ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

MULTI USER AND MULTI CHANNEL USING JOINT BEAM FORMING BASED POWER AND CHANNEL ALLOCATION ON MIMO SYSTEM

Y.Reegan Jebaraj[1], UG Student, V.Santha Kumar[2], UG Student,P. John Samuel Jebaraj[3],UG Student, T.Vignesh[4],UG Student[1,2,3,4]PSN College of Engineering and Technology, TN, India.

***Abstract*—In this paper, After Formulate process on CR Network We implement beam forming structure on particular user based particular distance analysis on SVD using receiver part of analysis.In our modification we implement on multi-channel on multiple user analysis of relay path based through put rate analysis on CR network using MIMO system on SVD with Comparison of Genetic Algorithm. Beam forming has been introduced to CR for directional signal transmission. In Normal MIMO System we can get achievable rate is efficient on capacity theorem. In CR network SU's they need to get improvement on achievable rate with help of PU's (Relay Path). So, we propose a solution for comparison between single relay path and multiple relay paths using joint beam forming based achievable rate improvement. In Proposed Method genetic algorithm (GA) based to determine suboptimal channel allocations using 3: 1: 6 MISO System using achievable rate improvement on 6 destinations with help of 18 paths. In Our Modification genetic algorithm (GA) based to determine suboptimal channel allocations using 3: 2: 6 MIMO System using achievable rate improvement on 6 destinations with help of 36 paths.**

***Index Terms*—Cognitive Radio Network, Genetic Algorithm, MIMO System, Relay path analyzed, Singular Value Decomposition.**

I. INTRODUCTION

Exponential growth in wireless subscribers along with limited availability of spectrum has compelled into more efficient way of utilizing radio spectrum. Traditionally, frequency bands are licensed by spectrum regulatory bodies in a manner that portion of the spectrum is licensed to be utilized by a specific user exclusively. This conservative approach results into inefficient utilization of radio spectrum due to spectrum holes. The idea of sharing the spectrum bands with licensed users and exploiting spectrum holes motivated the concept of cognitive radio (CR) technology. Cognitive Radio (CR) is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communications to run concurrently and also improve radio operating behavior. It allows unlicensed or secondary users (SUs) to maintain satisfactory data transmissions without causing harmful interference to primary user (PU) communications. The basic point in beam forming is, when you set multiple transducers next to each other sending out signals, you're going to get some kind of interference pattern, just like you see in a pond when you throw several stones in at once and create interfering ripples. If you select the spacing between your transducers and the delay in the transducers' signals just right, you can create an interference pattern that's to your benefit, in particular one in which the majority of the signal energy all goes out in one angular direction. The capacity of the general relay channel is still unknown. Motivated by the recent interest in multi-hop, a number of recent papers investigate the use of multiple relays. Some relevant references include. Even though the information theoretic model allows for the destination to listen to both the source and the relay, in most multi-hop systems the destination only processes the signal coming from the relay. Use relays (or multi-hop) to provide spatial diversity in a fading environment, Envision a collaborative scheme where the relay also has its own information to send so both terminals help one another to communicate by acting as relays for each other (called "partners").

Multiple-Input and Multiple-Output, or **MIMO** is the use of multiple antennas at both the transmitter and receiver to improve communication performance.Multiple antennas may be used to perform smart antenna functions such as spreading the total transmit power over the antennas to achieve an array gain that incrementally improves the spectral efficiency (more

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

bits per second per hertz of bandwidth,) or achieving a diversity gain that improves the link reliability (reduces fading,) or both.In (single-stream) beam forming, the same signal is emitted from each of the transmit antennas with appropriate phase and gain weighting such that the signal power is maximized at the receiver input. Recently, results of research on multi-user MIMO technology have been emerging. While full multi-user MIMO (or network MIMO) can have a higher potential, practically, the research on (partial) multi-user MIMO (or multi-user and multi-antenna MIMO) technology is more active.PU^{2}RC allows the network to allocate each antenna to a different user instead of allocating only a single user as in single-user MIMO scheduling. The network can transmit user data through a codebook-based spatial beam or a virtual antenna.Cross-layer MIMO enhances the performance of MIMO links by solving certain cross-layer problems that may occur when MIMO configurations are employed in a system. Cross-layer techniques can be used to enhance the performance of SISO and MISO links as well.

