Fall 2008

An economic incentive based routing protocol incorporating quality of service for mobile peer-to-peer networks

Anil Jade

AN ECONOMIC INCENTIVE BASED ROUTING PROTOCOL INCORPORATING QUALITY OF SERVICE FOR MOBILE PEER-TO-PEER NETWORKS

by

ANIL KUMAR JADE

A THESIS

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN COMPUTER SCIENCE

2008

Approved by

Sanjay Madria, Advisor

Maggie Cheng

Jagannathan Sarangapani

PUBLICATION THESIS OPTION

This Thesis consists of the following manuscript that has been submitted or intended to submit to the publication as follows

Pages 1-47 are intended for submission to DATA & KNOWLEDGE ENGINEERING JOURNAL.

ABSTRACT

Economic incentive models are becoming increasingly popular in Mobile Peer to Peer Networks (M-P2P). These models entice node participation to combat free riding and to effectively manage constraint resources in the network. Due to the dynamic topology of the M-P2P network, the connections between the peers become unpredictable and therefore, reliable routing becomes important. Many routing protocols proposed earlier (such as DSR, AODV) are based on best effort data traffic policy, such as the shortest route selection (hop minimization). Using economic models to find a cost effective optimal route from the source to the destination, while considering Quality of Service (QoS) aspects such as bandwidth and Service Capacity constraints for data delivery, remains a challenging task due to the presence of multiple paths and service providers. In this paper, we propose a Game theory based economic approach for routing with QoS support in M-P2P networks to forward data. Modeling the network as a directed weighted graph and using the cost acquired from the price function as an incentive to pay the intermediate nodes, we develop a Game theoretic approach based on stochastic games to find an optimal route. We formulate a capacity function, which provides the available bandwidth to support the QoS aspect. The performance of our routing protocol is also evaluated and compared with some existing routing protocols and the result shows that our protocol proves to be efficient compared to shortest-path DSR and multiple paths SMR in terms of average response time, energy utilization and bandwidth availability in the network.

ACKNOWLEDGMENTS

I wish to express my deepest gratitude to my advisor, Dr. Sanjay Kumar Madria for his valuable advice and guidance to this work. He has been extremely patient towards me and provided me the encouragement and support that I needed.

I thank Dr. Maggie Cheng and Dr. Jagannathan Sarangapani, my committee members, for the help and support they have provided throughout my Masters' degree program.

On a special note, I should mention Santhosh Muthyapu for the help he has provided me in designing the framework for the simulator. Without his help, this effort and its successful completion would not have been possible.

I also would like to thank my roommates at Rolla and the Indian community here who have been supportive in all my ventures.

Finally, I am particularly grateful to my family, my parents Ashok Kumar Jade and Shobha Jade and my sister Swathi Jade for helping me and assisting throughout my life. Without them this study would never have been possible

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

Figure Page

LIST OF TABLES

An Economic Incentive Based Routing Protocol Incorporating QoS for Mobile Peer to Peer Networks

[1]Anil Jade, [1]Sanjay Madria and [2]Mark Linderman

[1]Department of Computer Science, Missouri University of Science and Technology, Rolla, MO 65409

[2]Air Force Research Lab, Rome, NY
Email: {akjbnd@mst.edu}{madrias@mst.edu} {Mark.Linderman@rl.af.mil}

ABSTRACT

Economic incentive models are becoming increasingly popular in Mobile Peer to Peer Networks (M-P2P). These models entice node participation to combat free riding and to effectively manage constraint resources in the network. Due to the dynamic topology of the M-P2P network, the connections between the peers become unpredictable and therefore, reliable routing becomes important. Many routing protocols proposed earlier (such as DSR, AODV) are based on best effort data traffic policy, such as the shortest route selection (hop minimization). Using economic models to find a cost effective optimal route from the source to the destination, while considering Quality of Service (QoS) aspects such as bandwidth and Service Capacity constraints for data delivery, remains a challenging task due to the presence of multiple paths and service providers. In this paper, we propose a Game theory based economic approach for routing with QoS support in M-P2P networks to forward data. Modeling the network as a directed weighted graph and using the cost acquired from the price function as an incentive to pay the intermediate nodes, we develop a Game theoretic approach based on stochastic games to find an optimal route. We formulate a capacity function, which provides the available

bandwidth to support the QoS aspect. The performance of our routing protocol is also evaluated and compared with some existing routing protocols and the result shows that our protocol proves to be efficient compared to shortest-path DSR and multiple paths SMR in terms of average response time, energy utilization and bandwidth availability in the network.

1. INTRODUCTION

A Mobile Peer to Peer Network (M-P2P) is a dynamic set of co-operating peers, where any pair of nodes can communicate by sending messages either through a single hop using a direct wireless link or through multiple hops involving one or more peers using a series of wireless links. Wireless link formations between any two nodes occur when the two nodes which are far apart move to fall in the transmission range of each other. Wireless links between the communicating nodes can fail and thus, can disconnect two nodes. It can occur when a communicating node leaves the network or move such that they are not in the transmission range of each other.

M-P2P networks consist of peers which can act as routers in the network. In other words, each peer is not only responsible for sending and receiving its own data, but it also has to forward packets from other peers. M-P2P networks have a handful of advantages compared to the conventional wireless networks such as rapid deployment, robustness, flexibility and support for mobility, which are useful in a wider range of applications in military, emergency situations and social networking. M-P2P networks prove to be fruitful when temporary networks are needed or there is a lack of infrastructure such as during natural disasters or terrorist attacks.

M-P2P networks may have a centralized support or a single authority to achieve a common goal. For example, in military or rescue applications, the nodes in the M-P2P network are motivated to cooperate. In civilian scenarios, such as network of cars, the nodes do not belong to a single command and they do not pursue a common goal. Many M-P2P networks are hybrid; those which have the capabilities of both M-P2P networks and conventional wireless network. These are the networks that attach M-P2P devices to the infrastructure for bootstrap phase or content distribution. Examples include the network which has a fixed gateway; its M-P2P functionality can be used to extend the range of cellular networks. Such networks are becoming common in social networks domain or in a military application where soldiers can get the data from the commander's laptop for the distribution later in the field. All these types of networks may be large and some of the peers in these networks may be critical from the point of view of survivability. In other words, their failure can cause temporary disruptions in the network either due to their strategic location in the topology or the data they carry. Also, in order to increase the network life time, nodes with scare resources such as battery power will demand a high cost to route so that they can provide services for the longer time.

