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Optimization of Direction of Arrival and Polarization Using Whale Optimization Algorithm

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***Abstract:** A novel approach to the problem of finding the direction of arrival of signal for the mobile user at the cell edges and to minimize the inter cell interference (ICI) is proposed in this paper. The proposed system approaches the problem by training weights of the adaptive antenna array at the Base station by using the Radial basis Function (RBF). The trained weights are then applied to a meta heuristic algorithm called Whale Optimization Algorithm (WOA) to optimize the direction of arrival and the specific polarization of the signal from the user to the Physical Resource Block (PRB).A fast tracking system is needed to constantly estimate the directions of those users and then adapt the radiation pattern of the antenna to direct multiple beams to desired users and nulls to sources of interference. In this paper, the computation of the optimum weights is approached as a mapping problem which can be modelled using Radial Basis Function. The performance of the system is observed as the sharp beams towards the PRB.*

***Index Terms:** Physical Resource Block (PRB), Radial Basis Function (RBF), Inter cell Interference (ICI), Whale Optimization Algorithm (WOA), Beamforming*

I. INTRODUCTION:

Adaptive Beamforming is capable of separating user signals transmitted on the same carrier frequency, and thus provides a practical means of supporting multiusers in a space division multiple access scenarios. The minimum variance distortionless response (MVDR) beamformer has been considered. As a popular method for enhancing the signal from the desired direction while suppressing all signals from other directions as well as the background noise [1], but its relatively high sidelobe level would lead to significant performance degradation, especially with the unexpected increase in interference or background noise [2]. To enhance the robustness in the presence of array steering vector errors, doubly constrained robust capon beamformer used a norm constraint on the weight vector to improve the robustness [3]. To achieve a faster convergence speed and a higher steady state signal to interference plus noise ratio (SINR) [4] constrains its weight vector to a specific conjugate symmetric form.

Hence a multilayer neural network function called Radial Basis Function (RBF) is used to approximate the values of weights at the precoding to estimate the direction of arrival and polarization factor.

II. RADIAL BASIS FUNCTION (RBF)

The Radial Basis Function (RBF) networks are one type of layered feed forward neural networks (NN) capable of approximating any continuous function with a certain precision level. The basic architecture for a RBF is a 3-layer network, as shown in Fig 1.The input space to a high dimensional hidden space and a second linear mapping from the hidden space to the final output space. This operation is used in complex pattern classification problems because once the input space has been mapped in a high dimensional space in a nonlinear way; the patterns are easier separable by means of a linear transformation.

The aforementioned mapping used in the pattern classification problem can be viewed as a surface construction that can also be used in the interpolation problems. In the RBF networks the function that interpolates the data is of the form

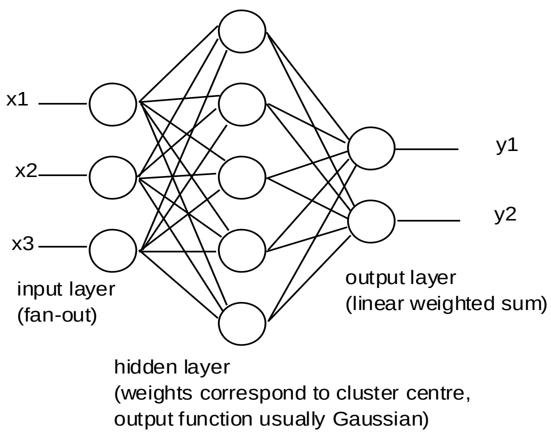

Fig 1: Different RBF Layers

F(x)=$\sum_{i=0}^{N} \omega_i \varphi(\|x - C_i\|)$ -------------------(1)

Where $\varphi(.)$ is the radial basis function, $\cdot$ is the Euclidean norm, N is the number of the training data pairs, and C_i is the center of the i-th radial basis function. In this approximation, there are so many centers as number of inputs, being their values the same as the input vectors, i.e., ci = xi. During the training stage a known set of input and output data pairs are delivered to the RBF network to select the centres and compute the output layer weights. F function has to satisfy the interpolation condition $F(x_i) = d_i$, where d_i is the desired training output value. The method applied to carry out the output layer weights is easier to explain if the RBF network performance is expressed in a matrix form:

$d=\Phi\,\omega$, -------------------------------------- (2)

Where $d=[d_1, d_2, d_3, \ldots d_N]^T$ is desired output vector, Φ is an N-by-N matrix with elements

$\varphi_{ij} = \varphi(\|x_j - C_i\|)$ ------------------------ (3)

with j = 1,2,3,4.....N and $\omega = [\omega_1, \omega_2, \omega_3, \ldots \omega_N]^T$ is the weight vector. The weight vector is computed as $\omega = \Phi^{-1}d$, where Φ^{-1} is the inverse of Φ.

The RBF network produces an output surface or function F that passes through all the training points. To measure the generalization capabilities of the trained network, i.e., its behaviour with patterns that have not been used in the training phase, new points are delivered to the RBF network.

The output of the training phases is as shown below in Fig2:

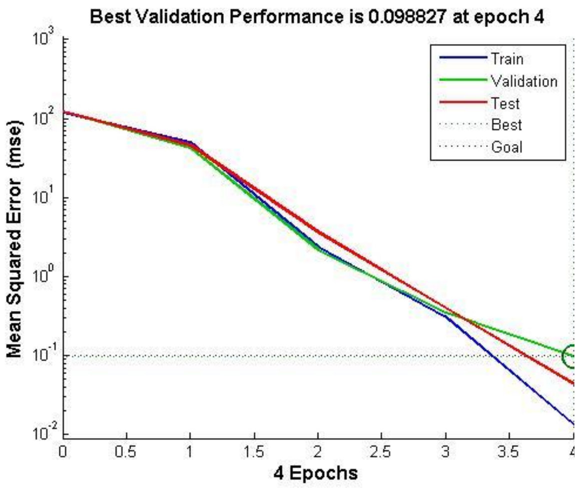

Fig2: Training performance of the RBF network

The Fig2 shows the best validation performance of the RBF network is at 0.098827 MSE which is a measure of quality of the estimator.

If RBF neural network were trained by excessive redundant information, network training will be overloaded, training time will be increased, and even the network generalization ability will be reduced. The major drawback of RBF neural network is the large dimensionality which requires optimal feature subset. It is important to choose a small subset of features that is necessary and enough to describe the target concept. This paper describes RBF neural network based on consistency evaluator for selection to find the best subset of features that not only maximizes the classification accuracy but minimizes the number of features. Although the RBF is quick to train, when training is finished and it is being used it is slower than a multi level approximation. To optimize the time and the accuracy of the location of PRB a meta heuristic algorithm named Whale Optimization Algorithm (WOA)is described in this paper .

III. WHALE OPTIMIZATION ALGORITHM (WOA):

The whale optimization algorithm (WOA) [2] proposed here is a recently developed swarm-based optimization algorithm inspired by the hunting behaviour of humpback whales. This study attempts to enhance the original formulation of the WOA in order to improve reliability and speed, as described in [2]. In this paper the shrinking encircling mechanism of hunting a prey is used to optimize the distance between the PRB and the cell edge user. The mechanism is as shown in the fig 3 below.

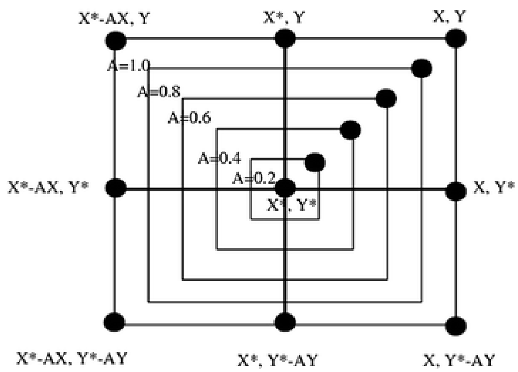

Fig3.shrinking encircling mechanism of bubble net search method.[2]

This behaviour is represented by the following equations:

$D = |\vec{C}\,\overrightarrow{X^*}(t) - \overrightarrow{X(t)}|$ ------------------------- (4)

