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Antenna Subset Selection with OFDM Using PSO Algorithm

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Abstract*—This paper deals with the receive antenna selection problem to maximize capacity in wireless MIMO-OFDMA communication system, which can be formulated as an integer programming optimization problem and cannot be directly solved because of its non-convex characteristics caused by the discrete binary antenna selection factor. To deal with this challenge, a computationally efficient approach, particle swarm optimization (PSO) algorithm is introduced, in which the particle is defined as the discrete binary antenna selection factor and the objective function is associated with the capacity corresponding to the specified antenna subsection represented by the particle.Furthermore, in order to meet the condition that the number of selected antennas can be varied as our requirement. It also optimized more eventually to be working in a condition where higher range of antennas can also be optimised. The DeJong, Griewank, Rastrigrin and Rosenbrock functions are used to denote the parameters of the spherical Lens antenna are used and the comparative statement is drawn. In that the best set is taken as the swarm and that swarm is optimised using PSO algorithm and using that it can be easier to get the best antenna subset has been selected in the receiving side of the antenna. The system is optimised by using by taking the position of the higher elements are taken as the index of the antenna subsection to be activated. Then the best antenna subset can be found by seeking the global optimal particle in PSO. Here since we are using a OFDM technique it can be used in the multi user environment as well. The best antenna subset is selected in order the maximize the capacity of the antenna to make it efficient in all state of affair.

Index terms -Antenna Selection Problem; Energy-maximization; Particle Swarm Optimization (PSO) Algorithm; MIMO-OFDMA.

I. INTRODUCTION

The antenna is a key component for reaching the maximum distance in a wireless communication system. The purpose of an antenna is to transform electrical signals into RF electromagnetic waves, propagating into free space and to transform RF electromagnetic waves into electrical signals.

Antenna specs from the majority of suppliers will reference their designs to an ideal Isotropic antenna. This is a model where the antenna is in a perfect sphere and isolated from all external influences. Most of the measurements of power are done in units of dBi where "i" refers to the condition of isotropic antenna. Power measurements for a theoretical isotropic antenna are in dBi. Dipole Antenna Power is related to an isotropic antenna by the relationship

$$0 \text{ dBd} = 2.14 \text{ dBi} \quad (1)$$

The radiation pattern is the graphical representation of the radiation properties of the antenna as a function of space. i.e. the antenna's pattern describes how the antenna radiates energy out into space (or how it receives energy). It is common, however, to describe this 3D pattern with two planar patterns, called the principal plane patterns. These principal plane patterns can be obtained by making two slices through the 3D pattern through the maximum value of the pattern or by direct measurement. It is these principal plane patterns that are commonly referred to as the antenna patterns.

The receive antenna selection problem to maximize capacity in wireless MIMO-OFDMA communication system, which can be formulated as an integer programming optimization problem and cannot be directly solved because of its non-convex characteristics caused by the discrete binary antenna selection factor. particle swarm optimization (PSO) algorithm is introduced, in which the particle is defined as the discrete binary antenna selection factor and the objective function is associated with the capacity corresponding to the specified antenna subsection represented by the particle.

Furthermore, in order to meet the condition that the number of selected antennas should keep fixed, the particle elements are relaxed to change between [0 1] and the position of the higher elements are taken as the index of the antenna subsection to be activated. Then the best antenna subset can be found by seeking the global optimal particle in PSO. And also it deals with the performance improvement in smart antennas, OFDMA allows different users to transmit over different portions of the broadband spectrum.

It eliminates the intra-cell interference avoiding CDMA type of multi-user detection, Orthogonality of code is destroyed by selective fading and only FFT processor is required. Bit Error Rate performance is better only in fading environment.

II. PREVIOUS WORK

Recently, several approaches have been proposedfor reducing the amount of network resources used in IP and WDM networks. Multiple-antenna systems, also known as multiple-input multiple-output radio, can improve the capacity and reliability of radio communication. However, the multiple RF chains associated with multiple antennas are costly in terms of size, power, and hardware. Antenna selection is a low-cost low-complexity alternative to capture many of the advantages of MIMO systems. This article reviews classic results on selection diversity, followed by a discussion of antenna selection algorithms at the transmit and receive sides. Extensions of classical results to antenna subset selection are presented. Finally, several open problems in this area are pointed out. A novel low-complexity antenna selection algorithm based on a constrained adaptive Markov chain Monte Carlo (CAMCMC) optimization method is proposed to approach the maximum capacity or minimum bit error rate (BER) of receive-antenna-selection multiple-input multiple-output (MIMO)–orthogonal frequency division multiplexing (OFDM) systems. Similar to the existing antenna-selection algorithms, both channel capacity and system BER improvements achieved by the proposed CAMCMC method are reduced as the channel frequency selectivity increases. Therefore, it is designed to maximize the channel capacity or minimize the system BER, the CAMCMC optimization-method-based antenna-selection technique is appropriate for a MIMO–OFDM system with low frequency selectivity.

