Fair Resource Allocation for OFDMA Multi-cell Networks

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***Abstract*—Fair resource allocation in OFDMA networks is studied in this paper. We propose a distributed algorithm requiring minimum inter-cell information that embodies the principle of balancing advantaged and disadvantaged user traffic flows. A simple interference deterministic channel model assuming zero queuing delay is used. We propose a hybrid power and bandwidth allocation algorithm. A two-dimensional simulation conducted on both uniform and random-sized-cells shows the benefits are significant when fair allocations are desired.**

***Index Terms*—dynamic bandwidth allocation, power control, OFDMA, fair resource allocation, distributed algorithm**

I. Introduction

In recent years, there has been increasing research interest in fair resource allocation in OFDMA wireless networks. While there are many results on the topic, the best schemes remain elusive. This is because different quality-of-service (QoS) requirements are used among existing studies, where the solution is usually application dependent. The major difficulty in dynamic channel and power allocation comes from interference coupling; resource allocation decisions for one user affect the others. Users that generate high interference to neighboring cells slow convergence of distributed schemes since other users must react to their changed resources with changes of their own. Further, as these are typically the users farther from their base stations and thus in need of more resources, fair allocation of rates also tends to reduce the overall capacity. Complicating matters further, the effectiveness of particular heuristics such as interference avoidance (e.g., in dynamic channel allocation) vs. interference averaging (e.g., as in CDMA) depends on the load of the network. Finally, in comparing algorithms, the appropriate quality of service measure depends upon the type of traffic (data vs. media). We believe that the most important application is that of high loading of media traffic, since without the ability to queue data it presents the most difficult resource decisions. At low loading, resources are more abundant and performance will only improve.

The novelty of our work is to propose a new distributed hybrid dynamic reallocation algorithm for bandwidth and power. It has the following features: i) It targets reduced user data rate variance rather than higher cell throughput. Low data rate variance is desirable in multimedia applications. ii) Our algorithm is non-iterative, to produce fast convergence. iii) The algorithm is truly distributed. It adapts to dynamic traffic load, and requires minimum inter-cell information exchange. We simulated the algorithm in a 2-dimensional large scale network consisting of 100 cells for both uniform-sized-cells (USC) and random-sized-cells (RSC). This provides robustness against cell edge effects.

In multi-cell OFDMA networks, uplink and downlink dynamic resource allocation differ in how they contribute interference into neighboring cells. We focus analysis on the uplink in this paper. However, simulations were done on both the uplink and downlink, showing improved QoS in both directions.

In our study, a simple interference channel model based upon the deterministic channel model is used. The variance of averaged user flow data rate is used as the measurement of fairness. Our goal is to achieve a high flow rate with low variance. We first review the literature on this topic in section II, and present our formulation of the problem in section III-B. Then optimization principles are derived from the formulation in section III-C. Based on these principles, a distributed power control and bandwidth allocation algorithm is designed in section IV. Finally, evaluation is done by simulating the algorithm in 2-dimensional USC and RSC, and results are explained in section V. For RSC, base stations are randomly located according to a Poisson point process (PPP) following the model for the node locations used in [1], [2] and [3]. We present our conclusions and suggestions for future work in section V.

II. Literature Survey

The majority of prior research on the resource allocation for inter-cell interference (ICI) reduction. Most of the proposed algorithms can be grouped by the following criteria: static or dynamic algorithm, centralized or distributed, iterative or non-iterative.

Fixed sub-channel allocation (FCA), fractional frequency reuse (FFR) and soft frequency reuse (SFR) are static bandwidth allocation algorithms. They reduce ICI by pre-planning the bandwidth among adjacent cells [4], [5], [6] and [7]. Fixed sub-channel allocation algorithms have low spectral efficiency, since they do not dynamically adapt to network traffic load variation. Dynamic channel allocation (DCA) techniques were invented to address this issue. Channel segregation (CS) is such an algorithm explained in [4]. CS prioritizes all sub-channels and employs a learning algorithm to update the sub-channel priorities according to the sub-channel historical utility information.

