# Energy Efficient Bandwidth And Resource Allocation Based on Heterogeneous D2D Communication

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***Abstract***- *An energy efficient bandwidth and power allocation is modeled as min–max fractional stochastic programming for packet delay to solve the resource allocation problem in heterogeneous networks. Each MT adjusts radio bandwidth and power based on the channel condition and the queue buffer occupancy, so as to minimize the maximum consumed energy per bit under the QoS constraints. The dual decomposition methods are utilized to design the ODBPA, and the SDBPA is proposed to reduce the computational complexity. There remain several issues to be studied, such as extending the analysis to network capacity using stochastic geometry, redesign of existing femtocell coordination schemes for FD communication, and designing an optimal scheduling algorithm. The intra cellular and inter cellular networks are combined using femtocell coordination algorithm. This femtocell coordination algorithm avoids the self interference between macrocell users and femtocell users. The transmission powers of femtocells and their connected users are adjusted by a coordination algorithm such that both data transmission and mode selection of an underlying macrocells are protected. Simulation results demonstrate the proposed algorithm which can improve the energy efficiency in terms of interference significantly.*

***Keywords***- MT, QoS constraints, femtocell, ODBPA, SDBPA

## I. INTRODUCTION

Device-to-Device (D2D) communication enables direct data exchange between D2D user equipments (DUEs) without traversing a base station (BS), such that the data traffic in a cellular system can be offloaded. By allowing DUEs to share the radio resources of cellular user equipments (CUEs), the sum rate of the communication system can be improved. However, given that a large number of DUEs may transmit data simultaneously over the same radio resource, the allocation of the radio resources, i.e., transmit power and the channels to the DUEs, is critical. The resource allocation design for D2D communication systems is particularly challenging because both the multi-user interference among the DUEs and the interference caused to the legacy CUEs have to be taken into account. Hence, this problem has been extensively investigated in the literature. In the following, we first review the conventional optimization-based resource allocation schemes for D2D communication systems and their drawbacks. Then, the recently proposed deep learning (DL)-based resource allocation schemes are discussed and their limitations for implementation in practical wireless systems are explained.

DL-based resource allocation strategies for multi-channel cellular systems with interfering users were proposed. In particular, consider a D2D communication-enabled cellular system where multiple users transmit data over the same channel simultaneously, causing co-channel interference. The main contributions of this method can be summarized as follows.

DNN-aided resource allocation strategies for multi-channel D2D enabled cellular systems. In our formulated problem, the channel indices and the discrete transmit power levels of the users are optimally selected such that the SE of the D2D users is maximized while a minimum data rate is guaranteed for the legacy cellular users. The solution of this problem is difficult to obtain analytically. In order to solve the formulated problem, a DL framework employing novel DNN models, which can approximate the optimal resource allocation strategy for arbitrary channel conditions and can efficiently handle the involved discrete optimization variables, is presented. A novel hybrid training strategy, which combines supervised and unsupervised training, and new loss functions are proposed to improve the training performance.

Both centralized and distributed resource allocation schemes are developed. In particular, for the proposed distributed scheme, the optimal sharing strategy for the local CSI, i.e., the optimal encoding strategy of the local CSI sent from individual users to the BS and the optimal encoding strategy of the collected local CSI sent from the BS to the users, is determined via DL. Thereby, the limited capacity of the feedback channel is taken into account. Compared to existing schemes for the joint optimization of resource allocation and CSI sharing, the proposed scheme can cope with discrete transmit power levels, which are commonly used in practical systems, targets a more complicated multi-channel resource allocation problem and employs a more sophisticated CSI sharing strategy.

The performance of the schemes is evaluated via computer simulations under various conditions. Simulation results confirm that the scheme can achieve near-optimal performance with low computation time. Also show that the proposed hybrid training strategy is beneficial for reducing the training time of DNNs and that the optimal encoding of the local CSI can be efficiently learned with the proposed DL-based resource allocation schemes.

## II. LITERATURE SURVEY

W. Lee and K. Lee, "Deep learning-aided distributed transmit power control for underlay cognitive radio network", 2021 investigate deep learning-aided distributed transmit power control in the context of an underlay cognitive radio network (CRN). In the proposed scheme, the fully distributed transmit power control strategy of secondary users (SUs) is learned by means of a distributed deep neural network (DNN) structure in an unsupervised manner, such that the average spectral efficiency (SE) of the SUs is maximized whilst allowing the interference on primary users (PUs) to be regulated properly. Unlike previous centralized DNN-based strategies that require complete channel state information (CSI) to optimally determine the transmit power of SU transceiver pairs (TPs), in our proposed scheme, each SU TP determines its own transmit power based solely on its local CSI. Our simulation results verify that the proposed scheme can achieve a near-optimal SE comparable with a centralized DNN-based scheme, with a reduced computation time and no signaling overhead.

