PERFORMANCE COMPARISON OF QOS METRICS FOR A DISTRIBUTED PRICING SCHEME

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ABSTRACT

De-centralized nature of nodes, in ad-hoc networks, results in the users adapting their operations independently. Such operations are mostly biased upon the figures and data available for the parameters which are imperative for superior performance or, in other words, improved Quality of Performance (QoS) of the nodes. In centrally controlled networks following cooperative game theory principles, collective operations are performed by the nodes for better QoS of the network. Although nodes in decentralized networks undertake individual operations, the final outcome of the whole network and thus the performance of the nodes in the network are influenced by the operations of other nodes. Hence, a distributed resource allocation approach in such a scenario can be modeled as a non-cooperative game. Asynchronous Distributed Pricing (ADP) is one such virtual pricing algorithm in which a user's payoff is determined by the difference between how much a given performance metric is valued and how much is paid for it. User service demands and priorities are modeled using numerically emulated QoS metrics termed as utility functions. The network objective is to maximize the sum of all users' payoff. However, for convergence of the sum of all users' payoff to a global maximum, the determination of the QoS metric's utility function with sufficient concavity is essential. Although supermodularity conditions have been previously defined and determined to obtain suitable utility functions, we have numerically and analytically illustrated that the convergence performance characteristics fluctuates with the choice of QoS metrics in the algorithm for similar utility functions as well. We have assessed the optimality of utility functions under Signal-to-Interference-plus-Noise ratio and Signal-to-Interference ratio based calculations. This paper also explores into the difference in performance characteristics obtained by the addition of a significant value noise variance in the ADP algorithm.

KEYWORDS

Game theory, Asynchronous distributed pricing, Distributed resource allocation

1. INTRODUCTION

As the name suggests, ad hoc networks, are impromptu networks without a fixed infrastructure where terminals or nodes themselves are used to relay traffic rather than assigning separate routers for the network. In other words, nodes are not only responsible for sending and receiving their own data, but also for forwarding the traffic sent by other nodes. Mobile ad hoc networks (MANET), a dynamic topology based on a collection of wireless devices, are self-organizing and self-configuring networks which do not require centralized administration. Such networks allow their nodes to organize themselves arbitrarily and unpredictably and can thus, be referred to as an infrastructure free network. MANETs range from small, static networks that are constrained by

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power sources, to large-scale, mobile, highly dynamic networks. Figure 1 shows an ad hoc network in comparison with a traditional cellular network.