For multi-cell networks, resource allocation performed by centralized authorities. One way to do it is to organize cells into clusters and have the radio network controller (RNC) allocate sub-channels to users in different cells. RNC will make sure two adjacent cells do not allocate the same sub-channel to their users [8]. A similar approach is taken by [9]. The difference is that [9] only assigns disjoint sub-channels to cell edge users. Users in the cell center area can be assigned any sub-channels. The requirement of using a centralized network controller limits its application to networks like femto cells and sensor networks. Therefore distributed resource allocation algorithms are favored in general. There are two major approaches; game-theory-based and graph-based [10]. Game-theory-based algorithms usually define utility function, action set and players corresponding to user data rate, resource allocation and network node or users respectively [11], [12] and [13]. The game solution is usually obtained by an iterative algorithm, which is in general inefficient. A graph-based sub-channels and power joint allocation algorithm is described in [14]. Users are represented by nodes in the graph. Two users are connected by an edge if they may interfere each other. Then the graph is colored and sub-channels are allocated according to colors to avoid interference. The computational complexity of this algorithm is very high when the number of users and channels become large.

Most optimizations are implemented by an iterative algorithm [15], [16], [17], [18], [19] and [20]. Iterative algorithms may need to reduce traffic load or sacrifice optimality to guarantee convergence, since they are sensitive to channel dynamics. However, they are scalable and are widely used in power control and channel assignments.

Algorithms differ according to the QoS measurements being optimized. Meeting a target transmission rate for all users is used by [15]. This is appropriate for data traffic with queuing. However, for delay sensitive traffic, i.e. multimedia traffic flows, low variance is preferred. A fairness index in terms of rate proportional constraints is used in [21]. The max fairness is achieved when all users have the same data rate.

The common issue the various resource algorithms address is the need to meet some QoS constraint for all users in the face of vastly different losses to the home base station and interference effects on neighbors, generally with users near cell centers having high SNR and low interference effects, and users near the edges having low SNR and large interference effects. Power control to equalize SNRs (and thus rates) has only polynomial complexity, but exacerbates the interference problem in precisely the users who most contribute to it, and due to the logarithmic dependence of maximum rate on SNR, extract an exponential price in total interference. Allocating extra channels (bandwidth) to such users by contrast linearly increases rate with only a linear increase in interference, but inherits an NP hard allocation problem. This motivates treating outer users (near the cell boundaries) differently than inner users, but fixed re-use for outer users can be inefficient and in any case is not practical for irregularly shaped and sized cells as are common in urban areas. Therefore, we seek means to capture this intuition with a distributed algorithm.

A more subtle issue is the question of what traffic loading a resource allocation algorithm should be optimized for. At low loading, there are many possible solutions, and all will work well since resources are plentiful. Whether one works better than another in this regime is not that important; the regime that causes blocking and dropping of transmission is high loading. This makes avoidance strategies markedly less effective and shows the cost of fixed re-use approaches. Therefore, in the results presented in this paper we consider high loading, and attempt to apply the intuition discussed above to design low complexity distributed algorithms that mitigate as far as possible the interference being caused to nearby cells while providing fairness of service.

III. Problem Formulation and Analysis

A. System Model

We describe the problem in three aspects: user traffic model, channel model, and optimization goal.

The Erlang loss model is used for the user traffic model. User flows arrival independently following a Poisson process. User traffic is not queued, meaning if the user arrives when there is no vacant channel, it will be blocked and lost. The amount of data in each flow is exponentially distributed. User flows are uniformly scattered in a cell. A user flow retires when all its data are transmitted, and releases all resources allocated to it.

In a multi-cell OFDMA network, each cell has a fixed number of channels. Transmission over a channel is further divided into time slots (ticks). We have selected the simplest model that captures the fact that some users are geographically advantaged, and that thus demands resource allocation if fairness is to be achieved. It includes only distance loss and interference. The model assumes that transmission is at the Shannon capacity, limited by interference, or alternatively, the limits of linearity of the receiver (in our case, 10 bits). The interference and linearity limits mean that noise can be neglected, as for the deterministic channel model. The model implicitly assumes that a high diversity order is achieved to ameliorate multipath fading, so that the latter is neglected. While shadowing losses would change the results somewhat, distance loss is far more important in its effects. Similarly the arrival model was selected as being particularly simple, but also a reasonable match to media traffic, which is more challenging for networks than data due to its latency constraints.

Most of proposed models use different objective functions that fall into two major categories: marginal rate (MA) and rate adaptive (RA) [22]. MA attempts to minimize the total transmit power while providing the required QoS for each user. The RA objective is to maximize the total data rate of the system with a constraint on the total transmit power. We take a different approach. Our optimization goal is to minimize the user flow rate variance, and improve network data throughput by means of reducing ICI. [23] summarizes different ICI coordination methods. However, these methods exchange indication signaling between cells, which is what we try to avoid here.