Miaomiao Liu, Li Zhang, "Resource allocation for D2D underlay communications with proportional fairness using iterative-based approach", 2020 this method, we develop a novel resource allocation scheme that aims to improve the system fairness, with minimum SINR (Signal to Interference and Noise Ratio) constraints and power limits for the Device-to-Device (D2D) underlay communications. Since the evaluation of the system fairness is different for $t = 1$ and $t \geq 2$, where t is the scheduling period, we divide our joint optimization problem into two cases: $t = 1$ and $t \geq 2$. For each case, we decompose the joint optimization problem into two sub problems: power and channel allocations. We then propose the corresponding power allocation algorithm for each case. By introducing virtual D2D links, we model the channel allocation as a 3-D (3-Dimensional) assignment problem, which is effectively solved by our proposed 2-D (2-Dimensional) iterative method. Simulation results show that our proposed iterative method can produce the close-to-optimal performance with low computational complexity. Moreover, comparing with existing schemes, our proposed scheme can not only enhance the system fairness but also improve the overall throughput.

W. Lee, O. Jo, and M. Kim, "Intelligent resource allocation in wireless communications systems", 2020 emergence of DL represents a potential paradigm shift in the design of WCS, from conventional handcrafted schemes based on mathematical models with assumptions, to autonomous schemes based on DL using large sets of data. In this article, we discuss the essential elements of DL and investigate an intelligent RA scheme based on a DNN, in which multiple goals with various constraints can be satisfied through DL. Having confirmed the optimality and feasibility of DNN-based RA through simulation, we discuss some of the key technical challenges that remain problematic for the application of DL in the practical application of WCS.

F. Liang, C. Shen, W. Yu, and F. Wu, "Towards optimal power control via ensembling deep neural networks", 2020 deep neural network (DNN) based power control method that aims at solving the non-convex optimization problem of maximizing the sum rate of a fading multi-user interference channel is proposed. Towards this end, we first present PCNet, which is a multi-layer fully connected neural network that is specifically designed for the power control problem. A key challenge in training a DNN for the power control problem is the lack of ground truth, i.e., the optimal power allocation is unknown. To address this issue, PCNet leverages the unsupervised learning strategy and directly maximizes the sum rate in the training phase. We then present PCNet+, which enhances the generalization capacity of PCNet by incorporating noise power as an input to the network. Observing that a single PCNet(+) does not universally outperform the existing solutions, we further propose ePCNet(+), a network ensemble with multiple PCNets(+) trained independently. Simulation results show that for the standard symmetric K -user Gaussian interference channel, the proposed methods can outperform state-of-the-art power control solutions under a variety of system configurations. Furthermore, the performance improvement of ePCNet comes with a reduced computational complexity.

S. Shrivastava, B. Chen, C. Chen, H. Wang, and M. Dai, "Deep Qnetwork learning based downlink resource allocation for hybrid RF/VLC systems", 2020 developing high data rate systems to meet the requirements of fifth generation mobile systems has become crucial. Hybrid radio frequency/visible light communication (RF/VLC) has appeared as a promising mechanism for achieving this objective. In hybrid RF/VLC, data rate maximization is subject to constraints on bandwidth, power and the user association. The joint optimization problem of bandwidth, power and user association to maximize the data rate is non-concave and obtaining an optimal solution is difficult with conventional optimization algorithms. The existing solutions are based on a presumption of at least one optimization variable. In this article, this issue has been overcome by solving the joint optimization problem in hybrid RF/VLC with a deep Q-network (DQN) learning based algorithm, which has been recognized as an efficient learning based mechanism for optimization. Our system model considers one RF and multiple VLC access points (APs). The idle APs are also incorporated in the system model. The application of DQN learning based algorithm is carried out by finding an optimal policy with the help of an action-value function. As the data sets for the considered system are large, a multi-layered network is used for approximating the action-value function estimator. Finally, a transfer learning based algorithm has been proposed for maximizing the total data rate of the system for the case of a newly entering user equipment (UE) that uses the information of the environment before the arrival of the new UE. Through simulations, it is found that our proposed algorithms can lead to an improvement of more than 10% and 54% in the achievable sum-rate and number of iterations for convergence respectively as compared to that obtained with existing conventional optimization algorithms.

H.-S. Lee, J.-Y. Kim, and J.-W. Lee, "Resource allocation in wireless networks with deep reinforcement learning: A circumstance-independent approach", 2020 in the conventional approaches using reinforcement learning (RL) for resource allocation in wireless networks, the structure of the policy depends on network circumstances such as the number of users and quality-of-service requirements. Due to this dependence, the policy is hard to be used in a practical system where the network circumstance is dynamically changing. To resolve this issue, we propose a circumstance-independent policy that can effectively address the different network circumstances even with a single policy. Thus, contrary to the conventional RL approaches, the proposed policy can be easily applied in the practical system. We then develop a deep RL algorithm to learn it. Through simulation results, we show that a single proposed policy can be used over different circumstances, and it achieves a close performance to the circumstance-dependent policy for each circumstance, which learns the optimal policy for the corresponding circumstance.

