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ENERGY-EFFICIENT CROSS-LAYER RESOURCE ALLOCATION FOR HETEROGENEOUS WIRELESS ACCESS

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Abstract: **In this project, an uplink cross-layer resource allocation problem based on imperfect channel state information (CSI) is modeled as min-max fractional stochastic programming for heterogeneous wireless access. The resource allocation is subject to constraints in delay, service outage probability, system radio bandwidth, and total power consumption. The joint bandwidth and power allocations are based on CSI at the physical layer and queue state information (QSI) at the link layer. In order to determine the transmission rate of each mobile terminal (MT) according to the queue buffer occupancy, a probability upper bound of exceeding the maximum packet delay in terms of a required transmission rate is presented based on M/D/1 model. Then, the bandwidth and power allocation problem is transformed into biconvex programming, and an optimal distributed (SDBPA) algorithm is presented. Simulation results demonstrate that the proposed algorithms improve the energy efficiency greatly.**

Index Terms: **Heterogeneous wireless access, energy efficiency, cross-layer resource allocation, min-max fractional stochastic programming.**

I. INTRODUCTION

A future wireless communication system is expected to integrate different radio access technologies, leading to a heterogeneous wireless access [1]. For example, a cellular network will include microcells to support low-to-medium rate services with a large coverage area, and femtocells to support high rate services in hotspots. Integrating microcells and femtocells can help to provide various classes of service to MTs and to support seamless user roaming [2]. In order to maximize user experience in a heterogeneous wireless access, extensive research works have been carried out to take advantage of multi-homing capability, where the data stream from an MT is split into multiple sub-streams and transmitted over multiple wireless media by different radio interfaces simultaneously in the uplink [3]. Existing studies in resource allocation for a heterogeneous wireless access can be divided into three categories [2], [4]–[13]. The first category is bandwidth allocation at the network layer, which aims to provide call-level quality-of-service (QoS) guarantee [2], [4], [5]. The available radio resources from multiple wireless access media can be aggregated to support services requiring a high transmission rate and to reduce call blocking probability [2]. The second category is packet scheduling of video traffic at the link layer, which provides packet level QoS guarantee [6], [7]. The packet scheduler determines which packet should be assigned to which radio interface of an MT based on CSI, available radio resources, and video traffic characteristics [6]. The third category is joint bandwidth and power allocation at the physical layer, to meet bit-level QoS requirements [8]–[13]. Compared with the call-level and packet level resource allocation, the bit-level resource allocation needs to jointly allocate the radio bandwidth and energy resources simultaneously. It not only exploits the multiuser diversity in wireless transmission among different MTs, but also takes advantage of the disparity of available resources among different wireless access media [13]. In [4], a bandwidth allocation algorithm with fairness consideration is proposed. In [5], a bandwidth allocation problem of video traffic is solved by convex optimization theory and the Karush-Kuhn-Tucher (KKT) condition. Further, a distributed prediction-based resource allocation algorithm for video traffic is presented to achieve an acceptable call blocking probability [2]. For packet scheduling, an energy management algorithm is proposed in [6], to support a sustainable video transmission over the call duration and to guarantee a target video quality lower bound. Also, a novel scheduling framework with delay-constrained high definition video transmission featured by frame-level data protection is proposed [7]. For joint bandwidth and power allocation at the physical layer, there exist energy-efficient and spectral-efficient resource allocation algorithms. In [8], a joint link selection and resource allocation algorithm using the branch and bound method is proposed. In [9], an energy-per bit minimized joint power, sub channel, and time allocation scheme for heterogeneous wireless networks is proposed with a double-loop iteration method. On the other hand, joint bandwidth and power allocation algorithms are proposed to maximize the spectral efficiency [10], [12], or to achieve max-min fairness and proportional fairness in resource allocation [11], [13]. The existing resource allocation mechanisms mainly limit to a particular networking protocol layer. However, cross-layer resource allocation has been shown to be beneficial in homogeneous wireless access [14], [15]. Extending cross-layer design to a heterogeneous wireless access requires further studies. In this paper, we investigate cross-layer resource allocation1 based on CSI and QSI for uplink energy-efficient video transmission in a heterogeneous wireless access. Specially, we summarize our contributions as follows: (i) An uplink energy-efficient cross-layer resource allocation problem is formulated as min-max fractional stochastic programming, and the probability upper bound of exceeding the maximum packet delay at the link layer is transformed to a required transmission rate based on an M/D/1 queue system; (ii) Using the Dinkelbach-type method, the min-max fractional stochastic programming problem is transformed into a bi-convex optimization problem, and an optimal distributed energy-efficient bandwidth and power allocation algorithm based on the dual decomposition method is proposed; (iii) In order to reduce the computational complexity, a suboptimal distributed algorithm is developed. Simulation results demonstrate that the proposed algorithms greatly improve the energy efficiency of video packet transmission in a heterogeneous wireless access.