$\vec{X}(t+1) = \overrightarrow{X^*(t)} - \vec{A}\vec{D}$ --- ----------------- (5)

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, X^* is the position vector of the best solution obtained so far, $\vec{X}$ is the position vector, | . | is the absolute value, and is an element-by-element multiplication. It is worth mentioning here that X^* should be updated in each iteration if there is a better solution. The vectors A and C are calculated as follows:

A = $2\vec{a} \times \vec{r} - \vec{a}$----------------------------- (6)

$C = 2 \times \vec{r}$ ----------------------------------- (7)

Where $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations (in both exploration and exploitation phases) and r is a random vector in [0, 1].

In this paper it is proposed to apply as a route finding problem for the user at the cell edge. Where the user requires finding the location of the PRB along with antenna beamforming and also needed to find the optimal path to connect to the same. It can be seen that WOA can also produce better transmit receive diversity results when used with space division multiple access (SDMA) in MU MIMO than traditional algorithm.

IV. IMPLEMENTATION:

In MU-MIMO, separate data streams are sent to spatially separated user over the same sub-channel, with each user serving as one of the multiple Rx antennas. This increases overall system capacity, though it does not increase throughput for individual user over single-antenna techniques.

Because multiple received replicas of the transmitted signal sometimes combine destructively, there is a significant probability of severe fading. Without proper means to mitigate such fading scenarios, ensuring reasonable reliability requires large power margins [33]. One of the most powerful techniques to mitigate the effects of fading is to use diversity combining of independently fading signal paths. Diversity-combining uses the fact that independent signal paths have a low probability of experiencing deep fades simultaneously. One method is to use multiple transmit or receive antennas, in an antenna array configuration, where array elements are separated enough in space.

In the MU MIMO system the number of users at the cell centres and cell edges do interfere causing inter cell interference (ICI). A probable solution for the resource allocation without interference to the cell centre user is given in [1] as dynamic resource allocation to the users using Fractional frequency ruse technique. Whereas the ICI issue with the cell edge users still persists. The resource allocation to the cell edge users is a point of research interest. In this paper the exact location of the PRB to the cell edge user is optimised. Where the user antenna can detect the resource from the same PRB using beamforming. and hence SDMA is used here. SDMA requires careful choice of zones for each transmitter, and also requires precise antenna alignment. A small error can result in failure of one or more channels, interference among channels, and/or confusion between surface coverage zones.
These results in wasting power on transmissions when there are no mobile units to reach, in addition to causing interference for adjacent cells using the same frequency, so called co-channel cells. Likewise, in reception, the antenna receives signals coming from all directions including noise and interference signals. The radiation pattern of the base station, both in transmission and reception is adapted to each user to obtain highest gain in the direction of that user.
And hence the use of WOA for the same enhances the throughput and the SINR of the user.
The Fig3 shows the estimation of the location of the PRB from the cell edge user in WOA. The design equations are as discussed in equations (1), (2) and (3). The beamforming from the receiver antenna and the transmit receive diversity comparison for different number of users is simulated using MatLab.
The trained weights from the RBF are fed to the points as shown in Fig3. For every change in the position a radiation pattern is generated. At the position when the maximum power is detected the user is dynamically allocated the resource and is continued in a connection.

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Then for each item of data in the training set, the distances are found from all of the k centres.

The closest centre is chosen for each item of data - this is the initial classification, so all items of data will be assigned a class from 1 to k.

Then, for all data which has been found, the average or mean values are found for each of co-ordinates as in fig 2.