Z. Xu et al., "ReCARL: Resource allocation in cloud RANs with deep reinforcement learning", 2020 cloud radio access networks (CRANs) have become a key enabling technique for the next generation wireless communications. Resource allocation in CRANs still needs to be further improved to reach the objective of minimizing power consumption and meeting demands of wireless users over a long period. Inspired by the success of Deep Reinforcement Learning (DRL) on solving complicated control problems, we present a novel framework, ReCARL , for power-efficient resource allocation in CRANs with deep reinforcement learning. Specifically, we define the state space, action space and reward function for the DRL agent, apply a deep neural network (DNN) to approximating the action-value function, and formally formulate the resource allocation problem as a convex optimization problem. Under ReCARL, we propose two different DRL agents: one has a regular DNN structure trained with the basic deep Q-learning method; while the other has a context-aware DNN structure trained with a hybrid deep Q-learning method. We evaluated the performance of ReCARL along with the two DRL agents by comparing them with two widely-used baselines via extensive simulation.

L. Wang, H. Ye, L. Liang, and G. Y. Li, "Learn to compress CSI and allocate resources in vehicular networks", 2020 resource allocation has a direct and profound impact on the performance of vehicle-to-everything (V2X) networks. In this paper, we develop a hybrid architecture consisting of centralized decision making and distributed resource sharing (the C-Decision scheme) to maximize the long-term sum rate of all vehicles. To reduce the network signaling overhead, each vehicle uses a deep neural network to compress its observed information that is thereafter fed back to the centralized decision making unit. The centralized decision unit employs a deep Q-network to allocate resources and then sends the decision results to all vehicles. We further adopt a quantization layer for each vehicle that learns to quantize the continuous feedback. In addition, we devise a mechanism to balance the transmission of vehicle-to-vehicle (V2V) links and vehicle-to-infrastructure (V2I) links. To further facilitate distributed spectrum sharing, we also propose a distributed decision making and spectrum sharing architecture (the D-Decision scheme) for each V2V link. Through extensive simulation results, we demonstrate that the proposed C-Decision and D-Decision schemes can both achieve near-optimal performance and are robust to feedback interval variations, input noise, and feedback noise.

D. Xu, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, "Resource allocation for IRS-assisted full-duplex cognitive radio systems", 2020 investigate the resource allocation design for intelligent reflecting surface (IRS)-assisted full-duplex (FD) cognitive radio systems. In particular, a secondary network employs an FD base station (BS) for serving multiple half-duplex downlink (DL) and uplink (UL) users simultaneously. An IRS is deployed to enhance the performance of the secondary network while helping to mitigate the interference caused to the primary users (PUs). The DL transmit beamforming vectors and the UL receive beamforming vectors at the FD BS, the transmit power of the UL users, and the phase shift matrix at the IRS are jointly optimized for maximization of the total spectral efficiency of the secondary system. The design task is formulated as a non-convex optimization problem taking into account the imperfect knowledge of the PUs' channel state information (CSI) and their maximum interference tolerance. Since the maximum interference tolerance constraint is intractable, we apply a safe approximation to transform it into a convex constraint. To efficiently handle the resulting approximated optimization problem, which is still non-convex, we develop an iterative block coordinate descent (BCD)-based algorithm. This algorithm exploits semi definite relaxation, a penalty method, and successive convex approximation and is guaranteed to converge to a stationary point of the approximated optimization problem. Our simulation results do not only reveal that the proposed scheme yields a substantially higher system spectral efficiency for the secondary system than several baseline schemes, but also confirm its robustness against CSI uncertainty. Besides, our results illustrate the tremendous potential of IRS for managing the various types of interference arising in FD cognitive radio networks.

W. Lee, T.-W. Ban, and B. C. Jung, "Distributed transmit power optimization for device-to-device communications underlying cellular networks", 2019 four transmit power control strategies for the underlay device-to-device (D2D) communications, in which the spectral efficiency (SE) of the D2D communications is maximized while the amount of interference caused to a base station (BS) is kept less than a predefined threshold. To this end, we first propose a centralized power control strategy based on instantaneous and global channel state information (CSI) by formulating a convex optimization problem. Then, three distributed power control strategies are taken into account in which each D2D pair adjusts its transmit power in a distributed manner based on interference price and its local CSI, which significantly reduces the signaling overhead. In the distributed strategies, the interference price can be determined based on (1) the instantaneous local CSI; (2) the statistics of the local CSI (average power); and (3) the number of the D2D pairs without any CSI knowledge. Through extensive computer simulations, we show that the performances of the proposed strategies optimally adjust the transmit power of the D2D communications. Especially, we find that the distributed power control strategies can achieve almost the same SE with the centralized strategy with much lower signaling and control overhead.

## III. PROPOSED SYSTEM

### INTER-CELL INTERFERENCE

The inter-cell interference scenarios observed in conventional HD heterogeneous networks (HetNets) are (1) small cell ↔ macrocell user; (2) macrocell ↔ small cell user; and (3) small cell ↔ other-small cell user. In addition to these, new scenarios are observed in FD HetNets as illustrated and described as follows. Users in proximity, but connected to different cells: In cell boundary areas, two users served by distinct cells may reside in close proximity to each other and this situation is more likely to happen if a large handover hysteresis value is used to avoid ping-pong handovers. If one of such users are in FD operation, he transmits a UL signal in the RB being used for DL reception of the other and produces severe interference to the other. If the RB is being used for UL transmission of the other, the former user experiences interference from him. If both are in FD operation, they will interfere with each other. Since users could get close to each other arbitrarily in this situation, the severity of this type of interference will be of significance. This gets even severer as a user is farther away from his serving cell since he may use a stronger transmit power to combat a large path loss.

