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A Game Theoretical Approach for an Optimal Resource Allocation in Decentralized Network

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Abstract: Decentralized networks are adhoc based networks. Flexibility and scalability are achieved in decentralized networks. Key parameters like limitation of spectrum resources, lack of central authority and coupling among the users needs to be considered for designing efficient resource allocation strategies for decentralized networks. The problem of channel selection and power control in a decentralized network consisting of multiple users is considered. User interaction in the network is used to formulate a Non cooperative Transmission Control Game (NTCG). A Utility based Transmission Control (UTC) algorithm is utilized to obtain a globally optimal solution. UTC can be adopted to efficiently allocate resources in general cases as the algorithm does not require the converging point to be Nash Equilibrium (NE) point of the formulated game.

Key words: Decentralized networks, resource allocation, Nash equilibrium, game theory, game theoretical

INTRODUCTION

Decentralized networks are the infrastructure less wireless networks consisting of multiple transmit-receive pairs. Each transmitter could dynamically adjust its transmission parameters and transmit data to its receiver. Compared to the conventional networks with the control of central authorities, e.g., BSs or APs, decentralized networks have more flexibility and scalability spanning a large number of real-world implementations, e.g., military communications, disaster relief or sensor networking (Rose *et al*., 2011; Rose *et al*., 2014). The main characteristics of a decentralized network can be summarized as follows.

The lack of central controller. In such an infrastructure-less network, each transmitter is responsible for tuning its transmission strategy, e.g., transmission frequency, bandwidth, power, modulation, etc., based on its local observation. Therefore, self-organization is one fundamental capability for a decentralized network (Aliu *et al*., 2013; Peng *et al*., 2013).

The limitation of spectrum resource. The available channels are limited in a decentralized network. Users should compete for this precious resource to improve their individual performance, e.g., transmission rate or energy efficiency, thereby satisfying their individual QoS requirement.

The coupling among different users. Interference occurs when different users transmit on the same channel simultaneously. Therefore, each user's performance could be tuned by properly adjusting the operational parameters of other users. In other words, the users are coupled.

According to the characteristics of the decentralized networks, there exist two kinds of conflicts in a decentralized network. One is the conflict between different users which is caused by the last two characteristics namely, the limitation of spectrum resource and coupling among different users and the other one is the conflict between system performance and individual requirement which is mainly introduced by the lack of a central controller. These two conflicts always make a decentralized network operate at an inefficient point.

In order to exploit the benefits promised by the decentralized networks, it is essential to design distributed resource allocation strategies which should fully consider these two conflicts. In Multi-user Multi-channel decentralized network each user (consisting of a transmitter and receiver pair) is capable of performing channel selection and power allocation to satisfy its transmission rate requirement. In addition to avoid the high communication overhead, the network where there is no information exchange among different users, i.e., No Common Control Channel (CCC) is introduced. This consideration makes the scenario more practical but on the other hand, brings in more difficulties in designing efficient resource allocation strategies (Bennis *et al*., 2013; Cominetti *et al*., 2010; Rose *et al*., 2011; Rose *et al*., 2014; Sastry *et al*., 1994).

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Due to the limitation of spectrum resource and coupling among different users, not all the rate requirements of users (i.e., transmit-receive pairs) can be simultaneously satisfied (Rose *et al*., 2014). Furthermore, recalling that there is no central controller being responsible for scheduling users' transmission, it is a great challenge to provide hard rate guarantee to every user in this decentralized network. For this reason, users' requirements are softened and a sigmoid function is used to measure their satisfaction (Lin *et al*., 2005; Sheng *et al*., 2014; Ngo *et al*., 2012; Zhang and Zhang, 2009). Specifically, one user has very limited satisfaction when its transmission rate is below the requirement but the satisfaction rapidly reaches an asymptotic value when its transmission rate is above the requirement. Based on this, the distributed channel selection and power control problem is formulated as a Non-Cooperative Transmission Control game (NTCG). To overcome the lack of communication between different users, a utility-based learning approach is adopted and a Utility based Transmission Control algorithm (UTC) is developed with which each user can configure its operational parameters just by measuring local interference.

