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Fuzzy Based Resource Allocation for Cognitive Radio Relay Networks

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Abstract: In cognitive radio relay networks, the resource allocation technique may result in increased power consumption and interference. In this study, we propose to design a fuzzy based resource allocation technique for cognitive radio relay networks. In this technique, a Proportional Fair Scheduling (PFS) based resource allocation is applied for all nodes in which node with good channel condition and high data rate is allocated more bandwidth. Then the adaptive transmit power adjustment algorithm used for optimal resource allocation. A Fuzzy Logic Decision (FLD) model is used for selecting the transmit power level based on the factors interference among relay nodes, transmission rate between relay and mobile node and predicted link availability. By simulation results, we show that the proposed technique reduces the energy consumption and link interference.

Key word: Resource allocation, cognitive, bandwidth, optimal resource, transmit power

INTRODUCTION

Cognitive Radio Networks: Cognitive Radio (CR) has been considered as one potential technology to activate the utilization of spectrum resources in the recent evolution of wireless communication systems (Cheng *et al*., 2010; Adian and Aghaeinia, 2013). Nodes in a Cognitive Radio Network (CRN) can be classified as Primary (licensed) users and Secondary (cognitive, unlicensed) users. A Primary User (PU) is the licensed owner of a particular spectrum band and has limited rights to access it whereas a Secondary User (SU) has the ability to detect portions of the spectrum temporarily unused by its PU and use them opportunistically while ensuring that Pus are unaware to the Sus (Gozupek and Alagoz, 2013).

Cognitive Radio (CR) networks can be partitioned as the infrastructure-based CR network and the CRAHNs. The former has a central network entity like a base station in cellular networks or an access point in wireless LANs whereas the latter without any infrastructure backbone communicate via ad hoc connection on both licensed and unlicensed spectrum bands (Akyildiz *et al*., 2009).

Cooperative relay can be used to improve diversity in cognitive radio networks and is viewed as a new paradigm that benefits spectrum sensing and spectrum sharing (Teng *et al*., 2013; Naeem *et al*., 2014)

Resouce allocation and scheduling in CRNs: In Cognitive Radio Networks (CRNs), resources in the secondary network should dynamically be allocated according to the sensed radio environment to maximize the utilization of radio spectrum and minimize the risk of overlapping the coverage of CRNs with adjacent primary networks (Xie *et al*., 2012a). But, CRNs are subjected to the interference power constraints which are imposed by a primary system. So, it is advantageous to mitigate the interference on the primary and to harvest multiuser diversity gains in the secondary. Joint optimization of bandwidth and power allocation is necessary for efficient resource utilization (Tachwali *et al*., 2013). The optimization problem of jointly designing sensing parameters and resource allocation is formulated subject to the total power constraint of the CRN and the average interference power to the primary network (Xu *et al*., 2013).

The basic elements of resource allocation in CRN includes power allocation, relay selection, user scheduling, routing, quality of service, delay and sub-carrier allocation traditional power allocation schemes for non-cognitive cooperative networks are not applicable to cooperative CRN as these schemes may cause unacceptable interference the primary network (Naeem *et al*., 2014).

The traditional infrastructure-based wireless networks' scheduling cannot be implemented in CRNs due to the unique features and challenges imposed by the DSA concept. Varying channel availability owing to PU activity and the requirement that PUs have to be oblivious to SUs make the required scheduling mechanisms in CRNs different from conventional wireless networks. The fact that PUs need to be unaware of the SUs conveys that, PUs should not be modified. Hence, it is an open

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challenge to design scheduling mechanisms for CRNs in line with this requirement (Gozupek and Alagoz, 2013).

Literature review: Game theory approach has been applied in works (Gozupek and Alagoz, 2013; Qu *et al.*, 2010) for resource allocation problem. In a game approach is designed for the problem of dynamic resource allocation in an OFDMA based cell as a two-tier game (Cheng *et al.*, 2010). In RA-Game, each PU dynamically accesses the sub-channels according to his payoff while in PS-Game, each SU buys a radio from some PU to maximize his utility. Furthermore, they propose two algorithms to allocate resource among PUs and SUs in a distributed manner. Their algorithms can converge to Nash Equilibrium automatically which maximizes the utilization of the whole network resource. The game theory based resource allocation based on incomplete information theory is proposed (Qu *et al.*, 2010). The utitlity function is derived in terms of SINR value.

Apart from game theory, swarm intelligence has been used in resource allocation in (Udgata *et al.*, 2010) for optimum allocation of available spectrum holes to cognitive radio users. Here, bidding strategy is used to allocate the channels to cognitive radio users. The base station allocates the spectrum band to the cognitive user by maximizing the total bid value received from all cognitive users. Binary Particle Swarm Optimization (PSO) technique is used to find an optimum allocation of channels.