BSs in proximity: If two BSs are close enough to each other and both are in FD operation, one's DL transmit signal becomes high UL interference to the other. In a general deployment scenario, femtocell BSs are installed by end-users in their premises without a carrier's planning. Thus this interference situation may happen frequently either between macro and femtocell BSs or between femtocell BSs.

### INTER-CELL COORDINATION

The proposed algorithm for coordination of femtocells restricts femtocells' usages of power resource to protect data services of a macrocell from overlaid femtocells' interference. The protection is needed in two aspects: (1) the transmission mode selection of a macrocell remains optimal in terms of capacity; and (2) the minimum SINR requirement of MUs is met.

To design the algorithm, we first identify how much interference femtocells are allowed to produce without violating both of the protection aspects. Let $I_k^f$ and $J_k^f$ be the DL and UL interference levels, respectively, experienced by the underlying macrocell due to co channel femtocells in RB k. We denote the limits of $I_k^f$ and $J_k^f$ for the minimum SINR requirement Γ by $\hat{\mathrm{I}}_{\mathrm{k}}^{\mathrm{f}}$ and $\hat{\mathrm{J}}_{\mathrm{k}}^{\mathrm{f}}$, respectively, and obtain them from by setting SINR to Γ as

$$\mathrm{I}_{\mathrm{k}}^{\mathrm{f}} = \begin{cases} \frac{h_{n,k}\, p_{n,k}}{\Gamma} - \frac{q_{n,k}}{\Delta} - I_k - \sigma & FD - FD(n) \\ \frac{h_{n,k}\, p_{n,k}}{\Gamma} - h_{m,n}^{k} q_{n,k} - I_k - \sigma & FD - HD(n,m) \end{cases}$$

The maximum interference level that the underlying macrocell can bear is then the minimum between those for SINR requirement and mode protection. In what follows, we find them for each transmission mode of a RB.

## COORDINATION ALGORITHM

Let $\tilde{K}$ be the set of RBs in which MUs experience excessive femtocell interference over the maximum allowed level and $\tilde{F}$ be the set of FUs who or whose serving femtocell BSs (FBSs) are close enough to Mus or the macrocell BS (MBS). We then restrict the power usage of the users in $\tilde{F}$ for RBs of ˜K $\mathrm{I}_{\mathrm{k}}^{\mathrm{f}}$ and $\mathrm{J}_{\mathrm{k}}^{\mathrm{f}}$ are expressed as

$$\mathrm{I}_{\mathrm{k}}^{\mathrm{f}} = \sum_{u\in\,\tilde{F}} \left( h_{s_u n_k}^{k} p_{u,k} + h_{u,n_k}^{k} q_{u,k} \right)$$
$$\mathrm{J}_{\mathrm{k}}^{\mathrm{f}} = \sum_{u\in\,\tilde{F}} \left( h_{s_u}^{k}, MBS p_{u,k} + h_{u,MBS}^{k} q_{u,k} \right)$$

In order to avoid the situation that several FUs decrease powers excessively while others do not, we use the proportional fairness regime for power resources of FUs. Thus the objective function of coordination is given by

$$V(p_f, p_f) := \sum_{k\in\tilde{K}} \sum_{u\in\tilde{F}} \left( \log p_{u,k} + \varepsilon_u \log q_{u,k} \right) \tag{3.4}$$

where $p_f$ and $q_f$ are DL and UL power vectors of the femtocells serving $\tilde{F}$; $\xi_u$ is a balancing constant, and the target problem P2 is formulated as

$$p2{:}\max_{p_f q_f} v(p_f q_f)$$

In solving P2, the gap between the current interference and the interference cap tells how high powers can be used by FUs and thus plays an essential role in coordination, i.e., we can update powers based on this gap, which we call interference room. In a linear scale, however, the values of the both are typically too small and it is hard to find an appropriate step size of an update; a wrong choice may lead to either saturation or slow convergence of powers.

Instead of controlling each femtocell's transmit powers directly in the algorithm, the underlying macrocell broadcasts per-RB variables for the RBs suffering femtocell interference. This approach is more scalable for the expected large number of femtocells. We can further control the signaling overhead by adjusting the threshold of constructing for reduced signaling, only the femtocells producing dominant interference can be coordinated.

The details of the whole procedure is given in Algorithm 3. The proposed femtocell coordination scheme can coexist with the further enhanced inter-cell interference coordination (FeICIC) mechanisms such as almost blank subframes (ABS) and cell range extension (CRE) discussed in 3GPP for LTE systems. For example, femtocells incurring excessive interference to a macrocell can use ABS while the others adapt transmit power using the proposed scheme for a higher spatial reuse of radio resources.