In this paper, we discuss an economical optimal cost routing protocol by taking into consideration QoS parameters such as bandwidth available, energy used and Service Capacity. The solution while discovering a route is approached using a Game theory incorporating the cost of transmission power directly related with the battery usage.

In order for an M-P2P network to work efficiently, peers need to collaborate in forwarding packets to other peers. However, a peer could be selfish and save its resources by not cooperating. That is, instead of forwarding the packets to others, a peer could use the resources of others in forwarding only self-originated packets. Since the resources are constrained by the devices and the network configuration, the peers tend to become selfish. In battlefield operations, though the nodes naturally co-operate, but at the same time, nodes should by pass some of the route requests if those nodes have a high cost to forward a packet. This could be due to the importance of the node's existence for a longer period which is critical for the successful completion of the mission. Therefore, it has to preserve the energy and forward only selective packets. In other words, such nodes can demand a high cost to forward a service packet.

Economic models [12] play an important role to avoid selfishness and promote co-operation among the peers. These models are designed based on incentive mechanisms to avoid free riding in the network. Every peer that is a part of the route is rewarded with an incentive (virtual currency) to forward the packet to the next peer in the route. The protocol discussed in [16] focuses on the problem of on demand routing in resource rationed ad hoc networks. Here, a concept of resource rationing in military scenario is introduced where the allocated resources are rationed to prolong the mission. By modeling the network as a directed weighted graph, an economic approach to address the routing issue is proposed namely HR^3 (Hierarchical Resource Rationed Routing). This approach begins with the hierarchical bidding process, through which the nodes in the network bid for virtual currency. The winning bids use the granted virtual currency to pay the intermediate nodes for packet forwarding. Nodes get rewards on successful delivery of the packet. This approach shows performance gains in terms of data throughput and energy consumption but it only succeeds in finding a shortest possible route like [2] in terms of virtual currency. Our approach takes into account QoS factors such as available bandwidth, energy used and Service Capacity, which not only helps in finding a low cost route but also finds a path which has less congestion in the route (more available bandwidth and less workload). As the available bandwidth at a node gives information about traffic condition itself, so using this information helps in finding an optimal route.

To analyze the problem, we consider a scenario of a military application where a soldier would like to send a message to his commander looking for some data or information or vice-versa. Any delay in the delivery of the information may result in abandoning the mission. The successful delivery of the information lies in sending it in the best possible route which has a low cost and faster turnaround time. Here, we consider each soldier in the battle field as a peer and the commanders as the peers who perform services to the requesting peers (customers) by sending the requested information. By modeling the network as a directed weighted graph and using the cost determined from the price function as an incentive to pay the intermediate nodes, we develop a Game theoretic approach based on stochastic games to find the next hop to finally build an optimal route. We also formulate a capacity function which provides QoS support in M-P2P networks to forward data.

The simulation results show that our proposed Incentive based Routing Protocol (IRP) for single path, multi path shows a better performance in terms of average response time, bandwidth availability and energy utilization in the network compared to the Dynamic Source Routing (DSR) [2] for the shortest path and Split Multipath Routing (SMR) [9].

The rest of the paper is organized as follows. Section 2 discusses the related work whereas Section 3 introduces the system architecture used in our protocol design. Section 4 discusses the problem formulation by defining virtual currency function discusses the approach using Game theory. Section 5 provides the algorithms and an example to explain these algorithms. We discuss the simulation and performance evaluation in Section 7. We conclude the outcome in the last section 8.

2. RELATED WORK

Several routing algorithms for M-P2P networks, with their advantages and disadvantages have been proposed in [14]. Destination Sequence Distance Vector routing [DSDV] (proactive routing) based on the Bellman Ford equation, Dynamic Source Routing [DSR] (reactive routing) based on the concept of source routing, Ad Hoc on Demand Distance Vector routing [AODV] (reactive algorithm) where every hop of the route maintains the next hop information by its own and Zone routing protocol [ZRP] [14] which combines proactive and reactive elements are presented. They can be divided into two main branches, the proactive or table driven routing and the reactive or on-demand routing algorithms. A peer running the proactive routing algorithm has a full knowledge of network as every time, a change in the network topology or any other changes is made known to all the peers by maintaining the information in the tabular format. Therefore the route establishment takes place very fast. The disadvantage of the proactive routing algorithms is the number of required topology updates in a given time period. The performance of this routing algorithm decreases with the increase of the number of peers in the network. In contrast, peers using the reactive routing algorithm that does not send any kind of topology updates to its neighbors. Only in the case when a route set up is required to a node it triggers the algorithm. They flood a route request through the network and based on the responses from the destination and intermediate nodes, route to the destination node is established through a set of intermediate nodes.

Various incentive mechanisms [5] have been proposed to promote selflessness and to foster co-operation in the network. Many Economic models have been designed based on these incentive mechanisms for M-P2P networks. For example, [12] discusses economic incentive models and their usefulness for extending existing solutions to entice node participation and handling of resource constraints.

Hierarchical Routing [2, 14] in resource rationed ad hoc network has been addressed in [16]. It presents an economic approach for routing, by modeling the network as a directed weighted graph and presents a mechanism where nodes acquire virtual currency to pay for packet forwarding. The price function defined is based on the parameters like residual energy, virtual currency and reputation credit. The output of the price function is in terms of virtual currency. The protocol described in [16] can be categorized as a routing protocol based on best-effort data traffic policy, as it completely relies on finding the best route in terms of cost. We extend the idea introduced in [16], by considering the QoS aspects while finding an optimal route. QoS aspects can be considered in different layers of M-P2P network. As routing is the main area of focus in this paper, therefore we concentrate QoS in network layer which takes into consideration constraints like bandwidth available and Service Capacity when selecting a route. To support QoS in M-P2P, it is necessary to know not only shortest distance to destination, but also available bandwidth and delay on it. This makes it a challenging task in MP2P networks.

