Optimal Max-SINR Scheduling in Full-Duplex OFDMA Cellular Networks with Dynamic Arrivals

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Abstract— **In this paper, we propose an optimal algorithm for scheduling in a full duplex Orthogonal Frequency Division Multiple Access network. This network exhibits a full-duplex base station that concurrently communicates with a pair of one uplink, and one downlink half duplex user equipment (UE). Our objective is to maximize the system's sum-SINR $i.e.$, the sum of the SINR values of all the UEs that are allocated resources. We formulate our optimal algorithm as an integer linear optimization problem. Our formulation of the problem has the originality of incorporating a non-full buffer traffic model. In order to deal with such type of traffic, we introduce a resource utilization factor along with additional constraints on the optimization. This factor helps tune the problem, affecting outputs such as UE SINR and throughput. We compare our algorithm with an iterative greedy heuristic full duplex Max-SINR algorithm we previously proposed, as well as with the related works. Simulation results show that the optimal solution provides improved throughput values in comparison with the heuristic algorithm, and that it constitutes a more realistic approach to scheduling than the proposals in the state-of-the-art. Finally, we study the effect of partial state information on the performance of our algorithm. Under imperfect channel information, our FD algorithm still provides higher UE throughput than traditional half duplex systems.**

I. Introduction

Global mobile data traffic grew 63 % in 2016, and exceeded 7.2 exabytes per month at the end of last year. These figures are expected to grow seven folds by the year 2021 [1]. Current half-duplex wireless communication systems are likely to soon fall short of satisfying the need for larger data rates. These systems allocate a radio resource exclusively to one user equipment (UE) either for transmission or reception. This limits the capability of the system, rendering the network bandwidth inefficiently used. However, recent developments in wireless technologies have led to establishing full duplex (FD) communications as a coping mechanism to the ever growing mobile industry. An FD Orthogonal Frequency Division Multiple Access (FD-OFDMA) system we simulate, exhibits a full duplex base station (BS) and half duplex (HD) UEs. This system allows allocating the same resource block to two different UEs: one on the uplink, and one on the downlink. The two UEs form a pair associated with the allocated resource block, on which the BS transmits and receives simultaneously. In theory, this leads to doubling the capacity. In practice, FD communications introduce new types of interferences that threaten to diminish their gains.

Arguably the biggest of these interference problems is self-interference. The transmitted signal from a full duplex device would be multiple times larger than the received signal, thus masking it. This is known as self-interference, a ramification of implementing FD. For the better part of the last century, self-interference was thought to make FD communication unachievable. However, the introduction of self-interference cancellation (SIC) techniques post 2010 altered the vision on FD communications, and boosted research in the domain. SIC is done via a set of advanced analog and digital processes as described in [2]. Our work builds on the presence of these technologies, as the efficiency of an FD system is tied to the SIC techniques in place.

In addition to self-interference, FD-OFDMA systems suffer from co-channel interference from within the same cell. An uplink UE, transmitting on a certain resource block with high power, will interfere, and generally degrade, the performance of a downlink UE receiving a relatively weak signal on the same resource block. While traditionally being an inter-cell problem, intra-cell co-channel interference is an additional issue FD systems need to tackle. Consequently, scheduling in the uplink and the downlink can no longer be done independently as in half duplex mode. The scheduler must ensure that the co-channel interference between the UEs of a selected pair does not hinder their performance. This mainly depends on the uplink UE's transmit power, as well as on the channel gain between the pair of UEs.

In our work, we tackle the complex issue of user equipment pairing. To this end, we formulate a matching problem between the UE pairs and the resource blocks. Additional constraints are imposed to insure the resources are distributed efficiently under the effect of non-full buffer traffic. Furthermore, we study the performance of our algorithm under imperfect channel state information. Specifically, we assume that the channel between the UEs of a pair cannot be estimated correctly. Precisely estimating this channel could incur a signaling overhead.