B. Formulation

To formulate the problem, we start from TX bits computation. We use a simple path loss model $\frac{p}{d^4}$, where p is transmission power and d is the distance between the transmitter and receiver. For each channel the number of TX bits is $log(1+\frac{p}{d^4 c})$. c is the interference level seen at the receiver. Current technology limits low-cost radios to support digital modulation formats of 6 bits per symbol or less; based on technological trends, we will suppose that up to 10 bits is plausible in the medium term. Hence, the equation to calculate rate is $r = min(10, log(1+\frac{p}{d^4 c}))$, where r is the instantaneous rate, number of TX bits for one channel in a tick.

The "min" function makes this formulation hard to analyze. In order to eliminate "min", we introduce the noise floor $n_0 = \frac{p_{max}}{2^{10}-1}$, where p_{max} is the max user transmission power possible. When the channel interference level is 0, the max number of bits that can be transmitted is 10. The user rate becomes $r = log(1+\frac{\alpha_i p/a_i}{d_i^4(c_k+n_0)})$).

The major optimization goal is to improve fairness among multiple users. We achieve this by minimizing the difference $\delta = r_u - r_n$, where r_u is the user average data rate and r_n is the average traffic rate of entire network. r_n is the only information the algorithm requires from other cells in the same network. With the knowledge of the difference, we define excess bits $e = \delta * t$, where t is the total time ticks a user flow has transmitted up to the moment. We determine the disadvantaged user flows by checking if the excess bits are below a threshold, which is negative.

Assume there are n active users in the cell, and the same number of channels in use. The algorithm runs an optimization in every tick. The power control and channel allocation problem is formulated as:

$$\min \sum_{i=1}^{n} \frac{\alpha_i p}{(D-d_i)^4} \tag{1}$$

$$\text{subject to:} \sum_{k=1}^{n} a_{ik} log(1+\frac{\alpha_i p/a_i}{d_i^4(c_k+n_0)}) = -e_i \tag{2}$$

$$\sum_{i=1}^{n} a_{ik} = 1 \quad (k = 1, 2, \cdots, n) \tag{3}$$

$$\sum_{k=1}^{n} a_{ik} = a_i \tag{4}$$

$$0 < \alpha_i p \leq p_{max} \tag{5}$$

p - default flow transmission power
p_{max} - flow transmission power upper limit
α_i - flow transmission power scaler
c_k - interference level of sub-channel k
e_i - excess bits for flow i
a_{ik} - channel k allocation indicator, $a_{ik} \in 1, 0$
r_{ik} - flow i's rate on sub-channel k

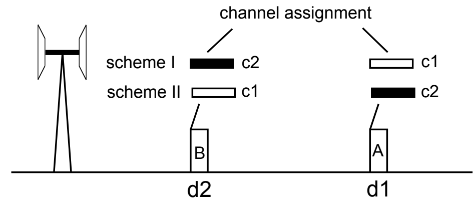

Fig. 1. Two users two channels assignment

d_i - the distance between user i to its BS
D - Distance between the BS to its nearest neighbor BS

Equation (2) is to make disadvantaged flows catch up to the average if they are lagging behind. This is to minimize user flow rate variance. Equation (3) guarantees one channel is allocated only to one flow. Equation (5) defines the dynamic range of power control. α_i and a_{ik} are optimization variables. The objective function minimizes the total interference power a cell emits to the environment. We hypothesize that minimizing the interference will improve the data throughput of the whole network. The major difference between the uplink and downlink models is in how the interference gets calculated. For uplink interference, sources are flows in other cells, and the distance of interest is from sources to the BS tower in the neighboring cell. For the downlink, BS towers interfere with users in neighboring cells.

C. Formulation Analysis

The idea behind the model is to find the optimal channel assignment to satisfy equation (2) and minimize total interference power emitted into the environment. Both channel assignment and d_i determine α_i to achieve optimality. One major challenge here is the channel state (CS) estimation. The CS of a sub-channel is hard to predict because dynamically reallocating sub-channels and power changes it. The algorithm proposed in [24] simply applies CS measured in the previous time tick into the next tick's resource reallocation calculation.

1) Channel Assignment Principle: Instead of finding the optimal solution, we try to establish optimization principles through simplified examples and design a heuristic algorithm based on these principles. These principles apply to both the uplink and downlink. However, the following discussion is based on the uplink.

First, assume there are two channels allocated to two users A and B at locations d_1, d_2 in a cell. They are both disadvantaged users. In other words, their excess bits are negative and below a threshold. Without loss of generality, let channel interference levels be $c_1, c_2, (c_1 < c_2)$. Figure 1 describes the example. The objective function then becomes $min\ \frac{\alpha_1 p}{(D-d_1)^4} + \frac{\alpha_2 p}{(D-d_2)^4}$. We have two possible channel allocation schemes: 1. $c_1 \to A$, $c_2 \to B$; 2. $c_2 \to A$, $c_1 \to B$. Since there is only one channel assigned to each user, according to (4) we obtain $a_1 = a_2 = 1$. Next, we compute the power scaler α_1, α_2 for the two schemes respectively.

