Optimized Frequency Allocation for Interference Mitigation in Femtocellular Networks

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***Abstract*—The recent introduction of femtocells enabled high data rates and better coverage indoors without the need for upgrading the network infrastructure or site establishment. However, Femtocells may suffer from major interference problems due to their dense and ad hoc deployment. In this paper, we propose a frequency assignment optimal scheme for downlink femtocell networks. The algorithm is based on optimization search rather than greedy or heuristic methods. Simulation results show that the proposed scheme outperformed two representative algorithms used for comparison.**

Keywords: femtocell; RRM; Interference; OFDMA

I. Introduction

[1] Femtocells have attracted significant attention as a solution to the problem of poor cellular indoor coverage and capacity. The importance of indoor coverage emerges as approximately two-thirds of calls and over 90% of data services occur indoors [1], while 45% of households and 30% of businesses experience poor indoor coverage [2]. Mobile operators need to provide a reliable and strong indoor coverage of voice, video and high speed data services to meet the ever increasing traffic demand. Femtocells are considered cost effective solution, which may provide high quality services and are expected to substantially reduce the operator's cost [3], [4] by offloading a significant amount of traffic to indoor spaces, freeing resources at the macrocells and helping outdoor users to receive an enhanced user experience. This process is also more accessible for indoor users; no special equipment or upgrades to current handsets are needed to operate the cells apart from the availability of the Femtocell Base Stations (FBSs) [5].

Due to their wireless nature, femtocell networks are subject to varying types and levels of interference [6]. Femtocell adhoc deployment might elevate interference to high levels, rendering the network inefficient [7] and sometimes unusable. The distributed nature of the problem makes it more challenging [8].

Interference occurs when two or more devices are transmitting 'near' each other. The definition of 'near' describes devices that are either physically near each other, or devices transmitting on similar frequencies or channels. The wireless medium faces different types of interference. For example, Inter-Symbol Interference (ISI), occurs when a symbol overlaps with succeeding symbols due to a delayed multipath signal. Furthermore, Inter-Carrier Interference (ICI) is the distortion of a carrier with other carriers. Co-Channel Interference (CCI) occurs when a device transmits on the same channel being used by a nearby device and Adjacent Channel Interference (ACI) happens when signals from a device transmitting on a certain channel jam the transmission of another device on another channel.

FBSs will be installed indoors to cover smaller areas when compared to traditional macrocells. Femtocells will always be overlaid on macrocells, unless deployed in remote areas, rendering such deployments as a two-tiered cell composed of a macro-tier and a femto-tier. This tiered deployment is vulnerable to cross-layer interference [9], [1], [6], which is the type of interference that occurs between cells of different types, such as Femto-to-Macro or Macro-to-Femto. Co-layer interference might also occur between two cells within the same layer.

Cross-layer interference can be significantly reduced by partitioning the available spectrum between the macrocellular and the femtocellular layers. However, this setup is considered less efficient and limits the amount of spectrum available for each layer [10]. The spectrum can be shared between the two layers resulting in larger system capacity, but rendering the system more vulnerable to interference. In [11], the authors proposed a hybrid spectrum sharing technique to achieve lower interference and a high capacity system simultaneously. Conversely, co-layer interference can be mitigated using proper frequency allocation and scheduling techniques, or dynamic power adjustment.

Different studies have recently addressed interference mitigation. In [12], the authors advocate the importance of distributed, self-optimizing schemes due to the fact that locations and the number of FBSs exploit a high level of uncertainty. The authors solve an optimization problem to control the overall transmission power of FBSs in a femtocell Orthogonal Frequency Division Multiple Access (OFDMA) network subject to individual rate and power constraints. An optimal solution requires information about all communication links, which is not readily available at all times, thus the authors proposed a distributed power control and scheduling

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algorithm.

Each user has a Quality of Service (QoS) constraint in the form of a threshold Signal to Interference and Noise Ratio (SINR) for a given service; the objective is to meet the required SINR at each user. The problem is modeled as a Linear Programming (LP) problem and solved using Particle Swarm Optimization, an example of a Swarm Intelligence (SI) approach. Many SI techniques exhibit the communal behavior of self-organizing entities in a distributed environment, such as ant colonies and animal herds. The proposed algorithm yields sub-optimal solutions on each femtocell. A heuristic sacrificial mechanism is employed, when no feasible solution is available, to defer some users' transmissions causing high interference based on the users' nominal SINR. The algorithm is based on heuristics and takes into account the femtocellular layer only. It involves a significant amount of signalling in favor of being decentralized.