The problem of energy efficiency is considered along with resource allocation by Xie *et al.* (2012b) and Teng *et al.* (2013). In a spectrum sharing and resource allocation for energy-efficient heterogeneous cognitive radio networks with femtocells has been proposed. They use the price of interference to model the interference between femtocells and macrocells. They formulate the problem of interference management and power allocation as a Stackelberg game. In addition, an iteration algorithm based on price updating is proposed to obtain the Stackelberg equilibrium solution to the resource allocation problem for energy efficiency. An energy efficient resource allocation is proposed in the multi-Secondary User (SU) cognitive radio networks with Network Coding based Cooperative Transmission (NcCT) (Teng *et al.*, 2013). They set up a framework for multi-SU resource allocation game with Nash Bargaining Solution (NBS) under the cognitive radio scenario (CR-MSU-NBS game). These is the sum of pairwise NBS function with pairing strategy is exploited as the network optimization objective and context conditions as constraints.

Resource allocation for OFDM based cognitive radio networks is considered by Tachwali *et al.*, 2013) and Adian and Aghaeinia (2013). In a novel resource allocation framework is proposed based on the bandwidth-power product minimization which is an effective metric in evaluating the spectral resource consumption in a cognitive radio environment. The spectral access of the cognitive radio network is based on OFDMA. A joint bandwidth and power allocation is performed so, that users' rate requirements are satisfied and the integrity of primary user communication is preserved. The resource allocation problem is considered for MIMO-OFDM based cooperative CR networks. In order to maximize the achievable data rate of the desired SU link, the subcarrier pairing, cooperating SU (relay) assignment and power allocation are performed jointly, using the dual decomposition technique while maintaining the interference introduced to the PU below a pre-specified threshold (Adian and Aghaeinia, 2013).

The problem of jointly designing spectrum sensing and resource allocation was addressed by Xu *et al.* (2013) and Alfonso and Agudelo (2013). An optimal cooperative sensing and resource allocation (Xu *et al.*, 2013) is proposed for the problem of jointly designing sensing paraments and resource allocation that maximize the throughput of CRN. The problem is solved by an iterative algorithm. They also formulate the problem to maximize minimum throughput of SUs with the consideration of SUs' fairness. Alfonso and Agudelo (2013) presented a new approach of spectrum sensing using a compressive sensing technique named Finite rate of innovation in a cognitive radio network with centralized spectrum management based spectrum broker in the next generation wireless communications networks. The use of compressive sensing techniques improves the performance of the control channel in cognitive radio due the traffic control protocol requires smaller packet sizes.

Apart from resource allocation, scheduling algorithms are proposed in various researches such as Gao *et al.* (2014), Gozupek and Alagoz 2013; Li and Nosratinia (2012) and Hongjuan Li *et al.* (2013). A centralized algorithm and a distributed algorithm (Gao *et al.*, 2014) are proposed to flexibly assign spectrum channel or spatial DoF exploiting the multiuser diversity, channel diversity and spatial diversity for a higher performance in a practical network. The algorithm further supports different transmission priorities, reduces transmission delay and ensures fair transmissions among nodes by providing all nodes with certain transmission probability. Didem and Fatih (2013)

(Gozupek and Alagoz, 2013) have proposed a very general scheduling model achieving goals such as making frequency, time slot and data rate allocation to secondary users with possibly multiple antennas, in a heterogenous multi-channel and multi-user scenario. Their schedulers ensure that reliable communication between the cognitive base station and secondary users. They also propose a heuristic algorithm for the fair schedulers.

Opportunistic scheduling and co-operative spectrum sensing scheduling approaches are proposed by Li and Nosratinia (2012) and Li *et al*., 2013), respectively. A two-step (hybrid) scheduling method is proposed (Li and Nosratinia, 2012; Li and Nosratinia, 2012) that pre-selects a set of secondary users based on their interference on the primary users. Among them, it selects the user(s) that yield the highest secondary throughput. The optimal number of active secondary transmitters is characterized as a function of the primary interference constraint, the secondary transmit power, and the number of secondary transmitters. A modified hybrid scheduling rule is proposed to ensure user fairness while still achieving the optimal growth rate for the secondary throughput (Li *et al*., 2013). Li *et al*. (2013) have proposed a novel idea of cooperative spectrum sensing scheduling when there exist M primary channels and N secondary users. They also introduced the concept of entropy to estimate the channel status distribution. The SUs make decisions about which channel to sense based on the entropy of each channel and each contributor always selects to sense the channel that brings the most information of the status distribution It achieves a high detection probability and a low false alarm probability.

MATERIALS AND METHODS

Proposed solution:
Overview: In this study, we propose to design a fuzzy based resource allocation technique for cognitive radio relay networks. In this technique, a Proportional Fair Scheduling (PFS) based resource allocation is applied for all nodes in which node with good channel condition and high data rate is allocated more bandwidth. Then the adaptive transmit power adjustment algorithm used for optimal resource allocation. A Fuzzy Logic Decision (FLD) model is used for selecting the transmit power level based on the factors interference among relay nodes, transmission rate between relay and mobile node and predicted link availability. Fig. 1.