Scheme I: solve equation (2). We have:

$$\because log(1+\frac{\alpha_1 p}{d_1^4(c_1+n_0)}) = -e_1 \therefore \frac{\alpha_1 p}{d_1^4(c_1+n_0)} = 2^{-e_1}-1$$

$$\alpha_1 p = d_1^4(c_1+n_0)(2^{-e_1}-1) \quad \alpha_1 = d_1^4(2^{-e_1}-1)(c_1+n_0)/p$$

Similarly $\alpha_2 = d_2^4(2^{-e_2}-1)(c_2+n_0)/p$

The objective function for scheme I becomes:

$$V_1 = \alpha_1\frac{p}{(D-d_1)^4} + \alpha_2\frac{p}{(D-d_2)^4}$$

$$= \frac{d_1^4(2^{-e_1}-1)(c_1+n_0)}{(D-d_1)^4} + \frac{d_2^4(2^{-e_2}-1)(c_2+n_0)}{(D-d_2)^4}$$

Let $F_1 = \frac{d_1^4}{(D-d_1)^4}(2^{-e_1}-1), F_2 = \frac{d_2^4}{(D-d_2)^4}(2^{-e_2}-1)$. The objective function can be rewritten as: $V_1 = F_1(c_1+n_0) + F_2(c_2+n_0)$.

Scheme II

$$\alpha_1 = d_1^4(2^{-e_1}-1)(c_2+n_0)/p$$
$$\alpha_2 = d_2^4(2^{-e_2}-1)(c_1+n_0)/p$$

The objective function for scheme II becomes:

$$V_2 = \alpha_1\frac{p}{(D-d_1)^4} + \alpha_2\frac{p}{(D-d_2)^4}$$
$$= F_1(c_2+n_0) + F_2(c_1+n_0)$$

Schemes I and II are the only two possibilities for channel assignment in this example. We should choose I if $V_1 < V_2$ and II otherwise. Without loss of generality, we assume $e_1 < e_2 < 0, d_1 > d_2$. This means A is further away from the BS than B and its average flow rate is lower than B's. With this assumption, the following inequalities hold:

$$\because (\frac{d_1}{D-d_1})^4 > (\frac{d_2}{D-d_2})^4, (2^{-e_1}-1) > (2^{-e_2}-1) \therefore F_1 > F_2$$

$$\because c_1 < c_2, \quad c_1 - c_2 < 0 \therefore F_1(c_1-c_2) < F_2(c_1-c_2)$$

$$F_1c_1 - F_1c_2 < F_2c_1 - F_2c_2 \Rightarrow F_1c_1 + F_2c_2 < F_1c_2 + F_2c_1$$

$$F_1c_1 + F_2c_2 + (F_1+F_2)n_0 < F_1c_2 + F_2c_1 + (F_1+F_2)n_0$$

$$F_1(c_1+n_0) + F_2(c_2+n_0) < F_1(c_2+n_0) + F_2(c_1+n_0)$$

$$\therefore V_1 < V_2$$

The above derivation shows that assigning the cleaner channel (channel with lower interference level, c_1 in this case) to the disadvantaged user (A) yields a better objective function. Therefore we can conclude that allocating cleaner channels to disadvantaged flows reduces the overall interference power the cell produces to neighbors. This is because most of the disadvantaged users are in remote locations around the cell edge. Cleaner channels in general indicates that it is not used by neighbor cells or the users are far from the cell boundary. Hence transmitting on it will not introduce effective interference to neighbors. Note that this heuristic is the basis for avoidance strategies and methods such as assigning non-trivial channel re-use distances to flows near cell boundaries. It also supports strategies such as pairing users near cell boundaries with those near base stations in nearby cells.

2) Hybrid Optimization Principle: To further increase the QoS and capacity, we introduce power control to form a hybrid optimization method. A similar approach is used in [25]. There are two power control schemes, signal-interference-ratio (SIR) based, and distance-based-power-control (DPC). We discuss the two schemes in turn.

Given user flow location, SIR based power control is a rate based algorithm. Since dynamic-channel-reallocation (DCR) is rate based, power control based on SIR measurement is an enhancement of channel reallocation rather than an independent optimization. Because user flows with lower rates already get more and cleaner channels after DCR, and TX bits are capped at 10 bits/tick, SIR based power control does not gain much. Our simulation results presented in section V support this.