In [13], the authors suggest two reuse partitioning schemes to be applied on overlaid - multiple layered - networks mainly involving the adaptation of cluster size to maintain high Signal to Interference Ratio (SIR), and applying channel assignment. Each hexagonal cell can be viewed as a set of concentric hexagonal cells, each with a different radius.

Two schemes were proposed: Maximal Dynamic Reuse Partitioning (MDRP) and Optimal Dynamic Reuse Partitioning (ODRP). In MDRP, excess channels are assigned to the innermost region, thus optimizing effective capacity from the subject cell. Comparatively, in ODRP, the system allocates unused channels in line with the areas and the distribution of users within the concentric SIR regions to maintain a certain Grade of Service (GoS). The adaptive nature of the proposed schemes makes them more powerful when compared to similar schemes.

In [14], the authors study the mitigation of downlink Femto-to-Macro interference through dynamic resource partitioning. The system is an OFDMA two-tiered network that uses universal frequency reuse. The transmission power of eNode B (eNB) is more than that of Home eNode B (HeNB) making it more likely that Macrocell User Equipments (MUEs), within the transmission range of femtocells, will cause interference to the surrounding User Equipments (UEs) and experience low SINR. The authors suggested prohibiting HeNB from accessing downlink resources that are assigned to neighboring MUEs to preserve universal frequency reuse. The interference to the most vulnerable MUEs is then effectively controlled at the cost of sacrificing a minor portion of the femtocell capacity. The study is based on the assumption that compromising some femtocell resources will lead to a better system throughput.

In [15], the authors propose a greedy based dynamic frequency assignment scheme by assigning the quietest channels to femtocells according to the received power level. The algorithm is two-fold: Each FBS scans the entire spectrum and selects the frequency bandwidth that describes the lowest received power level. Then, each FBS measures and sorts the received power level on every sub-channel of its frequency bandwidth and assigns the quietest sub-channels to its UEs. The algorithm works in a decentralized manner fast and without complexity but may not yield significant results when compared to other algorithms in the field.

In [16], the authors exploit coverage adaptation through balancing FBSs transmission powers. Power control decisions are made according to the available mobility information about the surrounding users. The purpose is avoiding pilot signal leakage outside a house, which may lead to increasing mobility events or decreasing power significantly resulting in the same outcome. The study is considered a contribution to the auto-configuration and self-optimization aspects in femtocell networks. The paper distinguishes between auto-configuration and self-optimization but allocating the former responsibility for initially configuring the FBS, while the self-optimization is concerned with enhancing the current configuration during the femtocell network operation.

In [17], the authors present the capacity-interference trade-off in a two-tier (femto-macro) environment comparing using shared bandwidth and dedicated bandwidth. The proposed scheme divides the area around a macrocell into inner and outer regions. A FBS within the inner region will not operate in a co-channel mode (shared bandwidth) to avoid interference. It instead uses a frequency band other than that used by the Macrocell Base Station (MBS). The authors attempt to find the best threshold that splits the two regions. Interference Limited Coverage Area (ILCA) is derived by estimating power levels using different path-loss models.

In [18], the authors study the effects of two power control schemes: Geo-static power control and adaptive power control. The transmitted power of a femtocell is based on its distance from the macrocell in geo-static power control. Comparatively, in adaptive power control, the transmitted power of femtocells are adjusted based on the network target rates, thus enhancing the femtocell users' throughput without compromising performance.

In [19], the authors use a non-cooperative game theoretic approach to model the distributed power control of femtocells, where each FBS determines the trasmit power with the maximum benefit. The system considers fairness in its model; femtocells serving more mobile stations are allowed to transmit at higher power levels to maintain service to its users. A payoff function based on revenue and cost was derived, where the cost is directly proportional with the transmission power to advise FBSs to reduce their transmission powers. Transmission powers reach Nash Equilibrium (steady state) in the simulated game. Game theory has been also used in other femtocell interference mitigation related studies [20], [21].

In [3], the authors study a centralized Radio Resource Management (RRM) for femtocell dense deployment and derive an objective function to maximize the system capacity. The problem was divided into two parts: sub-channel allocation and power allocation. The authors in [22] advocate the prevention of the usage of some frequencies by a femtocell if they are already assigned to a near MUE. Availability of macrocell frequency scheduling information is assumed.