II. HETEROGENEOUS NETWORKS

Wireless heterogeneous network refers to a group of spatially dispersed and dedicated sensors for monitoring and recording the physical conditions of the environment and organizing the collected data at a central location. WSNs measure environmental conditions like temperature, sound, pollution levels, humidity, wind, and so on.

These are similar to wireless ad hoc networks in the sense that they rely on wireless connectivity and spontaneous formation of networks so that sensor data can be transported wirelessly. Sometimes they are called dust networks, referring to minute sensors as small as dust. Smart dust [1] [2] [3] is a U C Berkeley project sponsored by DARPA. Dust Networks Inc. is one of the early companies that produced wireless sensor network products. WSNs are spatially distributed autonomous sensors to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and to cooperatively pass their data through the network to main locations. The more modern networks are bi-directional, also enabling control of sensor activity. The development of wireless sensor networks was motivated by military applications such as battlefield surveillance; today such networks are used in many industrial and consumer applications, such as industrial process monitoring and control, machine health monitoring, and so on.

The WSN is built of "nodes" – from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. Each such sensor network node has typically several parts: a radio transceiver with an internal antenna or connection to an external antenna, a microcontroller, an electronic circuit for interfacing with the sensors and an energy source, usually a battery or an embedded form of energy harvesting. A sensor node might vary in size from that of a shoebox down to the size of a grain of dust, although functioning "modes" of genuine microscopic dimensions have yet to be created. The cost of sensor nodes is similarly variable, ranging from a few to hundreds of dollars, depending on the complexity of the individual sensor nodes. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and communications bandwidth. The topology of the WSNs can vary from a simple star network to an advanced multi-hop wireless mesh network. The propagation technique between the hops of the network can be routing or flooding. [4][5]

III. PROPOSED METHOD

In this section, the system and video traffic models are described. Then, the transmission rate based on imperfect CSI, and power consumption models are presented. Finally, an uplink energy-efficient cross-layer resource allocation problem is formulated.

A. System Description 1

Consider a geographical region covered by heterogeneous wireless access. The coverage areas of BSs/APs can overlap as shown in Fig. 1. In Fig. 1, there exist N = {1, 2, • • •, N} wireless access networks, e.g., Microcell, Femtocell, and Wi-Fi, based on different access technologies and operated by different service providers2. There is a set, Sn = {1, 2, • • • , Sn}, of base stations (BSs)/access points (APs) for network n.

There is a set, M = {1, 2, • • • , M}, of MTs in the

geographical region, and Mns = {1, 2, • • • , Mns} ∈ M is a subset of MTs which reside in the coverage area of network n BS/AP s. Using multi-homing functions and multiple radio interfaces, an MT can communicate with multiple BSs/APs within its transmission range simultaneously.