This paper is structured as follows. Section II discusses related work. Section III presents the system model. Section IV details our proposed algorithm for scheduling in FD wireless cellular networks. Simulation results are presented and discussed in Section VI. Section VII concludes the paper and states our future work.

II. Related Work

The authors of article [3] present a hybrid FD-OFDMA scheduler based on a greedy subcarrier allocation method.

The scheduling problem is formulated as a combinatorial problem of high complexity, with the objective of maximizing the sum-rate. The authors then introduce a heuristic algorithm with lower complexity, and indicate that it produces near optimal performance. We implement the scheduling algorithm introduced in this paper with a non-full buffer traffic model, and compare it to our work.

In [4], a joint UE selection and rate allocation algorithm is proposed. It is formulated as a nonlinear non-convex problem, with mixed discrete and continuous optimization. Because of the complexity of this problem, a suboptimal method is considered. The article concludes that FD systems have the potential to significantly increase the capacity of small cells, under the presence of efficient self-interference cancellation.

The authors in [5] propose an optimization problem with the purpose of allocating resources in what is described as a three-node system. The scenario implemented exhibits a full-duplex BS, and half-duplex UEs which are paired on the resources. Constraints are added on the minimum SINR value for a UE to be allocated resources, and on the UE transmission power as well. The problem thus belongs to the category of mixed integer nonlinear programs with high complexity and computational intractability.

In [6], the authors formulate a problem for resource allocation in FD-OFDMA networks. The goal is to maximize the sum-rate, as well as addressing power allocation for the UEs. The problem is non-convex with exponential complexity.

Finally, in [7] we proposed a heuristic FD Max-SINR algorithm. As we detail in section VI.B, this algorithm comprises a heuristic version of the optimal algorithm we present in this paper. We compare and contrast the two in terms of throughput and SINR.

Our proposed algorithm is formulated as an integer linear program, bearing significantly less complexity than the algorithms in the articles mentioned above [3]–[6]. Our work has the originality of using a non-full buffer traffic model. This is a more realistic approach compared to the full buffer traffic assumed in the articles [3]–[6]. Non full-buffer traffic, like streaming and video, would make up to 78 % of the global mobile traffic by the year 2021 [1]. In addition, implementing a full-buffer model in real life dynamic traffic scenarios could have dire consequences on the system's performance, as we later on demonstrate. We propose an approach to dealing with dynamic traffic arrivals by introducing buffer constraints to the optimization problem. We also add a resource utilization factor, which allows us to tune the problem, and thus the resulting UE SINR and throughput. Finally, we take into account the effect lacking complete channel state information could have on the performance of the network. This is a likely scenario for the implementation of FD-OFDMA networks, as estimating UE-UE channels could cause a burden in signaling. This is not addressed in the majority of the state-of-the-art.

III. System Model

A. Radio Model

We consider a single-cell FD-OFDMA system. This system is comprised of a full-duplex BS, and half-duplex UEs. The UEs are virtually divided into two sets: an uplink UE set, denoted by $\mathcal{U}$ and a downlink UE set, denoted by $\mathcal{D}$. The scheduling algorithms would pair between uplink and downlink UEs on the resource blocks *k* of the set *K*. This system is illustrated in Fig. 1.

In our work, we assume that the physical layer is operated using an OFDMA structure. The radio resources are divided into time-frequency resource blocks. In the time domain, a resource block (RB) contains an integer number of OFDM symbols. In the frequency domain, a resource block contains adjacent narrow-band subcarriers and experiences flat fading. Scheduling decisions for downlink and uplink transmissions are made in every Transmission Time Interval (TTI). At the beginning of each TTI, K resource blocks are to be allocated. The TTI duration is chosen to be smaller than the channel coherence time. With these assumptions, UE radio conditions will vary from one resource block to another, but remain constant over a TTI. The modulation and coding scheme (MCS), that can be assigned to a UE on a resource block, depends on its radio conditions. For performance evaluation, we consider LTE like specifications, with a resource block being composed of 12 subcarriers and 7 OFDM symbols.

