \in C_b,}} [\lambda_m^d - \lambda_b^d] (\sum_n Ru_{m,b,n}(s) qu_{m,b,n}^d) \quad (12),$$

$$Qd^*(s) = \arg\max_{qd \in Qd(s)} \sum_{\substack{d,b,n \\ d \in C_b}} \lambda_b^d (\sum_n Ru_{d,b,n}(s) qd_{d,b,n}) \quad (13)$$

by setting $\phi(s, qu^*) = 1$ and $\phi(s, qd^*) = 1$.

Then, the dual problem **P2** becomes a stochastic convex optimization problem [8]

$$\text{Minimize} \quad E[\, D_5(s,\lambda) + D_6(s,\lambda) + \sum_{\substack{m,d \\ m \neq d}} D_{1,m}^d(\lambda) + D_4(\lambda)\,] \qquad \textbf{P3}$$

Subject to $\lambda \geq 0$

where

$$D_5(s,\lambda) = \max_{qu \in Qu(s)} \sum_b \sum_{\substack{(m,d) \\ m \in C_b,}} [\lambda_m^d - \lambda_b^d](\sum_n Ru_{m,b,n}(s) qu_{m,b,n}^d)$$

$$D_6(s,\lambda) = \max_{qd \in Qd(s)} \sum_{\substack{d,b,n \\ d \in C_b}} \lambda_b^d (\sum_n Rd_{d,b,n}(s) qd_{d,b,n})$$

C. Solving stochastic convex optimization problem by sub-gradient update method

We define a quasi-dual function at state s as

$$QD(s,\lambda) = D_5(s,\lambda) + D_6(s,\lambda) + \sum_{\substack{m,d \\ m \neq d}} D_{1,m}^d(\lambda) + D_4(\lambda)$$

Assuming that X^*, r^*, qu^*, qd^* are the optimal solutions to $\sum_{m,d,m\neq d} D_{1,m}^d(\lambda)$, $D_4(\lambda)$, $D_5(s,\lambda)$ and $D_6(s,\lambda)$, respectively, we have the sub-gradients of quasi-dual function $QD(s,\lambda)$ at λ_m^d, $\lambda_b^d, d \notin C_b$ and $\lambda_b^d, d \in C_b$, which are given, respectively, as follows [10],

$$G_m^d(s) = (1/2) \sum_{b \in D_m} \sum_n Ru_{m,b,n}(s) qu_{m,b,n}^{d*} - x_m^{d*}$$

$$G_{1,b}^d(s) = \sum_i r_{b,i}^{d*} - \sum_i r_{i,b}^{d*} - (1/2) \sum_{m \in C_b} Ru_{m,b,n}(s) qu_{m,b,n}^{d*}$$

$$G_{2,b}^d(s) = (1/2) \sum_n Rd_{d,b,n}(s) qd_{d,b,n}^* - \sum_i r_{i,b}^{d*} - (1/2) \sum_{m \in C_b} \sum_n Ru_{m,b,n}(s) qu_{m,b,n}^{d*}$$

To solve stochastic convex optimization problem **P3,** we use the quasi-gradient update method in stochastic optimization [8] [9] as follows.

Algorithm 1: stochastic quasi-gradient update method

At the tth step, we estimate the current channel state $s(t)$, solve the sub-problems (8), (9), (10) and (11) and get optimal X^*, r^*, qu^*, qd^*. Then we calculate sub-gradients $G_m^d(s(t))$, $G_{1,b}^d(s(t))$ and $G_{2,b}^d(s(t))$ of quasi-dual function $QD(s,\lambda)$ in this step, and update dual multipliers in the following fashion

$$\lambda_m^d(t+1) = \max(\lambda_m^d(t) - \varepsilon(t)(G_m^d(s(t))), 0)$$

$$\lambda_b^d(t+1) = \max(\lambda_b^d(t) - \varepsilon(t)(\,G_{1,b}^d(s(t))\,), 0), \text{for } d \in C_b \quad (14)$$

$$\lambda_b^d(t+1) = \max(\lambda_b^d(t) - \varepsilon(t)(\,G_{2,b}^d(s(t))\,), 0), \text{for } d \notin C_b$$

Where $\varepsilon(t)$ is a positive scalar step size.