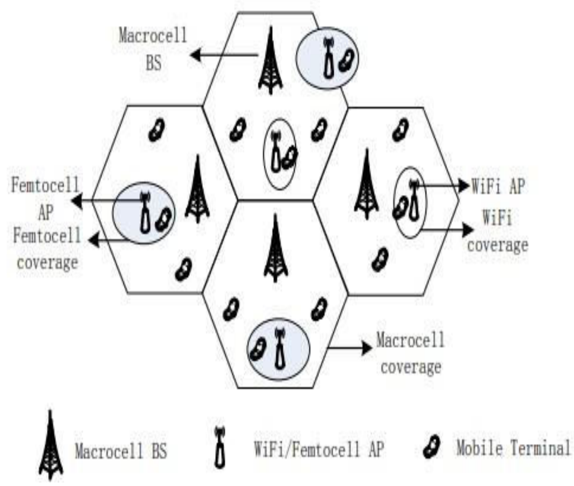

Figure: Heterogeneous wireless access.

In the heterogeneous wireless access, cooperation of different networks has a potential to improve service quality for MTs and enhance network performance. Hence, different networks cooperate in resource allocation via signaling exchanges over a wire line backbone. Time is partitioned into time slots, T = {1, 2, • • •}, of equal duration τ. The resource allocation is performed at the beginning of each time slot remains constant within one time slot and varies from one time slot to another time slot. Consider video applications. In order to improve the coding efficiency of multitier video coding, variable block-size motion estimation, disparity estimation, and multiple reference frames selection are adopted. Each MT has a video packet flow to transmit via nearby BSs/APs, which are the BSs/APs within MT's transmission range. For video applications, each packet should be transmitted before a deadline. If the transmission delay exceeds the bound, the packet is dropped from its queue at the source. At heterogeneous wireless access, we have considered the co-existence of LTE and WiFi. In Fig., there are Macrocell, Femtocell, and Wi-Fi, based on different access technologies and operated by different service providers. Additionally, we follow the previous literatures of heterogeneous wireless access in the system model, i.e., the co-existence of LTE and WiFi e.g., [2], [10], [11], [13]. They study the bandwidth and power allocation for heterogeneous wireless access. On the other hand, the video traffic transmission for heterogeneous wireless access has been studied in [6] for heterogeneous wireless access.

There are some assumptions in this work, i.e., 1) in the same network, different BSs/APs reuse the same spectral bands, and interference mitigation is achieved by interference management schemes. Consequently, we do not consider the co-channel interference. On the other hand, at the different networks, the cross-tier interference is also not considered for bandwidth allocation at heterogeneous wireless access, e.g., [2], [13]. Therefore, we follow the interference assumptions for the heterogeneous wireless access in the previous literatures [2], [13]. 2) Each MT has a packet queuing buffer and the buffer size is infinite. 3) The channel power gains remain constant within one time slot, and vary from one time slot to another time slot and from one link to another link, independently. 4) The video packet arrivals at the transmission buffer of MT m follow a Poisson process with an average arrival rate λm with a constant packet length of L bits [6]. The cross-layer resource allocation design is considered in this work. We consider the queuing buffer for each MT at the link layer, and joint bandwidth and power allocation at the physical layer. For each MT, the packet delay requirement for video traffic3 and the occupancy at the the queuing buffer influence the required minimum transmission rate at the physical layer. On the other hand, the joint bandwidth and power allocation determines the practical physical transmission rate, and influences the performance of the packet delay at the link layer. Consequently, it is necessary to design the joint bandwidth and power allocation at the physical layer incorporating the delay requirement information at the link layer.

B. Transmission Rate Based on Imperfect CSI

In wireless communications, the transmission rate should be determined based on CSI. BSs/APs estimate CSI for uplink transmission, and send it to MTs. Channel estimation algorithms can be used for heterogeneous radio networks based on machine learning techniques, e.g., support vector machine because there exist channel estimation errors and feedback delays, the CSI available at the transmitter of an MT is usually imperfect. Using imperfect CSI can result in a scheduled transmission rate greater than what the system can support (e.g., Shannon capacity for simplicity), resulting in outage events.