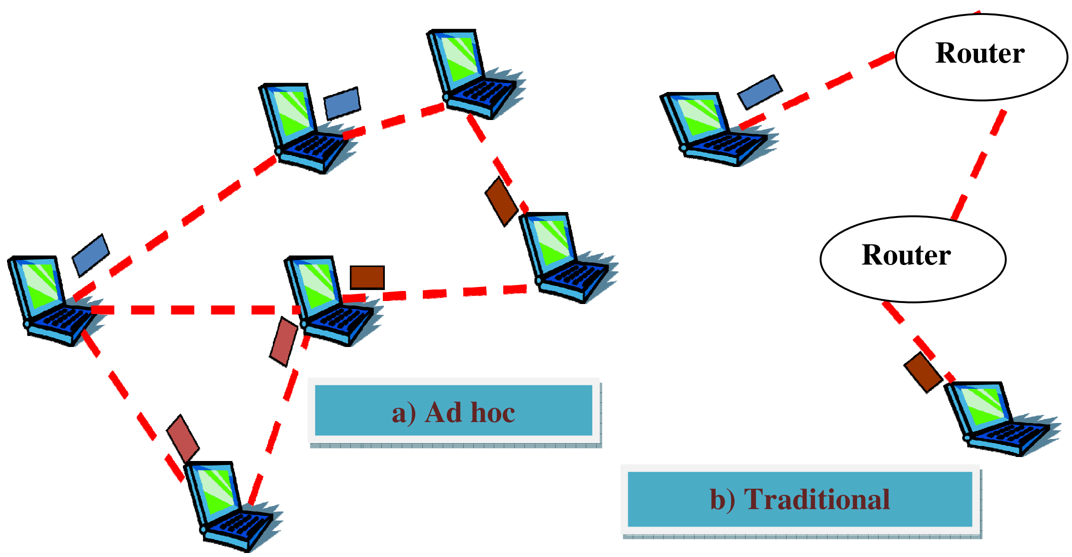


Figure 1 Ad hoc networks versus Traditional cellular networks

Robustness, rapid deployment, flexibility, mobility, and impromptu deployment of ad hoc networks make them very useful for a wide range of applications. Natural disasters and battlefield environments derive great benefits from the independence of infrastructure characteristic of ad hoc networks. Wireless Local Area Networks (WLANs) and Personal Area Networks (PANs) such as the IEEE 802.11 and Bluetooth standards support ad hoc networking. Future considerations in this area include the possibility of accommodating hundreds of routers in a single network with maximum utilization of each router and minimum power consumption in the network. Ad hoc capabilities extend the range and possibly the capacity of cellular networks, and also enable emergency and battlefield networks.

Hence, in this emerging technology, a central controller is often absent and operation is based mostly on the cooperation between the nodes, which being devoid of a fixed infrastructure, have limitations mostly on their battery power which must be judiciously consumed for transfer of data packets. Resource allocation is hence, being addressed in a distributed framework with power allocation being the most important component of it. Mostly, ad hoc networks find applications in emergency operations and military environment.

A distributed process is one that is not carried out centrally, but is independently at every node. The more the networks evolve, the more they tend to move towards decentralization without a base station controlling the amount of power or the band of frequencies for operation of the nodes of the network. E.g. wireless sensor networks, mobile ad hoc networks, and pervasive computing. These networks are self-organizing multihop networks. Thus distributed decision making shall potentially become the most important field of research in communications taking network conditions as well as channel conditions into account as used in our thesis.

When resources such as power, bandwidth, etc are allocated to a system of independent nodes having no central unit controlling them (ad-hoc networks), the process is called Distributed

Resource Allocation. In order to arrive at a distributed process for resource allocation, challenges such as conflict and non-cooperation among nodes must be overcome.

Game theory is the study of mathematical models of conflict and cooperation between intelligent rational decision makers as defined in [1]. It models individual, independent decision makers whose actions potentially affect all other decisions. Hence, the performance of ad hoc networks, in which each node can be treated as a rational, independent, selfish player, can be easily analyzed using game theory. The pricing algorithms have been used for resource allocation games ranging from bandwidth allocation, distributed beamforming, interference pricing algorithms to power control games using virtual currency in [2-5]. Game theoretic analysis of ad hoc networks has been widely applied and used for power control and waveform adaptation in the physical layer, medium access control as well as routing in the network layer besides others [6, 7]. Other applications include flow and congestion control and resource sharing in peer-to-peer networks [8, 9].

The limited degrees of freedom available in a communication networks with multiple users creates many problems. When the wireless spectrum is shared by two or more than two users, interference management using efficient resource allocation becomes one of the most important issues [10]. Centralized power allocation, for instance, cellular downlink, is an approach which creates a lot of overhead in the network. However, in ad hoc and mesh networks, distributed approaches are preferred which allocate power using limited information exchange. Hence, non-cooperative game theory can be used to solve this physical layer issue of adjusting transmitting power levels in order to adjust interference in the network keeping it below a threshold level beyond which interference becomes a significant problem [11, 12].

In this paper, we are dealing non cooperative game theory only. The concept of selfish nodes is an important theory that is needed to be taken into consideration in ad hoc networks where there does not exist any centralized network. In case of the existence of a centralized network, a node or a router in a wireless network can be made to forward a packet by the server by the authority assigned for the network which is not possible in a distributed framework.

Emerging pervasive computing communication environments will comprise of autonomous users with heterogeneous QoS requirements. Nodes, thus, typically belonging to dissimilar authorities may not pursue a common goal. Consequently, altruism does not exist among autonomous users in ad hoc networks but they rather tend to be selfish with the objective of attaining better utilities and hence, an extra share of the network resources. Without a proper framework of operation performance degradation in such networks will become frequent.