Multi-input multi-output (MIMO) systems, with multiple antennas at both the transmitter and receiver, are anticipated to be widely employed in future wireless networks due to their predicted tremendous system capacity. In order to protect the transmitted data against random channel impairment, it is desirable to consider link adaptation, such as rate adaptation and power control to improve the system performance and guarantee certain quality of service. Based on the observation that link adaptation and antenna selection problems are often coupled. After the formulation of the multi-dimensional joint optimization problem, specifically, one simplified antenna selection and link adaptation rule based on the expected optimal number of active antennas for uncorrelated MIMO with Rayleigh fading, and one for correlated MIMO channels only based on the slowly varying channel correlation information.

Multiple-input multiple output (MIMO) systems with multiple antennas at both the transmitter and receiver are able to achieve great capacity improvement. In such systems, it is desirable to select a subset of the available antennas so as to reduce the number of radio frequency (RF) chains. It addresses the problem of antenna selection in correlated channels. Simulations will be used to validate our theoretical analysis and demonstrate that the number of required RF chains can be significantly decreased using the proposed selection strategy, while achieving even better performance than the conventional MIMO system without antenna selection.

The receive antenna selection problem to maximize capacity in wireless MIMO communication system, which can be formulated as an integer programming optimization problem and cannot be directly solved because of its non-convex characteristics caused by the discrete binary antenna selection factor. To deal with this challenge, a computationally efficient approach, particle swarm optimization(PSO) algorithm is introduced, in which the particle is defined as the discrete binary antenna selection factor and the objective function is associated with the capacity corresponding to the specified antenna subsection represented by the particle. Furthermore, in order to meet the condition that the number of selected antennas is kept fixed, then the best antenna subset can be found by seeking the global optimal particle in PSO.

III. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

A. *Basic concepts of PSO*

PSO, first developed by Kennedy and Eberhart in 1995, is a kind of evolutionary computational technology based on the intelligent behaviour of organisms, which is put forward by learning from the behaviours of bird flock seeking food. In PSO algorithm, a group of random particles imitating bird flock are initialized in the searching space, all the particles have fitness values which are evaluated by the objective function to be optimized, and their velocities which direct their “flying” direction contribute an important part in PSO. The particles are “flown” through the problem space by follo wing the current optimum particles. PSO searches for optimal fitness value and the corresponding particle by updating generations of the particle $\mathbf{x}_i(\tau)$ and its velocity $\mathbf{v}_i(\tau)$ according to:

$$\mathbf{v}_i(\tau+1)=u\mathbf{v}_i(\tau)+c_1r_1(\mathbf{p}_i(\tau)-\mathbf{x}_i(\tau))+c_2r_2\mathbf{p_g}(\tau)-\mathbf{x}_i(\tau) \quad (2)$$

$$\mathbf{x}_i(\tau+1)=\mathbf{x}_i(\tau)+\mathbf{v}_i(\tau+1) \quad (3)$$

where pi (τ) is the local best particle that particle i has achieved so far and pg (τ) is the global best particle that all particles have achieved so far. c1 and c2 are acceleration constants and r1 and r2 are uniformly distributed random numbers in [0,1].

The velocity updating equation of each particle in consists of three parts: the first part represents the degree of momentum of the particle, the second part is the “cognition” part, which represents the independent behaviour of the particle itself, the last part is the “social” part, which denotes cooperation among particles. This iterative process will stop until the maximal iteration number is reached or a sufficient good solution is found.

We know that PSO is an iterative algorithm and continually exploits new and better solutions by updating generations. In order to apply PSO in solving the antenna selection problem, the two key parameters, i.e. the particle and its velocity, have to be determined first. Since the velocity term vi of particle i is correlated with the current individual best particle pi and the global particle pg, which can be obtained by evaluating this particle according to the fitness (objective) function. Then the key point becomes how to define the particle and the fitness (objective) function. Once these two issues have been solved, PSO-based antenna selection can be implemented by updating the iterative generation.