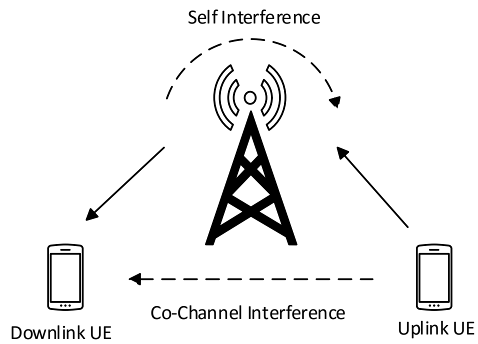

Figure 1. System Model

An adapted formula is used to calculate the SINR that takes into consideration the co-channel interference between a UE pair, and the self-interference cancellation performed by the BS. Let $P^u_{i,k}$ denotes the transmit power of the *i*th uplink user, on the *k*th resource block. Similarly, $P^d_{j,k}$ is the transmit power of the BS serving downlink user *j*, on the kth resource block. We denote by $h^u_{i,k}$ the channel gain from the *i*th uplink user to the BS on resource block *k*, and by and $h^d_{j,k}$ the channel gain from BS to the *j*th downlink user, on the kth resource block. Furthermore, $h_{ji,k}$ denotes the channel gain between the *i*th uplink user and *j*th downlink user, on the *k*th resource block. $P^u_{i,k}|h_{ji,k}|^2$ is thus the co-channel interference on downlink UE j caused by uplink UE i, using the same resource block k. The self-interference cancellation level at the BS is denoted C_{SI}. In particular, $\frac{P^d_{j,k}}{C_{SI}}$ represents the residual self-interference power at the BS on the *k*th resource block. Finally, $N_{0,k}$ and $N_{j,k}$ denote the noise

powers at the BS and at the *j*th downlink user, on the *k*th resource block, respectively. Equations (1) and (2) denote the formulas for SINR calculation for uplink and downlink UEs respectively [2].
For an uplink UE,

$$S_j^u(i,k) = \frac{P_{i,k}^u |h_{i,k}^u|^2}{N_{0,k} + \frac{P_{j,k}^d}{C_{SI}}}, \ i \in \mathcal{U}, \ j \in \mathcal{D}. \tag{1}$$

For a downlink UE,

$$S_j^d(j,k) = \frac{P_{j,k}^d |h_{j,k}^d|^2}{N_{j,k} + P_{i,k}^u |h_{ji,k}|^2}, \ i \in \mathcal{U}, \ j \in \mathcal{D}, \tag{2}$$

where $S_j^u(i,k)$ is the SINR of UE i on resource block k while using the same resources as UE j. Similarly, $S_i^d(j,k)$ is the SINR of UE j on resource block k while using the same resources as UE i.

In this paper, we consider two cases for the channel state information. At first, we assume that this information is available to the base station. Under this assumption, we compare our optimal algorithm to the heuristic proposal, and to the related works. Afterwards, we assume that channel state information is incomplete, and that channel between the UEs of an uplink-downlink pair is incorrectly estimated. Under this assumption, we compare the performance of our algorithm with traditional half-duplex Max-SINR scheduling. In this case, the value of the channel between a certain pair of UEs is estimated following a normal law, with a mean equal to the actual channel, and a varying standard deviation σ (Eq. 3). The standard deviation is used to simulate the algorithm under different channel estimation errors.