Game theory plays an important role in the route selection. Many game theory approaches have been studied in [15], introducing games such as co-operative games and non-cooperative games. [6] proposes a model for resource management in competitive wireless networks, where the interaction between the service provider and the users is modeled as a non co-operative game. A Game theory model in extensive form is studied in [15], which is the area of interest for our paper.

Our problem is based on the decision making process among a set of routes identified. Each player being a peer selects an edge on the path. Based on the actions of the peer, the next peer reacts, i.e. simultaneous actions are not allowed. As extensive games eliminate the limitation of simultaneous actions, and therefore, this form is more suitable for our problem.

3. MOBILE P2P SYSTEM ARCHITECTURE

Let us assume that a M-P2P network consists of n peers and each peer communicates in omni-direction and to start with, they all have the same transmission power. Thus, the transmission power of a peer is a circle of transmission range (say D). All the links are bi-directional. We model M-P2P network as a directed weighted graph *$G = (V, E, w_{ij})$, where V denotes the set of vertices (peers), E the edges (wireless links) on the graph and w_{ij}, the weight on the edge E from v_i to v_j.* The link between v_i and v_j exists if and only if these nodes are in the transmission range D. The weight on each edge is defined as the cost of communication from one node to the other.

Here, we give some of the definitions which will be used in the system architecture.

Broker nodes (BN): These nodes are the dominant nodes of the virtual backbone network. They are also termed as backbone nodes. Each backbone node is associated with at least one back bone/broker node.

Access point nodes (APN): These nodes are the nodes which are at one hop distance from the broker nodes. These nodes act as the access point for all other non back bone nodes in the network to connect to a broker node.

Non Broker nodes (NBN): All nodes other than the broker and access point nodes are the non broker nodes in the network.

Link Failure frequency (LFF): This parameter represents the total number of link failures/ losses of a particular node in a fixed time.

Link Failure frequency System Threshold (LFF_{th}): This parameter represents the system threshold that sets the preferred level of link losses for the backbone nodes.

Each node requesting for a service acts as the client, and the service provider node acts as the server. This type of architecture is called broker-less architecture, where client directs the request to the server for any kind of service. It can be argued that the broker-less architecture is more suited for M-P2P scenario, because there is no need of any fixed infrastructure. However, there are two very important aspects that advocate the use of a broker based system. The first major set of advantages is due to the following facts: 1) Scalability can be achieved when network becomes larger, as every newly joined node connects to the backbone structure 2) Response time for locating services reduces, as every query processes through the broker and these brokers has the current routing information and 3) Servers (peers) are not flooded with the service requests, as every service requests pass through the broker. The second advantage follows from the utilization of the virtual backbones or clusters for improving the efficiency and quality of routing protocols. These two important aspects makes the broker based architecture not only feasible but a preferred architecture for routing in M-P2P networks.

3.1 SYSTEM CONFIGURATION

Backbone network nodes are selected from a subset of the network nodes to form a relatively stable set. It discovers the paths between broker nodes, and adapts to the topology changes by adding/removing nodes into/from the set.

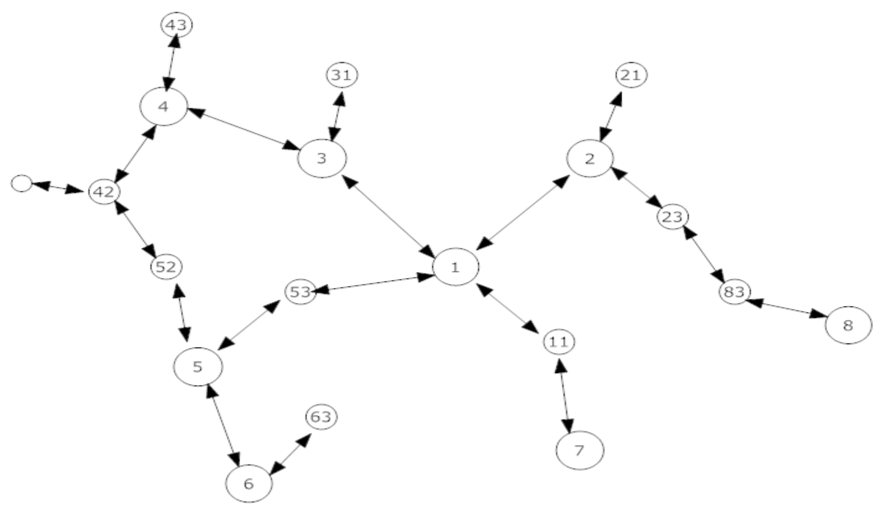

Figure 1: A simple M-P2P Network with Backbone Formation

Initially, every node is a non back bone (Non Broker) node. Before deciding on their role in the network, these nodes collect their neighborhood information by sending messages, for a time period say T. At the end of the waiting period T and considering the LFF information, any node which satisfies the stability constraint ($LFF < LFF_{th}$) joins the virtual backbone network and identified as the relatively stable node (Checking with the link loss threshold (LFF_{th}) helps to avoid the nodes with a lot of link losses relative to the backbone nodes). We term the nodes forming the back bone as Broker nodes. The other nodes still keeps on waiting for the messages in the network for the next waiting period T. At any point during the waiting period, if these nodes get messages directly from the Broker nodes, these nodes associates itself with the broker node, hence termed as APN's.(Access Point Nodes). These nodes can join the backbone network based on its LFF information in the next waiting period by satisfying the stability constraint. All nodes other than the BN's or APN's in the network are called as NBN's (Non Broker Nodes). These nodes interact with the broker nodes through the access point nodes which are the direct contact to the Broker nodes. Hence, every NBN has to check for the APN in its transmission range in order to interact with the BN or else find NBN's in its transmission range which has a APN in its transmission range.

3.2 ANALYSIS

The network in Figure 1 shows a simple M-P2P network with all the BN's, APN's and NBN's identified. The nodes labeled with the single digit are identified as Broker nodes (BN's), the nodes labeled double digit are the Access point nodes (APN's) with the most significant digit representing the broker node it is associated with. All the other nodes are the Non Broker nodes (NBN's).

