Intra-Net Cognitive Radio Intelligent Utility Maximization using Adaptive PSO-Gradient Algorithm

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***Abstract*— Intelligently utilizing resources to meets the growing need of demanding services as well as user behavior is the future of wireless communication systems. Autonomous learning of wireless environment at run time by reconfiguring its operating mode that maximize its utility; Cognitive Radio (CR) can be programmed and configured dynamically and their utility maximization inside a building is a challenging task. Re-configurability and perception are considered key features of CR for system adaptation. In this paper an adaptive model to enhanced CR utilization to be maximized is proposed, i.e., Particle Swarm Optimization (PSO) in combination with Gradient-method and intends to maximize the utility of CR. For this purpose the primary objective is allocation of optimum powers to Base Stations (BSs), which is achieved in an iterative manner keeping in view power constraints. A novel Distributed Power PSO-Gradient Algorithm (DPPGA) is introduced, which assures utility maximization under network power constraints. Simulations are carried out by considering different scenarios; Low power BSs deployed over 2 meter height are used to serve Mobile Stations (MSs) in triple story building, whereas size of building is 100 m * 50 m, size of room is 10 m * 10 m and corridor covering width of 5m. Omni directional antenna with 2.6 GHz is used in the simulation scenarios. Results are compared with existing algorithms; cooperative and non-cooperative schemes. The performance of proposed algorithm is remarkable.**

***Index Terms*— Cognitive Radio (CR), Particle Swarm Optimization (PSO), Gradient-Method, Network Utility Maximization, Base Stations (BSs).**

I. INTRODUCTION

The Cognitive Radio (CR) is the prime focus of researchers of current era of communication. Lot of research has been carried out for the problems pertaining to the outdoor wireless communication, whereas indoor setups however need further elaborations such as Intra-Net which is the prime focus of this work. In wireless communication, electromagnetic spectrum scarcity is being faced by the new systems. Features like spectrum availability, power consumption and reserve level during operation are considered to be key features to detect and percept system capability. Intelligent wireless systems being a key component of CR, i.e., make it easy for the device to adapt environment as well as maximize its utility within the available spectrum resources [1]. Contemporary 3G and 4G technologies broadly deployed in cities uses IMT-2000 band, having in the frequency range of 2 GHz, which is unable to easily penetrate inside huge buildings. Cognitive Radio based Internet of Thing (CR-IOT) is a leading step to smart world of technology in upcoming 5G networks [2]. The 5G, Machine to Machine (M2M) communication will be there which is beyond current mobile networks; CR networks therefore have the capacity to address key challenges of limited radio spectrum faced in 3G and 4G networks [3]. Two approaches used for efficient utilization of licensed spectrum, one is by using small cells (e.g. Femtocells) which extend licensed cellular services inside the building for users and other approach is CR to develop spectrum utilization and increase the efficiency of spectrum sharing systems. Josif Motila proposed the first concept of CRs in 1998 [4]. Spectrum holes are searched by CRs for communication, running applications, services and transporting data packets over the CRs nodes. These terminals are capable of sensing spectrum and communication environments. The CR adjusts and reconfigures itself according to well-read information with compliance to regulations. Downloading files from specific Access Point (AP), the CR mobile station sense the spectrum before communication. In order to communicate with other CRs, the CRs establish an ad-hoc network. The CR has three basic types, Interweave CR, Overlay and Underlay systems. In Interweave CR system; Primary Users (PUs) are active with CRs and able to transmit signal using unoccupied spectrum holes. The CR continuously monitors the transmission environment and search for vacant spectrum [5].

In Overlay system, PU provides their signal information including Codebooks and share massages with Secondary User (SU) and thus CR coordinate with PUs which further improve transmission efficiency [6]. In Underlay systems, the CRs are active using low powers in parallel with PU transmission under some threshold levels to avoid interference at PUs' side irrespective of PUs transmission. In License Shared Access (LSA) the SUs of CRs are allowed to access the shared spectrum subject to services of PUs are not distressed [7]. Alternative approach is centralized authority which calculate and assigns a transmit powers to CR network; this approach is discussed in details by a researcher [8]. Distributed power allocation algorithm for industrial sensor

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network is already being addressed [9]. Distributed power allocations among the CR users protocol based using auction is also being researched, which increase the network performance of CRs [10]. Pricing and bidding strategies were used to maximize the users weighted sum rates. Distributed power allocation in CR network under network power constraint is discussed in a research work [11]. Energy efficient power allocation in CRs network schemes have been proposed [12]; and power allocation strategy in CR network in signal carrier is being described thoroughly, with transmit average and interference power constraints [13]. A Particle Swarm Optimization (PSO) algorithm was proposed which finds the optimal solution of power allocation [14].