$$h'_{ji,k} \hookrightarrow \mathcal{N}(h_{ji,k}, \sigma^2) \tag{3}$$

B. Traffic Model

We consider a non full-buffer traffic model. The number of bits each UE requires to transmit, or receive, follows a certain demand and is not infinite. A downlink UE has a data queue, known at the base station, that it wants to receive. An uplink UE has its own queue of bits that it wants to transmit to the base station. The optimization is sequential and done each TTI. Maximizing the SINR every TTI is equivalent to maximizing it throughout the entire simulation. UE queues are filled according to a random process with a number of bits/s equal, on average, to the UE throughput demand. Once the optimization problem is solved, the queue length of each UE is deducted by a number of bits depending on the resources it was allocated, and following the MCS used. Any bits remaining in the queue after the scheduling in a certain TTI are carried on to the next. In our work, the scheduler records how many bits a UE has in its designated queue, can estimate the number of bits it can send depending on its SINR, and can thus recalculate the queue status after the resource blocks are assigned.

IV. Optimal Max-SINR Algorithm

The UE pair-resource assignment variable z_{ijk}, is defined $\forall \ k \in K$, $\forall \ i \in \mathcal{U}$, $\forall \ j \in \mathcal{D}$, and is equal to one if uplink UE i is paired with downlink UE j on resource block k. It is equal to zero otherwise. Z_{ijk} is a matrix containing all the variables z_{ijk}. We formulate the optimization problem as follows:

$$\text{Maximize} \quad \sum_{k\in K}\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{D}} z_{ijk}(S_j^u(i,k) + S_i^d(j,k)), \tag{4a}$$

$$\text{subject to} \quad \sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{D}} z_{ijk} \leq 1, \ \forall k \in K, \tag{4b}$$

$$\alpha_p \sum_{k\in K}\sum_{j\in\mathcal{D}} z_{ijk} T_{ijk}^u \leq D_i, \ \forall i \in \mathcal{U}, \tag{4c}$$

$$\alpha_p \sum_{k\in K}\sum_{i\in\mathcal{U}} z_{ijk} T_{ijk}^d \leq D_j, \ \forall j \in \mathcal{D}, \tag{4d}$$

$$z_{ijk} \in \{0,1\}, \ \forall i \in \mathcal{U}, \forall j \in \mathcal{D}, \forall k \in K. \tag{4e}$$

In the previous program, $S_j^u(i,k)$ is the SINR of uplink UE i on resource block k, while it is paired with downlink UE j. Likewise, $S_i^d(j,k)$ is the SINR of UE j on resource block k, while it is paired with uplink UE i. Furthermore, α_p represents the minimum percentage resource utilization. This means that the UE will transmit or receive at least α_p of its queued bits on the resources allocated to it. T_{ijk}^u is the number of bits UE i can transmit on resource block k while paired with UE j. Similarly T_{ijk}^d is the number of bits UE j can receive on resource block k while paired with UE i. T_{ijk}^u and T_{ijk}^d depend mainly on the radio conditions of the UEs. In addition, D_i is the demand of UE i *i.e.*, the number of bits in its queue. Likewise, D_j is the demand of UE j.

Equation (4a) expresses the objective of our problem, to maximize the total sum of UE SINR of the pairs that are allocated resource blocks *i.e*, the system sum-SINR. According to (4b), each resource block should be allocated to either one or no pair. Equations (4c) and (4d) dictate the efficiency of the resource allocation process. If $\alpha_p = 1$, then a UE is allocated a number resource blocks, if the number of bits in its queue is greater than or equal to the number of bits it can transmit, or receive, on these resources. If $\alpha_p = 0.8$, then a UE is allocated resource blocks if the number of bits in its queue is greater than or equal to 80 % of the number of bits it can transmit, or receive, on the resources allocated to it. The importance of this factor is that it allows us to tune the optimization problem based on different objectives. When $\alpha_p = 1$, the constraints in (4c) and (4d) insure that the resources are distributed efficiently, and not allocated to UEs that would not use them. This condition is needed because the UE buffer is not infinite and could be depleted. Furthermore, lowering this factor limits the number of resource blocks that a UE can get, and permits studying the effects of full buffer assumptions on the performance of real networks, where the buffers are actually finite.