MATERIALS AND METHODS

Game theory: Game theory is the study of optimization in situations of strategic interaction between one or more individuals. These strategic interactions are called games. The individuals involved are called players. Game theory is a discipline aimed at modeling situations in which decision makers have to make specific actions that have mutual, possibly conflicting consequences. It has been used primarily in economics in order to model competition between companies. Game theory has also been applied to other areas including politics and biology. Not surprisingly, game theory has also been applied to networking, in most cases to solve routing and resource allocation problems in a competitive environment.

UTC algorithm

Utility based learning: In a utility-based learning algorithm, there are two components that should be elaborated for each player:

- State profile-depicts each player's available local information
- Learning model-tells users how to make their decision based on this information

State profile: At each decision point $t\varepsilon\{1,2,...\}$, the state profile for each player n is described as a triplet $L_n(t) = (S_n(t), U_n(t), \alpha_n(t)$, where $S_n(t), U_n(t), \alpha_n(t)\epsilon\{0, 1\}$ represent its strategy, utility and mood, respectively. $\alpha_n(t)$ represent players' desire for changing the currently adopted strategy.

Learning model: A Utility based learning model is adopted with which each player n can update its strategy, utility and mood parameter at each decision point t. At the beginning of time t, individual player n first needs to determine the probability distribution over the set of available strategies:

$$Q_n(t) = \left(Q_n^1(t), Q_n^2(t), ..., Q_n^{|S_n|}(t)\right) \quad (1)$$

Where q_n^j (t) is the probability of choosing the jth strategy at time t:

$$q_n^j(t) \geq 0, \forall j\varepsilon\left\{1, 2, ...|S_n|\right\}, \sum_{j=1}^{|S_n|} q_n^j(t) = 1 \quad (2)$$

The probability distribution $Q_n(t)$ is adopted to describe players' dynamics. Player n would update $Q_n(t)$ based on its previous mood $\alpha_n(t\text{-}1)$ and action $S_n(t\text{-}1)$ Case (i) if $\alpha_n(t\text{-}1) = 0$:

$$q_n^{i(f_n)}(t) = \frac{1}{|S_n|}, \forall f_n \varepsilon S_n \quad (3)$$

Equation 3 shows that if the previous mood of the player is 0 the player will choose each strategy with equal probability. Case (ii) if $\alpha_n(t\text{-}1) = 1$:

$$q_n^{i(f_n)}(t) = \left\{\frac{\varepsilon^w}{|S_n| - 1}, \forall f_n \varepsilon S_n, f_n \neq S_n(t-1)\right. \quad (4)$$

Where:
ϵ = A constant belonging to (0,1)
W = A constant greater than N

The above equation means that if the previous mood is 1 then the player will change its strategy to different strategy with probability $\frac{\varepsilon^w}{|S^n| - 1}$ and same strategy will be adopted with probability $1\text{-}\epsilon^w$. Since, $1\text{-}\epsilon^w >> \frac{\varepsilon^w}{|S^n| - 1}$ each player will choose a different strategy with a relatively smaller probability if its mood is 1. After that, player n will choose an action $S_n(t)$ based on the probability distribution $Q_n(t)$, calculate the utility $U_n(t)$ by measuring the interference and finally updating the mood $\alpha_n(t)$ with the mood updating algorithm.

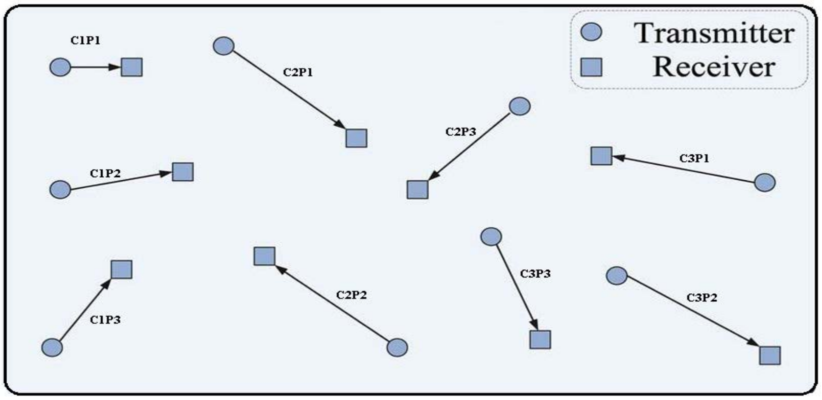


Fig. 1: Illustration of a decentralized network

Based on the above described state profile and learning model, UTC is developed where players can update their strategies in parallel. The stop criterion of the algorithm can be either the preset maximum no. of iterations T or for each player n, the variation of its utility during a period is trivial.