If the length of a queue is bounded, the queue is stable. If all the queues in the network are stable, the network is stable [5]. We can view the actual queue length as $QL_m^d = \lambda_m^d / \varepsilon(t)$ [11]. To facilitate distributed implementation, we prefer a constant step size ε. In such a case, the optimality and stability of the algorithm are addressed in the following theorem.

Theorem 1: if we use a constant step size ε, and the state process $\{s(t), t > 0\}$ is a stationary and ergodic process, then there exists positive constants *A*, *B* and *C*, and the algorithm ensures that

$$\limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{ \sum_{m,d,m\neq d} \frac{\lambda_m^d(\tau)}{\varepsilon} + \sum_{b,d} \frac{\lambda_b^d(\tau)}{\varepsilon} \} \leq A + \frac{1}{\varepsilon} B$$

$$\sum_{m,d,m\neq d} U_m^d((x_m^d)^*) - \liminf_{t\to\infty} \sum_{m,d,m\neq d} U_m^d(\overline{x}_m^d) \leq \varepsilon C$$

where $(x_m^d)^*$ is the optimal solution of the **P1**, and $\overline{x}_m^d = \frac{1}{t} \sum_{\tau=0}^{t-1} E\{x_m^d(\tau)\}$.

The first inequality in Theorem 1 states that the time average of the queue length is bounded and thus the network is stable, while second one states that the gap of optimal value and the time average value of **P1** is linear in the constant step size and can asymptotically approach optimal solution so long as ε is small enough. Thus with the assumption that the state process $s(t)$ is i.i.d. in each step, **Algorithm 1** does not need to know exactly the state distribution. The proof of Theorem 1 is similar to that in [13] using 'Lyapunov drift' and 'Lyapunov optimization' theorem and thus not given here. Numerical verification of the convergence and stability of the algorithm will be given by simulation in Section Ⅴ.

IV. DYNAMIC CONTROL AND DISTRIBUTED RESOURCE ALLOCATION ALGORITHM

In section III.B, we decomposed the dual problem into four sub-problems (8)-(11). For each step t and the corresponding Lagrange multipliers $\lambda(t)$ in **algorithm 1**, we should solve the following sub-problems: *1) rate control subproblem (8); 2) Uplink OFDMA sub-channel allocation subproblem (12); 3) Downlink OFDMA sub-channel allocation subproblem (13); 4) Joint scheduling, routing and rate allocation subproblem for forward links (11).*

The above decomposition method facilitates the implementation of distributed control algorithm. Due to channels being time-varying, link scheduling and decision variables may change from frame to frame. Thus, we propose distributed dynamic control algorithm for end-to-end data transmission based on the dual decomposition, which is detailed in the following **Algorithm 2** (assuming utility function $U(\bullet) = \ln(\bullet)$):

Algorithm 2: Distributed dynamic control for end-to-end data transmission

At the beginning of the frame t, the algorithm conducts the following steps

1) Source rate control: each MS calculates its data rate in this frame for flow x_m^d as following:

$$x_m^d(t) = 1/\lambda_m^d(t) \text{ bits/frame}$$

2) Control information exchange: each WBS b estimates the current channel state, finds

$$W_1(n,b) = \max_{\substack{(m,d) \\ m \in C}} (\,(\lambda_m^d - \lambda_b^d) Ru_{m,b,n}(s)\,)$$

$$W_2(n,b) = \max_{d \in C_b} (\,\lambda_b^d Rd_{d,b,n}(s)\,)$$

for each sub-channel n, and sends all $W_1(n,b)$, $W_2(n,b)$ and λ_b^d to its neighboring WBSs.

3) Distributed sub-channel allocation: WBSs allocate sub-channels for uplink and downlink access links using **Algorithm 3** which is given below.

4) Forwarding link scheduling: WBSs coordinate the transmission of forwarding links using **Algorithm 4** which is given below.

5) Routing: MSs and WBSs transmit on the allocated sub-channels or links determined in 3) and 4) during this frame.

6) The WBS updates its dual multipliers for the next frame according to (14) based on the results of the above resource allocation.

Unlike ad hoc networks, MS nodes have no capacity to allocate sub-channels. It's the responsibility of WBSs for allocating sub-channels for both uplink and downlink access links under the assumptions in section II. The sub-problems **SP2** are actually the 2-hop maximum weighted matching problems which are NP-hard problems [14]. A distributed greedy algorithm has been proposed for primary interference models in ad hoc or multi-hop networks [7] [11]. Here we propose a distributed OFDMA sub-channel allocation algorithm for both uplink and downlink accesses based on the greedy maximum weighted matching algorithm [12] by exchanging signals ($W_1(n,b)$, $W_2(n,b)$ and λ_b^d) among WBSs for 2-hop sub-channel interference model.