Within the game theoretic framework, the entities in the wireless network are as follows: players of the game are the nodes, i.e., transmitter-receiver pairs; utility function for the game is the performance metric or quality-of-service (QoS) metric of the users and strategy of the game is the algorithm or approach adopted for the network. The strategy in a power game for wireless networks is devised in such a way that the sum utility for all the players of the game is maximized within the least number of iterations. Our paper considers efficient resource allocation in ad hoc networks and hence, we deal with distributed algorithms. Shi et al. in [13] have shown that Asynchronous Distributed Pricing (ADP) converges within the least possible number of iterations as compared to previous distributed algorithms.

Selfishness of the autonomous users in a non-cooperative game can lead to unfair throughput distribution certain users. In particular, selfish users may possess different transmit power capabilities and those with lower power capabilities or poor channel conditions will not get a fair share of throughput. Selfishness modeled in non-cooperative game theory with a distributed framework can lead to uncontrollability of unfairness without extrinsic incentive mechanisms. A few examples are reputation propagation and virtual currency exchange where the assumption made is that cooperation gains are biased. Virtual pricing is also one such effective mechanism. In order to ensure cooperation in ad hoc networks, the concept of nuglets was first introduced in [15] used in the Terminodes project [16]. In a virtual pricing based power control method based on non-cooperative game theory where each user announces its set of prices that has to be paid by the other transmitters for the interference created by them which is proportional to the power with which they transmit. The particular algorithm in this work is motivated by [12]–[14]. ADP algorithm convergence has been proved in [13, 14]. Another advantage of the ADP algorithm is that it allows each user to transmit its power and prices completely asynchronously.

However, one of the most important entities in the ADP is the choice of utility function which has been proved in [17] because it determines the convergence of the algorithm. At Nash equilibrium of a game, both the power and price player chose not to deviate. The convergence of ADP algorithm, thus, can be ascertained by showing that the best response updates of the game converge. Nash equilibrium may or may not exist in all arbitrary games and even if it does exist, best response updates need not converge to it. The amount of concavity of a function determines its usability in the ADP algorithm but an important question to explore is the variation of the convergence parameters with varying utility functions. However, for the class of supermodular games defined and explained in [14], best response updates converge even when the algorithm for power or price update is arbitrarily asynchronous. ADP has been proved to contain a global optimum for supermodular games in [18].

Although it has been stated in [14], that the coefficient of relative risk aversion decides the convexity of a utility function and hence, its choice to be used in the algorithm, we find that the noise parameter when incorporated significantly changes the performance characteristics for various utilities lying within stated constraints of coefficient of relative risk aversion.

The fundamental objective of this research was to compare the convergence performance of a distributed algorithm, Asynchronous Distributed Pricing (ADP), for various utility functions and Quality-of-Service (QoS) metrics.

For analysing the convergence of ADP, we have primarily considered two main QoS metrics – Signal-to-Interference-Ratio (SIR) and Signal-to-Interference-plus-Noise-Ratio (SINR) for analysing the convergence of ADP. Other QoS metrics such as data rate, throughput and packet delay could also be implemented to analyse the convergence and performance of ADP. ADP is a useful algorithm but it does not take into account the allocation of resources and information overhead associated with channel estimation in its calculations. Analysing the algorithm for different channel estimation techniques is also an area of open challenge. A faster convergence rate and a better algorithm is another possible result in this area of resource allocation implementation.

This paper illustrates that the choice of QoS metric determines the different types of performance curves. Additionally, we have instituted that the performance characteristics for various utilities lying within stated constraints of coefficient of relative risk aversion depend significantly on the incorporation of noise parameter which has not been considered in references we have mentioned previously. Hence, this study also deals with the rate of convergence of the algorithm for a significant noise variance based calculations. In this paper, we deal with the rate of convergence of the algorithm for a significant noise variance and compare the characteristics for Signal-to-Interference-Ratio (SIR) and Signal-to-Interference-plus-Noise-Ratio (SINR) based calculations.

In the paper by C. H. Papadimitriou [19], the operation called price of anarchy was introduced which is the difference of performance between selfish, local goal oriented networks and communal mode of operation. Game theory can be used to assess this cost. In this paper, we have used the case of perfect information where all player know each others' utilities and there is a certain goal that each node tries to acquire, the goal of maximum utility. Future directions in this research include the area of the type of games called, games of imperfect information which would rather focus on Bayesian equilibrium than Nash equilibrium.