During the initialisation of the algorithm 2, each player n will choose the strategies randomly from the set of available strategies and set its mood to 0 and set the strategy counter $V_n = (0)_{1x|Sn|}$. V_n^i denotes the number of times the strategy i is adopted by user n making the user's mood to be 1. When the initialisation is completed, the algorithm goes into a loop in which each individual user n will first update its state profile $L_n(t) = (S_n(t), U_n(t), \alpha_n(t)$ with the utility based algorithm. The SINR estimation can be done by sending a pilot or training sequence from the transmitter to the receiver (Huang *et al*., 2006). Therefore, the utility can be measured by each autonomous user. Then, the strategy counter $V_n = (V_n^1, V_n^2, ..., V_n^{|S_n|}$ is updated based on the current mood $\alpha_n(t)$. If $\alpha_n(t) = 1$:

$$V_n^{i(S_n(t))} = V_n^{i(S_n(t))} + 1, \forall S_n(t) \varepsilon S_n \tag{5}$$

Where $V_n^{i(Sn(t))}$ is the i $(S_n(t))$th entry in the vector V_n. This updating rule implies that each player would like to record the strategy which makes its mood to be 1. When the loop is exited, individual players/users will make their final decision as follows:

$$S_n^D = \arg_{S_n}\left(V_n^{iS_n} = \max\left\{V_n^{i1}, V_n^{i2}, ..., V_n^{|S_n|}\right\}\right), \forall n \varepsilon N \tag{6}$$

From Eq. 6, the strategy recorded most frequently will be eventually adopted by the user.

Network scenario: A decentralized network featuring N communicating users, each consisting of a transmitter-receiver pair is shown in Fig. 1.

To transmit data, every user will choose one channel from the K orthogonal channels, each of which has bandwidth Bo. Each channel can be assigned to multiple users and meanwhile, the interference occurs when each channel is simultaneously utilized by more than one user. Without loss of generality, we suppose $N \geq K$. For notational simplicity, let vectors N and K denote the set of users and channels, respectively, i.e., N = {1, 2, ..., N} and K = {1, 2, ..., K}. The channel selected by user n is denoted by $C_n \in K$. It is considered that there is no CCC or central authority for coordination among users.

Signal to interference noise ratio Let G $R^{N \times N \times K}$ be the channel power gain matrix, where $g^k_{n,m}$ represents the channel gain between transmitter n and receiver m on channel k. It is assumed that the channel condition is static during the underlying operational period, e.g., the quasi static scenario. The additive noise is modeled as a zero-mean Gaussian random variable, and then for user n, its Signal-to Interference-Plus-Noise Ratio (SINR) can be expressed as:

$$\gamma_n = \frac{P_n g_{n,n}^{c_n}}{I_n^{c_n} + B_0 N_0} \tag{7}$$

Where:

I_n = Represents interference caused to user n
p_n = The transmit power of user n
N_0 = The noise power density. Each user n can choose the transmit power $P_n = \{p_n^1, p_n^2, p_n^3, ... p_n^{max}\}$

Achievable transmission rate: The achievable transmission rate of user n can be expressed as:

$$R_n = B_0 \log_2(1 + \gamma_n) \tag{8}$$

From Eq. 7 and 8 if user n transmits on channel C_n, R_n can be maximized with power P_n^{max} when there is no interference.