Global Database server (GLDB) for specific area (building) calculates the powers and controls the transmit powers which must be accepted by CR before transmission [15].

The transmit powers of CRs are synchronized with predefine powers P_{max} to avoid interferences in PU sides of license users [16]. Utility maximization, high reliable, outage probability and interference free are technical scenarios of Underlay CR network. As conferred different types of CRs, the prevalent type is Underlay network. These CRs are functioning in parallel with PUs without interfering by controlling its transmitting powers. The CRs are generally functioning inside the building as shown in Fig. 1. The SBs are installed in corridors of the building and communicating with their respective MSs [17].

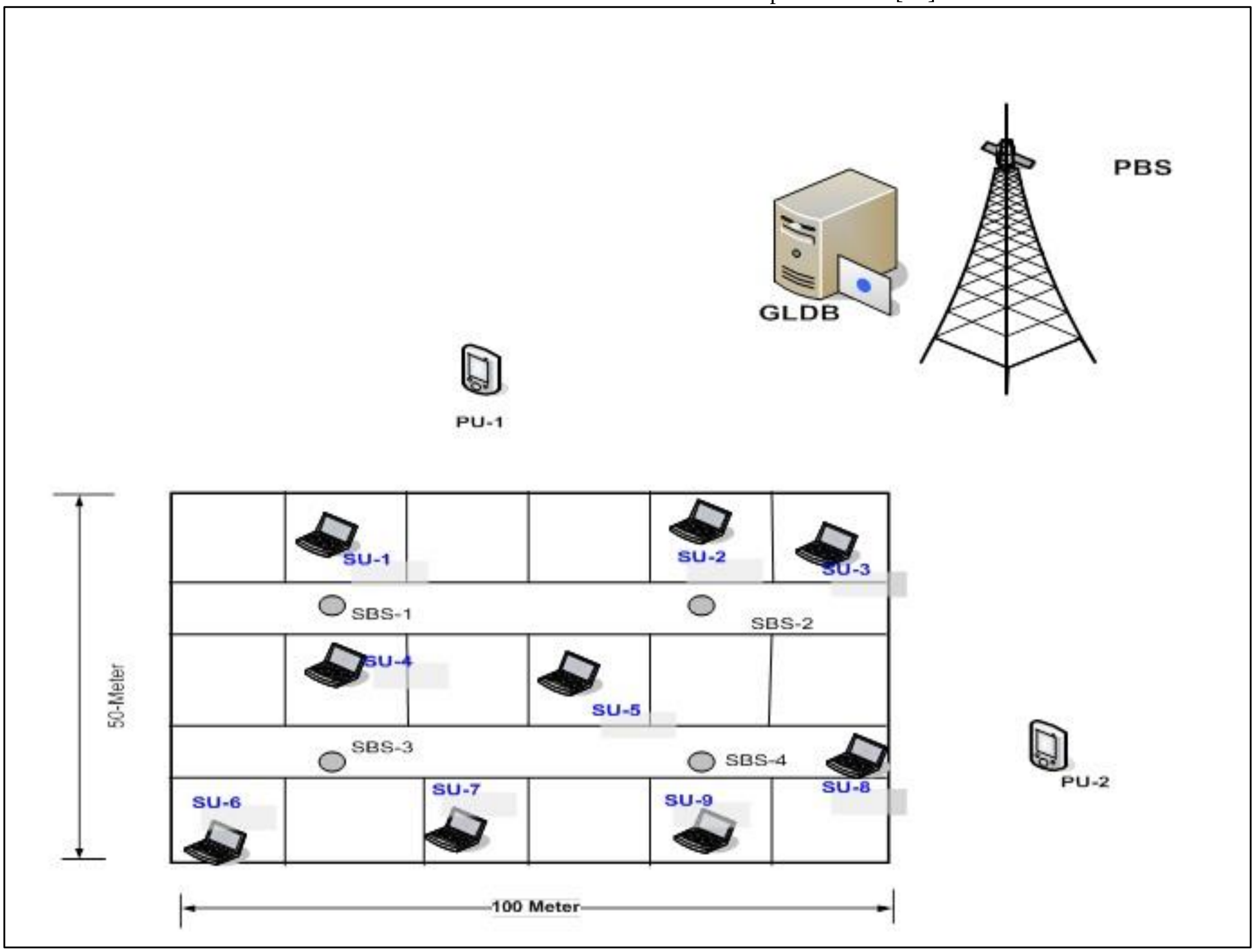

Fig. 1: Underlay Cognitive Radio Distributed Power Allocation Mode

GLDB provide maximum transmit powers P_{max} for that specific CR network to avoid interference with PUs. The gradient based optimization algorithm, proposed in literature used for maximization of CR network utility under network power constraint may be stuck in local optima [18]. Therefore the required utility maximization in Underlay CR network cannot be achieved. A new algorithm is required for CR network to utilize the internal resources and overcome the gradient optimization imperfections. The proposed algorithm must be capable to find-out the optimum transmit powers for Cognitive Radio Base Stations (CR-BSs) comprehensively and eventually to be able to enhance the overall network utility. Heuristic based gradient optimization technique is proposed for maximization of network utility.