This can be represented mathematically by the equations below:

$$\Sigma_1 \begin{cases} \xi_{1,i_1}(k+1) = f_{1,i_1}\left(\bar{\xi}_{1,i_1}(k)\right) + g_{1,i_1}\left(\bar{\xi}_{1,i_1}(k)\right)\xi_{1,i_1+1}(k), & 1 \le i_1 \le n_1 - 1 \\ \xi_{1,n_1}(k+1) = f_{1,n_1}\left(\xi(k)\right) + g_{1,n_1}\left(\xi(k)\right)u_1(k), & \end{cases}$$

$$\vdots$$

$$\Sigma_j \begin{cases} \xi_{j,i_j}(k+1) = f_{j,i_j}(\bar{\xi}_{j,i_j}(k)) + g_{j,i_j}(\bar{\xi}_{j,i_j}(k))\xi_{j,i_j+1}(k), & 1 \le i_j \le n_j - 1 \\ \xi_{j,n_j}(k+1) = f_{j,n_j}(\xi(k), \bar{u}_{j-1}(k)) + g_{j,n_j}(\xi(k))u_j(k), & \end{cases}$$

$$\vdots$$

$$\Sigma_n \begin{cases} \xi_{n,i_n}(k+1) = f_{n,i_n}(\bar{\xi}_{n,i_n}(k)) + g_{n,i_n}(\bar{\xi}_{n,i_n}(k))\xi_{n,i_n+1}(k), & 1 \le i_n \le n_n - 1 \\ \xi_{n,n_n}(k+1) = f_{n,n_n}(\xi(k), \bar{u}_{n-1}(k)) + g_{n,n_n}(\xi(k))u_n(k), & \end{cases}$$

$$y_j(k) = \xi_{j,1}(k), \qquad 1 \le j \le n$$

As discussed, aiming to improve the reliability of the system it is chosen to transmit the same data across the different paths (spatial). This results in spatial diversity a speciality of SDMA. This provides multiplexing gain and improving the data rate. This is achieved by the Alamouti that provides the degrees of freedom given by

Degrees of freedom = $\min(N_T, N_R)$ ------------ (6)

Diversity is given by Diversity = $N_T \times N_R$------(7)

The degree of freedom in MIMO governs the overall capacity of the system.

$y(n) = Hx(n) + z(n)$--------------------------------(8)

$y(n) \in C^{r\times1}$; $H \in C^{r\times t}$; $x(n) \in C^{t\times1}$;

$z(n) \in C^{r\times1}$ – $z(n) \sim CN(0, \sigma^2_z I_r)$ – $x(n) = \omega_t\, S(n)$---(9)

Where $\omega_t \in C^{t\times1}$ denotes the transmit beamforming vector, which satisfies the sum-power constraint: $\|\omega_t\|^2 \le P$

The receive beamforming vector is denoted by $\omega_r \in$ Cr×1. After applying ω_r to the received signal vector, the resultant receiver output is

$\hat{y} = \omega_r^H = \omega_r^H H \omega_t s + \omega_r^H z$ --------------- (10)

The receiver output SNR is then defined as

$$\gamma = \frac{E[|\omega_r^H H \omega_t s|^2]}{E[|\omega_r^H z|]^2} \text{ --------------------------- (11)}$$

V. SIMULATION RESULTS:

The proposed system is simulated using MATLAB. The Number of users at the cell edge is specified. The probable degree of freedom is also specified. The using space time block coding technique the beamformed output is depicted for the degree of freedom. The major lobe depicts the location of the PRB and the direction of maximum power. The side lobes depict the interfering signals from other users at the cell edge either connected to the same PRB or any nearby PRB. As seen in [5] a smart dual beam is used to transmit the same signal in all directions from the transreceiver of the user towards the PRB. Depending on the distance and the polarization of the signals they serve the mobile users (5) at the edge of the cell. The Fig6 and Fig7 depict the transmit v/s receive diversity for the above specifications. It is evident that as the degree of freedom increases the Bit Error Rate decreases and SINR increases. It is an optimised output when compared to only using the RBF with beamforming. The Fig4 and Fig5 show the beamforming for a degree of freedom of 5 degrees & for 8 users and beamforming for 8 degree of freedom & 10 users respectively.