V. Algorithm Complexity

The variables in this problem are all integers. The objective function and the constraints, which depend on the binary value of z_{ijk}, are linear. The optimization problem is thus an integer linear program (ILP). Its complexity depends on the number of binary values, as well as the number of constraints.

VI. Simulations and Results

A. Simulation Parameters

The simulation parameters, used to run our algorithms in MATLAB, and using the CVX tool, are presented in the table below.

Table I
SIMULATION PARAMETERS

Parameter	Value
Cell Specifications	Single-Cell, 1 km Radius
Number of RBs	20
Traffic Type	Poisson
TTI Duration	1 ms
BS Transmit Power/RB	0.1 W
UE Transmit Power/RB	0.02 W
SIC Value	10^{14}
Number of UEs	10: 5DL, 5UL
UE Distribution	Uniform
Demand Throughput	2 Mbps
Fast Fading	Exponential variable
Shadowing	Log-normal variable
Path Loss Model	Extended Hata Path Loss Model

The channel gain takes into account the path loss, the shadowing and the fast fading effects. The path loss is calculated using the extended Hata path loss model [8]. The shadowing is modeled by a log-normal random variable $A_s = 10^{(\frac{\xi}{10})}$, where ξ is a normal distributed random variable with zero mean and standard deviation equal to 10. The fast fading is modeled by an exponential random variable A_f with unit parameter. This model is used for urban zones and it takes into account the effects of diffraction, reflection and scattering caused by city structures.

B. Heuristic Algorithm

We introduce a heuristic algorithm with the same objective. This algorithm, Heuristic FD Max-SINR [7], seeks to couple between two half-duplex UEs, one uplink and one downlink, on the same resources. The algorithm functions as follows. Each TTI, the UE queues are filled following a random process. This makes the traffic non-full-buffer. As such, a UE that has depleted its queue is excluded from the resource allocation within the same TTI. For each resource block k of the set K, the algorithm calculates the SINR for each possible pair between an uplink UE and a downlink UE. We compute the SINR as indicated in equations (1) and (2), and allocate the currently selected resource block to the pair of UEs which has the highest value of the sum: $S_j^u(i,k) + S_i^d(j,k)$, where i belongs to the set of uplink UEs, and j to the set of downlink UEs. This algorithm is iterative, and allocates the currently selected resource block to the UE pair which has the highest sum of SINR. This is a local approach. It is in contrast with the globality of the optimization problem which makes the allocation decision for all the resources at the same time.

C. Optimal Solution vs. Heuristic Approach

We compare between the heuristic algorithm and the optimal solution (for α_p = 1). In Fig. 2, we plot the CDF of the UE SINR for different simulation runs. Both the optimal and heuristic FD Max-SINR algorithms generally produce similar SINR values for the UEs. However, the difference in the lowest attained SINR value by each of the algorithms is significant: -9 dB for the heuristic algorithm, and 4 dB for the optimal algorithm. This proves that our optimal algorithm allocates resources more efficiently. Only UEs with acceptable SINR will get allocated resources, thus increasing the spectral efficiency of the system. In addition, we plot the CDF of the UE SINR

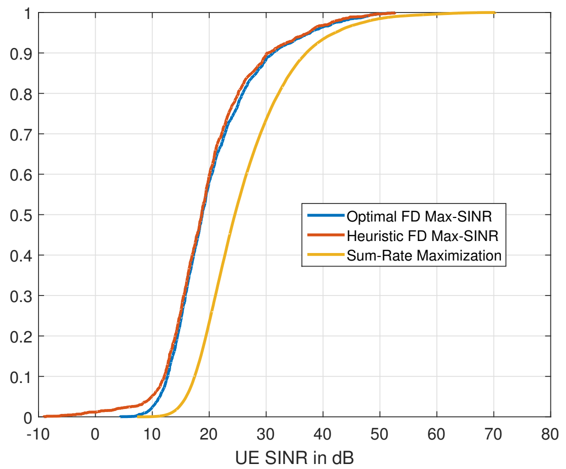

Figure 2. CDF plot of the UE SINR

for the sum-rate maximization algorithm proposed in [3], albeit with non-full buffer traffic. Sum-rate maximization algorithms are mainly concerned with maximizing the UE throughput. This algorithm tends to produce higher SINR values than our algorithm with an average of 3-5 dBs. This is to be expected as the sum-rate maximization algorithm puts no limits or constraints on UE pair selection.