The outage probability, Ponsm, for MT m ∈ Mns based on imperfect CSI. Since, in the same network, different BSs/APs reuse the same spectral bands and interference mitigation is achieved by interference management schemes, no interference is considered in Eq. (1), as in some existing studies, e.g., [8], [12]. In each cell, frequency division duplexing (FDD) is adopted for uplink and downlink. Due to channel estimate errors, the estimate complex uplink channel gain αˆnsm, e.g., using a minimum mean square error (MMSE) channel estimator is not equal to αnsm. Let αnsm = αˆnsm + Δαnsm, where the estimation error, Δαnsm, is assumed to be a zero-mean complex Gaussian random variable with variance σ 2 nsm, and is independent for different radio interfaces.

Therefore, |αnsm| follows a Rice distribution with the cumulative distributed function (CDF).

However, in most existing studies on resource allocation at the physical layer, Rnsm is assumed to be a continuous value in bandwidth and power allocations, e.g., [2], [9], [13]. Under this assumption, the scheduled transmission rate to satisfy the required outage probability for MT m uplink to network n BS/APS

C. Power Consumption Model 1

The power consumption at each MT consists of two components. The first component is a fixed power consumption Pc, which captures the power consumption of hardware at transmitter. The second component is transmission power consumption. Consequently, the total power consumption, Pm, for MT m

D. Problem Formulation

The total allocated bandwidth by network n BS/AP s should not be larger than its total available bandwidth, Where the total available power at MT m and is assumed to be a constant. The packet delay for MT m should probabilistically satisfy the maximum packet delay constraint4. Dm is the time of a packet from its generation to its transmission, Dmax m is the maximum packet delay after which the packet will be dropped at the transmitter, and γm is the probability upper bound of exceeding the maximal packet delay. Define the consumed energy per bit of MT m, ηm, as the ratio of the total power consumption to the total achieved transmission rate, i.e., ηm = Pm/Rm.

Rm=Pn∈N Ps∈Sn Rnsm is the achieved transmission rate for MT m. To guarantee the consumed energy fairness for all MTs, we minimize the maximum

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consumed energy per bit, am, for all MTs. Consequently, the resource allocation problem is formulated. A min-max fractional stochastic programming, In order to solve problem, we first analyze the relationship between the packet delay at the link layer and then the transmission rate at the physical layer, and transform the stochastic programming problem into a min-max fractional deterministic programming problem.

IV. JOINT BANDWIDTH AND POWER RESOURCE ALLOCATION

In this section, we first analyze the packet delay. Then, we propose an optimal distributed bandwidth and power allocation algorithm based on the dual decomposition method. Finally a suboptimal distributed bandwidth and power allocation algorithm is presented to reduce the computational complexity.

A. Packet delay Analysis

Although advanced video codec's are developed, the resource at each wireless network is limited and video packet will be dropped at the transmitter when exceeding a delay threshold, e.g... Given the service rate5, the service time for each packet at each MT is deterministic. Hence, the packet buffer is modeled as an M/D/1 queuing system6. For the stability of the queue, $\rho m = \lambda mL/Rm < 1$. Let $\pi = (\pi 0, \pi 1, \cdot \cdot \cdot)$ denote the stationary distribution of the number of packets at the queueing system. By the Pollaczek-Khinchin formula, we have the probability generating function π (z). Since the service time for all packets in the M/D/1 queueing system is the same given the packet length and service rate, the upper bound for the number of packets in the queue buffer to meet the maximum delay requirement is

Qmax m = bDmax m Rm/Lc, where bxc is the floor function. For each new packet arrival, the packet delay is the ratio of the number of packets at the queueing system to the service rate Rm.