B. The Definition of the Particle

From the evolutionary process of PSO, we know that each particle in PSO should be defined closely related to the antenna subset. Denote the particles in PSO as

$$\mathbf{x}_i = x_i 1 \ \ldots \ x_i D, \ i = 1 \ldots Q, \quad (4)$$

where D is the dimension of a particle and Q is the size of a randomly distributed initial population, then one direct approach is that the particle is defined as the antenna selection operator, i.e. $\mathbf{x}i$ = , $D = Nr$. However, this brings about the problem that the total number of selected antennas may be different in the searching process and may not meet the fixed numbers of L. To deal with this challenge, we relax the condition by $x_{ij} \in [0, 1]$, And in each particle the L larger values out of the Nr elements are picked out, which means the L antennas with higher weight will be activated. By this way, a direct relationship between each particle and the L selected antennas can be successfully established.

In PSO, each particle is evaluated by the fitness function to reflect its quality. According to the particle definition, the fitness function in the antenna selection scenario can be defined as the capacity value corresponding to the specified antenna subsection, i.e.,

$$F(\mathbf{x}_i) = log_2 \det(\mathbf{I}_{Nr} + \gamma N_t \cdot diag(\mathbf{x}_i) \cdot \mathbf{H}\mathbf{H}^{\mathbf{H}}) \quad (5)$$

It can be seen that this fitness function can readily reflect the capacity achieved by the specified antenna subset.The larger the fitness value, the better the corresponding particles is. With the definition of the particle as well as the fitness function above, the detailed PSO-based antenna selection method can be summarized as follows:

Step 1- Initialization. Randomly generate a total number of Q particles xi, i = 1 ... Qas well as their corresponding velocities vi.

Step 2- Evaluation. Evaluate the fitness value of each particle by using the fitness function in [20]. Set the local best particle pi = xi and select the particle xg with the highest fitness value as the global best particle pg = xg .

Step 3-Evolution. Using pi (τ) and pg (τ), each particle and its velocity is evolved according to [17] for the next iteration.

Step 4-Updating. Calculate the fitness values of all the particles. Then choose the current local best particle $\mathbf{p}i\ (\tau)$ of particle i as the better one between $\mathbf{x}i\ (\tau)$ and $\mathbf{p}i\ (\tau - 1)$ and determine the current global best particle $\mathbf{p}g\ (\tau)$ by comparing the best of $\mathbf{p}i\ (\tau)$ at current iteration with the global best particle at previous iteration $\mathbf{p}g\ (\tau - 1)$.

Step 5-Termination. Repeat the above Step 2 to Step 4 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number of generations being completed is satisfied. The global best one among all the particles is taken as the final answer.

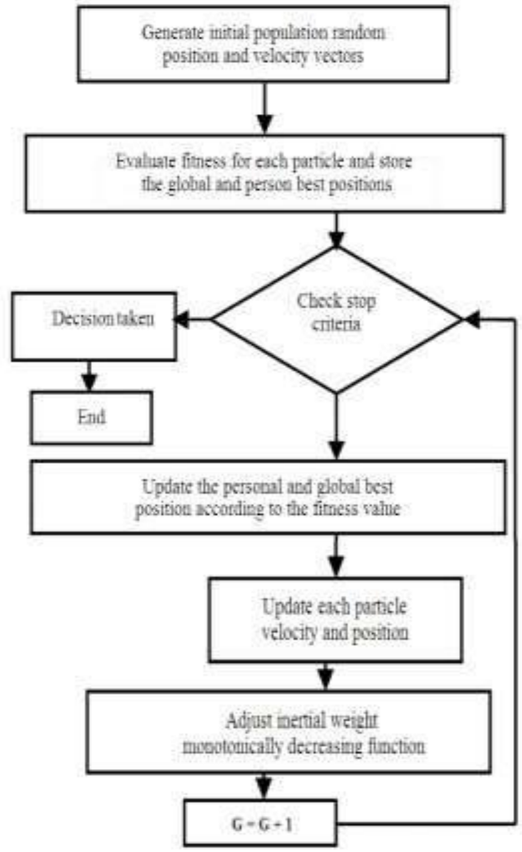

Figure 1. Flow chart of the PSO Algorithm

IV. PRELIMINARY EXPERIMENTS

It is also proved with certain benchmark functions as Rosenbrock, Griewank, Rastrigin Function are executed with respect to the antenna parameters The Rosenbrock function, also referred to as the Valley or Banana function, is a popular test problem for gradient-based optimization algorithms.The function is unimodal, and the global minimum lies in a narrow, parabolic valley. However, even though this valley is easy to find, convergence to the minimum is difficult.

The function is usually evaluated on the hypercube $x_i \in [-5, 10]$, for all i = 1, …, d, although it may be restricted to the hypercube $x_i \in [-2.048, 2.048]$, for all i = 1, …, d.