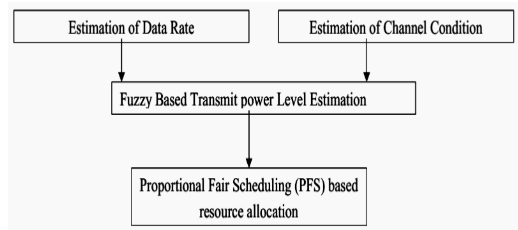

Fig. 1: Block diagram of proposed resource allocation

Proportional fair scheduling: The main purpose of this scheduling technique is to allocate bandwidth to each node based on their rates.

In general, the channel conditions in wireless networks are time-varying. Hence, the available data rate of each Mobile Station (MS) varies at different time. In order to maximize the throughput and long term fairness of the MSs, the proportional fair scheduling algorithm is used. The advantages of this technique are as follows:

- Offers best channel condition
- Increased Performance Level

Let X (t) nodes be the available in the network. Let q_i (t) be the allocated rate of the node i at time t. where 1 $\leq$I$\leq$M. Let Q_i (t) be the average rate at which the node had been serviced till the commencement of time-slot t. The set of average rates Q_i (t), 1$\leq$i$\leq$M 1is said to be proportional fair, if Q_i (t)'s are feasible:

For all feasible rates

$$Z_i(t)'s\sum_i \frac{Z_i(t)-Q_i(t)}{Q_i(t)}<0 \tag{1}$$

If Q_i(t)'s are proportional fair, then the set of long-term rates also m aximize the proportional fair metric:

$$\sum_i \log(Q_i(t))$$

There is a possibility that q_i(t)'s may vary owing to channel fluctuations in each scheduling round. In order to attain the long-term proportional fairness, the long term average throughput of node i is defined at time t as follows:

$$\sigma_i(t)=\eta Q_i(t)+(1-\eta)\sigma_i(t-1), 0<\eta\leq 1 \tag{2}$$

If in each scheduling round, we schedule the rates q_i(t)'s such that the following objective function is maximized among other feasible allocation of q_i(t)'s:

$$O(q)=\sum_i \frac{q_i(t)}{\sigma_i(t)} \tag{3}$$

Here, the long term rates $Q_i(t)$'s converges to the proportional fairness.

Estimation of transmission rate: The transmission rate of the node is estimated using the game theory based cooperative scheduling scheme. This technique either schedules a primary user to transmit in a given time slot, or schedule a pair of primary and secondary users to share the time slot in the chosen route according to the channel conditions. Let, R be the scheduling policy:

$$R: \{x, y, \sigma, \tau\}$$

Where:

R = The rule that selects four-tuple $\{x, y, \sigma, \tau\}$ to transmit at time slot t
$\{\sigma, \tau\}$ = Cooperation strategy
$\{x, y\}$ = Primary and secondary nodes

Let E^p and E^s (t) be the rate vectors of primary and secondary nodes. Let E^r (t) be the rate matrix. The transmission rate of the node is estimated based on the utility function ($UF_{x,y}$ (R,T)) at time t. Utility function for primary nodes:

$$UF^p{}_{x,y}(R,T)\begin{cases} s_1\left(E^p_{x'}(t)\right) & ;\text{if } y'=0 \\ s_1\left((1-\sigma)E^r_{x';y'}(t)\right), & \text{otherwise}\end{cases} \tag{4}$$

Utility function for secondary nodes:

$$UF^s{}_{xy}(R,T)\begin{cases} 0 & ,\text{if } y'=0 \\ s_2\left(\sigma(1-\tau)E^s_{y'}(t)\right), & \text{otherwise}\end{cases} \tag{5}$$

For all primary and secondary nodes {x, y} such that x= x' and y = y:

$$UF^p{}_{x,y'}(R,t)=UF^s{}_{x,y'}(R,t)=0 \tag{6}$$

In order to maximize the total expected utility of both primary and secondary systems, we perform the following:

$$O(R,T)\sum_{x=}^{X}\sum_{y=}^{Y} UF^p_{xy}(t)+UF^s_{xy}(t) \tag{7}$$

Estimation of channel condition: The channel condition is estimated based on the link availability. The link availability prediction is described below (Guan *et al*., 2010). Let t_{pr} be the predicted time period. Let P be the probability that the link lasts till the end of t_{pr}. During each random epoch, we assume that the node velocity remains constant during each random epoch. The link distance between two nodes is estimated as follows:

$$a^2=a_1t^2+a_2t+a_3 \tag{8}$$

Where, a_1, a_2, a_3 are constants. The constants can be obtained using the following points of measurements:

$$(t_0, d_0), (t_1, d_1) \text{ and } (t_2, d_2)$$

Sample time $t_i = t_0 + T_i$, d_i = distance between the two nodes. The estimation of t_{pr} involves following solutions: till the velocities of the two nodes which are in the transmission range remains constant, there is a possibility that it will travel out of this range. If a node travels away from primary users, then it will always be located outside the interference boundary. Then the maximum allowable time period t_{pr} is defined as follows:

$$\begin{cases}\sqrt{\dfrac{a_2^2+4\beta^2-4a_1a_2-a_2}{2a_1}}-t_2, & \text{if } \Delta\ge 0 \text{ and } \Delta\ge a_2^2 \\ \infty, & \text{otherwise}\end{cases} \tag{9}$$