We can obtain the minimum transmission rate, ψ (Dmax m, γm, λm, L), as a function of the delay requirement, the packet average arrival rate, and the packet length, by the binary search method over a range Rmin m, Rmax m, where Rmin m and Rmax m are the search lower and upper bounds for MT m, e.g., Rmin m = λmL and Rmax m = 10λmL. The transmission rate for MT m should be at least the required minimum transmission rate in order to satisfy the packet delay requirement, i.e.

$$\text{Mr.} \geq \psi\ (D \max m , \gamma m, \lambda m, L).$$

The below shown algorithms are designed to maximizing the energy efficient of cross layer resource allocation at heterogeneous wireless access comparing with existing algorithms (SRM) Sum Rate Maximization and BENCHMARK algorithm.

B. Optimal Distributed Bandwidth and Power Allocation Algorithm

With the delay requirement-equivalently represented by the minimum transmission rate constraint, problem is transformed into the min-max fractional deterministic programming. Solving the problem mean first solving the fractional programming problem and then solving the min-max programming problem. For the first sub problem, the Dinkelbach-type method is adopted, and ξ = max m∈M ηm is defined. For a given parameter, ξ = max m∈M ηm.

In order to obtain the optimal resource allocation solution, we find a root of equation F (ξ) = 0. This is the common procedure to solve the fractional programming problem. For the second sub problem, ϑ = max m∈M (Pm − ξRm), and add the constraint Pm − ξRm ≤ ϑ to transform the min-max programming problem to minimize the programming problem.

We solve the variables ϑ, Pnsm, and Bnsm, separately. Firstly, the variables Pnsm, and Bnsm are solved via the dual decomposition method with the fixed variable ϑ. Then, ϑ is obtained via binary search method with the given variables Pnsm and Bnsm.

If we want to obtain the optimal solution of bandwidth allocation variable Bnsm, we need to fix the power allocation variable Pnsm, and vice versa. By iteratively updating the Lagrangian multipliers, we can design the optimal distributed bandwidth and power allocation algorithm in a recursive manner. The optimal bandwidth allocation Bnsm, given Pnsm, um, vns, αm and βm, is calculated by applying the KKT condition.

Consequently, the proposed algorithm is designed in a recursive manner converging to the optimum solution by updating the Lagrangian multipliers with Additionally, the remaining steps are to determine the resource allocation solution to satisfy the constraints. Then, ϑ is solved via the binary search method. Finally, the Dinkelbachtype method can be applied to find the root of equation F (ξ) = 0 in an iterative manner according to the output, F (ξ). Note that Fm(ξ) is a parameter of the Dinkelbach-type method for MT m, εp is a small positive number; ϑ(i − 1) and ϑ(i) are the variable values at the (i − 1)th and it iterations, respectively; ηm(i − 1) and ηm(i) are the consumed energy per bit for MT m at the (i − 1)th and ith iterations, respectively; αm(i), βm(i), um(i) and vns(i) are the Lagrangian multipliers at the ith iteration, and αm(i+1), βm(i+1), um(i+1) and vns(i+1) are the updated Lagrangian multipliers at the (i + 1)th iteration. The ODBPA is implemented in the distributed manner by cooperation among BSs/APs of different networks and Mrs. This is because different networks are operated by different service providers and each MT utilizes the multi-homing technology to obtain the aggregated bandwidth from different networks. If we design a centralized algorithm to solve the cross-layer resource allocation problem, a central controller from a third party collects the CSI and QSI for all MTs, runs the algorithm and feeds the results back to all Mrs. However, the proposed distributed resource allocation algorithm (i.e., the ODBPA) updates the Lagrangian multipliers αm (i), βm (i) and um (i) at each MT, and ϑ (i) and vns(i + 1) at each BS/AP. Through the wireless broadcast, each MT can receive the updating variables from its serving BSs/APs, and the bandwidth and power allocations are calculated at each MT. Hence, it is desirable to design tdistributed resource allocation algorithm for a heterogeneous wireless medium.