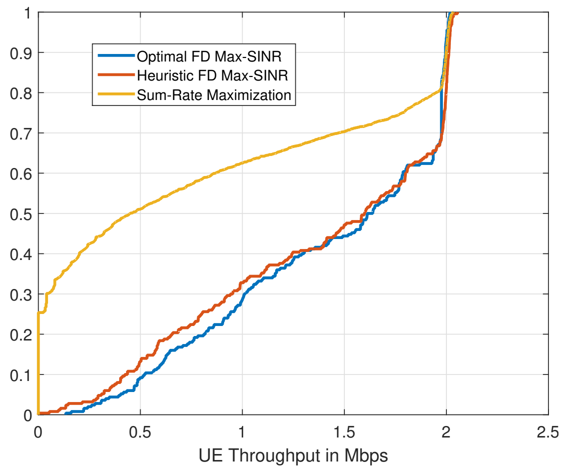

Figure 3. CDF plot of the UE throughput

We plot the UE throughput results in Fig. 3. The least attained throughput by an optimal algorithm UE is 200 kbps higher than the lowest by a heuristic algorithm run. In addition to the difference in SINR values for UEs which were allocated resources, this disparity is also justified by the constraints of the optimal problem (4c) and (4d). These restrictions imply that a resource block will only be allocated to a UE if and only if it is going to be used in its entirety, thus enhancing resource utilization.

Similarly, we plot the throughput attained by UEs following the sum-rate maximization algorithm described in [3]. For the same simulation parameters, this algorithm produces a heavily degraded performance compared to our algorithms. More than 25 % of the simulated UEs got zero throughput, with our optimal FD Max-SINR algorithm having almost double the amount of UEs attaining a throughput equal to the demand. At the median mark, half of the sum-rate algorithm UEs got a throughput higher than 500 kbps, compared to around 1.6 Mbps for the optimal FD Max-SINR algorithm. To conclude, this difference in results shows that mis-estimating the buffer capacity can produce a huge gap in the performance, reaffirming our statement that dynamic traffic produces a more realistic approach to scheduling. Furthermore, our optimal FD algorithm is adaptable to full buffer traffic, an important feature lacking in the state-of-the-art.

Finally, we compare the simulation duration for each of the optimal (branch and bound) and heuristic (iterative) algorithms. Under identical conditions and using the simulation parameters of section VI-A, we note the time taken by the simulator to allocate the resources during one TTI. A statistical interpretation of the results is given in Table II. The criteria are measured in seconds. The machine used for the simulations has an INTEL(R) core i3-4170 CPU at 3.70 GHz processor. It runs on 8 GB of RAM.

Table II
HEURISTIC VS. OPTIMAL: SIMULATION TIME

Criteria	Optimal (s)	Heuristic (s)
Mean	1.3125	0.1710
1^{st} Quartile	0.1563	0.1646
Median	0.1563	0.1692
3^{rd} Quartile	0.1836	0.1748

For more than 90 % of the simulations, results show simulation time of the same order for both algorithms. In fact, for around half of the simulations, the optimal algorithm takes fractionally less time. However, for a few number of cases, the optimal algorithm will take significantly more time to find the optimal solution. This can be seen in the mean values, where the optimal algorithm has a mean value greater by 1.14 s.