Another model accounting for uncertainties regarding other players' strategies are called games of imperfect monitoring. Each player observing the actions of every other player at the end of each stage in a repeated game is challenged in this type of games. E.g. in ad hoc networks, nodes can deny forwarding packets for others to conserve their limited resources and monitoring also requires and thus, forwarding of packets is not necessarily feasible. Instead of monitoring other players' actions, the nodes observe a random public signal at the end of every stage of the game which is correlated to the actions of all the other players in the game. Distribution function of the public signal depends on the action profile chosen by the other players but does not deterministically reveal other players' actions. In future, these games can be elaborately researched upon. Another research area which is still in its infancy is the area of privately monitored games where each player has a distinct assessment of others' actions in a repeated game format.

2. PROBLEM FORMULATION

Asynchronous Distributed Pricing is a distributed algorithm and hence, each node acts autonomously and each node updates its utility asynchronously according to the network statistics. The network objective in this problem is to find a global optimum solution for the maximum sum utility over all users. This objective accommodates a wide range of QoS metrics. This can be done by assigning the utility functions accordingly.

Every receiver declares its own interference price in the network which indicates the marginal decrease in utility due to a marginal increase in interference associated with a particular Degree of Freedom (DoF). A transmitter selects power according to a best response, which maximizes its utility minus the cost of interference incurred. Users iterate between price and power updates until the algorithm has converged. Convergence signifies that when the best response using the payoff function is obtained, the transmitted powers and interference prices do not change in subsequent iterations. Moreover, ADP algorithm's superiority lies in its advantage of fast convergence. While gradient based algorithms may take around 80 iterations to converge, ADP takes only 2-4 as proved in [20, 21].

In [22], it has been stated that SIR and SINR balancing is fundamental for characterization of QoS feasible region in wireless network problems. Although convergence analysis in previous papers [20-22] has revolved around supermodular games only, we have observed that the utilities lying within the constraint defining supermodular games also vary in their performance characteristics as proved in [17]. The amount of concavity of a function determines its usability in the ADP algorithm but an important question to explore is the variation of the convergence parameters with varying utility functions as well as SIR and SINR based calculations. We have defined the mathematical model for the problem within an assumed system framework in the next section. In the sections that follow, the test cases have been developed and the simulation results have been recorded and interpreted accordingly.

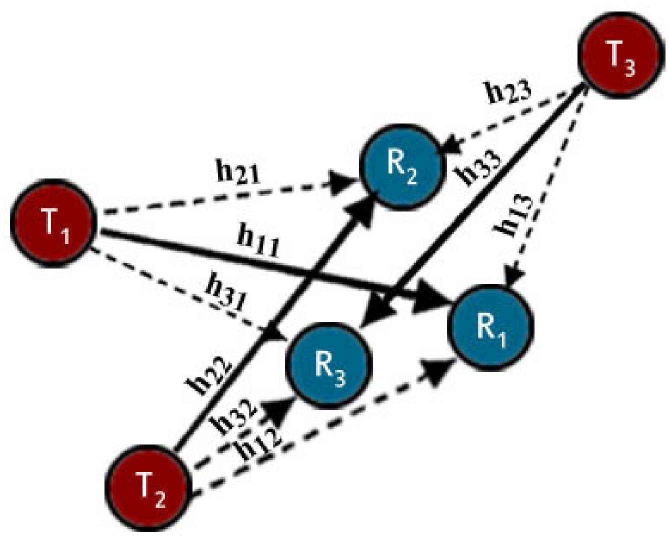
3. SYSTEM FRAMEWORK AND MATHEMATICAL PERSPECTIVE

We consider a time invariant network consisting of N "users". A single transmitter/receiver pair is a "user" with each transmitter having the same bandwidth. Each receiver is interested in the signal from its associated transmitter only. The message signals coming from other transmitters constitute the interference. In addition to interference, all the receivers experience equal amount of background noise. The conditions of the wireless channel are reflected in the channel matrices H_{ik}'s between each transmitter and each receiver which represents the channel from transmitter k to receiver i. The signal received at the ith receiver is given by:

$$y_i = H_{ii}x_i + \sum_{j\neq i}H_{ij}x_i + n_i$$

where x_k is the transmitted signal vector for kth transmitter and n_k is the noise in the channel.