C. Suboptimal Distributed Bandwidth And Power Allocation Algorithm

SDBPA’s bandwidth allocation and power allocation are designed separately. In the bandwidth allocation algorithm, the power across different radio interfaces at each MT is allocated equally9, 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. The bandwidth allocation algorithm in SDBPA is shown in the below algorithm. where Bt nsm and Rt nsm are the temporary bandwidth allocation and transmission rate variables for MT m ∈ Mns, respectively; ΔB is the bandwidth allocation increment, Br ns is the remaining bandwidth for network n BS/AP s; η t m and Rt m are the temporary energy-efficient and transmission rate variables for MT m, respectively.

Algorithm Bandwidth Allocation Algorithm in SDBPA.

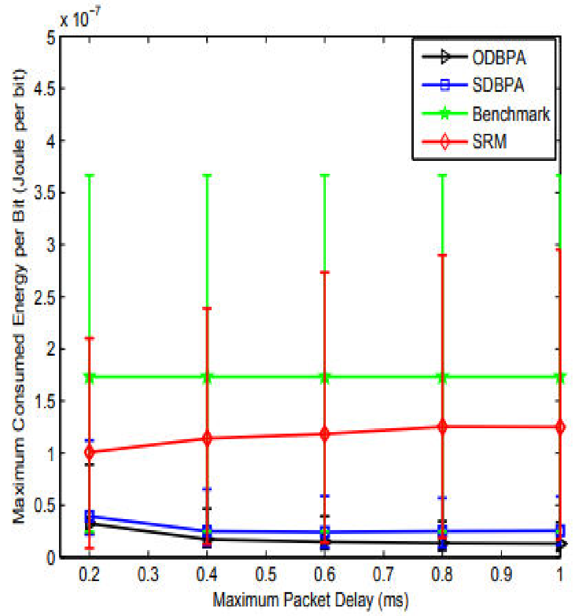
Input: $D_m^{\max}$, γ_m, λ_m, L, B_{ns} and P_m^T.
Output: B_{nsm}.
1: Initialize B_{nsm}, B_{nsm}^t, R_{nsm}^t, P_{nsm} and R_m.
2: **repeat**
3: All BSs/APs find $m^* = \min_{m \in M} R_m$, and MT m^* calculates $B_{nsm^*}^t = B_{nsm^*} + \Delta B$, R_{ns}^t
$(n^*, s^*) = \max_{(n,s) \in N, S_n} R_{nsm^*}^t$, $B_{n^*s^*m^*}$, η_{m^*} and R_{m^*}.
4: **if** $R_m \geq \psi(D_m^{\max}, \gamma_m, \lambda_m, L)$ **then**
5: All BSs/APs find $m^* = \max_{m \in M} \eta_m$, and MT m^* calculates $B_{nsm^*}^t = B_{nsm^*} + \Delta B$, R_n^t
and $(n^*, s^*) = \max_{(n,s) \in N, S_n} R_{nsm^*}^t$.
6: Network n^* BS/AP s^* calculates $\eta_{m^*}^t$ and $B_{n^*s^*}^r = B_{n^*s^*} - \sum_{m \in M_{n^*s^*}} B_{n^*s^*m}$.
7: **if** $B_{n^*s^*}^r > \Delta B$ and $\eta_{m^*}^t < \eta_{m^*}$ **then**
8: MT m^* updates $B_{n^*s^*m^*}$, and go to step 5.
9: **else**
10: Go to step 14.
11: **end if**
12: **end if**
13: **until**
14: Output B_{nsm}.

D. Orthogonal Frequency Division Multiplexing1

Using OFDM algorithm maximizing the energy efficiency per bit versus the number of femtocell at mobile terminal.

OFDM algorithm is low energy consumption with respect to femtocell MTs compared with existing methods ODBPA, SDBPA, BENCHMARK, and SRM Algorithms. As increasing the number of femtocell at mobile terminal, the maximum consumed energy per bit using OFDM is comparatively less than Optimum Distribution Bandwidth and Power Allocation, SDBPA, SRM, and Benchmark.

V. SIMULATION RESULTS



Iaximum consumed energy per bit vs. the maximum packet delay.