DPC, on the other hand, is in general an orthogonal optimization to DCR. A user may determine its distance to a BS by measuring downlink signal power loss. The concern for this scheme is that user flows near the cell border would get more TX power, and introduce more interference to neighbor cells. We analytically show the effect of DPC in a simplified example.

Assume there are two cells (c1, c2) adjacent to each other. Power scalar = d^4. P is default TX power. There are flows f1, f2 in c1 and c2. Let d = distance(f1, c1), αd = distance(f2, c2).($\alpha > 0$), and g = distance(f1,f2)

The interference from f1 to c2 without power control is:

$$I = \frac{P}{(\alpha d + g)^4} \tag{6}$$

With power control it is:

$$I_p = \frac{d^4 P}{(\alpha d + g)^4} \tag{7}$$

TX power for f2 is P for default and $(\alpha d)^4 P$ with power control adjustment. The corresponding SIR for f2 is:

$$SIR = \frac{P}{(\alpha d)^4 I} = \frac{(\alpha d+g)^4}{(\alpha d)^4} \tag{8}$$

$$SIR_p = \frac{(\alpha d)^4 P}{(\alpha d)^4 I_p} = \frac{(\alpha d+g)^4}{d^4} \tag{9}$$

Compare SIRs with and without power control:

$$\frac{SIR_p}{SIR} = \frac{(\alpha d+g)^4}{d^4}\frac{(\alpha d)^4}{(\alpha d+g)^4} = \alpha^4 \tag{10}$$

The result shows for $\alpha > 1$, (f2 is farther away from c2 than f1 to c1), f2's SIR still increases even if f1 increases its power. Therefore we conclude that remote flows always benefit from loss based power control in a network. Based on this conclusion, we can reasonably believe that DPC is beneficial in two aspects. First, it helps further reduce the user flow rate variance. This is because remote users are more likely to be disadvantaged ones. Second, increasing TX power of remote users improves their flow rate, and hence improves network throughput. We will show this matches to our simulation results.

These comments may strike the reader as contradictory to our claims regarding the use of bandwidth allocation to minimize ICI, since power control necessarily increases it. However, when we have already allocated channels in order to minimize ICI, the dynamic range of power control is reduced and the interference has less effect: channels have been allocated to minimize interference coupling. The overall network capacity for fair allocation of rates may be higher or lower, depending on the difference in rate benefit to the user gaining power vs. the users whose rate is decreased via the resulting increased interference. The result depends upon loading and the assumed propagation conditions. Simulations are required to determine the best balance between bandwidth and power allocation for a given scenario.

Given these heuristics we design a DCR and DPC hybrid optimization algorithm, which is described in more detail in following section.

IV. Power Control and Bandwidth Allocation Hybrid Optimization Algorithm

Based on the formulation and analysis presented in section III, the hybrid optimization algorithm we propose consists of three sub-algorithms. Every cell in the network runs them independently. *NetAvgRate* is the network average traffic rate known by all cells. *FlowAvgRate* is the user average data rate.

Algorithm 1: Flow Sorting Algorithm

for all flow in cell **do**
  compute flow average rate *FlowAvgRate*
  compute network average rate *NetAvgRate*
  if flow's *FlowAvgRate* = 0 **then**
    Save flow into Rate0FlowSet
  end if
end for
for all flows $\notin$ Rate0FlowSet **do**
  TxTime = current time - flow arrive time
  ExcessBits = *FlowAvgRate* - *NetAvgRate*
  ExcessBits = *ExcessBits* * *TxTime*
  if flow's *ExcessBits* $\leq$ *LowThreshold* **then**
    Save it into SlowFlowSet
  else if *ExcessBits* $\geq$ *HiThreshold* **then**
    Save it into HiFlowSet
  else
    Save it into MidFlowSet
  end if
end for

The sorting algorithm divides all the active flows in a cell into four sets. They are Rate0FlowSet, HiFlowSet, MidFlowSet, and SlowFlowSet, respectively. Flows in Rate0FlowSet, are most likely newly arrived user flows. They have zero data transmission. HiFlowSet and SlowFlowSet, as their names suggest, contain advantaged and disadvantaged flows. *LowThreshold* and *HiThreshold* are two tunable parameters.