The contribution of this paper is summarized as follows;

This research work is further organized in the following structure: **Section II** describes in depth study of choosing Particle Swarm Optimization (PSO) and its working in general. In **Section III** material and methods; discussion of proposed technique in respect of mathematically derived proofs and optimization problem formulations, **Section IV** a working algorithm PSO Gradient Algorithm (DPPGA) and all path loss office model, where all path losses and shadowing, fading factors are incorporated to calculate the channel gains between CR-BS and CR users, is presented. **Section V** presented simulation results achievement and its relevant discussion over the proposed scenarios. **Section VI** concludes the presented work whereas **Section VII** highlights the limitation as suggested future work for improvement.

II. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a stochastic optimization process used for global optimization. Its computational cost is high by carrying random searches compared to gradient-based optimization, used for local optimization. Deterministic Gradient based optimization may converge fast, however this method may held in local optima in multimodal problem. The research work presented in this paper is novel adaptive PSO-Gradient Algorithm which assures maximization of CR network utility. This Adaptive optimization technique maximizes Signal to Interference plus Noise Ratio (SINR) of CR network. The utility of Underlay CR network get maximized by using this Adaptive algorithm i.e. PSO-Gradient in comparison to independent gradient methods. We presented cooperated scheme which exchange prices/Interferences between CR-BSs and non-cooperative scheme where CR-BSs are not sharing their prices with other BSs. In this paper, we use both random and deterministic optimization that can search out combined benefit and avoid their limitation. PSO is used for global search and gradient-optimization used to get best local optimum. In order to formulate the problem using PSO we consider Eq. (16) and Eq. (17) as cost function to maximize the utility. The CR-BSs randomly initialized with transmit powers. We consider $m\ x\ n$ random powers for PSO, (1 x n) is called the particle (population) and compute its utility of every set of powers and search out the best utility as global best. These power particles are searched similar to a birds flock to get the optimum solution. After calculating its utilities each vectors of particle has its local best and among the local best select global best. To calculate the particles velocity we have,

$$V(k+1) = V(k) + F_1(P(k,f) - B_i(k,f)) + F_2(G(k,f) - B_i(k,f)) \quad (1)$$

Where:

$\boldsymbol{\Phi 1}$ and $\boldsymbol{\Phi 2}$ are uniformly random number generated independently for each dimension,
P is local best found by particle and
G is the global best in entire population
$\boldsymbol{V}$ is bounded by constraint
$\boldsymbol{P_{\min}}$ and $\boldsymbol{P_{\max}}$ to prevent divergence.

Selecting;

$$S = 1/(1 + exp(-V(k,f))) \quad (2)$$

III. MATERIALS AND METHODS

Consider a CR network having a set of Base Stations (BSs) i.e.

$$K = \{BS_1, BS_2, BS_3, \ldots\ldots BS_{\mathrm{L}}\} \quad (3)$$

and a set of Mobile Stations (MSs) i.e.

$$\mathrm{M} = \{MS_1, MS_2, MS_3, \ldots\ldots MS_{\mathrm{N}}\} \quad (4)$$

These BSs communicate with their respective MSs on common bandwidth.

The i[th] BS serves $\boldsymbol{M_i}$ MSs, where:

$$\{M_i \subseteq \mathrm{M}:\ \ i = 1,2,3\ldots\ldots.L\}$$

Network Power constraint provided by GLDB is supposed to be there i.e. P_{max} is the maximum power limit that must not be exceeded by the sum of individual transmit powers of BSs. Accordingly, the set of powers is:

$$p = \{p_{\mathrm{i}}\}_{\mathrm{i}=1}^{L} \quad (5)$$

and the corresponding power constraint is:

$$\textstyle\sum_{\mathrm{i}\in \mathrm{K}} p_{\mathrm{i}} \leq P_{\max}$$

The available resources in the network are equally distributed among the BSs, which are further uniformly distributed among the respective MSs [19]. The overall set of resources is given as:

$$W = \{\mathrm{w}_1, \mathrm{w}_3, \mathrm{w}_2, \ldots\ldots \mathrm{w}_{\mathrm{L}}\} \quad (6)$$