The system model used in this paper is illustrated in Fig 1.



. Figure 2. System model and channel gains

We have considered 3 users in the networks. We assume perfect channel estimation for all the nodes in our model. The wireless channel in the network is modeled with complex additive white Gaussian noise with a covariance σ_k for SINR calculations. The information exchange overhead in this framework is also significantly decreased because each user needs to know adjacent channel gains and interference prices only. User's QoS are preferences given by a utility function u_i (R_i (P)) where u_i (·) is increasing, twice differentiable and sufficiently concave function of R_i. Sufficient concavity is defined in [20] which is modeled in supermodular games relies on the constraint that the utility must neither be non-concave nor too concave.

Common QoS metrics used to perceive a user's performance in a network are the received SIR and SINR. ADP algorithm utilizes a virtual currency scheme to localize the optimization problem faced in maximizing the sum utility of the network, by allowing the nodes to autonomously solve the power optimization problem constrained by the strategy of the game and maximum of the principal entity which is the transmitting power in a power game.

The resulting payoff function for power optimization suggested by the algorithm is,

$$\prod(P_i, \pi_j) = u_i - \sum_{j \neq i} \pi_j h_{ji}^2 P_i \qquad (1)$$

where $\prod$ is the net payoff, u_i is the utility function, $\prod_j$ is the price announced by the j^{th} receiver, h_{ji} is the cross channel gain between the i^{th} transmitter and the j^{th} receiver and P_i is the power transmitted by the i^{th} transmitter.

The interference price is a virtual quantity which is the marginal cost of a user's own utility per unit interference as is given by:

$$\pi_i = -\frac{d}{dI_i}(u_i) \qquad (2)$$

The choice of utility function is essential for the convergence of the algorithm. In [23], J. Yuan and W. Yu have shown that the ADP power game becomes supermodular if the coefficient of relative risk aversion factor lies between 1 and 2, resulting in a global optimum solution for the sum utility.

We chose two main utility functions, which satisfy the necessary condition of supermodularity at the boundary. Satisfaction of boundary conditions implies similar characteristics of utilities lying between the boundary conditions. These utilities are:

i) log(x) with $CR_k(x) = 1$

ii) -1/x with $CR_k(x) = 2$

In [24] it has been shown that rate utilities also converge subject to a few constraints on the ADP algorithm. We consider a diagonally dominant channel and the convergence thus obtained is a local optimum which may be multiple depending upon the test cases considered. Also, we compared the results of the utilities for both SIR and SINR service metrics.

3.1. Case I: u(x)=log(x)

As the optimization problem is solved locally, for individual nodes, the variable parameter is P_i

$$\prod(P_i, \pi_j) = \log(a_i P_i) - \sum_{j \neq i} \pi_j h_{ji}^2 P_i$$

$$\prod(P_i, \pi_j) = \log(a_i P_i) - b_i P_i \qquad (3)$$

where $a_i = \frac{hii^2}{\sum_{j\neq i} hij^2 Pj + \sigma^2}$ $and\ b_i = \sum_{j\neq i} \pi_j h_{ji}^2$

Maximizing (3), the condition for power update in ADP algorithm is,

$$\boldsymbol{P_i} = \frac{\mathbf{1}}{\boldsymbol{b}_\mathbf{i}}$$

It is notable that the interference price broadcasted by the user is equal to the interference power seen by it. In case of SINR based utility functions, the price is given by the inverse of the sum of the interference power and the noise covariance at the receiver (σ^2).

$$\boldsymbol{\pi_i} = \begin{cases} \frac{\mathbf{1}}{\boldsymbol{I_1}} & for\ SIR\ based \\ \frac{\mathbf{1}}{\boldsymbol{I_1} + \boldsymbol{\sigma^2}} & for\ SINR\ based \end{cases}$$

3.2. Case II: u(x)=-1/x

Re-writing (1) in terms of the local variable P_i

$$\prod(P_i, \pi_j) = -\frac{1}{a_i P_i} - b_i P_i \tag{4}$$

where $a_i = \frac{hii^2}{\sum_{j\neq i} hij^2 Pj + \sigma^2}$ $and\ b_i = \sum_{j\neq i} \pi_j h_{ji}^2$