D. Effect of the Resource Utilization Factor α_p

We seek to study the effect of varying the resource utilization parameter α_p on the objective function. Recall that the objective function is expressed as the system sum-SINR, *i.e.*, the sum of the SINR values of all the UEs. We plot the CDF of the objective value for values of α_p equal to 1, 0.8, 0.6, 0.4, 0.2, and 0 in Fig. 4. The result for the heuristic algorithm we presented in section VI-B is also plotted on the figure.

Figure 4 shows that the value of the objective function is inversely proportional to α_p. For α_p = 1, the maximum attained value of the system sum-SINR is around 1000 dB. Almost half the runs of the optimization problem attained a value greater than 800 dB. In comparison, for α_p = 0.4, the maximum attained value is 1200 dB, with more than half the runs giving a value greater than 900 dB. This is due to the fact that for values of α_p lower than one, the algorithm can allocate a resource block to a UE even if does not need to use it completely. This allows the optimizer to maximize the objective value with looser constraints, or in other words, at the cost of resource utilization.

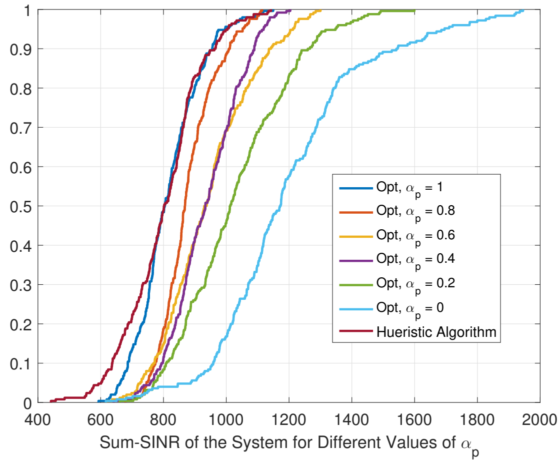

Figure 4. CDF plot of the objective value as a function of α_p

Furthermore, the results for the heuristic algorithm shows near optimal results when α_p is set to 1. In fact, for a few number of cases, the heuristic algorithm gave a higher sum-SINR value. This is because the heuristic algorithm's only constraint on the usage of the resource blocks is for a UE to have a non-empty queue. If a user pair has excellent radio conditions, it would be allocated the resource block even if the UEs had one bit to transmit.

In Fig. 5, we plot the throughput attained per UE as a function of α_p. Note that the relation between the UE SINR and the throughput is set by the MCS used. The UE throughput increases with α_p. For α_p = 1, almost 30% of the UEs attained the value of the demand of 2 Mbps. Half of the UEs had a throughput higher than 1.6 Mbps. In contrast, for α_p = 0.4, less than 20% of the UEs emptied their queues. Around 30% had a throughput higher than 1.6 Mbps. Moreover, for α_p = 0.4, around 20% of the UEs had zero throughput. Lower values of α_p mean that the few UEs with excellent radio conditions will take up the majority of the resources. Consider the case for α_p = 0. This means that the constraints (4c) and (4d) on the buffer occupancy are removed. This is in fact, comparable to the full-buffer models present in the majority of the state-of-the-art works [3]–[6]. The curve corresponding to α_p = 0, shows the consequences of implementing a full buffer model on UEs with dynamic arrivals. More than half the UEs were denied resources, rendering the scheduling ineffective. Finally, the contradiction between figures 4 and 5 is down to the effect of dynamic arrivals. Without constraints on the buffer, only UEs with excellent radio conditions would be selected, leaving many others denied throughput. We use Jain's fairness index [9] to determine whether the resource are getting allocated fairly under our proposed optimal Max-SINR algorithm. This index is computed according to the Raj-Jain equation as follows:

$$\mathcal{J}(x_1, x_2, ..., x_n) = \frac{(\sum_{i=1}^{n} x_i)^2}{n.\sum_{i=1}^{n} x_i^2}. \quad (5)$$

For the optimal case (α_p = 1), our optimal FD Max-SINR has a Jain index value of 0.9370. The algorithm allocates the resources fairly. Although this is counter intuitive, it is mainly due to the fact that FD wireless networks make double the resources available to the UEs.