From the figure, given any two broker nodes, three kinds of virtual links are possible: 1) Single hop virtual link, where two broker nodes are directly connected i.e. the broker nodes are at a 1-hop distance, 2) 2-hop virtual link, where an APN exists between the two broker nodes. For an instance of a 2-hop long virtual link, we can look at the case from the figure where an APN 53 lies between the broker nodes 1 and 5. While node 53 is associated with broker 5, it also receives messages from 1. Hence node 1 includes node 53 in its routing information. Thus both 1 and 5 have the information that they can reach each other via 53 and they update their routing tables. 3) 3-hop virtual link, where two APN's exist between the broker nodes. When there exists two APN's between any two broker nodes, they are at a 3-hop distance and hence it is called a 3-hop virtual link. We assume that a maximum of 3-hop distance is possible along the virtual link of two broker nodes when the network is large enough. For example, we look at the case from the figure when two APN's 23 and 83 exist between two broker nodes 2 and 8. Nodes 23 and 83 recognize from their messages that they have different brokers associated with them. Therefore node 23 caches 83 as the next hop to reach broker node 8 and node 83 caches node 23 as the next hop to reach broker node 2. Hence nodes 2 and 8 will know that nodes 23 and 83 are next hops respectively to reach the other.

Every backbone node keeps the routing information of the BN's in its vicinity or transmission range. If no BN exists in the transmission range it keeps the information of APN's located in its range to communicate with the BN's. Every node (*i*) that is a service provider has to register with its corresponding BN. If node *i* want to register its service, it has to register with the BN associated with it, assuming *i* as a non broker node. If the node *i* is already a BN, it registers the service at itself. Any time the location of the service provider node changes; it has to register its service with the corresponding BN and unregistering the service at the previous BN.

4. INCENTIVE BASED ROUTING PROTOCOL

This section provides the overview of the incentive based routing protocol using an economic model incorporating QoS factors discussed earlier. When a node V_S initiates a request for a data item *d* stored at a node V_D, all the nodes in the route co-operate in forwarding the data item to the next node to finally deliver the data to the source node V_S. A price p is associated at each intermediate node as the forwarding cost of the data item d. In the process, each node on the route is paid a Virtual Currency (VC), based on a price function associated for forwarding the packets. Using the virtual currency, available bandwidth and work load at each node, an algorithm using the Game theory is designed to find an optimal route to service the request. To calculate the virtual currency over an edge, we will develop an equation based on various network parameters.

4.1 RESOURCE PARAMETERS AND PRICE FUNCTION

In this section, we discuss resource parameters that node possess to accomplish the system goal.

Bandwidth: This parameter indicates how many free bandwidth slots a node possesses for forwarding the data. Each free slot denotes the available bandwidth at a node measured in KB (Kilo Bytes).

Virtual Currency (VC): It is calculated using a price function based on several parameters. Many parameters could be considered, but we confine ourselves to the following:

Table 4.1: Summary of the notations

Notation	**Significance**
P_t	Transmission power of a node
P_r	Receiving power of a node
$G_t G_r$	Antenna gains of the transmission and receiving nodes respectively $G(dB) \approx 10 \log_{10}(4\pi L_1 \times L_2/\lambda^2)$
$L_1 \times L_2$	Rectangular area of the antenna aperture in cm^2
λ	Wavelength
e	Euclidean distance
v_w	Constant (the speed of propagation of the wave)
w_{ij}	Weight on an edge
SS	Signal Strength

- *Transmission Power (P_t):* This involves the transmission power (battery power) utilized in forwarding the data packet from the transmitting node to the next immediate node.
- *Receiving Power (P_r):* It is the power involved in receiving a data packet at a particular node.
- *Euclidean Distance (e):* It is the aerial distance between any two nodes in the network. This can be calculated based on the signal strength of the transmitting peer.
- *Bandwidth (B):* This represents the frequency in which these peer's operate.
- *Elapsed Time (t):* It is the time allowed for a mobile peer to respond, after which the peer assumes that the packet is lost. The transmitting peer has to resend the packet or opt for a different route.

The total cost incurred on an edge of a shortest path between any two intermediate nodes is defined as

$$w_{ij} = w_{ki} + P_t\left[1 + \left(G_t G_r \left(\frac{v_w}{4\pi e B}\right)^2\right)\right]$$

According to the *Friis Transmission* [7] equation, the ratio of power received by the receiving antenna P_r to the power input to the transmitting antenna P_t is given by

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi e}\right)^2$$

$\lambda = \frac{v_w}{f} \approx \frac{v_w}{B}$ as the bandwidth represents the range of frequencies (f). Now the above formula reduces to

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{v_w}{4\pi e B}\right)^2$$

We formulate the cost equation into three cases:

Case 1: *(Cost at the source node)* At the Source node(data requesting node), the total cost constitutes to only the transmission power of the source node, i.e,

$w_{ij} = P_t$ as it does not have a previous node and $w_{ki} = 0$, where i, j, k are the current, next and previous nodes respectively

Case 2: (*Cost at an intermediate node)*: At any given intermediate node if P_t is the transmitting power and P_r the receiving power of that node, then the total power used in transmitting and receiving a packet is $T = P_t + P_r$

$$= P_t + P_t\left[\left(G_t G_r\left(\frac{v_w}{4\pi eB}\right)^2\right)\right]$$

$w_{ij} = w_{ki} + P_t\left[1 + \left(G_t G_r\left(\frac{v_w}{4\pi eB}\right)^2\right)\right]$ where i, j, k are the current, next and previous nodes respectively

Case 3: (*Cost at the destination node):* At the Destination node(data serving node), the total cost constitutes to only the receiving power of the node

i.e $w_{ij} = w_{ki} + P_t\left[\left(G_t G_r\left(\frac{v_w}{4\pi eB}\right)^2\right)\right]$ where i, j, k are the current, next and previous nodes respectively

If SS is the signal strength then Euclidean distance e can be calculated as $e \propto 1/SS$

w_{ij} calculated in the equations above is used as the virtual currency to forward the packets through the intermediate nodes

4.2 CALCULATION OF TRANSMISSION POWER (P_t)

We use the signal strength and propagation function to calculate the transmit power of a peer,

i.e $P_t - \gamma(l_i, l_j) = SS$ where $\gamma(l_i, l_j)$ is the propagation function defined over $L \times L \rightarrow Z$, L is the set of locations of the peers over a plane and $\gamma(l_i, l_j)$ gives the loss in bandwidth B due to propagation at location $l_j \in L$, when a packet is originated from location $l_j \in L$. Let the distance between l_i and l_j be e and e_{th} be the threshold distance then γ can be defined as

$$\gamma(e) = \gamma(e_{th}), if\ e < e_{th}$$

$$\gamma(e) = \gamma(e_{th}) + 10.\varepsilon.\log_{10}(e/e_{th}), if\ e \geq e_{th}$$

The value of ε is usually between 1 and 5 depending on the environment. Hence, the transmission power is defined as $P_t = SS + \gamma(l_i, l_j)$

4.3 INCENTIVE BASED ROUTING PROTOCOL USING GAME THEORY

The protocol discussed so far involved only the calculation of the virtual currency. In this section, we describe how we use the virtual currency in our Game theory model to find the optimal route. We also describe how resource parameters are used in our economic approach to find the best possible route.