Cooperative wireless communications can actually exploit interference, which includes self-interference and other user interference. In cooperative wireless communications, each node might use self-interference and other user interference to improve the performance of data encoding and decoding, whereas conventional nodes are generally directed to avoid the interference.Power and Channel allocation for cooperative relay in a three-node cognitive radio network. Different from conventional cooperative relay channels, cognitive radio relay channels can be divided into three categories: direct, dual-hop, and relay channels, which provide three types of parallel end-to-end transmission. In the context, those spectrum bands available at all three nodes may either perform relay diversity transmission or assist the transmission in direct or dual-hop channels. On the other hand, the relay node involves both dual-hop and relay diversity transmission. In this paper, we develop power and channel allocation approaches for cooperative relay in cognitive radio networks that can significantly improve the overall end-to-end throughput. We further develop a low complexity approach that can obtain most of the benefits from power and channel allocation with minor performance loss. Multi user power and channel allocation problem in cognitive radio is considered in this paper. Based on game theory, we modeled the problem into a non-cooperative game and proved that this problem is a super modular game with the purpose to maximize the total system capacity of the network in which secondary users choose their power allocated in each channel according to their payoff function which consider both the capacity gain of themselves and the loss of the others. A distributed multiuser power and channel allocation algorithm is proposed according to our analysis. Simulation results indicate that our algorithm can achieve greater performance improvement compared with selfish power and channel allocation scheme in channel capacity.

TABLE 1
LIST OF NOTATION

Symbol	Definition
s_n	Set of SU pairs using the n^{th} PU channel
K	Number of SU pairs
N	Number of PU channels
s_k/u_n	k^{th} SU transmit signal/n^{th} PU transmit signal
h_k	Channel response between the SU-TX_k and the SU-RX_k
h_{mk}	Channel response between the SU-TX_m and the SU-RX_k
h_{mn}	Channel response between the SU-TX_m and the PU-RX_n
g_{nk}	Channel response between the PU-TX_n and the SU-RX_k
g_n	Channel response between the PU-TX_n and the PU-RX_n
Q_n	PU-TX_n's transmit power
r_k^n	Rate of the k^{th} SU-TX on n^{th} PU channel
φ	Auxiliary vector to indicate the intra-user interference thresholds of each SU-RX
B	Transmission bandwidth of each PU channel
w_k	k^{th} SU-TX beam forming vector
W_k	k^{th} SU-TX positive semidefinite beam forming matrix
x_k^n	Binary variable to indicate the n^{th} PU channel allocation on k^{th} SU-TX

BLOCK DIAGRAM

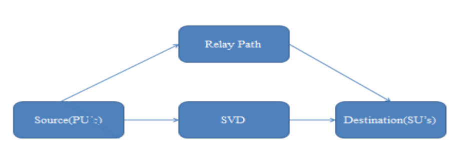

Fig.1. Block diagram of Relay Path based communication

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

II. SYSTEM MODEL AND PROBLEM FORMULATION

Here in this section the optimization problem is formulated and mathematically it can be given as the following,

$$\max_{w_s w_r} = \frac{1}{2}\log_2\left(1+\min\left(\gamma_{R,S}\gamma_{D,S}+\gamma_{D,R}\right)\right)$$
$$\text{s.t } \|w_s\|^2 = 1$$
$$\|w_r\|^2 = 1 \qquad (1)$$

Since the function

f(x) = $\frac{1}{2}\log_2(1+x)$ monotonically increases with the variable x and f(x) > 0 always holds for x > 0, the problem in (1) then can be refined to be a more concise version as

$$\max_{w_s w_r} = min\{\gamma_{R,S}\gamma_{D,S}+\gamma_{D,R}\}$$
$$\text{s.t } \|w_s\|^2 = 1$$
$$\|w_r\|^2 = 1 \qquad (2)$$

$\gamma_{D,S} = \left|h_{D,S}^T w_s\right|^2 P_s$→SNR at D during source phase(3)

$\gamma_{R,S} = \left\|H_{R,S} w_s\right\|^2 P_s$→ SNR at relay (4)

$\gamma_{D,R} = \left|h_{D,R}^T w_r\right|^2 P_r$→ SNR at D in the relay phase (5)

From the above equations (3), (4) and (5) we can see that only $\gamma_{D,R}$ is affected by the beamforming vector w_r, while both $\gamma_{D,S}$ and $\gamma_{R,S}$are independent.