Similarly, femtocells incurring high interference can choose to reduce power or shrink their service range such that some of their users are served by macrocells; the choice can be made based on the expected benefit and penalty of associated macro and femtocells. For the harmonized collaboration of the proposed scheme with FeICIC, a mechanism which manages all coexisting schemes jointly towards maximization of the overall performance needs to be developed.

The intra-cell resource assignment problem is formulated as a network utility maximization (NUM) problem and a suboptimal algorithm to solve it is designed. We define three available transmission modes of a RB according to the combination of the operation modes of a base station (BS) and associated user(s). We then study the relationship between power resource and the channel capacity along with relevant conditions by identifying crossover points between the achievable capacities of the modes, based on which the transmission mode of each RB is selected. Users are assigned RBs such that the total utility sum is maximized. We show that the capacity of each transmission mode has different sensitivity to transmit power. Based on this observation, power resource assignment is adjusted between RBs depending on their determined modes such that the utility sum is increased further. Contrary to a conventional intracell scheduler, ODBPA allocates the radio resources of downlink (DL) and uplink (UL) jointly since they are affected by each other's operation in FD communication.

In FD cellular networks with co-channel femtocells, new inter-cell interference scenarios are observed and they are severer than the conventional ones. ODBPA restricts the transmit powers of femtocells (DL) and their connected users (UL) such that they do not deteriorate the data services of an underlying macrocell (assuming that femtocell plays a supplementary role).

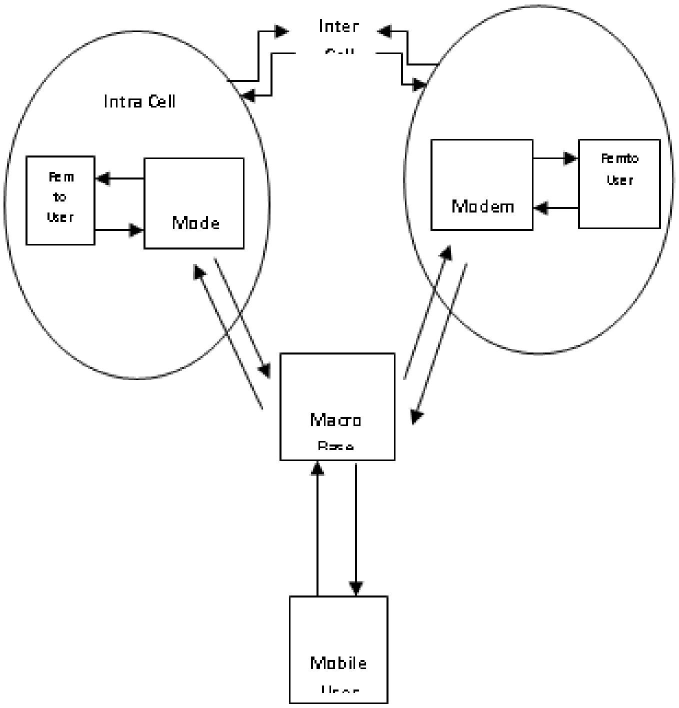


Fig.3.1 Proposed Block Diagram

Data services in a macrocell are protected by ODBPA in two aspects: (1) the minimum requirement of a signal-to-interference and noise ratio (SINR) is met in each RB; and (the selected transmission mode of a RB remains intact (still in an optimal range); the former has already been considered by previous proposals for conventional HD cellular systems while the latter is of importance for stable scheduling in macrocells. We define an interference room by which a macrocell user can bear interference from femtocells while meeting the above two constraints, and obtain it for each transmission mode. Then, femtocells and their users are allowed to use transmit powers within this interference room. To implement this mechanism without excessive signaling overhead, only a macrocell broadcasts over either the air or wired backhaul the prices of transmit powers in the RBs where macro- cell users suffer femtocell interference over a certain threshold.

Design of a radio resource management architecture for FD cellular networks.

- Identification of a RB's transmission modes and crossover points between mode capacities, which enables further understanding of FD-enabled networking and selection of a transmission mode.
- Design of an intra-cell scheduler that decides transmission modes of RBs, associated users and power levels for both DL and UL jointly to combat imperfect self-interference cancellation.

## INTRA-CELL INTERFERENCE

In conventional OFDMA-based cellular systems, users served by the same cell are allocated orthogonal RBs and time slots so that there exists no interference between them. In FD cellular networks, however, intra-cell interference arises as illustrated. When a user receives a DL signal from his serving BS, UL transmission in the same RB is also permitted to him or another user, which results in self and other-user interference, respectively, to the first user's DL communication. The UL signal from an assigned user also experiences interference due to the BS's DL signal radiated in the same RB, which corresponds to BS's self-interference.

