Resource allocation algorithm for symmetrical services in OFDMA systems

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Article Info

Article history:
Received Aug 9, 2019
Revised Nov 10, 2019
Accepted Nov 23, 2019

Keywords:
Adaptive resource allocation
Genetic algorithm
Linear programming
Multiobjective optimization and non dominance
OFDMA

ABSTRACT

The widespread acceptance of symmetrical services has urged for performance betterment techniques in wireless communication systems. In this paper, we propose an algorithm for resource allocation in MIMO-OFDMA system for applications that demand similar quality in uplink and downlink direction. The problem is formulated as multiobjective optimization problem with objectives to maximize the bidirectional data rates for individual users and to minimize the difference between the uplink and downlink data rate for each user. Fairness has been considered as a constraint in the optimization problem. The power allocation for each subcarrier in the OFDMA system is carried out using Linear Programming (LP) techniques, while the subcarrier allocation problem has been undertaken using an innovative multiobjective optimization technique that employs the concept of non-dominance in evolutionary algorithms. The results are extremely encouraging as they outperform the algorithms reported in literature using linear programming techniques or evolutionary algorithms solely.

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1. INTRODUCTION

The ubiquitous application of smart devices has impelled for radical change in the telecommunication industry to meet the requirements of services that demand higher spectral efficiency and data rate. Smart devices have been constantly on the rise and studies reveal that the number of smart phone users in India grew to 239 million by the end of 2015 and is expected to be 702 million by 2020 [1]. The tremendous increase in the need for high data rate turns up against the constraints of radio spectrum availability and the telecommunication infrastructure. Hence, the techniques deployed need to be extremely efficient and judicious in terms of the usage of the available spectrum and infrastructure.

Nowadays, symmetrical services have found wide popularity and the demand to ameliorate the performance of such services is at its peak. The attribute of symmetrical services, however, does not adhere to the framework of the existing wireless infrastructure [2]. The existing framework cannot support symmetrical services efficiently since the resources are non-intersecting in uplink and downlink direction and therefore cannot guarantee the flow availability in both directions.

Orthogonal Frequency Division Multiple Access (OFDMA) is a multi-user version of the popular OFDM digital modulation scheme, which splits the available system bandwidth into orthogonal subcarriers. Further, Multiple-input-multiple-output (MIMO) OFDMA system helps to improve the system capacity, transmission range reliability and suppress interfering signals. The channel throughput increases linearly with
every pair of antennas added [3] at the cost of hardware complexity. It demands careful design of the resource allocation algorithm in MIMO OFDMA systems when employed for symmetrical services.

With vehement expansion of the telecommunication industry, customers demand high Quality of Service (QoS) which includes high data rate and roaming facilities. In such a scenario the formulation of the resource allocation problem results in a constrained multiobjective optimization problem. Quite a large number of resource allocation problems in OFDMA systems have been investigated in literature [4-22]. The problems have been addressed using optimization theory, graph theory and game theory [7-8]. The works in which the resource allocation problem was addressed using optimization with Linear Programming (LP) techniques resulted in suboptimal solutions or optimal solution with high complexity [9-10]. In such cases, optimization of resource allocation is mostly a mixed binary integer programming problem which is non-convex in nature, thereby resulting in highly complex solutions, which may not be feasible always. The authors in [21] employs an evolutionary approach for optimization of routing in optical OFDM systems while in [22], this approach is used successfully for resource allocation in a single direction OFDM system. In [23], inverse water filling algorithm is proposed for power allocation in wireless systems, while the authors in [24] propose a genetic algorithm for resource allocation in IPTV applications. In [25], a Composite Genetic and Ordered Subcarrier Pairing algorithm is proposed to solve the problem of resource allocation in an OFDM based Cognitive radio system.

Since the resource allocation problem for improving the performance of the system with symmetrical services is a constrained multiobjective optimization problem, the exclusive use of linear programming techniques solely results in high order of complexity [6]. Therefore attaining optimal solution becomes difficult and pressurizes to compromise with suboptimal solutions.