Algorithm 2: Channel Reallocation Algorithm

for all flow $\in$ Rate0FlowSet **do**
  Assign one channel to each flow
end for
for all flow $\in$ HiFlowSet **do**
  Deprive channel from flow
  add the channel into ChannelPool
end for
NumOfOccupCHs = number of occupied channels
NumOfFlows = number of flows
if *NumOfOccupCHs* $<$ *NumOfFlows* **then**
  Diff = *NumOfFlows* - *NumOfOccupCHs*
  pick up *Diff* vacant channels
  add these channels into ChannelPool
end if
ChannelPoolSize = total number of channels in ChannelPool
Sort channels in ChannelPool in ascending order of interference level
Sort flows in SlowFlowSet in ascending order of *FlowAvgRate*
TotSlowness = $\sum_{flow \in SlowFlowSet}$ flows' *ExcessBits*
for all flow $\in$ SlowFlowSet **do**
  NumChs = *ChannelPoolSize* $\times$ *ExcessBits* $\div$ *TotSlowness*
  NumChs = $\lceil$ *NumChs* $\rceil$
  Allocate *NumChs* of channels from *ChannelPool* top to the flow
end for

Algorithm 2 implements the channel assignment principle. It allocates channels with lower interference, and more channels to slower flows. A high rate flow is deprived transmission opportunity until it becomes a low rate flow. Flows with rate in between remain unchanged. We will see from simulation results that this algorithm reduces flow rate variance significantly.

Algorithm 3: Distance Based Power Control Algorithm

for all flow $\in$ SlowFlowSet **do**
  D = flow distance to BS
  $S = D^4$
  if S $>$ PowerUpLimit **then**
    Set flow TX power scaler = PowerUpLimit
  else
    Set flow TX power scaler = S
  end if
end for

The DPC algorithm calculates the flow TX power scaler directly from its distance to the BS. DPC runs after the channel allocation algorithm to form the hybrid resource allocation

TABLE I
UNIFORM-SIZED-CELLS SIMULATION

Simulation Case	DCR	DPC	Traffic load (μ)	Block Probability	Average Flow Rate	Flow Rate Variance
Uplink	off	off	208	0.0103725	3.35845	4.68144
	on	off	195	0.0103518	2.19499	0.366221
	off	on	207	0.0109084	2.62311	1.29451
	on	on	207	0.010478	2.20599	0.153314
Downlink	off	off	186	0.00986185	3.26002	5.29739
	on	off	166	0.0125137	1.86105	0.502044
	off	on	189	0.00995174	2.55796	1.50823
	on	on	185	0.01101372	1.89913	0.259036

TABLE II
RANDOM-SIZED-CELLS SIMULATION

Simulation Case	DCR	DPC	Traffic load (μ)	Block Probability	Average Flow Rate	Flow Rate Variance
Uplink	off	off	93	0.0100228	4.10052	7.05569
	on	off	83	0.010998	2.82515	3.52516
	on	on	93	0.0109574	2.41013	1.56038

algorithm.

V. SIMULATION

Much prior research has simulated multi-cell OFDMA network resource allocation algorithms with 7 or even fewer cells. In order to better evaluate the heuristic algorithm, we simulate on a large scale network consisting of 100 cells for USC and 91 cells for RSC. All cells work independently and simultaneously. The results, however, are only collected from 36 cells also in the middle area of the network. Fig 3 shows the layout of RSC with different cells marked by different colors. This layout is generated according to PPP suggested in [1], [2] and [3]. A square in the center area includes the cells, whose performance statistics are collected during the simulation. We use this method to mitigate the inaccuracy introduced by cells at network edges. Given the computational complexity of our simulation, we ran simulations on a computer cluster. Simulations run for a predefined number of time ticks. User flow averaged data rate, block probability and rate variance are computed. We evaluate algorithm performance at a 1% blocking rate, which is achieved by adjusting the traffic load factor μ.

A. Uniform-sized-cells

Table I presents USC simulation configuration and results. We can see that the user flow rate variance is significantly reduced with our optimization. This is also shown in figure 2, which has two histogram plots of user flow rate. The rate histogram with optimization turned off is on the left. The one on the right is with DCR and DPC turned on. The results also indicate that DCR plays a major role in optimization.