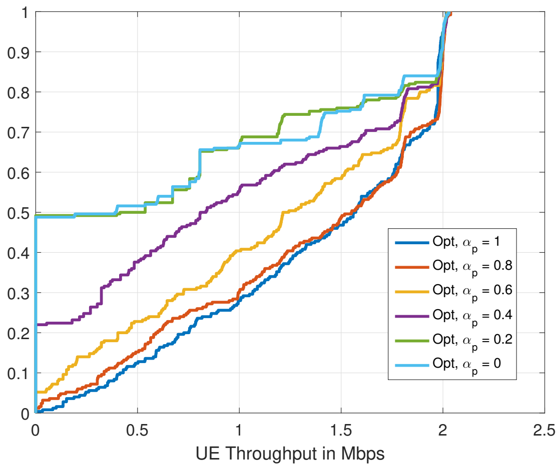

Figure 5. CDF plot of the UE throughput as a function of α_p

E. Effect of Incomplete Channel State Information

In this section, we assume that the channel between the UEs of a certain pair is not known. It is estimated following a normal law, with a varying standard deviation. The standard deviation is taken as a percentage of the real channel value. The error on the channel is as such relative to the actual value. We simulate our proposed algorithm for different values of σ, and compare it to a traditional HD Max-SINR algorithm. Figure 6 shows the throughput attained by the UEs throughout the simulations.

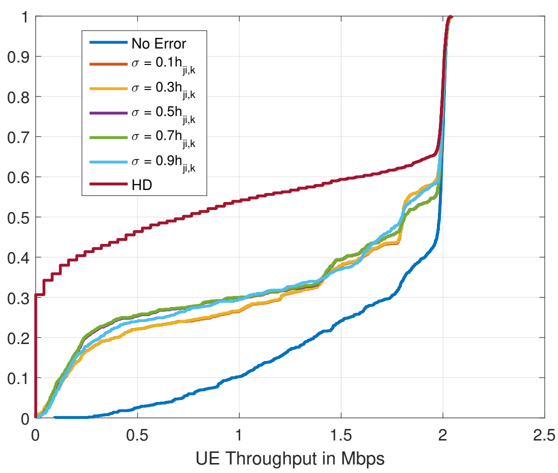

Figure 6. Effect of Incomplete Channel State Information

The UE throughput curves in Fig.6 show significant gains for FD systems over their HD counterparts. Between 40-60% of the FD UEs attained a throughput equal to the demand. Less than 35% of the HD UEs achieved that mark. Furthermore, even in the worst case scenario for our optimal FD Max-SINR algorithm ($\sigma = 0.9h_{ji,k}$), every FD UE attained a throughput higher than its HD counterpart. Around 30% of the HD UEs were denied any resources, attaining zero throughput. While it is evident that mis-estimating the channel between the UEs degrades the performance of FD-OFDMA systems, it is also evident that FD scheduling still heavily outperforms HD systems.

VII. Conclusion

In this article, we presented our optimal algorithm for scheduling in FD-OFDMA networks. Our formulated problem is an integer linear program with the objective of maximizing the system's sum-SINR. In our work we considered a resource utilization parameter α_p to help incorporate a non-full buffer traffic model. In contrast to the state-of-the-art, which assumes full buffer traffics and works on snapshots, our model takes into account dynamic arrivals. Our simulation results show that the parameter α_p enables us to tune the performance of the optimal algorithm. Simulation results also show higher UE SINR and throughput values for our optimal algorithm, in comparison with the heuristic one. Finally, an under incomplete channel state information, we show that our FD algorithm outperforms scheduling in traditional HD systems. Future work includes adding power control to the objective function as well as implementing other, more fair, algorithms such as proportional fair.

VIII. Acknowledgment

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