$$w_r^* = \frac{h_{D,R}}{\|h_{D,R}\|} \qquad (6)$$

Substituting the optimal beamforming vector w_r^*into (5) we obtain the maximum of $\gamma_{D,R}$as

$$\gamma_{D,R}^* = \left\|h_{D,R}\right\|^2 P_r \qquad (7)$$
$$\max_{w_s} = min\{\gamma_{R,S}\gamma_{D,S}+\gamma_{D,R}^*\}$$
$$\text{s.t } \|w_s\|^2 = 1 \ (8)$$

Specifically, by introducing a new real variable, the max-min problem in (8) can be easily transformed into the following problem

$$\min_{w_s} = -t$$
$$\text{s.t.}\left\|H_{R,S}w_s\right\|^2 P_s \ \geq t$$
$$\left|h_{D,S}^T w_s\right|^2 P_s + \gamma_{D,R}^* \ \geq t$$
$$\|w_s\|^2 = 1(9)$$
$$W \geq 0$$

Since

$H_{R,S}^H w_s w_s^H H_{R.S} = tr(w_s w_s^H H_{R.S} H_{R,S}^H)$by defining G= $H_{R.S}H_{R,S}^H$ and F= $h_{D.S}h_{D,S}^H$.

And a new matrix variable w = $w_s w_s^H$with W ≥ 0 then the problem in (9) can then be transformed into

$$\min_{W} = -t$$
$$\text{s.t.tr(WG)} \geq t$$
$$\text{tr(WF)} + \gamma_{D,R}^* \ \geq t$$
$$\text{tr(W)} = 1$$
$$\text{rank(W)} = 1$$
$$W \geq 0(10)$$

. Since the matrix V = $(v_1, v_2, \ldots, v_{N_s})$ in the following equation

$$H_{R,S} = U\Lambda V^H \qquad (11)$$

is a unitary matrix of full rank, for an arbitrary beamforming vector

$w_s\ with\ \|w_s\|^2 = 1$there exists a unique complex vector w= $(\omega_1, \omega_2, \ldots, \omega_{N_s})^T$satisfying

$$w_s = V_w = v_1\omega_1 + v_2\omega_2 + \ldots + v_{N_s}\omega_{N_s} \ \ (12)$$

Noting that w = $V^H w_s$ which is also a unit-norm complex vector.

By substituting (12) into (3) and (4) it follows that the received SNR $\gamma_{D,S}$ and $\gamma_{R,S}$ can re-expressed as

$$\gamma_{D,S} = \left\|h_{D,S}^T w_s\right\|^2 P_s = \left\|h_{D,S}^T V_w\right\|^2$$
$$= \left|h_{D,S}^T v_1\omega_1 + h_{D,S}^T v_2\omega_2 + \ldots + h_{D,S}^T v_{N_s}\omega_{N_s}\right|^2 P_s$$
$$= \left(\sum_{i=1}^{N_s}\left|h_{D,s}^T v_i\omega_i\right|\right)^2 P_s \qquad (13)$$

And

$$\gamma_{R,S} = \left\|H_{R,S}w_s\right\|^2 P_s = \|U\Lambda V^H V_w\|^2 P_s$$
$$= \|U\Lambda w\|^2 P_s = (U\Lambda w)^H (U\Lambda w) P_s$$
$$= w^H \Lambda^H U^H U \Lambda_w P_s = \|\Lambda_W\|^2 P_s$$
$$= \sum_{i=1}^{N_s}\lambda_i^2|\omega_i|^2 P_s \qquad (14)$$

respectively. Note that $\lambda_i = 0, for\ i = N+1, \ldots, N_s$where N = $\min\{N_s, N_r\}$ Therefore, to seek the optimal beamforming vector w_s^* for the optimization problem (8) is equivalent to find the corresponding optimal vector w^* for the following optimization problem,

$$\max_{w} = \min\{\gamma_{R,S}\gamma_{D,S}+\gamma_{D,R}^*$$
$$\text{s.t.}\|w\|^2 = 1(15)$$

Once the optimal $w^*$is obtained, the optimal beamforming vector w_s^* can be calculated in terms of (12).

Furthermore, by observation of (13) and (14), we find that the phase angle of each element of w only affects $\gamma_{D,S}$ while $\gamma_{R,S}$ is just determined by the amplitudes of the elements of vector w, which indicates that to solve the optimization problem in (15), the phase angles and amplitudes of the vector w can be separately designed.