The objective is to maximize the sum utility of the CRs given as:

$$\mathrm{U}_{\mathrm{sum}}(\mathrm{p}, W) = \textstyle\sum_{\mathrm{i}\in \mathrm{K}} \mathrm{U}_{\mathrm{i}}\,(\mathrm{p}, w_{\mathrm{i}}) \quad (7)$$

Where:

$\mathbf{w_i}$ is set of Weights, of all MSs served by $\mathbf{BS}_{\boldsymbol{i}}$ and
$\mathbf{U_i}$ is the utility of $\mathbf{BS}_{\boldsymbol{i}}$.

$$\mathrm{U}_{\mathrm{i}}(\mathrm{p}, w_{\mathrm{i}}) = \textstyle\sum_{\mathrm{l}\in \mathrm{M_i}} \mathrm{u_l}\,(\mathrm{p}, w_{\mathrm{i}}) \quad (8)$$

The utility of the each MS is defined as:

$$u_l = \mathrm{In}\{\mathrm{w}_l[\mathrm{In}(1 + \Gamma_l(\mathrm{p})], l \in \mathrm{M}_i \quad (9)$$

Where:

$\boldsymbol{\Gamma_l}(\mathbf{p})$ is the Signal to Interference plus Noise Ratio (SINR) calculated by $\mathbf{MS}\boldsymbol{l}$ served by $\mathbf{BS}_{\boldsymbol{i}}$.

Where:

$\boldsymbol{u_l}$ is Proportionality fair rate as defined [20].

$$H(u_1, u_2, \ldots\ldots.u_S) = \textstyle\sum_{s=1}^{S} In(u_s) \quad (10)$$

Where:

$\boldsymbol{u_s}$ is the Shannon Rate capacity in (Nats/s/Hz). PF-rate share the common resources power and scheduling weights in fair distribution among the MSs served by BS_i. This logarithmic form of utility will improve the user's data rates, even those users that are experiencing low data rates due to high channel interference. SINR for each Mobile Station (MS) $\Gamma_l(\mathrm{p})$ is defined as:

$$\Gamma_l(\mathrm{p}) = \frac{\mathrm{p}_i h_{i,l}}{I_l + N_0} \, l \in \mathrm{M}_i \tag{11}$$

Where:

$$I_l = \sum_{j \neq i} \mathrm{p}_j h_{j,l} \, l \in \mathrm{M}_i \tag{12}$$

Where:

$\boldsymbol{h_{i,l}}$ is channel power gain, between BS_i and MSl

$\boldsymbol{I_l}$ is the interferences from the other cells and

$\boldsymbol{N_0}$ is the background noise, here we assume that the channel is frequency flat.

The objective function which, need maximization is given as:

$$\begin{aligned} &\underset{\mathrm{p},w}{\text{Maximize}} \sum_{i \in \mathrm{k}} \mathrm{U}_i(\mathrm{p}, w_i) \\ &\text{subject to } \sum_{i \in \mathrm{k}} \mathrm{p}_i \leq \mathrm{P}_{\max} \end{aligned} \tag{13}$$

Considering Eq. (14), this equation is non-convex, which can be made convex if one variable is fixed and optimization performed on other variable briefly discussed by in a study [20]. We considered the decomposition method, which will eventually allow us to write pricing algorithm for finding solution of Eq. (14) in distributed way using PSO and gradient methods. Here we use single channel model of frequency flat channel.

When there is more than one variable, the primal decomposition is a suitable method used for decomposition [21]. This Eq. (14) can be solved by using primal decomposition, by fixing powers and decouple the problem into sub-problems independent optimization problems of scheduling weights, so the problem divide into two stage optimization problems. At one stage fixing powers, then the problem decouple into scheduling weights optimization sub-problems $\forall i \in \mathrm{K}$.

$$\begin{aligned} &\underset{\mathrm{w}}{\text{Maximize}} \sum_{i \in \mathrm{k}} \mathrm{U}_i(\mathrm{w}_i) \\ &\text{subject } to \ \mathrm{w}_i \in W \end{aligned} \tag{14}$$

Now Eq. (14) turns into convex problem and can be solved at each BS and updating coupling variable power. Optimization over "p" is perform using pricing algorithm, the master problem is:

$$\begin{aligned} &\underset{\mathrm{p}}{\text{Maximize}} \sum_{i \in \mathrm{k}} \mathrm{U}_i(\mathrm{p}) \\ &\text{subject } to \sum_{i \in K} \mathrm{p}_i \leq \mathrm{P}_{\max} \end{aligned} \tag{15}$$

In equation (10) we have the master problem having network utility:

$$\mathrm{U}_{sum}(\mathrm{p}) = \mathrm{U}_i(\mathrm{p}) + \sum_{j \neq i} \mathrm{U}_j(\mathrm{p}) \tag{16}$$