Where, α interference boundary radius:

$$\Delta=a_2^2+4a_1\beta^2-4a_1a_2$$

If the cognitive user is in the interference region of a primary user, then t_{pr} is set to 0. The probability p_t to t_{pr} is defined as follows:

$$P_i\approx e^{-\delta \bar{t}_p e^{-\delta \bar{t}_p}}+\lambda(1-e^{-\delta \bar{t}_p}) \tag{10}$$

Where, λ, δ are constants. The [t_{pr}, P_t] and [t_{pr}, p_t] pair is used to predict link duration related to interference to primary users. The time during which the link is available is estimated using the following equation:

$$T_{LA}=\min_{i=1,2;j(PUs)}\{t_p\times P_t, \bar{t}^j_{rpi}\times P^j_{ti}\} \tag{11}$$

Where:

i = Two ends of a link
PU = Set of primary users present in the network
i, j = A link will be busy or unavailable

If any of its ends moves into the interference region of any primary users.

Fuzzy based transmit power level estimation: The transmission power level of the node is estimated based on the Fuzzy Logic Decision (FLD) model. Here, the interference among relay nodes, transmission rate

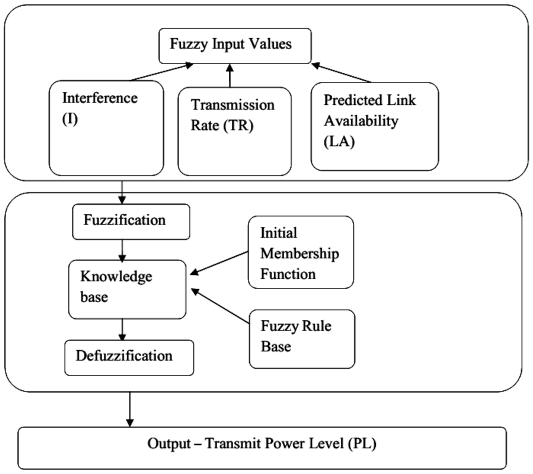

Fig. 2: Fuzzy inference system

between relay and mobile node and predicted link availability are provided as input to the fuzzy logic model and fuzzy decision rules are formed. Based on the outcome of the rules, the transmit power level is decided based on which the resources will be allocated. The steps that determine the fuzzy rule based interference are as follows.

Fuzzification: This involves obtaining the crisp inputs from the selected input variables and estimating the degree to which the inputs belong to each of the suitable fuzzy set.

Rule evaluation: The fuzzified inputs are taken and applied to the antecedents of the fuzzy rules. It is then applied to the consequent membership function.

Aggregation of the rule outputs: This involves merging of the output of all rules.

Defuzzification: The merged output of the aggregate output fuzzy set is the input for the defuzzification process and a single crisp number is obtained as output. The fuzzy inference system is illustrated using Fig. 2.

Fuzzification: This involves fuzzification of input variables such as interference among relay nodes (I), transmission rate between relay and mobile node (TR) and predicted Link Availability (LA). These inputs are given a degree to appropriate fuzzy sets. The crisp inputs are combination of I, TR and LA. We take three possibilities, high, medium and low for I, TR and LA.

Figure 3-6 shows the membership function for the input and output variables. Due to the computational