In Game theory, the basic assumption is that the decision makers pursue some well defined objectives and take into account their knowledge or expectations of the other decision maker's behavior. Here all the nodes in the network are the players of the game.

Based on each other's decision making behavior, a policy or strategy is developed which helps in finding the best possible route. Game theory is used here in designing a new system; instead of fixing the game and analyzing the outcome, the desired outcome is fixed and the game ending in that outcome is looked for. We fix our outcome as finding the destination peer and look forward to end the game with that desired outcome.

A game is played with a set of peers in the network, involving possible actions of the peers, and consequences of the actions. The peers are decision makers, who choose how they act. The actions of the peers result in a consequence or outcome. The peers try to ensure the best possible consequence according to their preferences. The preferences of a peer can be expressed with a utility function, which maps every consequence to a real number.

When a peer makes a decision, it chooses one peer over the other, which is defined as the action of the peer. Sometimes these actions can be defined as the probabilistic distribution which is dependent on the game's behavior, whether it provides the complete information or not.

The set of all actions taken by a peer to reach a possible outcome can be defined as a strategy. If the actions of the peer are deterministic, then it is said to use a pure strategy. If probabilistic actions are defined to describe the actions of a peer, a mixed strategy is used.

A stochastic game is a dynamic, competitive game with probabilistic transitions, played by one or more peers. The game is played in a sequence of stages. At the beginning of each stage the game is in some state and the peers select their actions. Each peer receives a payoff (virtual currency) that depends on the current state and the chosen actions. The game then moves to a new random state whose distribution depends on the previous state and the actions chosen by the peer. The procedure is repeated at each new state and the game continues for a finite number of stages until it reaches a termination stage and an optimal route is found.

To formulate the game in the M-P2P scenario, we consider a discrete time stochastic process, Markov Decision Process (MDP) characterized by a set of states. Each state defines the state of the mobile peer. For each state there are several actions from which decision maker must choose. Any action on a state, results in the change of state for the peer. For a game in a state S, the application of Action A, will result in a new state $s' \in S$. This is determined by a transition function $P(s)$ which is based on the transition probabilities. Formally, MDP is defined as,

I. A finite state space $S = \{x_1, x_2 \dots\dots\dots\dots . x_n\}$

II. A finite set of controls $U(x)$ for each state $x_i \in S$

III. Transition probabilities $P(x_i, u, x_j)$ $\forall$ $u \in U(x_j)$ that are equal to the probability of next state being x_j after applying control u in state x_i.

IV. A cost $C(x_i, u)$ associated to $u \in U(x_i)$ and $x_i \in S$

As discussed in Section 3, we consider a MP2P network as a directed weighted graph, with a cost assigned to each arc (edge) of the graph. The game is played among the peers with a peer acting either as a source node, intermediate node or a destination node. A peer as a decision maker can be in one of the states $S = \{x_1, x_2 \dots\dots\dots\dots . x_n\}$.

We represent each state as the combination of peers from the source to any intermediate or destination peer

Table 4.2: Summary of notations

Notation	**Significance**
x_i	A state in the finite state space
$Successor(x_i)$	A successor state of the state x_i
$U(x_i)$	Set of controls for the state x_i
$C(x,u)$	Cost associated with the state x_i and the control u, $u \in U(x_i)$ calculated from the virtual currency price function
$B(x,u)$	Available bandwidth of a node in state x_i
π	Strategy or policy, a finite set of sequence of controls
$C_\pi(x_n)$	Cost associated with the policy
$P(x_i,u,x_j)$	Transition probability

For example, we say that the game is in state x_i if the game has traversed through the peers say p_1, p_2. Then the state x_i is represented as $\{p_1, p_2\}$ so every time a peer is reached, the game is moved to a new state and the state is represented as described above. The problem now reduces to finding a path from a graph with a set of states and cost associated with each transition (from one state to the other). This can be treated as a stochastic shortest path problem to select a successor state $Successor(x_j)$ at each state x_j, such that $(x_j, Succesor(x_j))$ is an edge, and the path formed by a sequence of successor states starting at any state x_1 terminates at the destination state x_n and has a length with minimum sum of costs over all paths that start at x_1 and terminate at x_n.

A stochastic shortest path problem is an MDP problem in which the state space $S = \{x_1, x_2 \dots\dots\dots\dots. x_n\}$ is such that x_1 is the starting state and x_n the destination state. Each state is associated with a finite set of controls $U(x)$. The system dynamics are controlled by transition probabilities that maps states and controls to states. Every time the player leaves the state, a cost $C(x, u)$ is incurred which is associated with u where $u \in U(x_i), x_i \in S$ and the available free bandwidth $B(x, u)$ (a QoS factor) is also considered. A strategy or policy π (route) is a finite sequence $\mu_0, \mu_1 \dots\dots .. \mu_n$ of functions where μ_i maps states to controls, so that the player applies the control $U(k)$ in state x_i. The cost $C_\pi(x_n)$ associated with policy π, when system starts at x_i (initial state) is $C_\pi(x_n) = E\{C\big(x_k, \mu_k(x_k)\big)\}$ where the expected value E is induced from the probability distribution of transition probabilities. The cost for a policy $C_\pi(x_n)$ is further refined by eliminating the expectation operator.