The upper bound of the rate R_n for user n can be defined as:

$$R_n^{max} = \max\left\{B_0 \log_2\left(1+\frac{P_n^{max} g_{n,n}^{c_n}}{B_0 N_0}\right) \middle| C_n \varepsilon K\right\} \quad (9)$$

It is assumed that each user n has rate requirement to satisfy its QoS requirement and assume that $0 \leq R_n^{min} \leq R_n^{max}$. Intuitively, in this network all the users' rate requirements are not guaranteed when they transmit simultaneously, especially for the case where all the users' rate requirements are high. For instance if $R_n^{min} = R_n^{max}$ then there are at most K transmissions being permitted. Softening the user's rate requirement and measuring its degree of satisfaction with a sigmoid function is considered.

Utility achieved: Utility of each individual user can be expressed as:

$$U_n(R_n) = \frac{1}{1+e^{-\beta_n(R_n - R_{min})}}, \forall n \varepsilon N \quad (10)$$

Where:

β_n = A constant deciding the steepness of the satisfactory curve

$U_n(R_n)$ = A monotonic increasing function with respect to R_n

The individual users will feel more satisfied when they have higher rate. The utility of each user n is scaled between 0 and 1, i.e., $U_n(R_n)$. Before starting a transmission, each individual user should decide to adopt which power level and transmit on which channel. A pair of channel index and power level is referred to as a strategy S_n:

$$S_n = (C_n, p_n) S_n, S_n = K \times P_n nN \quad (11)$$

From Eq. 7-10, it is clear that each user's rate is affected by the transmissions of other users and higher rate brings higher satisfaction level to the user. Therefore to improve the degree of satisfaction or utility, each user should choose its own strategy by considering the actions of other users. That is, there is a coupling among the strategies employed by different users. NTCG has been formulated to study the conflict among different users.

RESULTS AND DISCUSSION

Simulation parameters: Simulation scenario involves a decentralized network consisting of N transmit-receiver pairs which are randomly deployed in the circular region of radius r m. It is assumed all channels undergo identically and independent lognormal shadow fading and path loss. The path loss exponent α and the shadow fading standard deviation σ_φ is taken as 4 and 4 dB, respectively. This channel model is empirically proven to accurately model both indoor and outdoor radio propagation environments (Table 1).

The minimal rate requirement for each user R_n^{min} is set to $1/2R_n^{max}$. Each user can choose from a set of 3 power levels available for transmission. FHSS standard is used for communication between the transmitter and receiver. The transmitter-receiver pair operate in the 2.4 GHz ISM band. The frequency band is split into 3 non-overlapping frequency sets. Each frequency pattern is used for transmission using FHSS standard. The maximum number of channel set possible is 3 in this case.

From Fig. 2, it is clear that the algorithm converges to a optimal solution which yields a maximal average data rate for all the users.

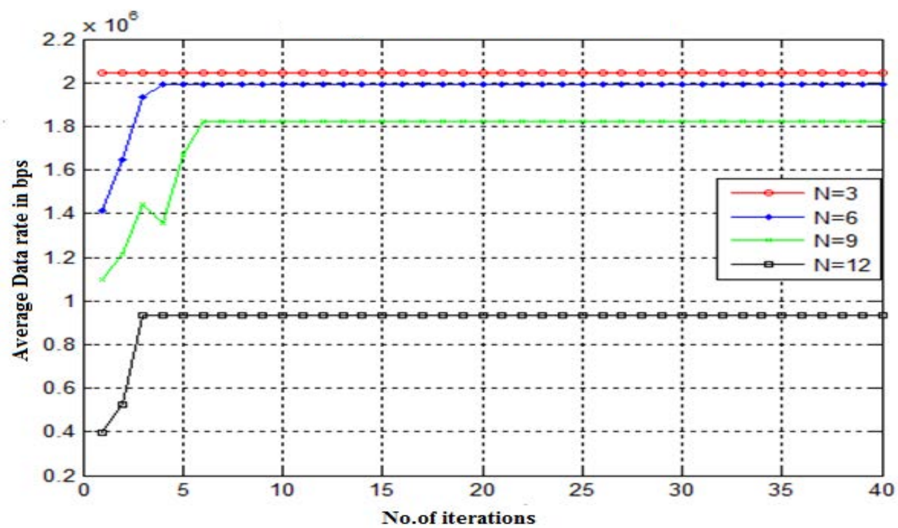


Fig. 2: Average data rate vs no. of iterations

Table 1: Simulation parameters

Parameters	Value
Number of channels sets K	3
Maximum distance D	20 m
Bandwidth per channel B_0	1 MHz
AWGN power density N_0	-174 dBm/Hz
Power level set P_n	{0, 10, 20} dBm
Steepness of the sigmoid function β_0	5
Path loss component α_0	4
Shadow fading standard deviation σ_φ	4 dBm