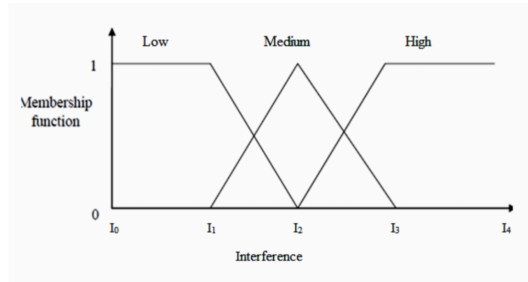

Fig. 3: Membership function of interference

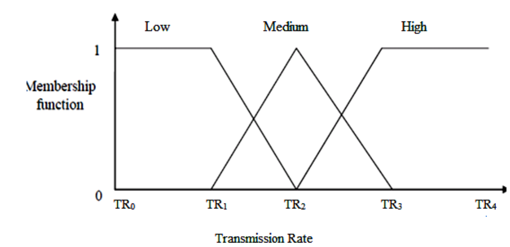

Fig. 4: Membership function of transmission rate

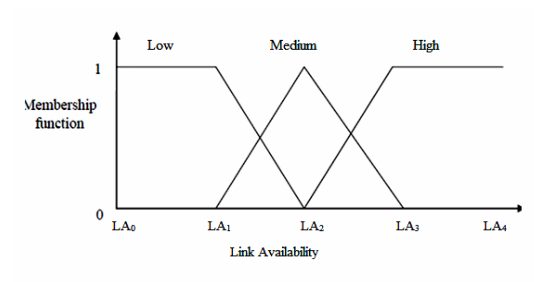

Fig. 5: Membership function of link availability

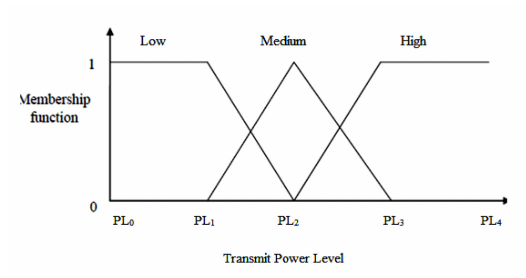

Fig. 6: Membership function of transmit power level

efficiency and uncomplicated formulas, the triangulation functions are utilized which are widely utilized in real-time applications. Also a positive impact is offered by this design of membership function.

In Table 1, I, TR and LA are given as inputs and the output represents the transmit power levels. (PL_0, PL_1, PL_2, PL_3 and PL_4).

Table 1: Fuzzy inference system

Interference	Transmission rate	Link availability	Transmit power level
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Low
Low	Medium	Low	Low
Low	High	Low	High
Low	Medium	Medium	Medium
Low	High	High	High
Medium	Low	Low	Low
High	Low	Low	Low
Medium	Low	Medium	Medium
Medium	Low	High	Medium
Medium	Medium	Low	Low
Medium	Medium	High	Medium
High	Low	Medium	Low
High	Low	High	Low
High	High	Low	Low
High	High	Medium	Medium
High	High	High	High

PL_0 = Very Low
PL_1 = Low
PL_2 = Medium
PL_3 = High
PL_4 = Very High

The fuzzy sets are defined with the combinations presented in Table 1. Table 1 demonstrates the designed fuzzy inference system. This illustrates the function of the inference engine and method by which the outputs of each rule are combined to generate the fuzzy decision (Algorithm A).

Fuzzy decision; Algorithm A:

For example
Let us consider Rule 7
If (I = low, TR and LA = High)
Then
Transmit power level = High
End if

Defuzzification: The technique by which a crisp values is extracted from a fuzzy set as a representation value is referred to as defuzzification. The centroid of area scheme is taken into consideration for defuzzification during fuzzy decision making process. Equation 6 describes the defuzzifier method:

$$\text{Fuzzy\_cost} = \left[\sum_{\text{allrules}} f_i\right]^* \psi(f_i) / \sum_{\text{allrules}} \psi(f_i) \quad (12)$$

Where:

fuzzy_cost = Used to specify the degree of decision making
f_i = The fuzzy all rules and variable
Ψ (f_i) = Its membership function

The output of the fuzzy cost function is modified to crisp value as per this defuzzification method.

Algorithm B; Optimal resource allocation:

Consider the cognitive relay network with one Base Station (BS), multiple Relay Stations (RS) and multiple Mobile Stations (MS).
Let S (D) be the set of links in the tree topology of the network
Let S (PL) be the set of available transmit power levels for the relay stations. (Estimated in section 3.4)
Let VC be the vacant sub-channels in the vicinity of the BS and RS.
Let R_{max} be the maximum sustainable rate over each link using each power level.
Let σ_m be the long term average rate of each mobile station, ($m \in MS$)
For all $q \in Q$ do
For all available power do
$\Psi_{(q, pl)} \leftarrow 0$
for all $vc \in VC$ and $v_{(q,vc)} = 1$

$$b(q, vc, pl) \leftarrow \max_{m \in q'} \frac{R_{max}(vc, pl)}{\sigma_m} \text{ o}$$

$$\Psi_{(q, pl)} \leftarrow \Psi_{(q, pl)} + b\ (q, vc, pl)$$

End for
End for
End for
Let pl(q) be the scheduled power level of q.

$$pl\ (q) \leftarrow \arg \max_{\text{all\_power\_level}} \psi\ (q, pl)$$

If there are multiple maximum $\psi_{(q,pl)}$, set as the lowest pl among them

In this algorithm, we compute the score for each combination of relay station and power level. The score is determined by selecting the mobile station with most contribution R_{max} (vc, pl/σ_m) to the objective function on each available sub-channel of the relay station. The power level of relay station is selected such that the priority is given to the (q,pl) combination with highest score.

That is, for each relay station, its transmit power level p is set to the one that has highest score among all other (q, pl) combinations. If there are multiple (q, pl) combinations that have the same scores, ties are broken by giving priority to the lowest power level.