## INTRA-CELL SCHEDULING

Let $a_{n,k} \in \{0, 1\}$ and $b_{n,k} \in \{0, 1\}$ be the indicators of user n's allocation for RB k in DL and UL, respectively; $a_{n,k} = 1$ ($b_{n,k} = 1$) means that user n is allocated RB k in DL (UL). These indicators can describe which transmission mode is selected for each RB. Since only a single user can be assigned in DL and UL, respectively, for a RB, we have constraints $\sum_n a_{n,k} \leq 1$ and $\sum_n b_{n;k} \leq 1$ for each k. Then, the DL and UL capacity, denoted by $R_{n,k}$ and $s_{n,k}$ , respectively, that can be achieved by user n in RB k is given as

$$R_{n,k} := a_{n,k} W \log_2(1 + \gamma^{DL}_{n,k})$$
$$s_{n,k} := b_{n,k} W \log_2(1 + \gamma^{UL}_{n,k})$$

And the total date rates of user n, denoted by $r_n(DL)$ and $s_n(UL)$, are obtained as

$$r_n := \sum_{k \in K} R_{n,k}, \quad s_n := \sum_{k \in K} S_{n,k},$$

Let a, b, p and q be the vectors of $a_{n,k}, b_{n,k}, p_{n,k}, q_{n,k}$, respectively. Then, $r_n$ and $s_n$ are the functions of these vectors. We denote the vectors of $r_n \, and \, s_n$ by r and s, respectively. The target problem P1 is then formulated as n, pn, k and s 1 and n

The target problem P1 is then formulated a$^{s^1}$

P1: $\max_{a,b,p,q} U(r,s)$

s. t.

C1.1 : ($\sum_{n \in N} a_{n,k,} \; \sum_{n \in N} b_{n,k}) \leq 1, k \in K$

C1.2 : $a_{n,k,} b_{n,k} \in \{0,1\}$

C1.3 : ($\sum_{n \in N} \sum_{k \in K} p_{n,k,} \;\; \sum_{k \in K} q_{n,k} \leq (P,Q)$

where U is the utility function of achieved data rates; P and Q are the transmit power limits of a BS and a user device, respectively. We define U as the sum of user utility functions u with arguments $r_n \, and \, s_n$ as below:

$$U(r,s) := \sum_{n \in N} u(r_n, s_n)$$

For example, u can be defined as a form of

$$u(r_n, s_n) := u(r_n) + \zeta_n u(s_n)$$

where $\zeta_n$ is a balancing constant between DL and UL utility values. Although we select u among convex functions, P1 is not a convex optimization problem due to In order to transform it into a solvable form, we divide P1 into two sub problems, one for finding (a, b) provided that (p, q) is fixed and the other for finding (p, q) provided that (a, b) are fixed, as below:

P1-1: $\max_{a,b} U(r,s)$

s.t. C1.1,C1.2,

P1-2 : $\max_{p,q} U(r,s)$

s.t. C1.3.

**SUBOPTIMAL ALGORITHM**

The ODBPA gives an upper bound of network performance, but its computational complexity is high due to its bandwidth and power allocations in the recursive manner. This motives us to develop a suboptimal distributed bandwidth and power allocation algorithm (SDBPA) with lower computational complexity, and its bandwidth allocation and power allocation are designed separately. Hence, the SDBPA includes a bandwidth allocation algorithm and a power allocation algorithm. In the bandwidth allocation algorithm, the power across different radio interfaces at each MT is allocated equally, and the bandwidth is allocated, based on the greedy method, to different MTs and different radio interfaces at each MT. In the power allocation algorithm, the bandwidth allocation is fixed, and the power is allocated across different radio interfaces at each MT, by the greedy method to maximize the energy efficiency.