The convergence of the algorithm depends on the number of users present in the decentralized network. The convergence depends on the rate for all the users. The convergence of the algorithm depends on the number of users present in the perturbation factor ϵ. When the value of ϵ is 10^{-3} the algorithm takes more number of iterations to converge than when ϵ is 10^{-5}. Average rate is given by:

$$\overline{R} = \frac{\sum R_n}{N} \tag{12}$$

Figure 3 shows that users will be more satisfied when the transmission rate achieved is more than the minimum rate required by them. In this sense, the utility achieved by the users in each iteration for the corresponding strategy chosen, will be closer to 1. This results in the user being happy and mood will be set to 1. The user whose mood is set to 1, more often than not, will stick to the same strategy in the next iteration too. Average utility is given by (Fig. 3):

$$\overline{U} = \frac{\sum U_n}{N} \tag{13}$$

With the increase in number of users in the decentralized network, the average rate of transmission achievable decreases. The threshold of minimum rate required for keeping the users satisfied is not met when the users exceed beyond 9 (i.e., K x P_n) (Fig. 4 and 5).

Utility is modeled using sigmoid function curve where the satisfaction curve asymptotically approaches a maximum value 1 when the transmission rate achieved is more than the minimum rate R_n^{min}. Also if the user rate achieved is below the minimum rate R_n^{min}, the utility achieved decreases and moves closer to 0.When the utility achieved is low, users will not be satisfied and hence the mood parameter will be set to 0.

This results in the user making a decision in favor of another strategy for the next iteration. This loop is continued until all the users are satisfied with the chosen strategy (Fig. 6).

Figure 6 shows the strategies being adopted by all users in the network when the number of users is equal to 9 (K x P_n) where power level {0, 1, 2} indicates {0, 10, 20} dBm, respectively.

Repeated Game solution using RG solver: The users are autonomous. There is no centralized controller to monitor the transmission parameters of each user. Each user doesn't have the information about other user's strategy and hence this scenario is configured as a non cooperative transmission control game. The solution for a two player game in which two players compete for the resources is obtained through Repeated Game Solver (RG Solver). The payoff value of each user for each strategy employed depends on the SINR possibly measured in the channel by the respective users.

When more than one user is trying to access the same channel, interference increases and the SINR decreases resulting in less achievable transmission rate. But whenever a user is satisfied with the achievable rate known via the sensed SINR, the sensed channel will be used for the transmission by the user. Meanwhile, the same channel will not be preferred by the other user as interference is more due to the transmission of the first user. The channel with the maximum SINR sensed by the user is considered to be the best channel for the user. The payoff values for the game thus formed will be the value of SINR sensed by the user in each channel. The game with two users competing for the channels available is shown in Fig. 7.

Pure strategy nash equilibrium: An action profile is a set of actions/strategies available for each user competing in a game. Nash equilibrium point is a solution of the game and it is defined as the action profile α^* with the property that no other player i can do better by choosing an action that is different from α_i^* given that every other player j adheres to α_j^*:

$$U_i\left(a^*\right) \geq U_i\left(a_i, a_{-i}^*\right) \tag{14}$$

Figure 8 and 9 shows the two pure strategy Nash Equilibrium points and payoff graph for the formulated game for two users competing for 3 channels respectively. There is no binding constraint on the users to choose a particular channel. The channel whichever is available to the user will be chosen among the two. Once a user chooses a channel, other user should choose the channel such that maximum payoff is obtained with that channel (Strategy) (Fig. 9).