Now, let us begin to discuss how to design the phase angles and amplitudes of the vector. Clearly, the optimal phase angle must satisfy that for a given set of amplitudes of, the maximal $\gamma_{D,S}$can be achieved, while the optimal amplitude must satisfy that with the optimal phase angle, it can lead to the optimal solution of problem (15).

LEMMA:1

The optimal phase angle $\angle w^* = (\angle\omega_1^*, \angle\omega_2^*, \ldots, \angle\omega_{N_s}^*)$ for the entries of wcophases the products $h_{D,S}^T v_i\omega_i\ for\ i = 1, 2, \ldots, N_s$ i.e.,

$$\begin{cases}\angle\omega_1^* = \theta - \angle\left(h_{D,S}^T v_1\right) + 2k_1\pi \\ \angle\omega_2^* = \theta - \angle\left(h_{D,S}^T v_2\right) + 2k_2\pi \\ \vdots \\ \angle\omega_{N_s}^* = \theta - \angle\left(h_{D,S}^T v_{N_s}\right) + 2k_{N_s}\pi\end{cases} \qquad (16)$$

and the resulting $\gamma_{D,S}$depending only on the amplitudes of ω_i is then given by

$$\gamma_{D,S} = \left(\left|h_{D,S}^T v_1\right||\omega_1| + \left|h_{D,R}^T v_2\right||\omega_2| + \cdots + \left|h_{D,R}^T v_{N_s}\right|\left|\omega_{N_s}\right|\right)^2 P_s \qquad (17)$$

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

Where $\angle(h_i^T v_i)$ represents the phase angle of the vector $h_i^T v_i$(i = 1, 2,….,N_s), θ can be any constant phase value and the set of all integers

$$\max_{|\omega_1|,\ldots,|\omega_{N_s}|} = \min\{\sum_{i=1}^{N_s} \lambda_i^2 |\omega_i|^2 P_s \, (\sum_{i=1}^{N_s} |h_{D,S}^T v_i||\omega_i|)^2 P_s + \gamma_{D,R}^*\},$$
$$\text{s.t.} |\omega_1|^2 + |\omega_2|^2 + \cdots + |\omega_{N_s}|^2 = 1 (18)$$

For notation conciseness in the following derivation, we define $\alpha_i = |\omega_i|^2$ and $\beta_i = |h_{D,S}^T v_i|$
Thus, the optimization problem in (18) is simplified into

$$\max_{|\alpha_1|,\ldots,|\alpha_{N_s}|} = \min\{\sum_{i=1}^{N_s} \lambda_i^2 \alpha_i P_s \, , (\sum_{i=1}^{N_s} \beta_i \sqrt{\alpha_i})^2 P_s + \gamma_{D,R}^*\}, \quad (19)$$

$$\text{s.t.} \sum_{i=1}^{N_s} \alpha_i = 1$$

III. A TWO-STAGE SOLUTION APPROACH

Consider a network model consisting of a source S, a relay R and a destination D, as shown in Fig. 1. It is assumed that the direct link between S and D exists in the system and the relay R helps the information transmission from S to D. Multiple antennas are deployed both at S and R, and only one antenna is equipped at D. Half duplex mode is adopted so that R cannot transmit and receive signals at the same time. Therefore, each round of information transmission from S to D can be divided into two phases, i.e., a source phase and a relay phase, as illustrated in Fig.8. In the source phase, S broadcasts its information to both R and D, while in the relay phase; R decodes the received information and then forwards the decoded information to D. Thus, D can obtain the desired information by decoding the combined signals received over the aforementioned two phases. We assume that all channel state information (CSI) for each round of transmission is known at the transmitters, by using techniques such as channel training, feedback and channel reciprocity exploiting, etc. As a result, S and R can configure their beamforming vectors accordingly to achieve the best transmission performance. Without loss of generality, the transmitted information from S and R can be represented by symbols x_s and $x_r$respectively. Assume that N_s antennas and N_r are deployed at S and R, respectively. Then, the information transmission process mentioned above can be specifically described as follows. In the source information symbol phase $x_s$is the is first multiplied with a beamforming vector w_s, two algorithms are proposed with different computational complexity.