Based on the aforementioned representative schemes from

TABLE I: Comparison of recent interference mitigation studies.

	Direction	Locality	Technique	Optimization Method
[12]	Downlink	Decentralized	Power control, frequency scheduling	Particle Swarm Optimization and heuristics
[13]	N/a	Decentralized	Channel allocation	N/a
[14]	Downlink	Decentralized	Spectrum partitioning	N/a
[15]	Downlink	Decentralized	Frequency planning, Frequency assignment	Greedy based
[16]	N/a	Decentralized	Power control	Feedback-based iterative optimization
[17]	Downlink	Centralized	Frequency planning	N/a
[18]	N/a	Decentralized	Power control	Feedback-based iterative optimization
[19]	N/a	Decentralized	Power control	Game theory
[3]	Downlink	Centralized	Sub-channel allocation	Iterative optimization
Proposed scheme	Downlink	Centralized	Frequency allocation	Graph theory, Network Flow

literature, it can be inferred that optimized solutions are not fully realized. In this paper, our objective is to provide an optimal frequency allocation scheme, compare it with other representative schemes, and recommend a choice of scheme based on balancing the tradeoff between complexity and performance to be used later in benchmark studies. The recommended scheme consists of a centralized frequency allocation algorithm that uses graph theory and optimization. Both femtocell and macrocell layers are incorporated since the scheme recognizes the overlaying nature of femtocells on macrocells. The trade-off between complexity and performance to produce a high quality applicable solution will supplement the current interference mitigation solutions. Table I shows a comparison between recent studies from literature. The proposed scheme can be seen in the last row.

II. System Description and Problem Definition

We consider an OFDMA network with two layers, a femtocellular layer within a macrocellular layer. The macrocellular layer is the traditional layer in the cellular network which encompasses MBSs deployed at specific cell sites, whereas the femtocellular layer consists of several shorter range cells resulting from the deployment of FBSs in an ad-hoc manner. Each Base Station (BS) has a number of UEs to serve. UEs that belong to the femtocellular layer, i.e., connected to FBSs, are referred to as Femtocell User Equipments (FUEs), whereas UEs connected to a MBS are referred to as Macrocell User Equipments (MUEs). UEs are served in units of Resource Blocks (RBs). In OFDMA downlink, a RB is a basic time-frequency unit. It consists of 12 consecutive subcarriers in the frequency domain and 7 OFDM symbols in the time domain, assuming normal cyclic prefix. The minimum unit to serve a UE is a RBs, that is, a user is either admitted access to a whole RB or not. The problem investigated in this work is the assignment of resource blocks among system users. An optimal assignment algorithm is proposed, aimed at maximizing the system capacity.

III. Mathematical Model

Given L mixed - femto and macro - BSs labeled 1 through L, let U_j be the number of UEs associated with BS j, where $1 \leq j \leq L$. For each cell one can measure the SINR for each UE per each RB. This can be arranged in a matrix $S_{U_j,R}$ where R is the number of RBs in the accessible spectrum. Each entry in this matrix signifies the SINR that a UE will experience when assigned a specific RB as calculated in [23].

All resulting SINR matrices of all BSs are aggregated into one matrix $\Gamma_{U,R}$ by adding the rows representing the UEs into the matrix. Let $\gamma_{u,r}$ be an entry in Γ, it represents the SINR that UE u, $(1 \leq u \leq U)$, will experience if assigned RB r, $(1 \leq r \leq R)$.

Let $\omega_{u,r}$ be a binary output function indicating whether a RB r is assigned to a UE u or not, such that $\omega_{u,r} = 1$ if RB r is assigned to UE u and 0 otherwise.

The proposed algorithm maximizes the summation of the chosen SINR values as follows:

$$\sum_{u=1}^{U} \sum_{r=1}^{R} \omega_{u,r} \cdot \gamma_{u,r} \tag{1}$$

Subject to constraint:

$$\sum_{\forall u} \omega_{u,r} \in \{0, 1\} \tag{2}$$

The objective function in expression 1 indicates that the summation of SINR of all assigned RBs is to be maximized, while the only constraint in expression 2 means that a RB will be assigned to at most one UE.