## IV. RESULT AND DISCUSSION

4.1 SIMULATION OUTPUT

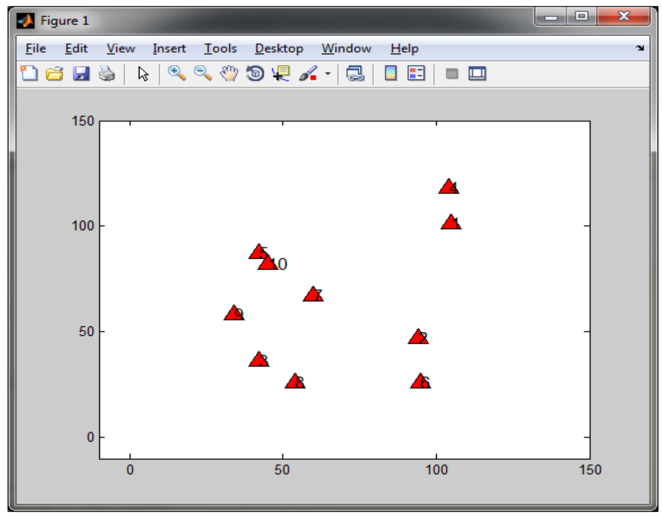


Fig 4.1 Number of nodes

4.2 FD CSI COMMUNICATION USING FEMTO CELL

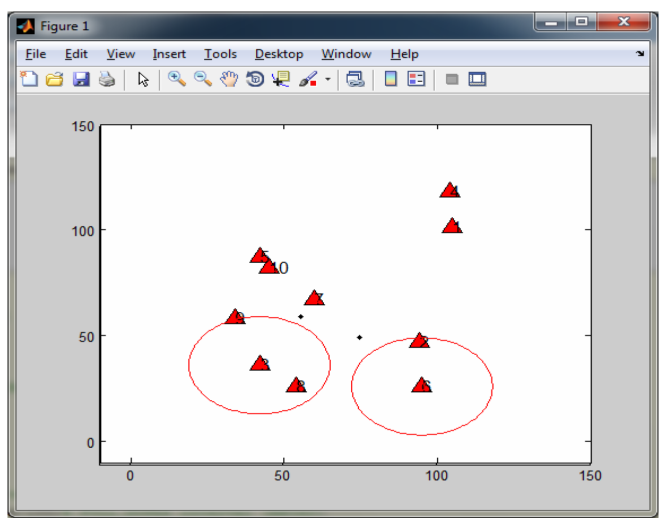


Fig 4.2 FD CSI communication using femto cell

4.3 MAXIMUM CONSUMED ENERGY RATES WITH CSI FOR PACKET DELAY INTERFERENCE RATE

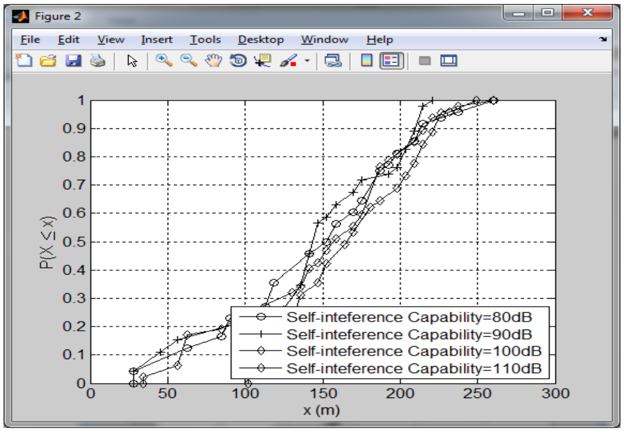


Fig 4.3 Maximum consumed energy rates with CSI for Packet delay interference rate

## 4.4 MAXIMUM CONSUMED ENERGY RATES WITH CSI FOR PACKET ARRIVAL INTERFERENCE RATE

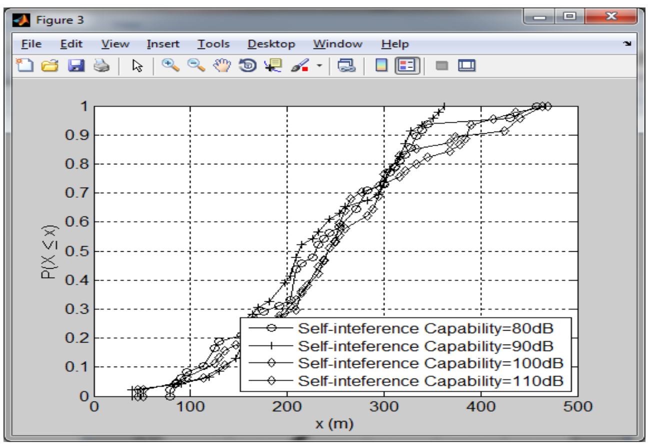


Fig 4.4 Maximum consumed energy rates with CSI for Packet arrival interference rate

## 4.5 USER'S PERFORMANCE ANALYSIS WITH A VARYING NUMBER OF CO-CHANNEL FEMTOCELL

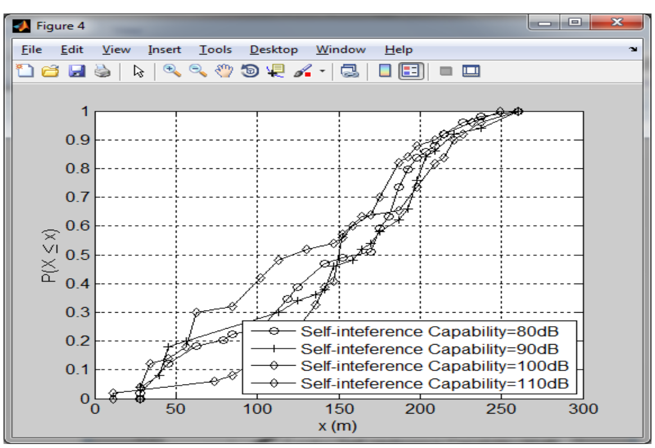


Figure 4.5 User's performance analysis with a varying number of co-channel femtocell