$C_\pi(x_i) = \sum_{i=1}^{N} P(x_{i-1}, u, x_i)\, C(x_i, u)$ Where $C(x, u)$ is the cost on an edge and $P(x_i, u, x_j)$ is the transition probability, which is based on the virtual currency, bandwidth, Service Capacity and the type of node (BN, APN or NBN, based on Link Failure Frequency defined earlier). All these QoS factors are considered in defining the transition probabilities. Initially, we categorize each of these factors into three different levels {low, med, high} depending on their values. We define a probability function for each of these levels and, the combination of all the probabilities with different factors would determine the transition probability. The probability function is defined in terms of the four independent probabilistic functions described below.

$P(s_1, u, s_2) = \ P(VC \mid s_2) * \ P(BW \mid s_2) * \ P(WL \mid s_2) * \ P(TY \mid s_2)$ where,

$P(VC \mid s_2) = P(s_2 \ \cap \ VC)/P(s_2)$, $P(BW \mid s_2) = P(s_2 \ \cap \ BW)/P(s_2)$

$P(WL \mid s_2) = P(s_2 \ \cap \ WL)/P(s_2)$ and $P(TY \mid s_2) = P(s_2 \ \cap \ TY)/P(s_2)$.

We define$P(s_2)$ as the probability of reaching a state s_2 among the set of states identified

i.e. $\frac{selection\ of\ a\ state}{Total\ number\ of\ reachable\ states}$

and $P(s_2 \cap \ VC)$ as the probability of reaching a state s_2 among the set of states identified with a virtual currency VC (VC can be in any of the three levels {low, med, high}). Similarly $P(s_2 \ \cap \ BW)$ as the probability of reaching a state s_2 among the set of states identified with a bandwidth BW (BW can be in any of the three levels {low, med, high}), $P(s_2 \ \cap \ WL)$ as the probability of reaching a state s_2 among the set of states identified with a workload WL (WL can be in any of the three levels {low, med, high}) and $P(s_2 \cap \ TY)$ as the probability of reaching a state s_2 among the set of states identified with a node type TY (TY can be in any of the three levels {BN, APN, NBN}).

For example let's consider that the virtual currency is divided into three different levels {low, med, high} with probability of selecting an edge of low cost is 3/6, medium is 2/6 and high is 1/6. As we need to consider an edge of low cost we give a higher probability for the cost being low. Similarly we define the probabilities for all the QoS factors. This can be seen in the table 4 defined below.

The node is categorized as BN, APN and NBN as defined in Section 3.1. Using this categorization, we define probabilities for the selection of a node. The probability for selecting a Broker Node (BN) is higher (based on the network architecture, LFF) than that of APN which is higher than NBN. The probabilities for BN, APN and NBN are 4/7, 2/7 and 1/7, respectively.

Table 4.3: Summary of Notations

Notation	Significance
$P(s_1, u, s_2)$	Probability of reaching a state s_2 from state s_1 on control u
$P(VC \mid s_2)$	Transition probability of the virtual currency to reach state s_2
$P(BW \mid s_2)$	Transition probability of the bandwidth to reach state s_2
$P(WL \mid s_2)$	Transition probability of the workload to reach state s_2
$P(TY \mid s_2)$	Transition probability of selecting node type to reach state s_2

The transition probability of an edge is defined as the product of the four independent factors listed above. For example selecting an edge which has low cost, medium bandwidth, medium Service Capacity and the node type as BN will have the probability of (3/6)(2/9)(2/8)(4/7) i.e. 1/63. From the Game theory approach defined above, we select an edge which has the highest transition probability over the set of all possible edges. Hence, it is clear that the transition probabilities of selecting an edge with low cost, high bandwidth, low Service Capacity and node type of BN is always higher ((3/6)(6/9)(5/8)(4/7) i.e. 5/21) than that of selecting an edge with high cost, low bandwidth, high Service Capacity and node type NBN is always lower (which is (1/6)(1/9)(1/8)(1/7) i.e. 1/3024).

Table 4.4: Probabilities of different levels of QoS Factors

Probability	**Low**	**Med**	**High**
VC	3/6	2/6	1/6
Bandwidth	1/9	2/9	6/9
Service Capacity	5/8	2/8	1/8

A situation might arise where the transition probabilities of edges may be equal. In such a scenario, to select an edge, we prioritize the aforementioned QoS factors in the following order, type of node, virtual currency, bandwidth and Service Capacity. A higher priority is given to the node type in order to select the most reliable path, as the type of node is classified in terms of LFF (Link Failure Frequency). It is unlikely that the transition probabilities of all the QoS factors are equal and if such a case arises, selection of any of the edges proves to be fruitful.

There are always one or more policies that are better than or equal to all the others. These are called the optimal policies. We denote them by π^*. The optimality is achieved when

$$C_{\pi^*}(x_i) = \min_{u \in U(x_i)} \{C_\pi(x_i)\} \ \ or \ \ C_{\pi^*}(x_i) \ \ni \ C_{\pi^*}(x_i) \ \leq \ C_\pi(x_i)$$

Where $i = 1,2, \dots \dots . . n$, for every policy π

$$\Leftrightarrow C_{\pi^*}(x_i) = \min_{u \in U(x_i)} C(\, x_{i-1}, u) + \sum_{j=1}^{i-1} P(x_j, u, x_i) C_\pi(x_j)$$

The capacity/free bandwidth for the policy is calculated based on the available free slots at a node. The bandwidth at a node is divided into slots and each node maintains the slot information of its neighbor by transferring messages. The free bandwidth between any two nodes is denoted by $B(XY)$ where *X, Y* are the nodes. To calculate the free bandwidth we take into consideration$free_slots(X)$, which gives the available free slots at a node *X*. Hence the formulation of the free bandwidth for a policy π is as follows:

If the nodes are at a single hop distance

$$B(XZ) = \min\,(free\_slots(X), free\_slots(Z))$$

If the nodes are separated by a multi hop distance

$$B(XYZ) = \min\,(\min\,(free\_slots(X), free\_slots(Y)), free\_slots(Z))$$

The generalized form is the recursive equation of a minimization function i.e.

$$B(XYT \dots \dots Z) \min\,(\min\,(\min\,(free\_slots(X), free\_slots(Y)), free\_slots(T)) \dots \dots \dots . . free\_slots(Z))$$

Service Capacity is also one of the QoS factors which we consider in defining an optimal policy. We define Service Capacity in terms of workload at a node. If a node is processing more number of requests at a given time we consider the Service Capacity to be high and do not prefer to opt that node in the route.