Algorithm 3: Distributed OFDMA sub-channel allocation

---

1) For sub-channel *n*, WBS *b* compares $W_1(n,b)$ and $W_2(n,b)$ of itself and its neighbors'.

- If the value of $W_1(n,b)$ is larger than all of its neighbors', it sends an OCC_UP (n,b) message to all its neighbors to inform them that WBS *b* will occupy sub-channel n on the uplink in this frame. Similarly, if the value of $W_2(n,b)$ is larger than all of its neighbors', it sends an OCC_DOWN (n,b) message to all its neighbors to inform them that WBS *b* will occupy sub-channel *n* on the downlink in this frame.
- If a WBS receives an OCC_UP (OCC_DOWN) message regarding sub-channel *n* from any of its neighboring WBSs, then it sends a QUIT_UP (QUIT_DOWN) message on this sub-channel to inform that it quits competing for this channel for uplink (downlink) in this frame.
- If a WBS receives a QUIT_UP (QUIT_DOWN) message regarding sub-channel *n* from all its neighbors, it will occupy this sub-channel for uplink (downlink).

2) For the sub-channels on which a WBS has not received any OCC_UP (OCC_DOWN) message, and not received the QUIT_UP (QUIT_DOWN) message from all its neighbors, the WBS will do the similar things to step 1) except that the WBS compare $W_1(n,b)$ and $W_2(n,b)$ of itself and those of its neighbors' from whom it has not received QUIT_UP (QUIT_DOWN) message, until all the sub-channels have been allocated.

3) For the sub-channel n occupied by WBS *b* on uplink, WBS finds

$$[m^*,d^*] = \arg\max_{(m,d),m\in C_b} ((\lambda_m^d - \lambda_b^d) Ru_{(m,b),n}^d)$$

and informs MS m^* that the sub-channel n is allocated to its flow which is destined to d^*.

4) For the sub-channel n occupied by WBS b on downlink, the WBS finds

$$d^* = \arg\max_{d\in C_b} (\lambda_b^d Rd_{(d,b),n}^d) .$$

And then the WBS will use sub-channel n to send data destined to d^* in this frame.

In general, link scheduling in multi-hop networks is also a NP-hard problem under *k*-hop interference model ($k \geq 2$) [14]. Due to the use of directional antennas, forwarding link scheduling in the WIDCN becomes simple and just needs the coordination between WBSs on the two ends of an individual forwarding link.

Algorithm 4: Link Coordination Between Adjacent BSs

For each link (b,j) between WBS *b* and WBS *j*:

1) WBS *b* finds $d^* = \arg\max_{d\notin C_b} |\lambda_b^d - \lambda_j^d|$.

2) If $\lambda_b^{d^*} - \lambda_j^{d^*} > 0$, then WBS *b* will send data destined to d^* on link (b,j) with rate Γ, otherwise, not send anything in this frame.

V. Simulation And Results

We set up a simple scenario to verify the convergence and stability of the proposed distributed dynamic control algorithm. Then we consider a wireless-infrastructured cellular network shown in Fig.3, which follows the assumptions of the system model in section II. There is one wireless BS in each cell with a radius of 100 (with an arbitrary unit). There are four MSs in the network. Their positions are (100 50), (290 82), (600 470) and (390 460), respectively. We assume that a MS can access the WBSs within the distance of less than 150 so that each MS can access at most three WBSs if the MS is located near the boundary of the three cells. In the present setup, each MS can access three WBSs. As we assumed in section II, neighboring WBSs are not allowed to allocate the same sub-channel to their MSs in the same frame both in uplink or downlink. Thus, MS1 and MS2, MS3 and MS4 will contend for the same sub-channels in some adjacent WBSs. There are two sessions in the network: the first is x_1^3 MS1-> MS3 and the second x_2^4 MS2->MS4. To simplify the simulation, we assume the capacity of each sub-channel has an i.i.d over (16/N)*[1, 2, 3, 4, 5] (*N* is the number of OFDMA sub-channels). Each forwarding link has a capacity of $\Gamma = 50$. In the implementation, we use a small step size $\varepsilon(t) = 0.001$ in (14).