Differentiate with respect to p_i:

$$\begin{gathered} \mathrm{D}_i = \frac{\partial \mathrm{U}_{sum}(\mathrm{p})}{\partial \mathrm{p}_i} \\ \frac{\partial \mathrm{U}_{sum}(\mathrm{p})}{\partial \mathrm{p}_i} = \frac{\partial \mathrm{U}_i(\mathrm{p})}{\partial \mathrm{p}_i} + \sum_{j \neq i} \frac{\partial \mathrm{U}_j(\mathrm{p})}{\partial \mathrm{p}_i} \end{gathered} \tag{17}$$

Where:

$$\frac{\partial \mathrm{U}_i(\mathrm{p})}{\partial \mathrm{p}_i}$$

is equal to

$$\pi_{i,i} = \frac{\partial \mathrm{U}_i(\mathrm{p})}{\partial \mathrm{p}_i} \forall i \in \mathrm{K} \tag{18}$$

$$\pi_{j,i} = \sum_{\mathrm{j} \neq \mathrm{i}} \frac{\partial \mathrm{U}_j(\mathrm{p})}{\partial \mathrm{p}_i} \forall j \in \mathrm{K}, j \neq i \tag{19}$$

$\pi_{i,i}$ is called the power benefit calculated by i^{th} BS and $\pi_{j,i}$ is called power prices, which are calculated and shared by other BSs. $\pi_{i,i}$is calculated by using PF-rate utility.

Proposition 1: $\pi_{i,i}$ at each BS is calculated using PF-rate utility and shared by BS:

$$\pi_{i,i} = \frac{\Gamma_l(\mathrm{p})}{\mathrm{In}(1+\Gamma_l(\mathrm{p}))(1+\Gamma_l(\mathrm{p}))\mathrm{p}_i} \tag{20}$$

Proof: See Appendix A1

Proposition 2: $\pi_{j,j}$is calculated using PF-rate utility:

$$\pi_{j,j} = \frac{\Gamma_l(\mathrm{p})}{\mathrm{In}(1+\Gamma_l(\mathrm{p}))(1+\Gamma_l(\mathrm{p}))\mathrm{p}_j} \tag{21}$$

Proof: See Appendix A2

Proposition 3: Calculating$\pi_{j,i}$using PF-rate utility we have:

$$\pi_{j,i} = -\sum_{l \in \mathrm{M}_j} \frac{h_{i,l} \Gamma_l(\mathrm{p})^2}{\mathrm{In}(1+\Gamma_l(\mathrm{p}))(1+\Gamma_l(\mathrm{p}))h_{j,l}\mathrm{p}_j} \tag{22}$$

Proof: See Appendix A3

Proposition 4: Calculating$\pi_{i,j}$:

$$\pi_{i,j} = -\sum_{l \in \mathrm{M}_i} \frac{h_{j,l} \Gamma_l(\mathrm{p})^2}{\mathrm{In}(1+\Gamma_l(\mathrm{p}))(1+\Gamma_l(\mathrm{p}))h_{i,l}\mathrm{p}_i} \tag{23}$$

Proof: See Appendix A4

In Eq. (14) PF-rate utility function the optimization carry out over w_i in frequency flat static channel, the scheduling weights allocated in round Rabin allocation for equal distributions of bandwidth among all MSs and optimization is carried out on transmit powers iteratively. BSi receives power prices $\pi_{j,i}$ and D_j from all interfering BSs $j \neq i$ then it calculates:

$$D_i = \pi_{i,i} + \pi_{j,i} \tag{24}$$

Similarly BSj receives power prices $\pi_{i,j}$ and D_i from all interfering BSs $i \neq j$ then it calculates:

$$D_j = \pi_{j,j} + \pi_{i,j} \tag{25}$$

In available D_j for BSi $j \neq i$, selects BS_G that can increase the network utility the most

$$G = \arg \max D_j \quad j \neq i \tag{26}$$

If D_G is larger then D_i, by BS_i reduce its power by

$$\begin{aligned} \delta' &= \min(\delta(D_G - D_i), \delta\max) \\ p_i &= p_i - \delta' \\ p_G &= p_G + \delta' \end{aligned} \tag{27}$$

Small δ is selected current BS power by BS_i updates interference prices to interferers BS $j \neq i$ and updates are announces its D_i. Repeat the process until convergence or maximum iteration is accomplished.