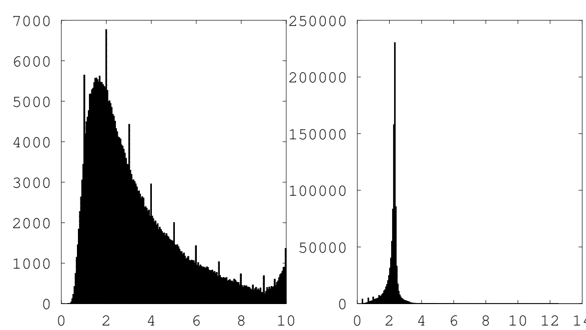

Fig. 2. USC user rate distribution

B. Random-sized-cells

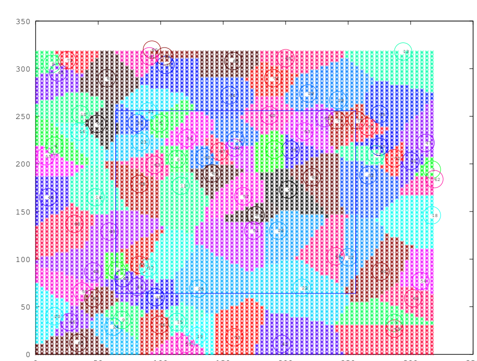

Fig. 3. RSC network layout

The network layout for RSC is shown in figure 3. It is

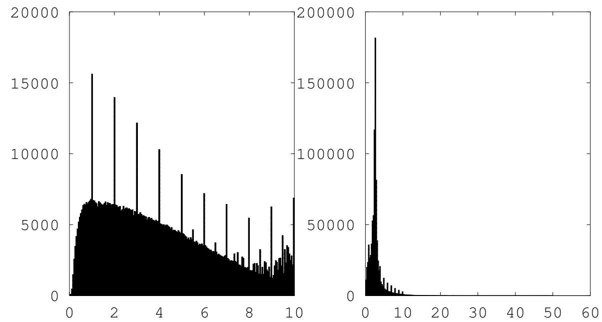

Fig. 4. RSC user rate distribution

constructed by first generating BS' positions following PPP. Then for every potential MS location, we find its nearest BS and mark it by the same color. All BS' identification numbers are noted in the layout. Table II shows uplink simulation configuration and results. There is more than a 55% traffic load drop from USC to RSC. This is because the ICI gets worse in RSC. For USC, the flow rate variance drops 96.8% when the hybrid algorithm is on. For RSC case, it is 78%. Figure 4 shows the user flow rate distribution with and without optimization. Overall our hybrid algorithm works better in USC than RSC. This is because the geographical randomness introduces extra variance in the flow rate. However, our hybrid algorithm still shows significant improvement.

VI. Conclusion

Our analysis and the simulation results clearly shows that in order to reduce the user flow rate variance in a multi-cell OFDMA network while providing high throughput, the hybrid bandwidth reallocation and power control algorithm performs very well. The algorithm was successful in producing fair allocations in a distributed fashion in conditions of high loading. In the future, we plan to investigate additional impairments such as user mobility in networks such as overlays of macro and femto cells for which convergence time of resource allocation becomes more critical. This may demand measures such as mobility prediction and allocation of users among the layers according to both resource availability and user velocity.

References

[1] S. Singh, J. Andrews, and G. de Veciana, "Interference shaping for improved quality of experience for real-time video streaming," *Selected Areas in Communications, IEEE Journal on*, vol. 30, no. 7, pp. 1259–1269, 2012.

[2] R. Ganti and M. Haenggi, "Interference and outage in clustered wireless ad hoc networks," *Information Theory, IEEE Transactions on*, vol. 55, no. 9, pp. 4067–4086, 2009.

[3] R. Ganti, F. Baccelli, and J. Andrews, "Series expansion for interference in wireless networks," *Information Theory, IEEE Transactions on*, vol. 58, no. 4, pp. 2194–2205, 2012.

[4] I. Katzela and M. Naghshineh, "Channel assignment schemes for cellular mobile telecommunication systems: A comprehensive survey," *Communications Surveys Tutorials, IEEE*, vol. 3, no. 2, pp. 10–31, 2000.

[5] E. Yaacoub and Z. Dawy, "A survey on uplink resource allocation in ofdma wireless networks," *Communications Surveys Tutorials, IEEE*, vol. 14, no. 2, pp. 322–337, 2012.

[6] A. Hamza, S. Khalifa, H. Hamza, and K. Elsayed, "A survey on inter-cell interference coordination techniques in ofdma-based cellular networks," 2013.

[7] Y. Yu, E. Dutkiewicz, X. Huang, and M. Mueck, "Adaptive power allocation for soft frequency reuse in multi-cell lte networks," in *Communications and Information Technologies (ISCIT), 2012 International Symposium on*, pp. 991–996, 2012.

[8] J. Li, X. Chen, C. Botella, T. Svensson, and T. Eriksson, "Resource allocation for ofdma systems with multi-cell joint transmission," in *Signal Processing Advances in Wireless Communications (SPAWC), 2012 IEEE 13th International Workshop on*, pp. 179–183, 2012.