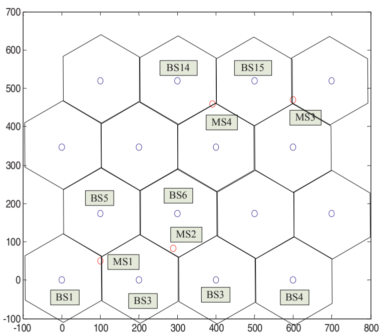

Fig 3. Scenario in the simulation

A. Convergence of the algorithm

Variation of data rates of the two flows with iteration (or the number of frames) for 16 sub-channels is illustrated in Fig. 4. It can be seen from the figure that two source rates quickly converge to the vicinity of the optimal values, 11.8 and 3.7, respectively, but oscillate around them. The oscillation is due to the time-varying of access channels and discrete OFDMA sub-channel allocation and forwarding link scheduling. The time averaging of the source rates of both flows results in a smooth convergence, as shown in Fig. 5.

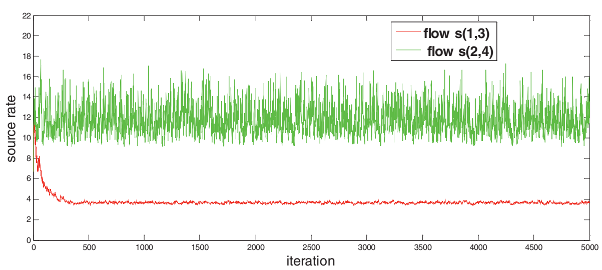

Fig 4. Source rates of two flows with bit rates, x_1^3 and x_2^4 (N=16)

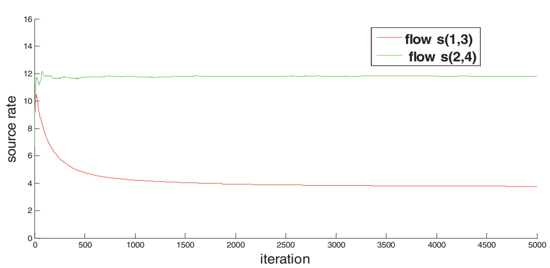

Fig 5. Average source rates of two flows (N=16)

B. Queue length and Stability of the network

Fig. 6 shows the queue lengths in sources MS1 and MS2, respectively when the number of sub-channels is 32. From the figure we can see that the queue lengths in MS1 and MS2 converge rapidly to the vicinity of the contants and oscillate around them (since $\lambda(t) \to \lambda^*$ as $t \to \infty$), which shows both queue lengths are bounded and thus stable. Similarly, Fig. 7 shows the average length of the queues in the network, and we can see from the figure that it is also bounded, which means that the network is stable with the proposed algorithm.

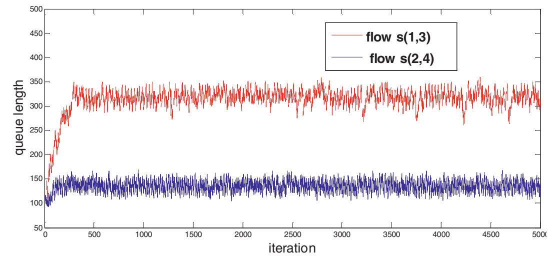

Fig 6. Queues lengths in MS1 and MS2 (N=32)

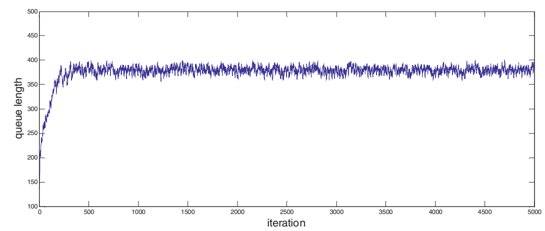

Fig 7. Average length of the queues in the network

C. Performance of Multi-receiver diversity.

In the end, we compare the performance of a single-receiver scheme with that of a multi-receiver scheme. For such a single-receiver scheme, we assume that an MS can only access one WBS. In the setup, thus, we let MS1 attach to BS1, MS2 to BS6, MS3 to BS15, and MS4 to BS14. Because an MS can access multiple WBSs by using different OFDMA sub-channels, then a multi-receiver scheme can increase diversity space and thus uplink and downlink access capacity. Accordingly it can fully utilize the capacity of forwarding links between WBSs. This is shown in Fig. 8 in which it can be seen that the converged average data rates of the multi-receiver scheme are greatly larger than those of the single receiver scheme.