The problem of assigning RBs to UEs can be modeled as a Transportation Problem [24]. In a Transportation Problem, a set of graph nodes N is partitioned into two subsets U and V (not necessarily of equal cardinality) such that:

1) Each node in U is a supply node.
2) Each node in V is a demand node.
3) A set of edges running between the two subsets exist. Each edge (i, j) joins a node $i \in U$ with a node $j \in V$

U above represents the demand nodes and V represents the supply nodes, a link (i, j) means a node i is supplied via node j. Note that since the two subsets U and V are disjoint. Accordingly, the ordering of sets does not matter, and edges that run between subsets can still be modeled as directed edges.

The generic modeling of this problem is a bipartite graph as shown in Figure 1, with two disjoint sets U and V. Minimum

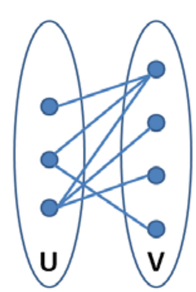

Fig. 1: Example of a bipartite graph.

Cost Flow (MCF) gives the optimal solution to a network

$$\begin{matrix} \gamma_{1,1} & \gamma_{1,2} & \cdots & \cdots & \gamma_{1,R} \\ \gamma_{2,1} & \gamma_{2,2} & & & \gamma_{2,R} \\ \vdots & & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ \gamma_{U,1} & \gamma_{U,2} & \cdots & \cdots & \gamma_{U,R} \end{matrix}$$

Fig. 2: Example of SINR matrix.

visualized as a directed weighted graph. The optimal solution represents a set of edges chosen the results in the minimization of the sum of their weights/costs. Given the SINR matrix Γ, the problem can be visualized as a directed graph with two disjoint sets of nodes representing UEs and RBs, U and V respectively. Graph edges originate from nodes in U to nodes in V, and the cost of a link between node $i \in U$ and node $j \in V$ equals $\gamma_{u,r}$. It can be seen how the matrix in Figure

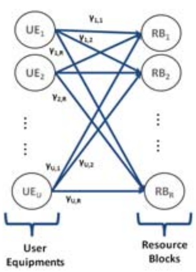

Fig. 3: Mapping SINR matrix to a Bipartite graph.

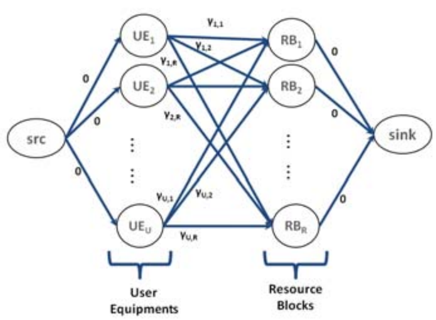

Fig. 4: Bipartite graph after adding artificial source and sink.

2 can be mapped to the directed graph in Figure 3. Since a typical MCF problem calculates the flow between a single source and a sink; an artificial source preceding all nodes in U and an artificial sink following all nodes in V were added as shown in Figure 4. Links from/to the artificial source/sink are of zero cost, in order not to affect the calculations. For each BS the SINR values for all its UEs against all available RBs are evaluated. All the resulting matrices are aggregated into one matrix of all UEs per each RB. The matrix is then converted to a directed graph and solved via MCF. The resulting assignment will highlight edges that give the maximum summation of the SINR values on these edges after running the algorithm, thus making it one of the possible optimal assignments.

IV. Simulation Setup

The system simulated consists of a two-tiered OFDMA network composed of a macro-tier and femto-tier. The macro-tier encompasses a sole macrocell and a number of macrocell users. Similarly, The femto-tier consists of a number of femtocells and their respective users. Figure 5 shows the network layout of the simulated environment.

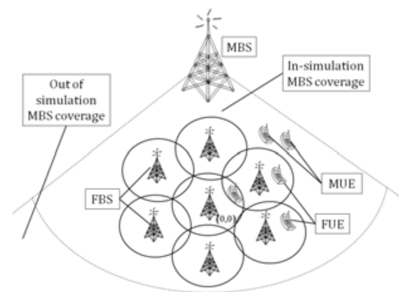

Fig. 5: Physical layout of the simulated environment.