The optimal policy is achieved based on the cost, free bandwidth and Service Capacity i.e. minimum cost, minimum Service Capacity and maximum free bandwidth.

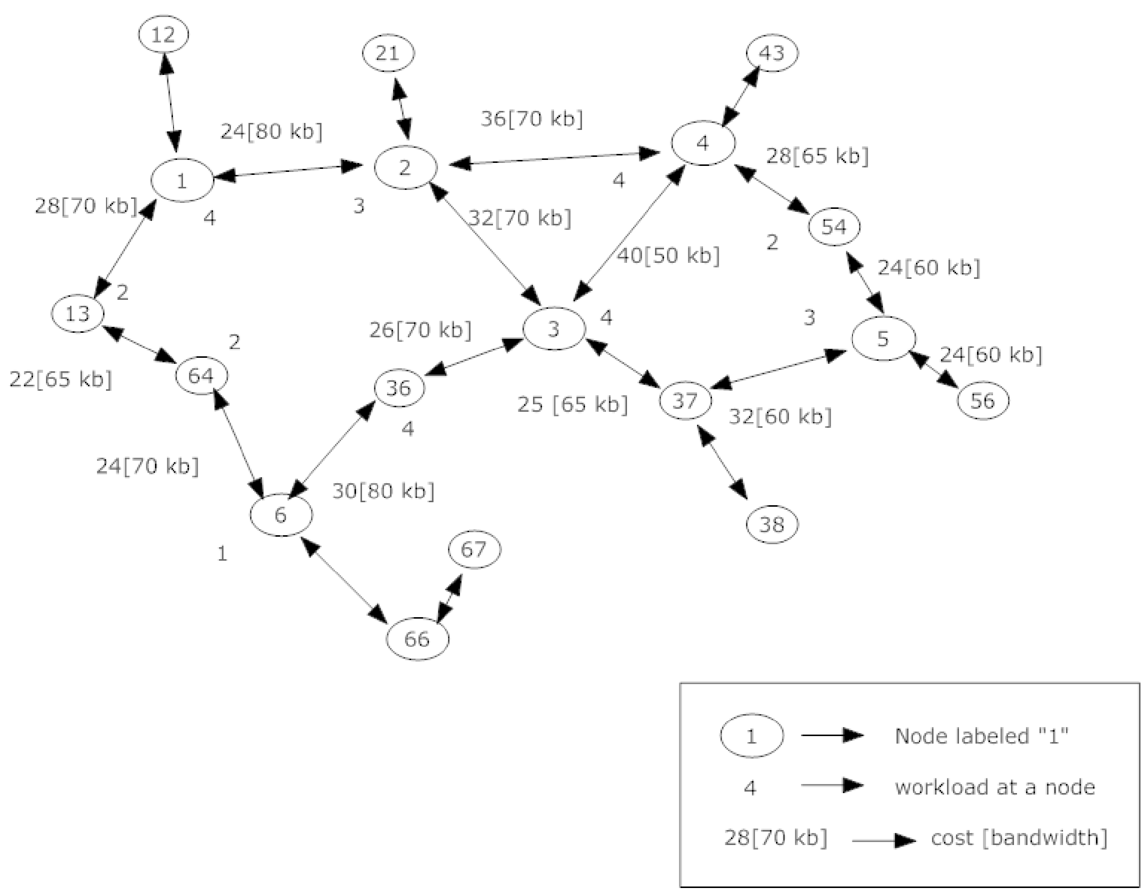

Figure 2: A simple network of 18 nodes showing costs and Bandwidth

Example: Let us take an example of the approach explained above. Suppose that we have 18 nodes in the network and each node can afford a maximum bandwidth of 128 KB. The cost of an edge between each pair of nodes is calculated using the virtual Currency price function (*defined in Section 4.1*). Fig 2 shows the network of 18 nodes formed into an architecture defined in section 3.1. The network is divided into three types of nodes Broker Nodes (BN), Access point Nodes (APN) and Non Broker Nodes (NBN). Fig 2 shows nodes 1, 2, 3, 4, 5 and 6 as BN's. All the nodes which are directly in contact with these nodes are APN's and all other nodes are NBN's. Fig 2 also shows the costs and bandwidth associated with each pair of nodes. It also shows the Service Capacity at each node in terms of workload (number of requests processed by a node at a given time).The bandwidth on an edge is calculated as the minimum of the bandwidths of each pair of nodes.

Let us suppose that node 1 requests a service from a node 56 i.e., node 1 acts as a source node and 56 as the destination node. Our aim is to find an optimal route between these two nodes while considering the QoS factors. Initially we find the set of all possible routes from 1 to 56 using the network architecture described in Section 3.1. Once we have all the sets of routes identified, we then apply our Game theory approach explained earlier. Following the approach we can see that the Game can be in any of the states as shown in the state diagram in Figure 3.

The game starts at state 1 and depending upon the cost, Service Capacity, bandwidth and the type of node it selects, one of the states [1,2] or [1,13] is selected based on the transition probability. As explained above, the cost, Service Capacity and bandwidth are categorized into different levels with probabilities defined. From Figure 2, as [1,2] has low cost, low Service Capacity , high bandwidth and 10 being the BN it selects the state [1,2] over [1,13] as the transition probability of selecting [1,2] is 5/21 which is higher compared to 5/378 for selecting [1,13] (form Table 3). At the state [1,2], the game has two possible states which can be reached; [1,2,4] and [1,2,3]. As the state [1,2,3] has transition probability higher compared to the state [1,2,4] the game chooses to move to state [1,2,3] as it has a lesser cost. Hence, the game now moves to state [1,2,3]. Similarly based on all the criteria(cost, bandwidth,Service Capacity and type of node) described above in choosing the appropriate states the game continues until it reaches the goal state. From the example above, we can see that it ends in a goal state with a policy [1,2,3,37,5,56], which is the optimal route.