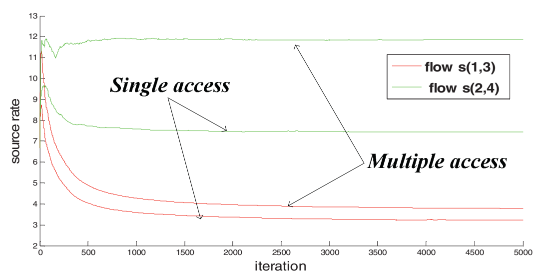

Fig 8. Comparison of single receiver and multiple receiver schemes (N=32)

VI. CONCLUSION

We have presented a jointly optimized end-to-end data transmission control and resource allocation strategy for wireless infrastructured distributed cellular networks (WIDCNs) that have wireless-connected BSs, time-varying OFDMA access links and multi-receiver schemes. With formulating the joint design as a stochastic network utility maximization (SNUM) problem, we deduced distributed dynamic control algorithms for end-to-end data transmission using dual decomposition method and stochastic optimization theory. The algorithms are shown to be adaptable to OFMDA channel variation and to converge asymptotically to the optimal solution. An algorithm for distributed OFDMA sub-channel allocation access links and an algorithm for the coordination of links between WBSs have been developed. Through simulation, we have showed that the proposed algorithms are convergent and stable, and that the multi-receiver scheme is superior to the single-receiver scheme

VII. Acknowledgements

In this work Lei You and Ping Wu are financially supported by VINNOVA Sweden through grant 2008-00954. Mei Song, Junde Song and Yong Zhang are financed by the Ministry of Science and Technology (MOST) China through National International Science and Technology Cooperation Project (NO. 2008DFA12090).

References

[1] M. Chiang, S. H. Low, R. A. Calderbank, and J. C. Doyle, Layering as optimization decomposition, Proceedings of the IEEE, vol. 95, pp. 255 - 312 , Jan. 2007.

[2] M. Chiang, Balancing transport and physical layers in wireless multihop networks: Jointly optimal congestion control and power control, IEEE J. Sel. Area Comm., vol. 23, no. 1, pp. 104-116, Jan. 2005.

[3] L. Xiao, M. Johansson, and S. Boyd, Joint routing and resource allocation via dual decomposition, IEEE Trans. Commun., vol. 52, no. 7, pp. 1136–1144, Jul. 2004.

[4] L. Tassiulas and A. Ephremides, Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks, IEEE Transactions on Automatic Control, vol. 37, no. 12, pp. 1936–1948, 1992.

[5] M. J. Neely, E. Modiano, and C. E. Rohrs, Dynamic power allocation and routing for time varying wireless networks. Proceedings of Infocom, pp.745-755, vol.1, 2003.

[6] A. L. Stolyar, Maximizing queueing network utility subject to statbility: greedy primal-dual algorithm, Queueing Systems, 50(4):401-457, 2005.

[7] L. Chen, S. H. Low, M. Chiang, and J. C. Doyle, “Cross-layer congestion control, routing and scheduling design in ad hoc wireless networks,” in Proc. IEEE INFOCOM, pp.1-13, Barcelona, Spain, Apr. 2006.

[8] Yu. Ermoliev. Numerical Techniques for Stochastic Optimization. Springer-Verlag, 1988.

[9] Y. H. Lin and R. Cruz. Opportunistic link scheduling, power control, and routing for multi-hop wireless networks over time-varying channels. Proceedings of 43rd Annual Allerton Conference on Communication, Control, and Computing, September 2005.

[10] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[11] X. Lin and N. Shroff, Joint rate control and scheduling in multihop wireless networks, 43th IEEE CDC, pp.1484-1489, Vol.2, 2004.

[12] R. Preis, Linear time 1/2-approximation algorithm for maximum weighted matching in general graphs, 16th STACS, (Eds., C, Meinel and S. Tison), LNCS 1563, Springer, 1999.

[13] L. Georgiadis, M. J. Neely, and L. Tassiulas. Resource allocation andcross-layer control in wireless networks. Foundations and Trends inNetworking, vol. 1, no. 1, pp. 1-149, 2006.

[14] Gaurav Sharma , Ravi R. Mazumdar , Ness B. Shroff, On the complexity of scheduling in wireless networks, Proceedings of the 12th annual international conference on Mobile computing and networking, September 23-29, 2006, Los Angeles, CA, USA