## 4.6 GRAPHICAL REPRESENTATION FOR TOTAL THROUGHPUT VS NUMBER OF TOTAL UES

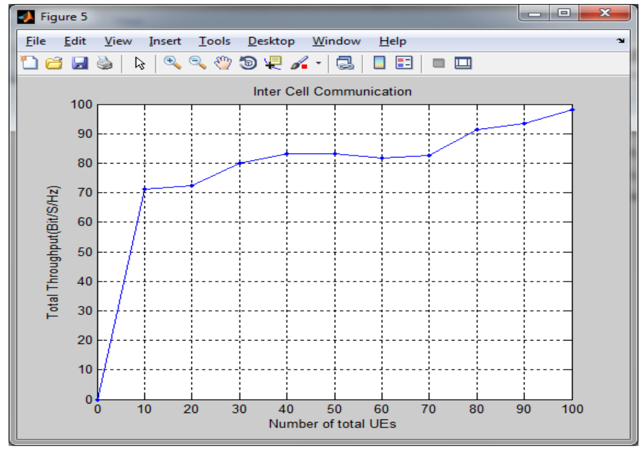


Figure 4.6 Graphical Representation for Total Throughput Vs Number of total UEs

## 4.7 GRAPHICAL REPRESENTATION FOR POWER EFFICIENCY VS NUMBER OF TOTAL UES

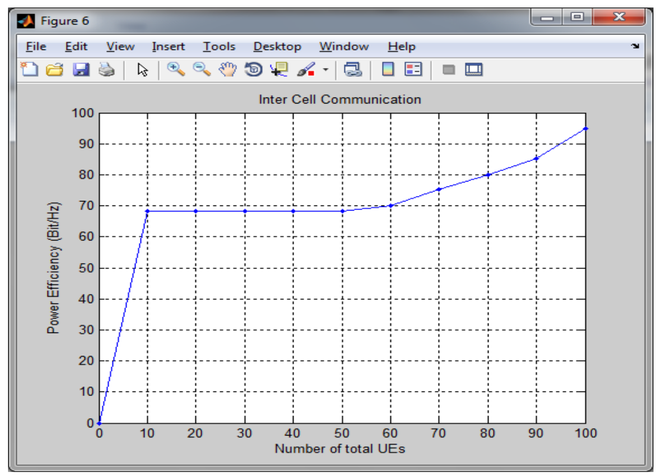


Figure 4.7 Graphical Representation for Power Efficiency Vs Number of total UEs

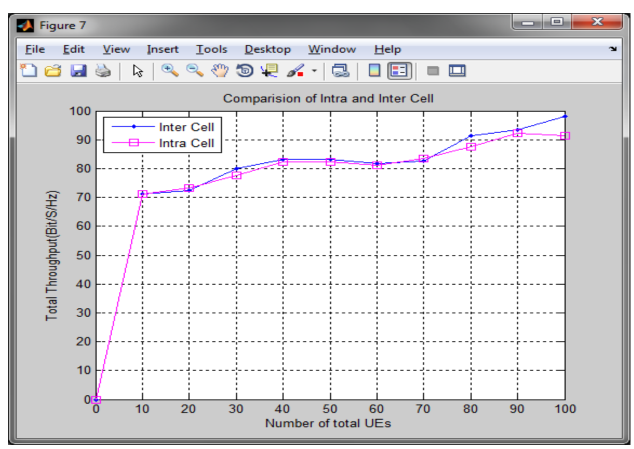


Fig 4.8 Comparison chart for Total Throughput Vs Number of total UEs

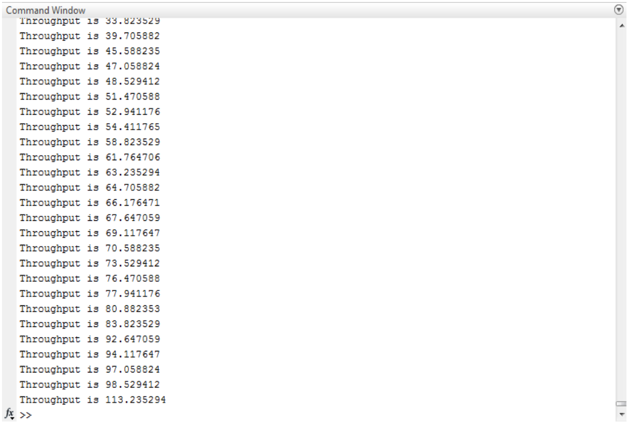


Fig 4.9 Throughput calculation window

## V. CONCLUSION

Thus, the uplink energy-efficient crosslayer resource allocation problem for a heterogeneous wireless access. Each MT adjusts radio bandwidth and power based on the channel condition and the queue buffer occupancy, so as to minimize the maximum consumed energy per bit under the QoS constraints. In order to solve the resource allocation problem, here modeled the energy-efficient bandwidth and power allocation problem as min-max fractional stochastic programming, and analyze the packet delay. The dual decomposition methods are utilized to design the ODBPA, and the SDBPA is proposed to reduce the computational complexity. There remain several issues to be studied, such as extending the analysis to network capacity using stochastic geometry, redesign of existing femtocell coordination schemes for FD communication, and designing an optimal scheduling algorithm. In future the intra cellular and inter cellular networks are combined using femtocell coordination algorithm. These femtocell avoid the self interference between macrocell users and femtocell users. The transmit powers of femtocells and their connected users are adjusted by a coordination algorithm such that both data transmission and mode selection of an underlying macrocell are protected. Simulation results demonstrate proposed algorithms can improve the energy efficiency in terms of interference significantly.

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