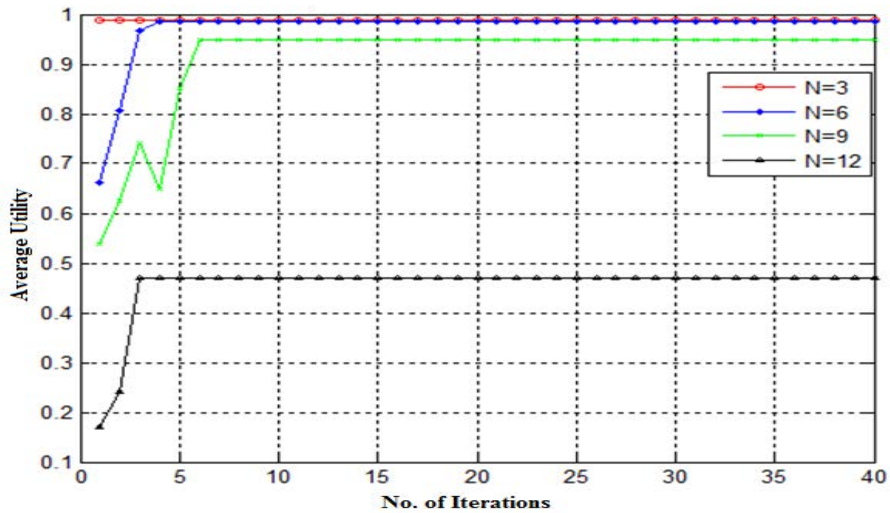


Fig. 3: Average utility vs. no. of iterations

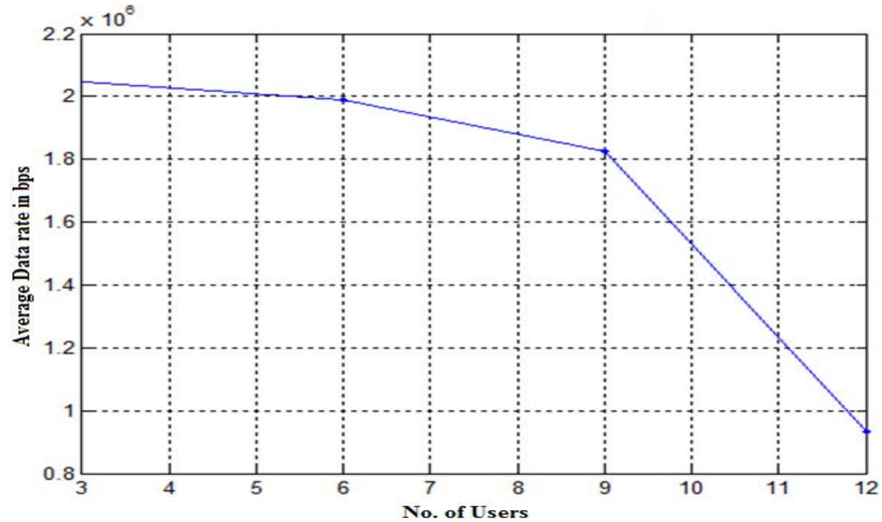


Fig. 4 : Average data rate vs. no. of users

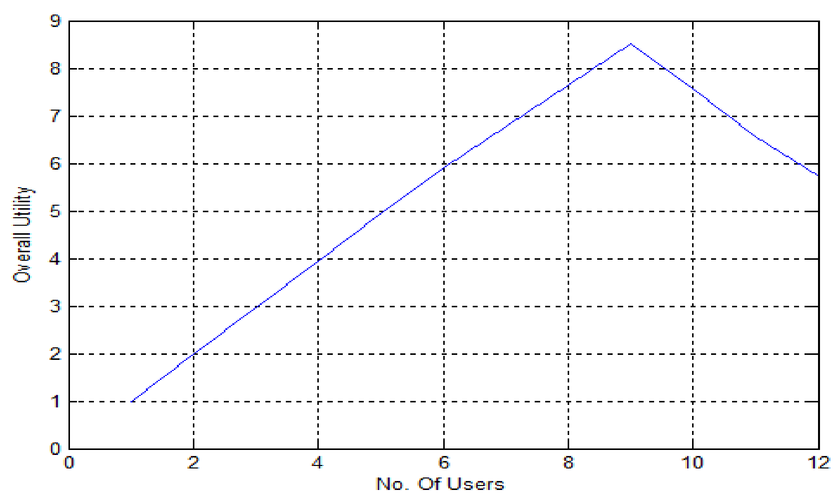


Fig. 5: Overall utility vs. no. of users