RESULTS AND DISCUSSION

Simulation parameters: We use NS2 to simulate our proposed Fuzzy Based Resource Allocation (FBRA) protocol. We use cognative radio relay network as the MAC layer protocol. It has the functionality to notify the network layer about link breakage. In our simulation, the packet sending rate is varied as 250,500,750 and 1000 Kb. The area size is 1500 m×300 m^2 region for 50 sec simulation time. The simulated traffic is Constant Bit Rate (CBR) , Exponential (Exp) and TCP Our simulation settings and parameters are summarized in Table 2.

Performance metrics: We evaluate performance of the new protocol mainly according to the following parameters. We compare the Proportional Fair-Scheduling based resource allocation (PFS) technique (Liang and Chen, 2013) with our proposed FBRA technique.

Table 2: Simulation parameters

No. of Nodes	100
Area	1500×300m
MAC	Maccon
Simulation time	50 sec
Traffic source	CBR, Exp and TCP
Rate	250,500,750 and 1000 Kb
Propagation	TwoRayGround
Antenna	OmniAntenna
ErrorRate	0.01,0.02,0.03,0.04 and 0.05

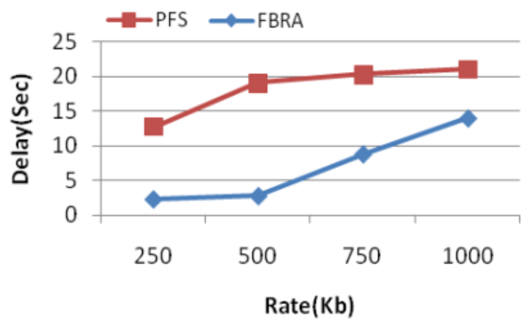

Fig. 7: Rate vs delay

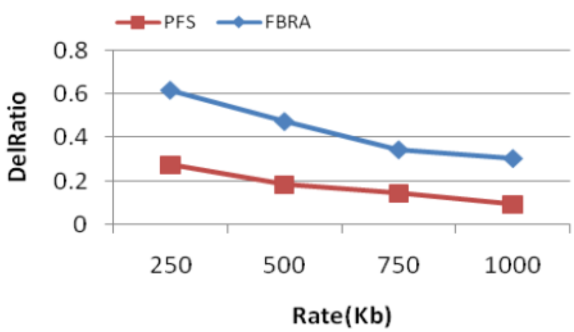

Fig. 8: Rate vs delivery ratio

Average packet delivery ratio: It is the ratio of the number of packets received successfully and the total number of packets transmitted.

Average end-to-end delay: The end-to-end-delay is averaged over all surviving data packets from the sources to the destinations.

Bandwidth: It is the number of bits transmitted to the receiver per second.

Results and analysis: The simulation results are presented in the next section.

Based on rate: In our first experiment we are varying the data sending rate as 250,500,750 and 1000Kb. The utilized bandwidth and fairness are measured for CBR, Exponential (EXP) and TCP traffic classes.

Figure 7 and 8 show the results of delay and delivery ratio for all the traffic classes by varying the data sending rate from 250-1000 Kb. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 64% in terms of delay, 61% in terms of delivery ratio.

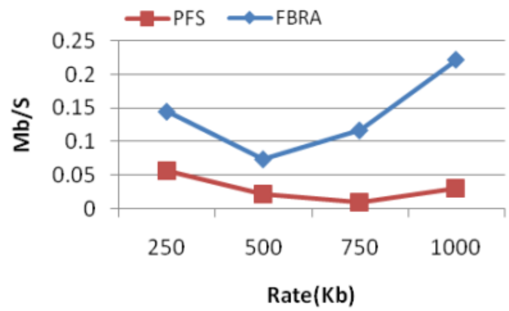

Fig. 9: Rate vs bandwidth for CBR traffic

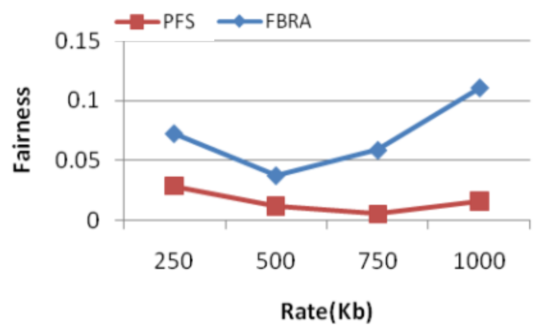

Fig. 10: Rate Vs fairness for CBR traffic

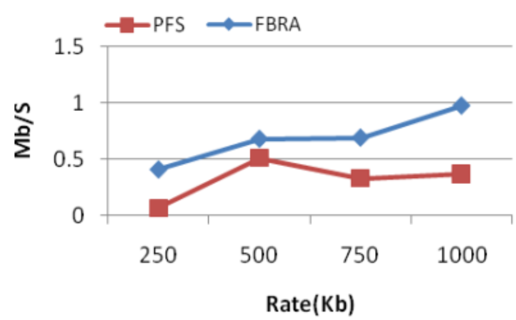

Fig. 11: Rate Vs Bandwidth for EXP Traffic

Case-1; for CBR traffic: Figure 9 and 10 show the results of bandwidth utilization and fairness for CBR traffic by varying the data sending rate from 250-1000 Kb. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 76% in terms of bandwidth and 75% in terms of fairness.