IV. ALGORITHM-DPPGA

- At $R_i[n]$, Calculate Power particles for PSO
- Calculate the fitness of each particle using Utility Cost function:

$$U_{sum}(p) = U_i(p) + \sum_{j \neq i} U_j(p)$$

- Compare the fitness with best fitness:

If

Newfitness > P-Best

P-Best=Newfitness

Else

P-Best= P-Best

- Calculate velocity and update each power particle S=1/(1+exp(-v)):

If

S>r and ()

P=P+δ

Else

P=P-δ

- Check for convergence or maximum iteration reach
- $T_i[n]$, Calculate D_i, using interference prices, D_j :

If

$D_i > D_j \quad \forall \quad j \neq i$

Then i[th] BS power is optimum

Else

$$G = argmaxD_j \; j \neq i \tag{28}$$

Reduce power by δ'= min (δ (D_G $-D_i$), δ_{max})

and send power increment message to BS_G

and BS_G updates its power to $P_G = P_G + \delta'$

- BSi updates interference prices to interferers $j \neq i$
- BSi updates and announces its D_i
- Repeat until convergence or Max-Iteration reached.

Table I: WINNER-II Office Path Loss Model

S.No	Description	Details	S.No	Description	Details
1	Buildings Dimensions	100x50 Meters	8	Path Loss Coefficient A	18.7
2	Room Dimensions	10x10 Meters	9	Path Loss Coefficient B	46.8
3	Corridor Widths	5 Meter	10	Path Loss Coefficient C	20
4	Numbers of Floors	3 Meter	11	Lw Inner Wall Loss in db	5 db
5	Antenna Pattern	Omni Direction	12	Height of Rooms	3 Meter
6	Carrier Frequency	2.6 (GHZ)	13	Mobile Stations Heights	1 Meters
7	BSs Heights in Meters	2 Meters	14	Line Of Sight (LOS)	Same Room or Corridor

After getting this new population, cost function evaluated to find the utilities of each population and get the local and global best. Repeat the process until converge or maximum iteration is reached. The global best powers are used for gradient based optimization to get (maximum) utilities. Complete code DPPGA algorithm shown above i.e., Table I.

Table II: Simulation Parameters in WINNER-II Model

S.No	Description	Details	S.No	Description	Details
1	Max Tx Power	100 mw	5	Noise Figure(Nf)	9
2	Min Tx Power	1 mw	6	Thermal Noise[dbm/Hz]	-174
3	No of MSs	12	7	Shadowing Fading Correlation	0.5
4	No of BSs	12	8	Shadowing Fading (Sd) in db	3

V. RESULTS AND DISCUSSION

This research study analyzes the performance of proposed algorithm on the basis of results achieved with cooperative and non-cooperative schemes. The simulations schemes using

Table II as parameter values are presented in **Section IV** then the simulation results are discussed in **Section V**. In this study low power small cell network consisting of low power BSs to provide services to its MSs in three-story building. As shown in Fig. 1. Cognitive Base stations placed in building corridors, rooms having multiple MSs communicating with their BSs. The size of the three-stories building is 100x50 meters with height of 10feet of each story. A top view of the building shown Black little circled the installations of low power BSs. The signal propagations from BS to MS are modeled by using WINNER-II office model i.e., Path loss model parameters are shown in Table I [22].

The path-loss calculated as:

$$PL = Alog_{10}(d) + B + Clog_{10}(\frac{fc}{5}) + DL_w \qquad [29]$$

Here:

Path-loss measured in decibel and A, B, C and D is coefficients of WINNER-II A-1 office model. d is the distance in meters between MS and serving BS and D is the number of walls between BS and MS. L_w is the loss of wall in db and fc is the carrier frequency in Giga hertz (GHZ).

In Table II we take parameters of simulations of WINNER-II model, we use 12 BSs and 12 MSs. Maximum transmit powers of BSs is set to 100-mw and 1-mw power minimum. Noise figure, shadowing and thermal noise are also incorporated.

In order to make the simulation scenario simple, among each cognitive base station, only select one cognitive base station according to received signal strength. Assuming the backhaul connections are available between BSs to communicate and exchange prices.

In order to solve our optimization problem, i.e., Eq. (16) is being used; ER proposed Distributed Power PSO Gradient Algorithm (DPPGA) for CR network utility maximization. In Cooperative scheme measuring power prices all BSs $j \neq i$ in the network and receive D_j and $\pi_{j,i}$ from other BSs $j \neq i$. In non-cooperative scheme each BS calculate its power benefits D_i, $\pi_{i,j}$however not sharing the powers prices. The SINR at MSs significantly increased, by implementing DPPGA. PSO-cooperative scheme has more SINR than cooperative and non-cooperative schemes as shown in Fig. 3. It is to mention that by using non-cooperative scheme the possible cause that BSs does not share their pricing information among the neighboring BSs. The determination of the paper is to enhance the network utility by using DPPGA. The network utility in this case is increases by DPPGA. In DPPGA PSO algorithm is incorporated to find the optimum global maxima of powers allocated to Cognitive Base Stations and then using this optimum powers, calculate power prices at BSs then each BS share its D_i , $\pi_{i,j}$ to all BSs $j \neq i$ and receive D_i and $\pi_{j,i}$ from all other BSs $j \neq i$, which indicate the benefit of PF-rate utility as the data rates of MSs experiencing low SINR increase, as shown in Fig. 2.