The frequency planning model used in the simulation is co-channel allocation where a certain frequency band is shared between the femto-tier and the macro-tier. This setup is adopted by operators who seek larger system capacity and can tolerate more interference in their networks. The frequency band is split into a number of subcarriers, which are grouped together to form RBs. RBs are considered the smallest units that a UE can obtain in terms of frequency allocation. The core of the simulation is based on the SINR experienced by every UE at each RB. SINR generation is based on the model proposed in [23] where a closed form modeling for the downlink SINR is presented. Using the antenna gains of a BS and a UE connected to it, transmission power of the BS and locations of interfering BSs as well as location of the UE, the authors have derived a Probability Density Function (PDF) for the downlink SINR conditioned on the location of a UE within a femtocell.

Table II shows the simulation parameters used in all experiments.

Two representative schemes are chosen to evaluate the performance of the proposed algorithm [3] and in-house greedy algorithm. In [3], the authors study a centralized RRM for femtocell dense deployment. We implemented two versions of this algorithm to support both Open Subscriber Group (OSG) and Closed Subscriber Group (CSG) femtocells. The OSG version is referred to as Kim09OSG, while the CSG version is Kim09CSG. We compared both versions with the proposed MCF scheme, and the results can be seen in section V.

V. Simulation Results

System capacity is chosen to be the performance evaluation metric. Capacity is regarded as the achievable theoretical system throughput given a certain assignment of

Parameter	Symbol	Value
Antenna Gain of BS	G_b	3 dBi
Antenna Gain of MS	G_m	0 dBi
Constant of path loss	C_s	43.8 dB
Path loss exponent on the link between a BS and a MS	α_j	3.6
MS Noise figure	φ	7 db
Channel Bandwidth	W	10 MHz
Central Frequency	f	5.25 GHz
Ambient Temprature	T	293 K
Number of Subcarriers per Resource Block	N_{SC}	12
Number of Resource Blocks	N_{RB}	50
Number of Femtocells	N_f	2-7
Number of users per femtocell j	N_{f_j}	3-5
Number of macrocell users	N_m	10-20
Transmission power of femtocell j	P_j	10-30 dBm
Transmission power of macrocell	P_m	43-46 dBm
Variance of shadow fading	σ_{X_s}	1-4
Distance between user i and femtocell j	D_{ij}	1-30 m
Distance between femtocell j and the center femtocell	D_j	10-50 m
Distance between the macrocell and the center femtocell	D_m	100-300 m
Distance between user i and the macrocell	D_{im}	50-200 m
Adjusting factor	β	$\ln(10)/10$

TABLE II: General Simulation Parameters

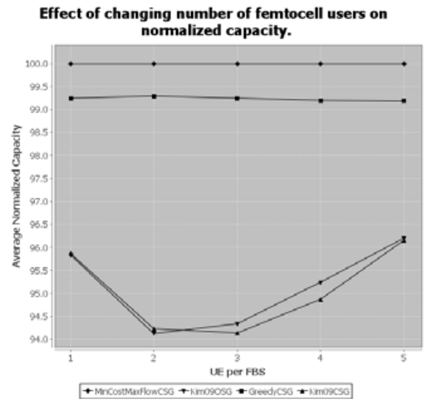

Fig. 6: Experiment A1: Average Normalized Capacity vs. changing number of users per femtocell.

RBs to UEs. Capacity C for an assignment is calculated as $B \sum_r \sum_{p=1}^{P} \log_2(1+\gamma_{rp})$ where B is the physical bandwidth in Hz, r is a RB assigned to a user, P is the number of subcarriers per RB, and γ_{rp} is the SINR of the p^{th} subcarrier in RB r.

1) Experiment A1: Effect of changing number of users per femtocell: In this experiment, capacity is evaluated in response to changing the number of users per femtocell. The experiment has been repeated 20 times for each value from the set [1, 2, 3, 4, 5]. For each experiment run with a certain seed, all capacities attained from all schemes are normalized relative to 100, i.e. the capacity value of the algorithm that scores best is set to 100, and capacities from other algorithms are set to a percentage of the best capacity, as in equation 3. Then, for each value of N_{f_j}, all normalized capacities are averaged as in equation 4

$$\text{Normalized capacity at seed } s = \frac{\text{Capacity at seed } s}{\text{Best capacity at seed } s} * 100 \quad (3)$$

$$\text{Normalized capacity at a certain value } N_{f_j} = \frac{\sum_s \text{Normalized capacity at seed } s}{20} \quad (4)$$

Figure 6 shows the simulation results of experiment A1. The proposed optimal algorithm, MCF, outperforms all other schemes as expected. The in-house greedy approach scores near-optimal capacity, 0.5% to 1.0% less performance than optimal. Kim09OSG and Kim09CSG scored alternating results at 3.5% to 6.0% less performance than optimal. The near-optimal performance of the in-house greedy approach can be attributed to the data distribution of SINR values. A UE will experience slightly varying SINR values per each RB. Hence, choosing greedily to assign a certain RB to a UE will not incur a significantly large cost in terms of blocking another UE to use the same RB if it results in a total higher capacity.