[9] Y. Yu, E. Dutkiewicz, X. Huang, and M. Mueck, "A resource allocation scheme for balanced performance improvement in lte networks with inter-cell interference," in *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, pp. 1630–1635, 2012.

[10] E. Pateromichelakis, M. Shariat, A. ul Quddus, and R. Tafazolli, "On the evolution of multi-cell scheduling in 3gpp lte / lte-a," *Communications Surveys Tutorials, IEEE*, vol. 15, no. 2, pp. 701–717, 2013.

[11] Q. D. La, Y. H. Chew, and B. H. Soong, "Performance analysis of downlink multi-cell ofdma systems based on potential game," *Wireless Communications, IEEE Transactions on*, vol. 11, no. 9, pp. 3358–3367, 2012.

[12] L. Wang, Y. Xue, and E. Schulz, "Resource allocation in multicell ofdm systems based on noncooperative game," in *Personal, Indoor and Mobile Radio Communications, 2006 IEEE 17th International Symposium on*, pp. 1–5, 2006.

[13] Z. Liang, Y. Chew, and C. C. Ko, "Decentralized bit, subcarrier and power allocation with interference avoidance in multicell ofdma systems using game theoretic approach," in *Military Communications Conference, 2008. MILCOM 2008. IEEE*, pp. 1–7, 2008.

[14] Y. Yu, E. Dutkiewicz, X. Huang, and M. Mueck, "Downlink resource allocation for next generation wireless networks with inter-cell interference," *Wireless Communications, IEEE Transactions on*, vol. 12, no. 4, pp. 1783–1793, 2013.

[15] T. Thanabalasingham, S. Hanly, L. Andrew, and J. Papandriopoulos, "Joint allocation of subcarriers and transmit powers in a multiuser ofdm cellular network," in *Communications, 2006. ICC '06. IEEE International Conference on*, vol. 1, pp. 269–274, 2006.

[16] M. Moretti, A. Todini, A. Baiocchi, and G. Dainelli, "A layered architecture for fair resource allocation in multicellular multicarrier systems," *Vehicular Technology, IEEE Transactions on*, vol. 60, no. 4, pp. 1788–1798, 2011.

[17] Y. Liu, L. Cuthbert, X. Yang, and Y. Wang, "Qos-aware radio resource allocation for multi-cell ofdma network," in *Communication Systems (ICCS), 2012 IEEE International Conference on*, pp. 408–412, 2012.

[18] M. Qian, W. Hardjawana, Y. Li, B. Vucetic, J. Shi, and X. Yang, "Inter-cell interference coordination through adaptive soft frequency reuse in lte networks," in *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, pp. 1618–1623, 2012.

[19] M. Moretti, A. Todini, and A. Baiocchi, "Distributed radio resource allocation for the downlink of multi-cell ofdma radio systems," in *Teletraffic Congress (ITC), 2010 22nd International*, pp. 1–7, 2010.

[20] C. Hansen, C. Wang, and G. Pottie, "Distributed dynamic channel resource allocation in wireless communication systems," in *Signals, Systems and Computers, 1994. 1994 Conference Record of the Twenty-Eighth Asilomar Conference on*, vol. 1, pp. 78–82 vol.1, 1994.

[21] Z. Shen, J. Andrews, and B. Evans, "Adaptive resource allocation in multiuser ofdm systems with proportional rate constraints," *Wireless Communications, IEEE Transactions on*, vol. 4, no. 6, pp. 2726–2737, 2005.

[22] S. Sadr, A. Anpalagan, and K. Raahemifar, "Radio resource allocation algorithms for the downlink of multiuser ofdm communication systems," *Communications Surveys Tutorials, IEEE*, vol. 11, no. 3, pp. 92–106, 2009.

[23] C. Kosta, B. Hunt, A. Quddus, and R. Tafazolli, "On interference avoidance through inter-cell interference coordination (icic) based on ofdma mobile systems," *Communications Surveys Tutorials, IEEE*, vol. 15, no. 3, pp. 973–995, 2013.

[24] L. Liu, J. Zhu, X. Tao, Y. Wang, and P. Zhang, "A novel scheme for ofdma based e-utra uplink," in *Wireless Communications and Networking Conference, 2007.WCNC 2007. IEEE*, pp. 1373–1377, 2007.

[25] W. Shim, Y. Han, and S. Kim, "Fairness-aware resource allocation in a cooperative ofdma uplink system," *Vehicular Technology, IEEE Transactions on*, vol. 59, no. 2, pp. 932–939, 2010.