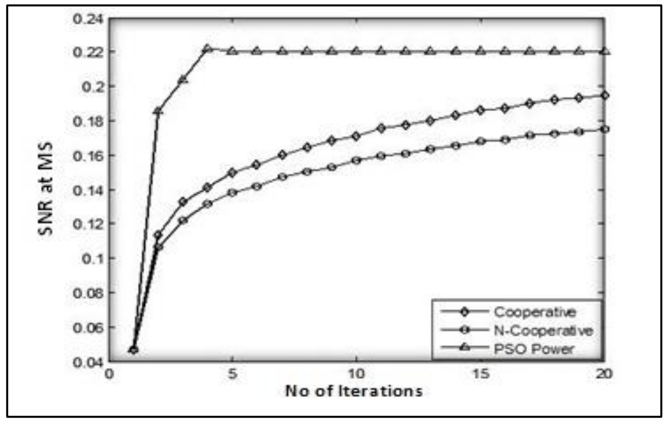

Fig. 2: Comparison of SINR vs. PSO.

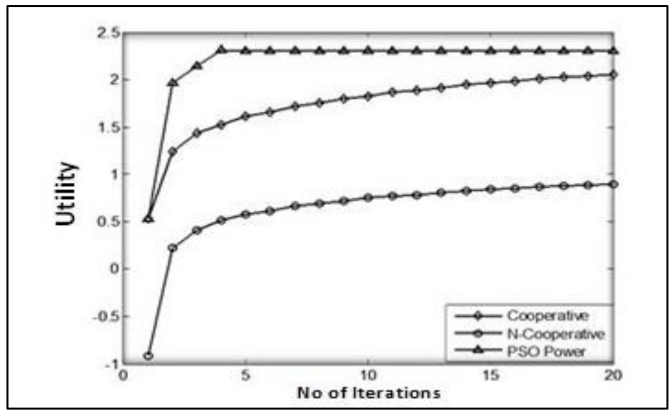

Fig. 3: Comparison of PF-Rate Utility Maximization

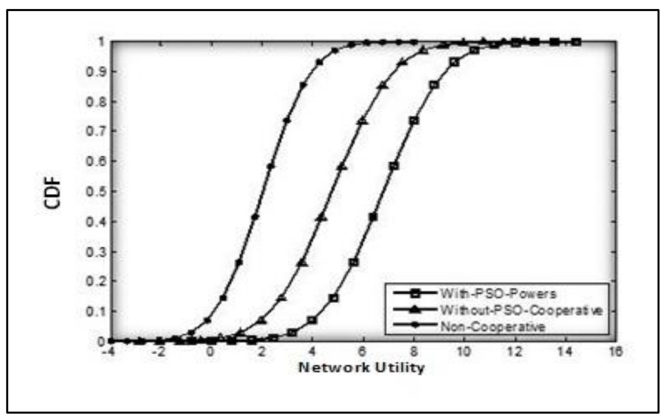

Fig. 4: CDF Plot of Network Utility Maximization Achieved

Fig. 2 above illustrated relationship between SNIR with the number of iterations used in simulations. In comparison to other cooperative and non-cooperative technique the proposed PSO techniques has ends up with 0.22, whereas non cooperative end at 0.16 and cooperative at 0.18. So SINR has increased gradually for all the techniques, gradually as number of iterations has increased as they started over at 0.5 and ends up at 0.16, 0.18 and 0.22. Fig. 3 shows that as the number of iterations has increased gradually so in comparison to the other techniques proposed PSO power technique provides high utility value as it started over 0.5 and ends up at 2.3. Fig. 4 has shown relationship between Cumulative Distribution Function (CDF) with respect to network utilization underperformed simulations. In comparison to other cooperative and non-cooperative technique the proposed PSO techniques utilizes network initially at start with 0 % but while non-cooperative started at 2 at start; proposed PSO technique has ended at 15%. While other two techniques ended at 7% and 12 %. So network utilization has increased gradually for all the techniques. Different schemes, PF-rate utility plots have been shown in Fig. 2, 3 and 4. In this case, the overall network utility is enhanced and maximized.