Maximizing (4),

$$=> \boldsymbol{P_i} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{a_i b_i}}}. \tag{5}$$

The parameter a_i incorporates the noise variance factor in case of SINR based utility function. The interference price of the user is found to be independent of its interference power and noise, and is given by:

$$\boldsymbol{\pi_i} = \frac{\mathbf{1}}{\boldsymbol{h_{ii}^2 P_i}} \tag{6}$$

When choosing SIR as a service metric for measuring the performance of a system and for power optimization, it is to be noted that the solution arising from the algorithm may not be universal. The resulting SIR, being a ratio of powers which are optimized by the algorithm, may not be unique. In a three user system, if the solution of the SIR based algorithm gives rise to three powers P_1, P_2 and P_3, then the set of powers kP_1, kP_2 and kP_3, where k is a constant, also give the same SIR. Therefore, the converged value of transmission powers obtained through one utility function may differ from that obtained from another, depending on the initial state of the algorithm.

In case of SINR based utility functions, the solution obtained through the algorithm is unique, owing to the noise variance factor in the denominator of the service metric. The existence of the noise variance parameter increases the number of iterations required for convergence. Comparing the sum utilities after convergence of SIR based and SINR based algorithms, it is evident that SINR based utility functions give a better performance than their SIR based counterparts, due to the incorporation of the noise variance parameter, though consuming larger time.

4. TEST CASES

We have evaluated the performance of SIR based and SINR based utility functions in ADP algorithm using the following test cases:

Table 1. Test Cases for Simulation

Case	Utility function	QoS metric
1	u(x) = log(x)	SIR
		SINR
2	u(x) = -1/x	SIR
		SINR

Each of the test cases were individually calculated and simulated. The results of the test cases have been graphically plotted and analysed in the sections that follow. In order to compare the performance of the two cases, we assumed that the algorithm was initiated by the same set of arbitrary powers, prices and channel gains.

5. OBSERVATIONS AND RESULTS

The simulation of the ADP algorithm for the test cases mention in the previous section found that the algorithm converged for all the test cases. The inclusion of noise variance parameter by SINR based utility functions allowed the ADP algorithm to converge to relatively higher sum utilities as compared to the SIR based utilities.

ADP algorithm using SIR based utility functions offered a much lower performance when compared with that achieved by SINR based utility functions. The negation of noise variance parameter leads to premature convergence of the algorithm thereby reducing the sum utility of the system.The simulation of the ADP algorithm for the two chosen QoS metrics (SIR and SINR) using -1/x as utility function, found that the algorithm converged for all the cases, including the Shannon rate utility function log(1+SINR) as confirmed in fig. 2..

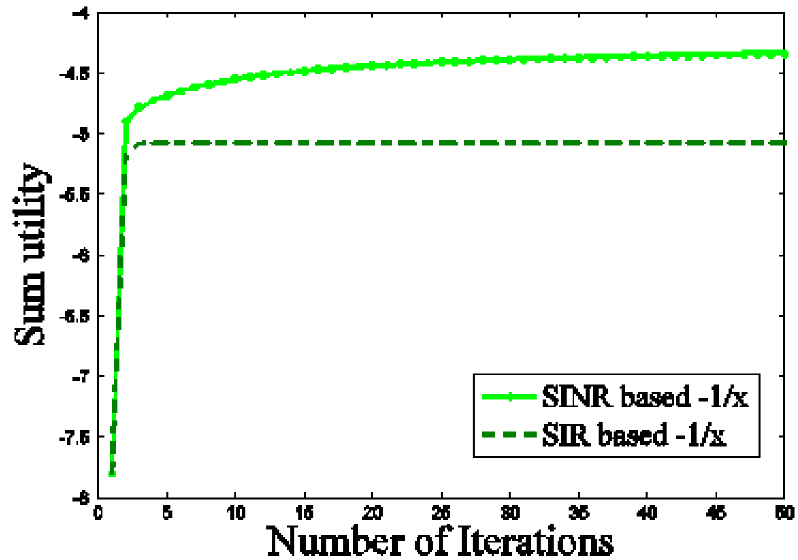


Figure 2: Comparison of rate utility, SIR based log(x) and-1/x utility function

As observed with -1/x utility function, ADP algorithm using SIR based utility functions offered a much lower performance when compared with that achieved by SINR based utility functions due to the inclusion of noise variance parameter by SINR based utility functions. Fig. 3 confirms the result by proving convergence for the log(x) utility function.