3.827×105 (6) wherexi=15xi-5, for all i = 1,2,3

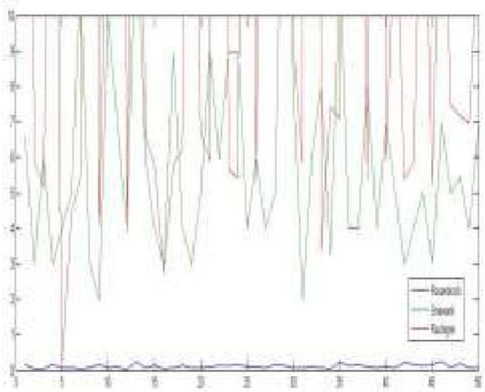

Figure 2 - Comparisonofthebestvalueofvariousfunctionsin50runsforPSO

The Griewank function has many widespread local minima, which are regularly distributed. The complexity is shown in the zoomed-in plots.

The function is usually evaluated on the hypercube $x_i \in [-600, 600]$, for all $i = 1, \ldots, d$.

The Rastrigin function has several local minima. It is highly multimodal, but locations of the minima are regularly distributed. It is shown in the plot above in its two-dimensional form.

The function is usually evaluated on the hypercube $x_i \in [-5.12, 5.12]$, for all $i = 1, \ldots, d$.

The inertia weight factor in PSO are chosen as $w$max = 0.9, $w$min = 0.4For convenience, the benchmark functions are defined in Table 1 and the dimensions of those benchmark functions in the experiment is chosen

It is clearly seen that PSO achieves a much lower fitness value than that of GA as iteration proceeds.Sometimes GA performs better than PSO in terms of fitness values, this is because different types of bench functions may adapt to different evolutionary mechanisms. Nevertheless, PSO provides better final results as iteration goes on, which indicates that it has a more efficient exploitative behavior.

V. SIMULATION RESULTS

In this section, simulations are provided to validate the PSO antenna selection method derived previously. To demonstrate the performance of the PSO method, simulation results of the MATLAB.

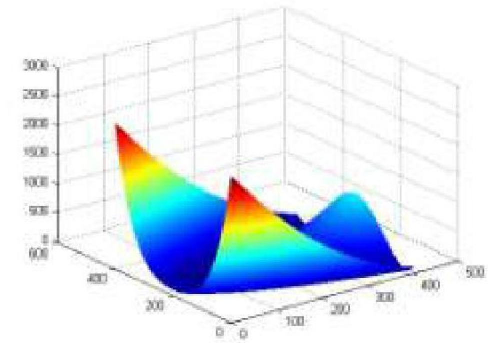

Figure 3 – Swarm created for the best in PSO

The simulation result completely proves evidently that the capacity of the system is increasing with the convergence rate versus number of particles in the swarm combination. It can be discovered when the number of the receive antennas Nr can be varied to any extent, the more the number of the selected antennas, the better the system performance is.

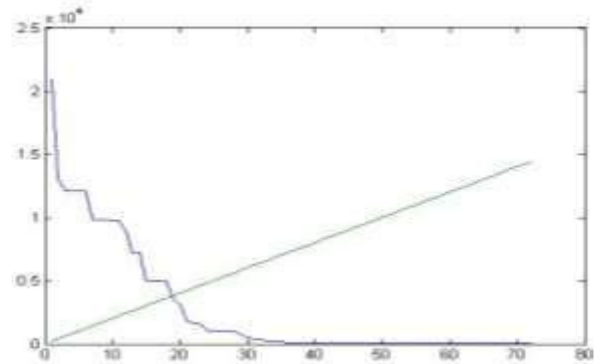

Figure 4 - CapacityconvergenceratioversusnumberofparticlesinPSO

The capacity convergence ratio versus the number of particles using PSO where the number of the selected antennas is fixed at L = 10 Capacity convergence ratio can be defined as the capacity obtained by fitness functions used in the algorithm divided by the capacity achieved by PSO. It can be discovered that, the more particles, the higher the capacityconvergence ratio is, which means the closer between the capacity of the proposed PSO- based antenna selection algorithm, This reveals a fact that when the number of selected antennas L can also be varied it won't majorly affect the capacity in the system but the number of receive antennas has been increased, then more particles and iterations are required if we want to obtain a high capacity convergence ratio. This is because more possible combinations need to be considered with the increasing number of the receive antennas, which directly enlarge the searching space of the antenna selection problem by using PSO.

VI. CONCLUSION

New PSO-based antenna selection strategy is proposed for the OFDM-MIMO system, which utilizes the

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particles searching ability to find the best antenna subset to maximize the system capacity. Moreover, the particle has been attached the new definition of the indices of the antenna subset and benchmark functions are employed to testify the performance of PSO. Experiment results show that PSO may strike a much better balance between capacity and computational complexity. As better characteristic can be achieved, the proposed algorithm is expected to be applied to other wireless communication problems.

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