VI. CONCLUSION

In this research study an intelligent DPPGA pricing algorithm based on decomposition method is proposed that maximizes resource utilization under CRs network under network based on power constraint. PSO based gradient algorithm for PF-rate maximization to meet the network power constraint. Simulations are carried out on small cell CRs network; different cooperative and non-cooperative scenarios are compared and results shows that the proposed intelligent PSO based gradient adaptive method is efficient then general gradient based optimization to maximize the network resources utilization.

VII. FUTURE WORK

In future, artificial intelligence latest techniques such as Deep Learning could be investigated so that human interaction could be minimized under Cognitive Radio Networks; by doing this more intelligence could be possible to utilize resources efficiently and with limited power utilization.

AUTHOR CONTRIBUTIONS

Javed Iqbal and Imranuallah Khan proposed idea and conceptualized the problem. Mukhtar Rana guided to formulate proposed methodology, Ahthasham Sajid write initial draft and revised draft, Imran Baig improved-original draft and revised draft to be submitted, Afia Zafar works on formatting of the paper according to Journal requirements and improved quality of figures.

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Appendix Proof of Proposition A1:

$$\mathit{\Gamma}_l(\mathrm{p}) = \frac{\mathrm{p}_i h_{i,l}}{I_l + N_0}\, l \in \mathrm{M}_i$$

$$\mathrm{u}_l = \mathrm{In}[\mathrm{In}(1 + \mathit{\Gamma}_l(\mathrm{p}))], l \in \mathrm{K}_i$$

And

$$I_l = \sum_{j=i} p_j h_{j,l} \quad l \in M_i,$$

So

$$p_i = \frac{\Gamma_l(p)(I_l + N_0)}{h_{i,l}}$$

$$\pi_{i,i} = \frac{\Gamma_l(p)}{\mathrm{In}(1+\Gamma_l(p))(1+\Gamma_l(p))p_i}$$

And

$$\frac{\partial U_i(p)}{\partial p_i} = \frac{h_{i,l}}{\mathrm{In}(1+\Gamma_l(p))(1+\Gamma_l(p))(I_l+N_0)}$$

$$\pi_{i,i} = \frac{h_{i,l}\Gamma_l(p)}{\mathrm{In}(1+\Gamma_l(p))(1+\Gamma_l(p))(I_l+N_0)\Gamma_l(p)}$$

Appendix Proof of Proposition A2:

$$\Gamma_l(p) = \frac{p_j h_{j,l}}{I_l+N_0} \quad l \in M_j,$$

$$u_l = \mathrm{In}[\mathrm{In}(1+\Gamma_l(p))], \quad l \in K_j$$

And

$$I_l = \sum_{i=j} p_i h_{i,l} \quad l \in M_j$$

$$\pi_{j,j} = \frac{\Gamma_l(\mathbf{p})}{\mathrm{In}(1+\Gamma_l(\mathbf{p}))(1+\Gamma_l(\mathbf{p}))p_j}$$

Appendix Proof of Proposition A3:

$$\Gamma_l(p) = \frac{p_j h_{j,l}}{I_l+N_0} \quad l \in M_j,$$

$$u_l = \mathrm{In}[\mathrm{In}(1+\Gamma_l(p))], \quad l \in K_j$$

And

$$I_l = \sum_{i \neq j} p_i h_{i,l} \quad l \in M_j$$

$$\frac{\partial U_j(p)}{\partial p_i} = -\sum \frac{p_j h_{j,l} h_{i,l}}{In(1+\Gamma_l(p))(1+\Gamma_l(p))(I_l+N_0)^2}$$

$$\pi_{j,i} = \frac{\partial U_j(p)}{\partial p_i} = -\sum_{l \in M_j} \frac{h_{i,l}\Gamma_l(p)^2}{In(1+\Gamma_l(p))(1+\Gamma_l(p))h_{j,l}p_j}$$

Appendix Proof of Proposition A4:

Calculating $\pi_{i,j}$,$\Gamma_l(p) = \frac{p_i h_{i,l}}{I_l+N_0} \quad l \in M_i$,

$$u_l = \mathrm{In}[\mathrm{In}(1+\Gamma_l(p))], l \in K_i$$

And

$$I_l = \sum_{j \neq i} p_j h_{j,l} \quad l \in M_i$$

$$\frac{\partial U_i(p)}{\partial p_j} = -\sum \frac{p_i h_{i,l} h_{j,l}}{In(1+\Gamma_l(p))(1+\Gamma_l(p))(I_l+N_0)^2}$$

$$\pi_{i,j} = \frac{\partial U_i(p)}{\partial p_j} = -\sum_{l \in M_i} \frac{h_{j,l}\Gamma_l(p)^2}{In(1+\Gamma_l(p))(1+\Gamma_l(p))h_{i,l}p_i}$$