2) Experiment B1: Effect of changing the total number of serving Femtocell Access Points (FAPs): In experiment B1, capacity is evaluated against changing the total number of serving femtocells, while keeping the number of users constant. The total number of femtocell users is split equally among the number of femtocells. The experiment has been repeated 20 times per each value from the set [1, 2, 3, 4]. Capacities of all algorithms are calculated and normalized per each seed value.

The results of experiment B1 are shown in figure 7. MCF still outperforms the other schemes. The in-house greedy approach comes next at 99% to 99.5% optimal performance. Whereas, Kim09OSG and Kim09CSG scored alternating results at 95% to 97.5% optimal performance.

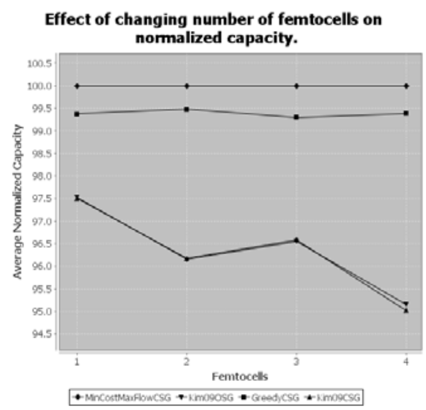

Fig. 7: Experiment B1: Average Normalized Capacity vs. changing number of femtocells.

3) Experiment C1: Effect of User Mobility: In experiment C1, capacity is calculated to assess the effect of user mobility on the performance of the algorithms under investigation. A simple Random Waypoint (RWP) mobility model was applied. Across the interval of 50 iterations, each UE may randomly move to another position. The new position can be one meter away in the horizontal direction, and/or one meter away in the vertical direction from the old position. The number of FUEs simulated in this experiment is 16, and the number of MUEs is 9, for a total of 25 UEs. This results in two RBs per user.

The layout generation is performed once at the beginning of this experiment. The positions of all UEs are updated at each iteration by applying RWP mobility model. The SINR matrix is calculated at each iteration before the algorithms run again for this iteration. The results of experiment C1 are shown in figure 8. The proposed benchmark MCF stays at the top, while the in-house greedy approach is just below it at 98.5% to 99.7% optimal performance. Kim09OSG and Kim09CSG fluctuate around 95.5% to 98% optimal performance.

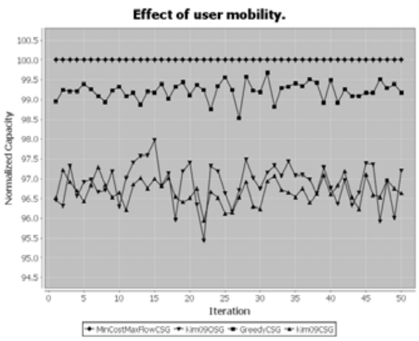

Fig. 8: Experiment C1: Effect of applying Random Waypoint mobility model on the Normalized Capacity.

In the experiments above, a greedy scheme performed significantly well when compared to the optimal scheme while the other two approaches, Kim09OSG and Kim09CSG, did not achieve a similar performance. The main drawback in Kim's approach proposed in [3] is that it deals with one RB at a time, trying to maximize the benefit (capacity) from using this RB. The problem is that a UE can be sufficiently served from earlier RBs, thus alienating better capacity RBs that might come later and wasting good RBs on other UEs. This flaw in Kim's approach did not let it benefit fully from being a greedy-based scheme.

Conclusions

We proposed a resource allocation algorithm for OFDMA femtocells, which mitigates interference at the two network tier levels; the femto-femto tier and the femto-macro tire. The proposed algorithm is modeled as a transportation problem to optimally allocate frequency subcarriers with the objective of maximizing the system capacity. The proposed algorithm can serve as an optimal solution for allocating frequency resource-blocks in OFDMA femtocell network or as a benchmark to evaluate heuristic or suboptimal frequency assignment schemes proposed in literature.

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