Case-2; for exponential traffic: Figure 11 and 12 show the results of bandwidth utilization and fairness for EXP traffic by varying the data sending rate from 250-1000 Kb. When comparing the performance of the two

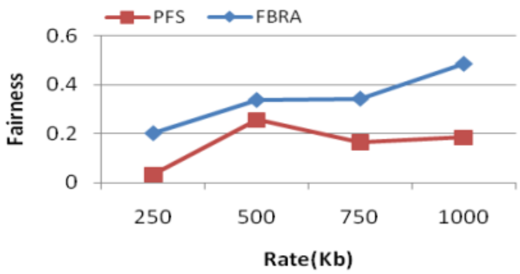

Fig. 12: Rate vs fairness for EXP traffic

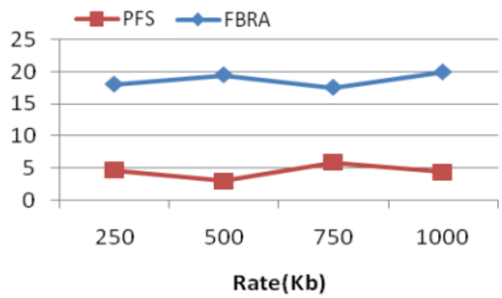

Fig. 13: Rate vs bandwidth for TCP traffic

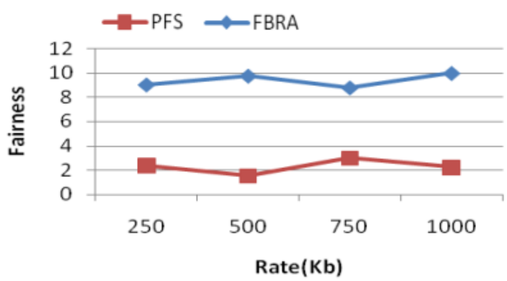

Fig. 14: Rate vs fairness for TCP traffic

protocols, we infer that FBRA outperforms PFS by 55% in terms of bandwidth and 55% in terms of fairness.

Case-3 : For TCP Traffic: Figure 13 and 14 show the results of bandwidth utilization and fairness for TCP traffic by varying the data sending rate from 250-1000Kb. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 75% in terms of bandwidth and 75% in terms of fairness.

Based on error rate: In our second experiment we vary the channel error rate as 0.01, 0.02, 0.03, 0.04 and 0.05 for data sending rate of 250Kb.

Figure 15 and 16 show the results of delay and delivery ratio of all the traffic classes by varying the error rate from 0.01-0.05 in FBRA and PFS protocols. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 71% in terms of delay, 51% in terms of delivery ratio.