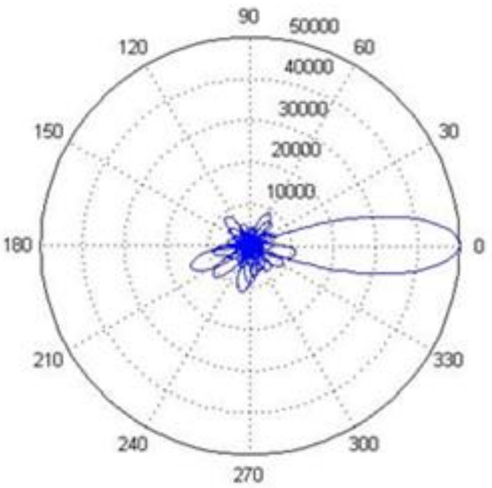

Fig4: Beamforming for 5° and 5 users

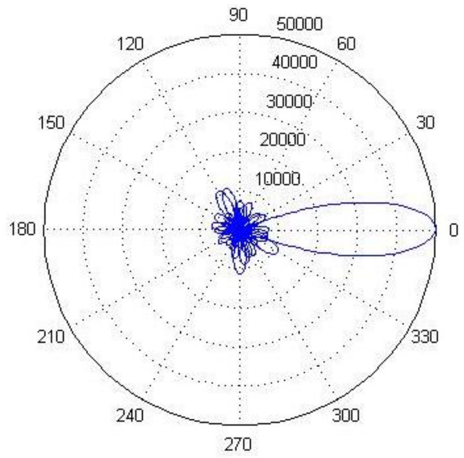

Fig5: Beamforming for 8° and 10 users

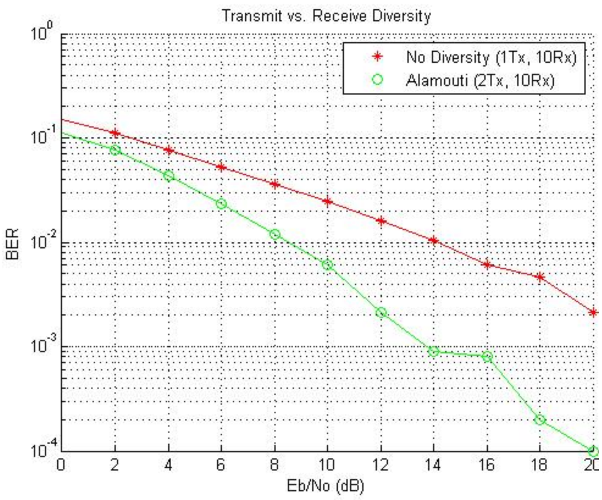

Fig6: Transmit v/s receive diversity for 5° and 5 users

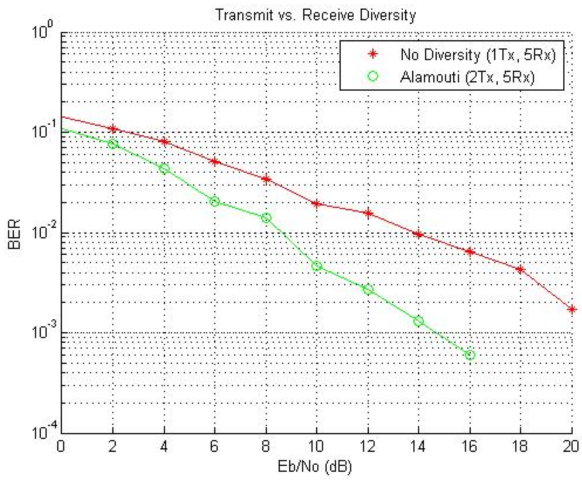

Fig7: Transmit v/s receive diversity for 8° and 10 users

VI. CONCLUSION:

In a MU MIMO network the resource allocation to the user in the cell is the major criteria. In a cell the resource to the cell centre user and cell edge users can be allocated by dynamic allocation of resource with fractional frequency reuse. Hence the interference between them can be reduced. To choose a proper PRB for access of the channel the RBF beamforming technique is used. It is the best method to locate and localize the PRB. The number of computational steps and approximations in RBF beamforming technique the location of PRB are more. Therefore, an optimization is proposed by using Whale Optimization Algorithm. Using Space time block coding and WOA the exact location of the PRB is provided to the users. Similarly the transmit v/s receive diversity due to optimization has been shown to increase with rise in SINR.

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