Fig describes that ODBPA algorithm is low energy consumption with respect to maximum packet delay compared with existing methods SDBPA, BENCHMARK, SRM Algorithms. Vertical lines stating max consumed energy per bit and max packet delay in the fig are called stem. At max packet delay 0.2 max consumed energy of four algorithms varies from 0.1 to 3.8. In Maximum Energy Consumed Energy per bit vs Maximum Packet Dealy, it shows that when the time delay increases from 0.2 to 1 energy consumption is reducing from between 0.5 to 0.1 and max consumed energy per bit become constant at max packet delay at particular period ex: at 0.8 as shown in fig 1.In legend there shown four different algorithms marking four different colors

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which gives easy analysis of low energy consumption algorithm. We get to know that ODBPA is good energy reducing technique where the energy is efficiently utilized.

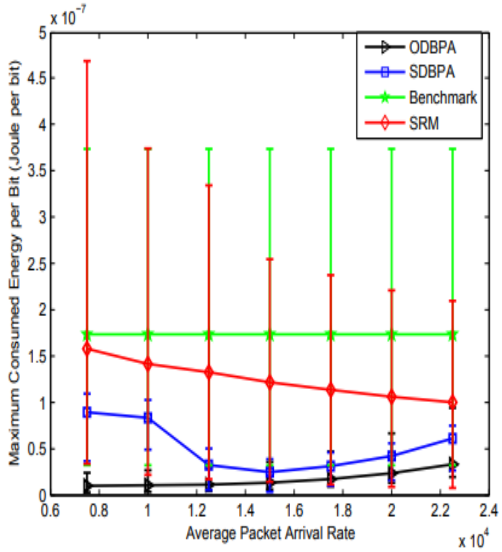


Fig. 2. Maximum consumed energy per bit vs. the average packet arrival rate.

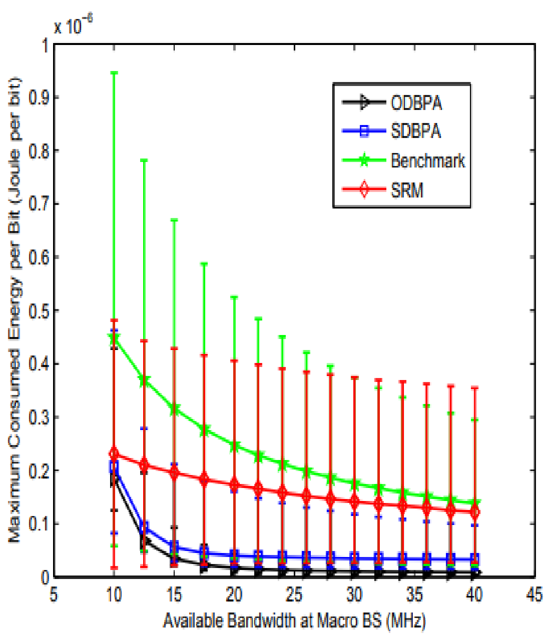
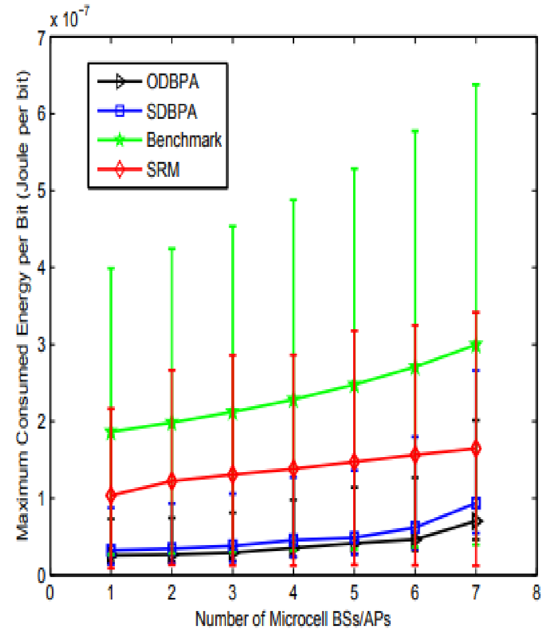


Fig. 3. Maximum consumed energy per bit vs. the total available bandwidth at macro BS.