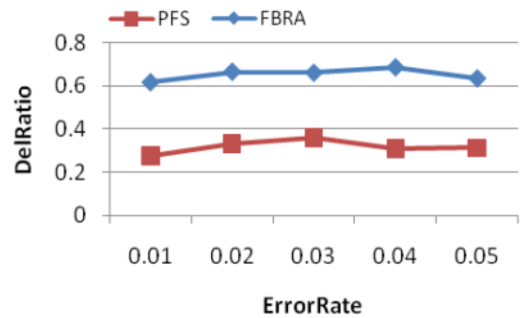

Fig. 15: Error rate vs delay

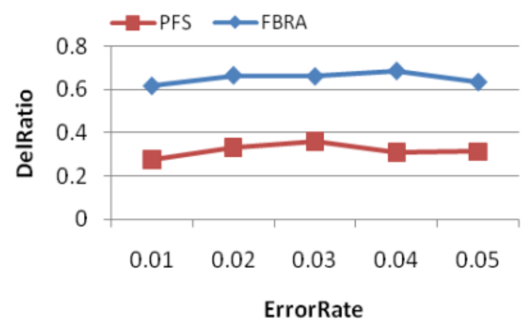

Fig. 16: Error rate vs delviery ratio

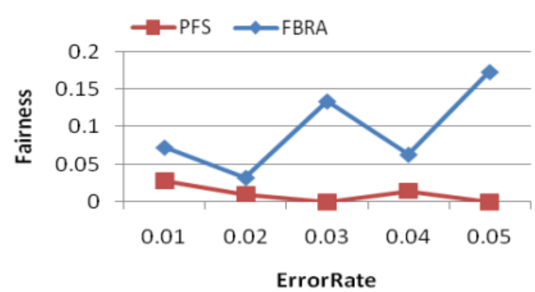

Fig. 17: Error rate vs bandwidth for CBR traffic

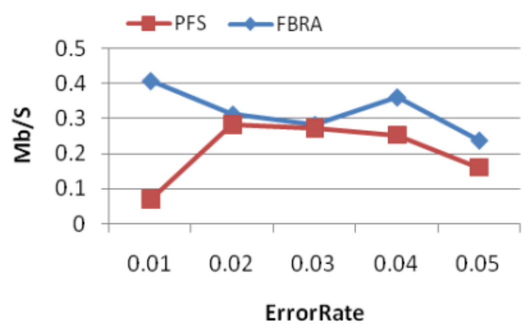

Fig. 18: Error rate vs fairness for CBR traffic

Case-1 CBR traffic: Figure 17 error rate vs bandwidth for CBR traffic. Figure 17 and 18 show the results bandwidth utilization and fairness for the CBR traffic by varying the error rate from 0.01-0.05. When comparing the

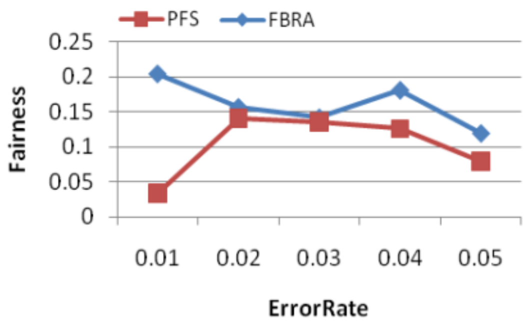

Fig. 19: Error rate vs bandwidth for EXP traffic

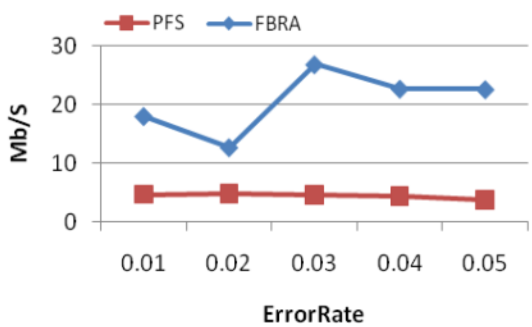

Fig. 20: Error rate vs fairness for EXP traffic

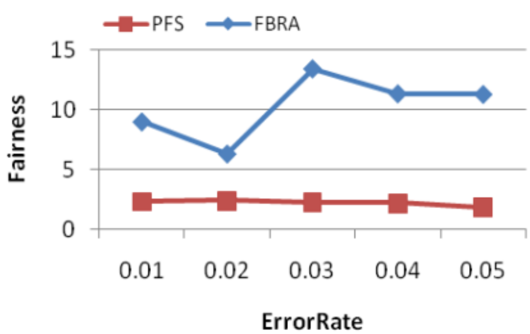

Fig. 21: Error rate vs bandwidth for TCP traffic

performance of the two protocols, we infer that FBRA outperforms PFS by 80% in terms of bandwidth and 80% in terms of fairness.

Case-2; Exponential traffic: Figure 19 and 20 show the results bandwidth utilization and fairness for the EXP traffic by varying the error rate from 0.01-0.05. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 31% in terms of bandwidth and 30% in terms of fairness. Case-3 TCP Traffic

Figure 21 and 22 show the results bandwidth utilization and fairness for the TCP traffic by varying the

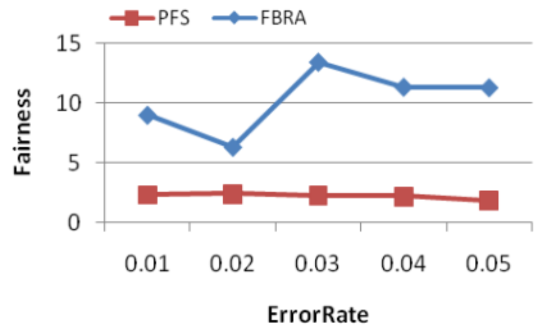

Fig. 22: Error rate Vs fairness for TCP traffic

error rate from 0.01-0.05. When comparing the performance of the two protocols, we infer that FBRA outperforms PFS by 76% in terms of bandwidth and 75% in terms of fairness.

CONCLUSION

In this study, we have proposed to design a fuzzy based resource allocation technique for cognitive radio relay networks. In this technique, a Proportional Fair Scheduling (PFS) based resource allocation is applied for all nodes in which node with good channel condition and high data rate is allocated more bandwidth. Then the adaptive transmit power adjustment algorithm used for optimal resource allocation. A Fuzzy Logic Decision (FLD) model is used for selecting the transmit power level based on the factors interference among relay nodes, transmission rate between relay and mobile node and predicted link availability. By simulation results, we have shown that the proposed technique reduces the energy consumption and link interference.

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