The proposed work sets its goal to maximize the data rate and minimize the difference in the bidirectional rates for individual user in the MIMO OFDMA system. Works of similar nature have been reported, wherein the authors have tried to maximize the overall data rate of the system rather than considering each individual user case. Genetic algorithm (GA) has been adopted in this paper for subcarrier allocation and weighted sum method for power allocation. The inspiration for adopting genetic algorithm comes from the fact that GAs are ideal for optimization problems with a large feasible solution space where a quick sub-optimal solution will suffice. Non-dominance Sorting Genetic Algorithm II (NSGA-II) is a multiobjective optimization algorithm belonging to the category of evolutionary algorithms and is being employed here for subcarrier allocation.

To this end, our main contributions in this paper are consolidated as given below:

We consider maximizing the data rates and minimizing the difference in uplink and downlink data rates for each individual user in the system, under the assumption that all the users in the system demand symmetrical quality.

We have combined weighted sum method and NSGA-II for power allocation and subcarrier allocation respectively. The combination of these two techniques for resource allocation in MIMO OFDMA system has resulted in better system performance in terms of data rates and computational complexity.

While implementing NSGA II, we have redefined the chromosomes in a novel manner which helped in further reducing the complexity of the solution.

2. RESEARCH METHOD

The algorithm is applied at the MIMO OFDMA transmitter of both uplink and downlink directions, to allocate power and subcarriers to the users in a manner that the user attains almost similar quality in both uplink and downlink directions. The power allocation is performed using conventional linear programming techniques. The objective of the multiobjective optimization problem is to maximize the data rate in both the uplink and downlink direction and minimize the difference in the data rates between the two for each individual user. The base station and user equipment is updated every time the sub-channel information changes.

A single cell MIMO OFDMA system for downlink and uplink is considered. The cell spectrum of B Hz is divided into a set of M subcarriers and shared by a set of K users. It is assumed that no two users share the same subcarrier. The base station and user equipment have perfect information about channel states (CSI) through feedback channels. To support this assumption the wireless channel is considered to be slowly time-varying, frequency-selective Rayleigh faded.

The transmission process comprises of two phases:
a. Uplink Phase

In the uplink phase the data from the user is sent through an OFDMA system to the base station. The signal-to-noise-ratio $\gamma_{ij}^2$ is $\frac{h_{ij}^2}{No.B/N}$. $\omega_{ij}$ takes the value 1 if $j^{th}$ subcarrier is allocated to the $i^{th}$ user or else it is set to 0.

b. Downlink Phase

In the downlink phase, the data from the base station is passed through an OFDMA system to the user. The signal-to-noise-ratio $\gamma_{ij}^2$ is $\frac{h_{ij}^2}{No.B/N}$. $\omega_{ij}$ takes the value 1 if $j^{th}$ subcarrier is allocated to the $i^{th}$ user, else it is set to 0. Notations as shown in Table 1.

| Symbol | Description |
|--------|-------------|
| $B$ Hz | Total Bandwidth |
| $M$ | Number of subcarriers |
| $K$ | Number of users |
| $P_T$ | Total Uplink Power |
| $P_{BS}$ | Total Downlink Power |
| $i$ | User |
| $j$ | subcarrier |
| $h_{ij}$ | Uplink channel gain in the subcarrier $j$ |
| $No.$ | Noise power spectral density |
| $N$ | Noise power |
| $R_{i1}$ | Data rate of user $i$ in uplink |
| $\omega_{ij1}$ | Uplink Subcarrier allocation metric |
| $\gamma_{ij}$ | Uplink signal-to-noise-ratio |
| $h_{ij}$ | Downlink channel gain in the subcarrier $j$ |
| $R_{i2}$ | Data rate of user $i$ in downlink |
| $\omega_{ij2}$ | Subcarrier allocation metric in downlink |
| $\gamma_{ij}$ | Downlink signal-to-noise-ratio |

The objectives of the problem are to:

Maximize $R_{i1}$

Maximize $R_{i2}$

Minimize the difference in the magnitudes of the two rates of user $i$, i.e., $\|R_{i1} - R_{i2}\|$

The expression for $R_{i1}$ is given as,

$$\sum_{j=1}^{M} \omega_{ij1} \cdot \log \left[ 1 + \frac{p_{ij} \cdot h_{ij}^2}{No.B/N} \right]$$

Similarly the expression for $R_{i2}$ is,

$$\sum_{j=1}^{M} \omega_{ij2} \cdot \log \left[ 1 + \frac{p_{ij} \cdot h_{ij}^2}{No.B/N} \right]$$

The third objective is to minimize the difference in the rates of the $i^{th}$ user i.e., $\text{Minimize} \|R_{i1} - R_{i2}\|$, with the following constraints,

$$C1: \omega_{ij1}, \omega_{ij2} \in [0,1]$$
$$C2: \sum_{j=1}^{M} \omega_{ij1} \leq 1$$
$$C3: \sum_{j=1}^{M} \omega_{ij2} \leq 1$$
$$C4: \sum_{j=1}^{M} P_{j1} \leq P_T,$$
$$C5: \sum_{j=1}^{M} P_{j2} \leq P_{BS}.$$  

(3)

The constraint $C1$ is introduced for relaxing the optimization problem to binary values. $C2$ and $C3$ ensure that a particular subcarrier will be allocated to a single user in each direction. The constraint $C4$ and
C5 shows that the sum of all power allocated to all subcarriers in the uplink and downlink respectively is limited to the total power. The constraints C6 and C7 ensure that the rate of each user i in the uplink and downlink will be at least $R_{\text{min}}$, to ensure fairness among the users. Employing linear programming techniques solely leads to a solution which is highly complex and thus has motivated us to combine evolutionary techniques with LP and thereby arriving at better solutions.

GA belongs to the category of global search heuristics that facilitate to find solutions to optimization problems. It is a class of evolutionary algorithms that uses techniques inspired from biology such as inheritance, mutation, selection, and crossover. During the initial phase of implementation of GA, a set of chromosomes are assumed. The assumed chromosomes are random possible solutions to the optimization problem. Representation of these chromosomes plays a major role in determining the complexity of the solution to the optimization problem. Generally in literature, the chromosomes are represented as binary strings [22], non-binary strings, matrices etc. The fitness value is computed for each assumed chromosome in the first generation. It is then made to undergo crossover and mutation. The new chromosomes so formed are selected for the next generation population. These are further made to undergo mutation, selection and crossover. The algorithm terminates when either the maximum number of generations are reached or if a satisfactory fitness value is obtained. If the algorithm terminates due to maximum number of generations, a satisfactory result may or may not have been reached.

NSGA II is allied to the category of GAs, primarily for solving multiobjective optimization problems. NSGA II uses the concept of non-dominance in its search for the computed fitness function in each generation. Solutions are compared for non-dominance and sets of non-dominated solutions are categorized into different fronts. The new offspring’s are created using a selection process followed by crossover and mutation. There are different types of selection process to select the offspring, most popular being the tournament selection. Number of techniques to carry out mutation and crossover is presented in literature. This offspring is used as the solution/chromosome for the next iteration. As in GA, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

In this work, NSGA II is utilized to allocate the subcarriers and weighted sum method for power allocation in a MIMO OFDMA system for symmetrical services.

Since the resource allocation problem formulated is multiobjective in nature, the fitness functions are multiple, namely the data rates in uplink and downlink and the difference between the two for each individual user. The steps followed for subcarrier allocation is as follows:

Step 1: Input number of generations (G), Size of population, Channel gain $h_{1i}$ and $h_{2i}$ for each user in each subcarrier, Total Power ($P_T$ and $P_{BS}$), $B$, $M$ and $K$.