1Fig. 4. Maximum consumed energy per bit vs. the number of microcell BSs/APs.

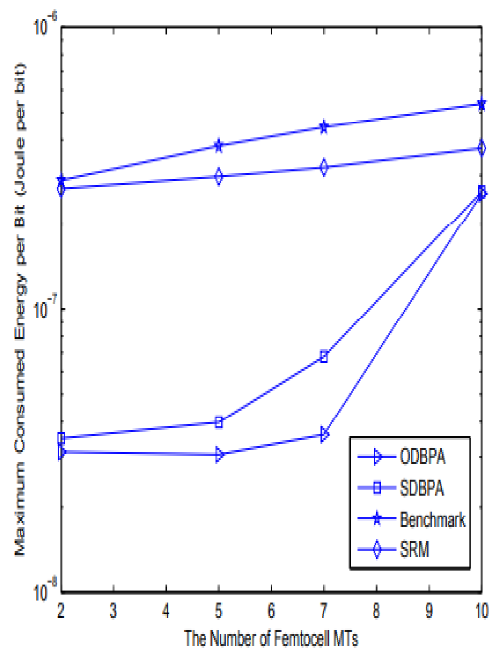
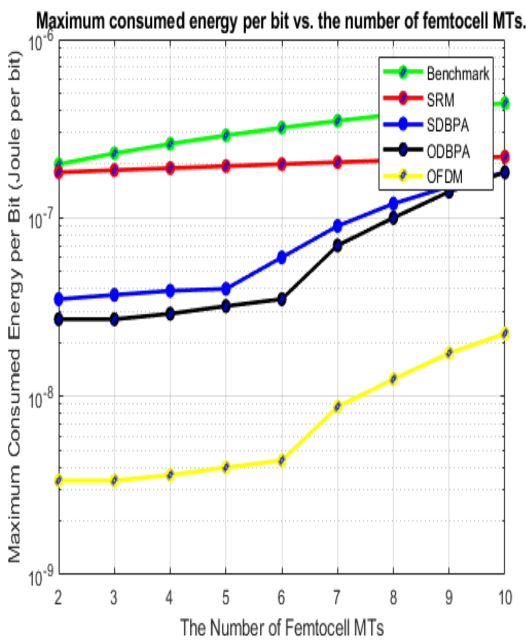


Fig. 5. Maximum consumed energy per bit vs. the number of femtocell MTs.

Fig describes that ODBPA algorithm is low energy consumption with respect to femtocell MTs compared with existing methods Sub Optimal Distribution Bandwidth and Power Allocation, BENCHMARK, SRM Algorithms. Initially max consumed energy lies between 10^-8 to 10^-7 with respect to the no. of femtocell at MTs i.e.2. As increasing the no.of femtocells at MTs energy consumption is increasing, but comparatively ODBPA algorithm gives efficiently utilization of energy as shown in the above fig.



6. Proposed OFDM performance compare with existing algorithms

OFDM algorithm is low energy consumption with respect to femtocell MTs compared with existing methods

ODBPA, SDBPA, BENCHMARK, and SRM Algorithms. As increasing the number of femtocell at mobile terminal.

VI. CONCLUSION

In this project, we study the uplink energy- efficient cross-layer resource allocation problem for a heterogeneous wireless access. In order to solve the above resource allocation problem, we model the energy-efficient bandwidth and power allocation problem as min-max fractional stochastic programming, and analyze the packet delay. Then, the Dinkelbach-type and dual decomposition methods are utilized to design the ODBPA and the SDBPA and OFDM is proposed to reduce the computational complexity. Simulation results demonstrate proposed algorithms can improve the energy efficiency significantly.

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