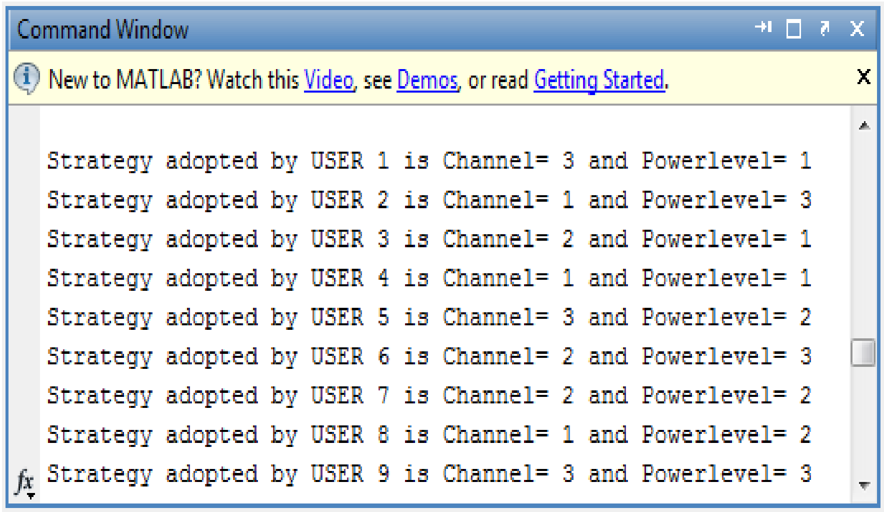
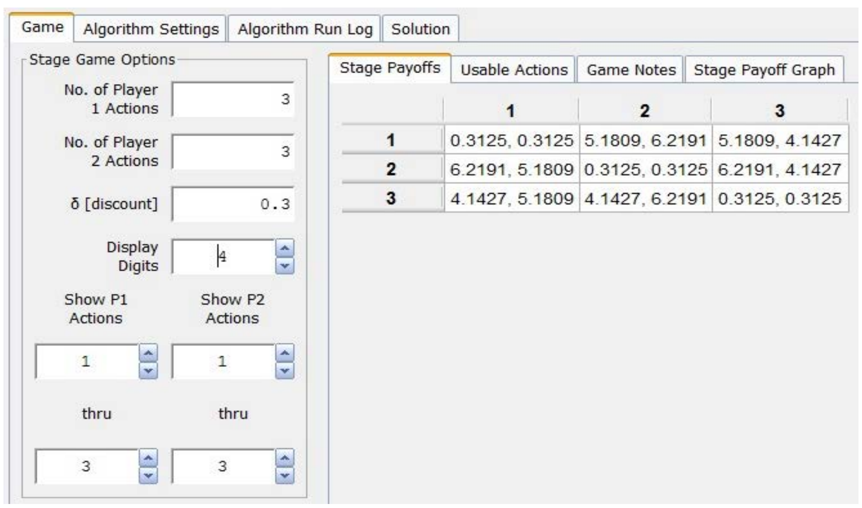


Fig. 6: Strategies chosen by users



	1	2	3
1	0.3125, 0.3125	5.1809, 6.2191	5.1809, 4.1427
2	6.2191, 5.1809	0.3125, 0.3125	6.2191, 4.1427
3	4.1427, 5.1809	4.1427, 6.2191	0.3125, 0.3125