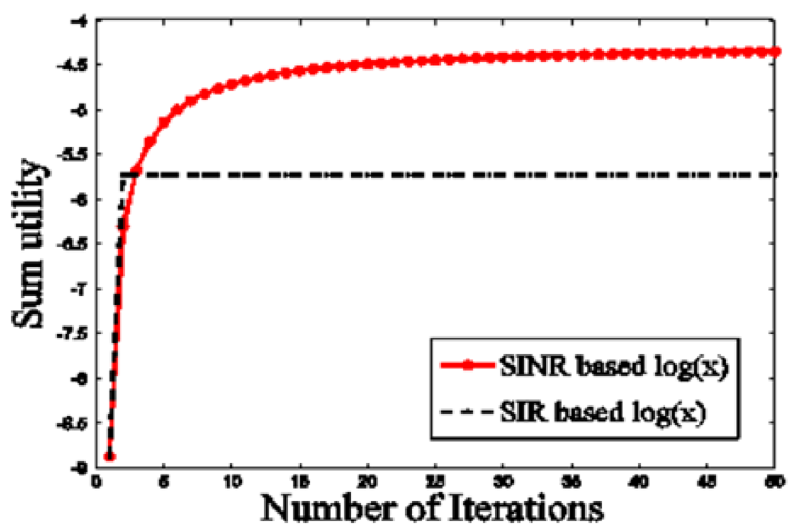


Figure 3: Comparison of rate utility, SINR based log(x) and-1/x utility function

Figures 2 and 3 provide a comparative study of SINR and SIR based -1/x and log(x) utility functions respectively. -1/x utility function provides a much better convergence when compared with log(x) utility function. The implementation of log(x) utility function in ADP algorithm is a popular technique for obtaining a sufficiently concave function of sum of utilities [25], owing to its close association with the rate-utility function corresponding to the Shannon capacity of the channel. However, we observe that the -1/x utility function gives a better sum utility than log(x) in SIR based calculations although it converges to a value similar to log(x) in the SINR based calculations. In the comparison between the sum utility curves of ADP algorithm using SINR based and SIR based utility functions, it is notable that SINR based utility functions offer better performance. But comparing individual utility functions with SIR and SINR arguments, the ADP algorithm using SINR based utility functions require larger number of iterations for convergence; whereas ADP algorithm using SIR based utility functions, converge faster.

6. CONCLUSIONS

The game theoretical approach to QoS based distributed resource allocation acts as a preferable alternative to the centralized scheme owing to its advantages of reduced overhead and information exchange. For a distributed algorithm, ADP, we found that the selection between SIR and SINR QoS metrics for convergence calculation show different performance curves. Moreover, our model implementing ADP derives that using SINR based utility functions provides a much better sum utility when compared to SIR based utility functions in lossy channels. The advantage of SIR based utility functions lies in its faster convergence although to a relatively poorer solution with respect to SINR based utility functions. SINR, when used as a metric in the rate utility function of log(1+SINR) for the ADP algorithm, is observed to converge to a locally optimal solution, due to the non-uniqueness of the set of powers obtained in the solution. This result is consistent with the previous papers which base this observation on the coefficient of relative risk aversion. Hence, this paper finds that while SIR leads to quicker convergence, the inclusion of the noise variance parameter in the SINR, allows the ADP algorithm to converge to a better globally optimum solution. Furthermore, our results validate the use of log utility for SIR based calculations because of its faster convergence than -1/x utility for supermodular games. This paper also shows than for SINR based calculations, -1/x utility provides a better convergence.

Applications of these networks are found in ubiquitous civilian and commercial usage, where nodes typically belong to different authorities and may not pursue a common goal. Achieving maximum performance out of such a system involves in controlling the nodes' selfishness where they deviate from the algorithm to achieve higher individual performance but degrading the performance of the system.

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