A. *Power and beam forming vector determination based on a given channel allocation*

In this section, the beam forming vector and power allocation for each SU-TX will be determined based on a given channel allocationWith SDP, the quadratic terms, $|w_k^{\dagger} h_{kn}|^2$, $|w_m^{\dagger} h_{mk}|^2$ and $||w_k||^2$,can be equivalently represented as

$$|w_k^{\dagger} h_{kn}|^2 = \text{Tr}(w_k^{\dagger} h_{kn} h_{kn}^{\dagger} w_k)$$
$$= \text{Tr}(W_k H_{kn}), \quad \forall k \in \text{S}, \forall n \in \text{P} \quad (20)$$

$$||w_k||^2 = \text{Tr}(W_k), \quad \forall k \in \text{S} \quad (21)$$

$$|w_m^{\dagger} h_{mk}|^2 = \begin{cases} Tr(W_m H_{mk}), \ \forall m \neq k, \ m \in S_n \\ Tr(W_k H_k), \ m = k \end{cases} \quad (22)$$

Where$W_k = w_k w_k^{\dagger}$, $H_{kn} = h_{kn} h_{kn}^{\dagger}$,$H_k = h_k h_k^{\dagger}$ and $H_{mk} = h_{mk} h_{mk}^{\dagger}$.From (15) - (17), we have i) w_k is a rank one positive semidefinite (PSD) matrix, i.e.,$w_k \geq 0, \forall k$.

With (15), (16), (17) and the assumption of a known channel allocation, the optimization problem P1 can be rewritten as

$$\text{P1:} \quad max_{W_1,\ldots,W_K} \sum_{k=1}^{K} \sum_{n=1}^{K} r_k^n \quad (23)$$

$$\text{s.t} \sum_{k=1}^{K} x\hat{}_k^n \text{Tr}(W_k H_{kn}) \leq I_{th}^n, \forall n = 1,\ldots, \text{N} \quad (24)$$

$$SINR_k \geq \Gamma_k, \quad \forall k = 1,\ldots, \text{k} \quad (25)$$

$$\sum_{k=1}^{K} \sum_{n=1}^{K} x\hat{}_k^n \text{Tr}(W_k) \leq P_{max}, \quad (26)$$

$$w_k \geq 0, \forall k = 1,\ldots, \text{k} \quad (27)$$
$$Rank(W_k) = 1, \quad \forall k = 1,\ldots, \text{k} \quad (28)$$

B. *Suboptimal channel allocation*

In the previous section, we have determined the optimal power and beam forming vectors for a known channel allocation. In order to find the optimal channel allocation; an exhaustive searching algorithm can be used, which needs to compute beam forming vectors, power allocations and sum rates for all possible channel allocations

*Genetic Algorithm (GA):*The word "genetics" is derived from the Greek word "genesis" meaning "to grow" or "to become". Genetic Algorithms (GAs) was invented by John Holland. Holland proposed GA as a heuristic method based on "Survival of the fittest". An implementation of genetic algorithm begins with a population of (typically random) chromosomes. A chromosome is a long, complicated thread of DNA (deoxyribonucleic acid). Hereditary factors that

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

determine particular traits of an individual. Each trait is coded by some combination of DNA (there are four bases, A (Adenine), C (Cytosine), T (Thymine) and G (Guanine). Like an alphabet in a language, meaningful combinations of the bases produce specific instructions to the cell. GA was discovered as a useful tool for search and optimization problems. As GA is rule based probabilistic approach and always search for global optimum. Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions (usually randomly) and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.

Initially many individual solutions are (usually) randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, allowing the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

SVD Algorithm: In narrowband multiple-input multiple-output (MIMO) communication systems with perfectly known channel state information (CSI), the singular value decomposition (SVD) may be used to decompose the MIMO channel into multiple independent single-input single-output channels, enabling interference-free data multiplexing. The SVD technique decouples the channel matrix in spatial domain in a way similar to the DFT decoupling the channel in the frequency domain. The channel matrix H is the T x R channel matrix. If H has independent rows and columns, SVD yields:

$$H = U\sum V^h$$

Where U and V are unitary matrices and V_h is the hermit an of V. U has dimension of R × R and V has dimension of T x T. $\sum$ is a T × R matrix. If T = R, then $\sum$ become a diagonal matrix. If T > R, it is made of R x R diagonal matrix followed by T – R zero columns. If T < R, it is made of T × T diagonal matrix followed by R – T zero rows. This operation is called the singular value decomposition.

In case, where T ≠ R, the number of spatial channels become restricted to the minimum of T and R. If the number of transmit antennas is greater than the receive antennas (T > R), U will be an R × R matrix, V will be a T × T matrix and $\sum$ will be made of a square matrix of order R followed by T-R zero columns.