Step 2: Create initial population of chromosomes and calculate their data rates using (1) and (2) and the difference in data rates. For the initial iteration, the power is equally allocated to all the users in both directions. As mentioned earlier representation of the chromosome plays an important role. Here the chromosomes are the subcarriers that are allocated to the users. Therefore basically, each solution is a matrix of size $K \times M$. If the size of the population is 20, means $20 \times M$ matrices, which makes the problem solving very tedious and complicated. E.g: For a 4 subcarrier 2 user system, a sample solution looks like,

\[
\begin{bmatrix}
1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1
\end{bmatrix}
\]

Handling 20 such matrices in a single iteration itself makes the solution very complex and time consuming. This is overcome by defining the chromosomes in a novel manner. Instead of the matrices, the chromosomes are represented as a non-binary string where the position and the value of the data indicate which subcarrier is allocated to a user. The representation for the chromosomes in the above example is given as 1122. Since the first position is a ‘1’, it means that the first subcarrier is allocated to user 1. Similarly, the value in the next position is also ‘1’, indicating that the second subcarrier is allocated to user 1. The third and fourth position has a value ‘2’ which means that the third and fourth subcarrier is allocated to user 2. This type of design reduces the complexity of the solution to large extent.

Step 3: Compute the fitness function for each chromosome, i.e., value of $Ri1$ and $Ri2$ and the difference in data rates.

Step 4: Sort all chromosomes in a manner that all solutions that are not dominated by any other into front 1, and dominated by any one into front 2 and so on.

Step 5: Generate probability levels for each chromosome based on fronts allotted, such that the chromosome in front 1 has highest probability of selection for crossover.

Step 6: Based on fitness value select two chromosomes from the entire population and two points randomly on the parent chromosome for crossover. Two point crossover is opted in this solution. If the
chromosomes selected are 1112 and 2221, then in two point crossover, two points are randomly selected. For example, if 1 and 3 are selected, then after the first crossover the resultant is 2112 and 1221. When the crossover is carried out in position 3, it becomes 2111 and 1222. So obtained is the child chromosome after crossover.

Step 7: Replace the two chromosomes of lowest fronts with the two new child chromosomes.
Step 8: Select a chromosome from the entire population for mutation.
Step 9: Flip the channels allocated to users in the selected chromosome.
Step 10: If a particular user has more channels than he should, corresponding channel is allocated to the user with less number of channels.
Step 11: If any user has less number of channels, unallocated channel with highest channel gain is allocated to that user.
Step 12: Compute the power for each subcarrier using LP technique.

The lagrangian of the objective function in (1) to (3) is written as,

$$L(.) = \alpha_i R_{i1} + \alpha_{i2} R_{i2} - \lambda_i \sum_{j=1}^{K} \omega_{ij1} - 1] - \lambda_{i2} \sum_{j=1}^{K} \omega_{ij2} - 1] - \lambda_{i3} \left[ \sum_{j=1}^{K} \omega_{ij2} p_{ij2} - P_T \right] - \lambda_{i4} \left[ \sum_{j=1}^{K} \omega_{ij1} p_{ij1} - P_{BS} \right]$$

(4)

The lagrangian is modified as,

$$L(.) = \sum_{j=1}^{M} \omega_{ij1} (\overline{f}(p_{ij1})) + \sum_{j=1}^{M} \omega_{ij2} (\overline{f}(p_{ij2})) + \lambda_{i1} \left[ \sum_{j=1}^{K} \omega_{ij1} - 1 \right] - \lambda_{i2} \left[ \sum_{j=1}^{K} \omega_{ij2} - 1 \right] + \lambda_{i3} P_T + \lambda_{i4} P_{BS}$$

where \( \overline{f}(p_{ij1}) = \log_2 \left[ 1 + \gamma_{ij2} p_{ij2} \right] (\alpha_{i2}) - \lambda_{i4} \sum_{j=1}^{K} p_{ij1} \) and \( \overline{f}(p_{ij2}) = \log_2 \left[ 1 + \gamma_{ij2} p_{ij2} \right] (\alpha_{i2}) - \lambda_{i3} \sum_{j=1}^{K} p_{ij2} \)