Fig. 7: Payoff matrix for the two player game

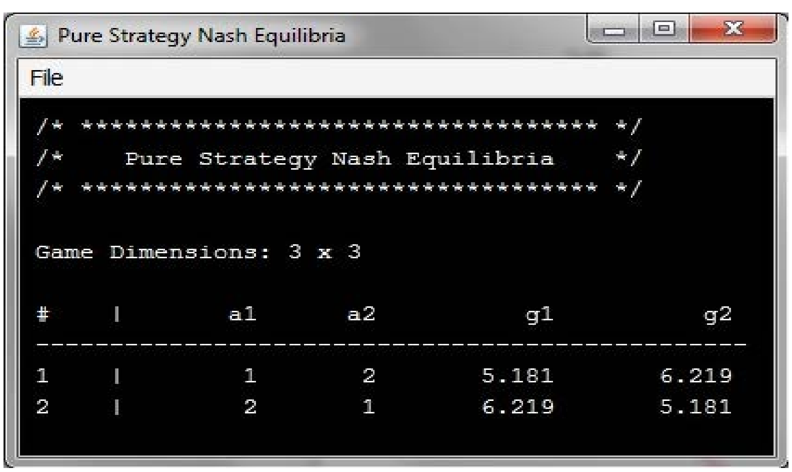


Fig. 8: Pure strategy Nash equilibrium

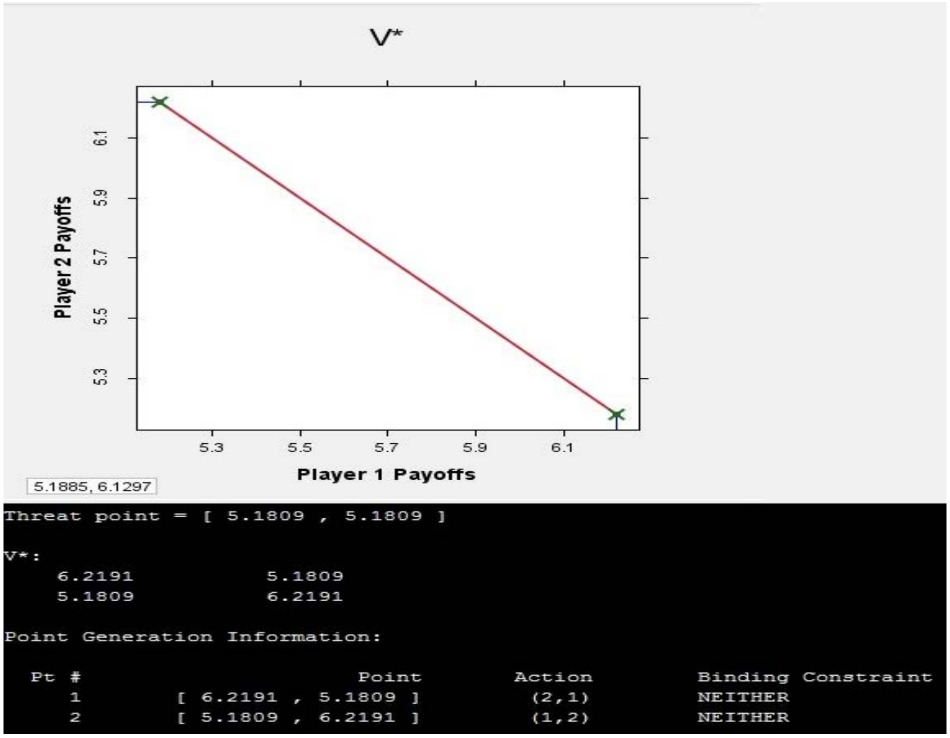


Fig. 9: Payoff graph for the two player game

CONCLUSION

In this study, the need for optimal resource allocation for Multi User Multi Channel decentralized networks is realized. Each user in the decentralized network is autonomous to choose a channel. An Utility based Transmission Control (UTC) is utilized to find an optimal solution for the multi user decentralized network and thus increasing the overall rate of transmission for each user. The utility function for the users is modeled using sigmoid function. Satisfaction of each user varies based on the utility achieved. When all the users are satisfied with the achieved rate, the strategy with the maximum number of counts at the end of the iterations is chosen by the users.

The simulations are carried out using MATLAB. Use of Game theory is the best way to obtain a solution which is equal for all the players involved.

The Nash Equilibrium solution for a game with two users competing for the resource is discussed and analyzed with repeated game solver. Analysis of the stability of the algorithm based on convergence and finding the solution for N player games as in real scenario using Bargaining games can be extended as the future work.

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