MIMO SVD-based methods include the well-known water filling solution which maximizes information throughput over the MIMO channel given a fixed transmission power. Given sub channel power levels, such as those provided by the water filling solution, the signal-to-noise ratios of the SVD sub channels may be used to devise bit-loading and coding schemes that approach the available channel capacity. When noisy or outdated CSI is used in conjunction with an SVD-based multiplexing method, the MIMO sub channels become coupled, resulting in potentially severe sub channel power loss and interference. As a consequence, sub channel bit-loading levels selected using the signal and noise powers of the perfect CSI assumption may no longer meet required probability-of-error levels.

IV. SIMULATION RESULTS

In this section, the performance of both GA and SVD algorithms is evaluated by using computer simulations.

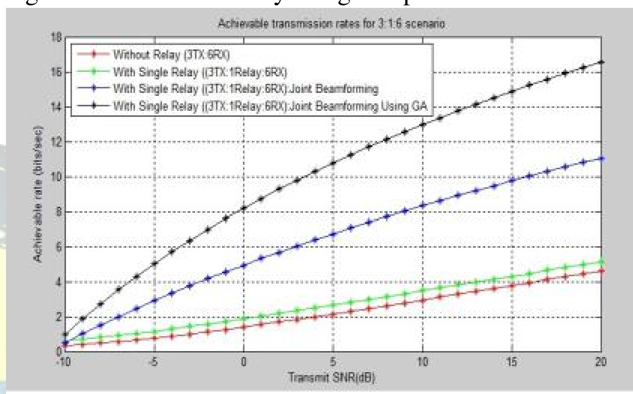

Fig 2: Achievable transmission rates for 3:1:6 scenario

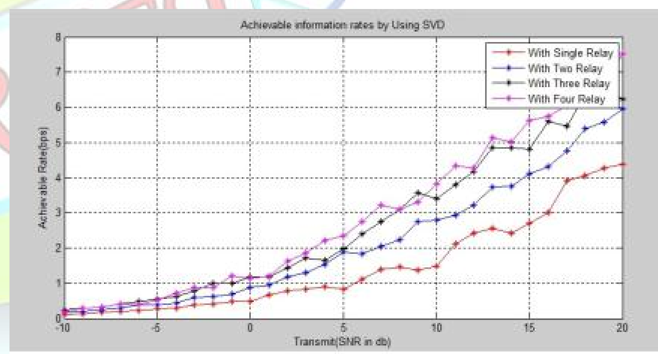

Fig 3: Achievable information rates by using SVD

V. CONCLUSION

In this paper, In order toreducethecomputationalcomplexity,wedecoupletheoriginal channel into many sub-channels. At first, a feasible solution for beamforming vectors and power allocation is obtained for a known channel allocation by an iterative algorithm, After that, GA and SVD-based algorithms have been applied to determine suboptimal channel allocations. Simulation results show that GA can obtain close-to-optimal solution with a price of high computation complexity. Whereas, SVD can significantly reduce the computational complexity with marginal performance degradation compared to GA. Simulation results for GA is better than SVD. In this paper secondary user transmitter act as relay path and it has several channel path.

ACKNOWLEDGEMENT

This research paper is organized by Department of ECE, PSN College of Engineering &Technology, TN. This project is guided by Mrs. Jegatheswari Assistant professor of ECE, PSN College of Engineering and Technology. She has a deep knowledge in the signal processing field.