The variables are now distinct and therefore maximization over them can be carried out by taking the derivatives of \( \overline{f}(p_{ij1}) \) and \( \overline{f}(p_{ij2}) \) and setting it to zero, yields,

$$\frac{df(p_{ij1})}{dp_{ij1}} = \left( \alpha_{i2} + \lambda_{i6} - \lambda_{i7} \right) \frac{\gamma_{ij1}}{\log_2 \left( 1 + \gamma_{ij1} p_{ij1} \right)} + \lambda_{i4}$$

$$\left( \alpha_{i2} + \lambda_{i6} - \lambda_{i7} \right) \frac{\gamma_{ij1}}{\log_2 \left( 1 + \gamma_{ij1} p_{ij1} \right)} - \lambda_{i4} = 0$$

$$\left( \alpha_{i2} + \lambda_{i6} - \lambda_{i7} \right) \frac{\gamma_{ij1}}{\log_2 \left( 1 + \gamma_{ij1} p_{ij1} \right)} = \lambda_{i4}$$

$$\overline{p}_{ij1} = \left[ \frac{\alpha_{i2}}{\lambda_{i4} \log_2 \left( 1 + \frac{1}{\gamma_{ij1}} \right)} \right]^+$$

Similarly, \( \overline{p}_{ij2} = \left[ \frac{\alpha_{i2}}{\lambda_{i4} \log_2 \left( 1 + \frac{1}{\gamma_{ij2}} \right)} \right]^+$$

Step 13: Calculate rates for each chromosome using (1) & (2).
Step 14: Iterate till the number of generations is reached.

Here the convergence of the algorithm is considered as the point where there is no significant change in the fitness function over generations.

3. RESULTS AND ANALYSIS

A Rayleigh fading channel is assumed between the transmitter and the receiver. A maximum delay spread of 5μs and maximum Doppler frequency of 30 Hz has been assumed [6]. The channel information is updated every 1ms. These constants are used for the calculation of the data rates in uplink and downlink direction. Total uplink power is assumed to be 250mW and downlink power is assumed to be 30W. The system is simulated using Matlab Software R2018b.

Figure 1(a) clearly depicts that the data rates for both users in the uplink and downlink direction computed from the initial population is lower than the other generations. This is due to the fact that the initial population was randomly chosen and the data rates achieved may or may not be good ones with this population. Moreover, for the initial population the power is equally divided among all the subcarriers. Figure 1(b) shows that the data rates increase with generations and data rates exhibit almost similar values as
the number of generation’s increases. This can be justified by the fact that after computing the fitness function in each generation, they are sorted according to non-dominance criteria. As the generations proceeds, all possible combination of chromosomes are tried out and the best values are attained. Since one of the objectives of the optimization problem was to minimize the difference in data rates, the difference is within limits irrespective of the number of generations. For higher value of generations the difference in data rates for both uplink and downlink direction are very small and consistent.

Figure 1. Simulation results for a 2 user system for various generations

Figure 2 depicts the system performance for 12 users and 64 subcarriers in the 80th generation with 12 db SNR. From the figure the difference in the data rates is seen to be reduced compared to that of the initial population and an increase in data rates as expected is seen.

Figure 2. Simulation results for a 12 user system

4. CONCLUSION

In this paper, NSGA II is proposed as a solution for rate adaptive subcarrier allocation and linear programming approach for power allocation of symmetrical services in MIMO OFDMA system. To this end, a multiobjective optimization problem was formulated which involved the optimization of two objectives. Adoption of evolutionary techniques and representation of chromosomes in an innovative manner helped in the reduction of the problem’s complexity as compared to linear programming techniques solely. The simulation results demonstrate that the proposed method not only helps in attaining high data rates in both
uplink and downlink directions, but also minimizes the difference in the data rates. Almost stable results are achieved as the number of generations is increased to 80, irrespective of the number of users. The proposed algorithm achieves higher data rates than [4], and is computationally less expensive as compared to previous algorithms available in literature using exclusive linear programming techniques.

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