REFERENCES

[1] “Spectrum policy task force, spectrum policy task force report,” Federal Communications Commission ET, 2002.
[2] S. Haykin, “Cognitive radio: brain-empowered wireless Communications,” IEEE J. Sel. Areas Commun., vol. 23, no. 2, pp. 201–220, Feb. 2005.
[3] R. Qiu, Z. Hu, H. Li, and M. Wicks, Cognitive Radio Communication and Networking: Principles and Practice. Wiley, 2012.
[4] C. Yi and J. Cai, “Two-stage spectrum sharing with combinatorial auction and stackelberg game in recall-based cognitive radio networks,” IEEE Trans. Commun., vol. 62, no. 11, pp. 3740–3752, Nov. 2014.
[5] C. Yi and J. Cai, “Multi-item spectrum auction for recall-based cognitive radio networks with multiple heterogeneous secondary users,” IEEE Trans. Veh. Technol., vol. 64, no. 2, pp. 781–792, Feb. 2015.
[6] B. Van Veen and K. Buckley, “Beam forming: a versatile approach to spatial filtering,” IEEE ASSP Mag., vol. 5, no. 2, pp. 4–24, Apr. 1988.
[7] S. Yiu, M. Vu, and V. Tarokh, “Interference reduction by beamforming in cognitive networks,” in Proc. IEEE Globecom, Nov. 2008, pp. 1–6.
[8] R. Xie, F. Yu, and H. Ji, “Joint power allocation and beamforming with users selection for cognitive radio networks via discrete stochastic optimization,” in Proc. IEEE Globecom, Dec. 2011, pp. 1–5.
[9] B. Zayen, A. Hayar, and G. Oien, “Resource allocation for cognitive radio networks with a beamforming user selection strategy,” in Signals, Syst. and Comput., Conf. Rec. of the Forty-Third Asilomar, Nov. 2009, pp. 544–549.
[10]O. Abdulghfoor, M. Ismail, and R. Nordin, “Power allocation via interference compensation in underlay cognitive radio networks: A game theoretic perspective,” inInt.lSymp. Telecommun.Tech. (ISTT), Nov 2012, pp. 296–301.
[11] K. W. Sung, M. Tercero, and J. Zander, “Aggregate interference in secondary access with interference protection,” IEEE Commun. Lett., vol. 15, no. 6, pp. 629–631, Jun. 2011.
[12] Y. Wen, S. Loyka, and A. Yongacoglu, “Asymptotic analysis of interference in cognitive radio networks,” IEEE J. Sel. Areas Commun., vol. 30, no. 10, pp. 2040–2052, Nov. 2012.
[13] C. Jiang and L. Cimini, “Downlink energy-efficient multiuserbeamforming with individual sinr constraints,” in Proc. Milcom, Nov. 2011, pp. 495–500.
[14] Y.-L. Liu, M.-L.Ku, and L.-C. Wang, “Joint beamforming,scheduling, and power allocation for hierarchical cellular systems,” in Proc. IEEE ICC, Jun. 2012, pp. 1773–1778.
[15] M.-L. Ku, L.-C.Wang, and Y.-T. Su, “Toward optimal multiuser antenna beamforming for hierarchical cognitive radio systems,” IEEE Trans. Commun., vol. 60, no. 10, pp. 2872–2885, Oct. 2012.
[16] E. Gharavol, Y.-C. Liang, and K. Mouthaan, “Robust downlinkbeamforming in multiuser miso cognitive radio networks with imperfect channel-state information,” IEEE Trans. Veh. Technol., vol. 59, no. 6, pp. 2852–2860, Jul. 2010.
[17] S.-H. Moon, C. Lee, S.-R. Lee, and I. Lee, “Joint user scheduling and adaptive intercell interference cancelation for miso downlink cellular systems,” IEEE Trans. Veh. Technol., vol. 62, no. 1, pp. 172–181, Jan. 2013.
[18] Hamdi,W.Zhang,andK.Letaief,“Jointbeamforming Andscheduling in cognitive radio networks,” in Proc. IEEE Globecom, Nov. 2007, pp. 2977–2981.
[19] K. Cumanan, R. Krishna, L. Musavian, and S. Lambotharan, “Joint beamforming and user maximization techniques for cognitive radio networks based on branch and bound method,” IEEE Trans. Wireless Commun.vol. 9, no. 10, pp. 3082–3092, Oct. 2010.
[20] C. Pitz, E. Ortiz Batista, and R. Seara, “On the joint beam forming and power control in cellular systems: Algorithm and stochastic model,” IEEE Trans. Wireless Commun., vol. 13, no. 12, pp. 6943–6954, Dec. 2014.

Y. Reegan Jebaraj[1] currently pursuing his BE in Electronics and Communication Engineering in PSN College of Engineering and Technology. His current research areas are DSP, DIP, Wireless Communication

V. Santha kumar[2] currently pursuing his BE in Electronics and Communication Engineering in PSN College of Engineeringand Technology. His current research areas are DIP, Mobile Communication.

P. John Samuel Jebaraj[3] currently pursuing his BE in Electronics and Communication Engineering in PSN College

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 13, March 2016

of Engineeringand Technology. His current research areas are DIP, Satellite Communication.

T,Vignesh[4] currently pursuing his BE in Electronics and Communication Engineering in PSN College of Engineeringand Technology. His current research areas are DIP, Mobile Communication.