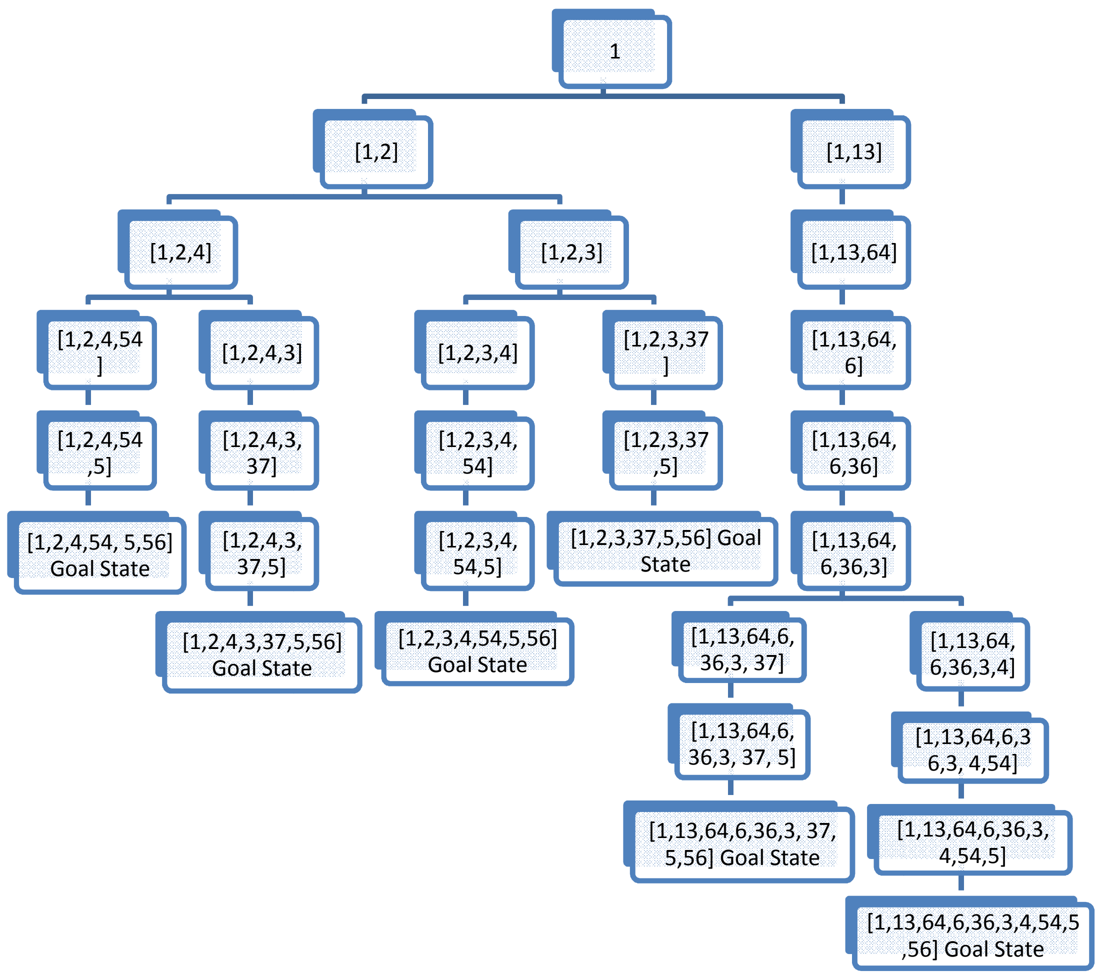

Figure 3: State diagram showing all the possible states

5. AN OPTIMAL COST POLICY ALGORITHM

This Section discusses the optimal cost policy algorithm based on the Game theory to find the minimum cost and the maximum available bandwidth route in the network. The algorithm starts, once we have all the set of routes identified over the network, provided the source and the destination node. The architecture described in Section 3 helps in keeping the number of routes to be the minimum set of all the routes.

As the algorithm for OPTIMAL_COST_POLICY explains, the algorithm takes the input as a Graph and outputs the policy for a requested service. There are two initial parameters, currState (defines as the current node) and Policy (a set of nodes). Initially the currState is set to node 1 (the start node) and the Policy is set to be empty. As the algorithm starts, it checks whether the currState is the goalState (destination node). If yes, the algorithm stops and returns the policy, else, it moves to the next step which is the selection of a control (action) u and evaluating the value of $C_{\pi}(x,u)$ (cost of the policy). A control (action) maps states to states. The value of $C_{\pi}(x,u)$ is calculated based on the cost of the edge ($C(x,u)$) which is defined in Section 4.1, the transition probability ($P(x,u,i)$) to move to the next state and the value $J(i)$ (cost of the policy till the last node). If the value of $C_{\pi}(x,u)$ is minimum, we run the algorithm FREE_BANDWIDTH (P) over the policy P to find the available free bandwidth for the policy. If the bandwidth is maximum then the algorithm moves to the next state based on the transition probabilities. The policy is updated and the algorithm continues from the step BEGIN.

If any of the conditions,min ($C_{\pi}(x,u)$) or max(FREE_BANDWIDTH (P)) is not true, then the algorithm moves to the else condition and the control goes to BEGIN. The algorithm continues until the destination node is reached. The Final step is to return the policy which is the optimal route.

```
OPTIMAL_COST_POLICY () {

/* Cπ(x,u) = cost of the policy π on node x, C(x,u) = cost of an edge going out from x, u = control variable (action), P(x,u,i)= Transition probability to move to state I on control u, H(i),J(i) are the temporary variables, FREE_BANDWIDTH (P) is a function defined in Figure 5*/

INPUT: Graph G = (V,E,w_ij) OUTPUT: Policy P

INTIAL PARAMETERS: Set currState x = 1, policy P = { }

While (i ≠ goalState ) {

BEGIN: Select u ∈ U(x)and evaluate Cπ(x,u) = C(x,u) + Σ_{x,i∈S} P(x,u,i)J(i)

If (Cπ(x,u) is minimum && FREE_BANDWIDTH (P) is Maximum) {

                H(x) = Cπ(x,u)

                MOVE_TO_NEXT_STATE (i,P(x,u,i))

                J(i) = H(i)

                P+= currState

        } Else {

                Go to BEGIN

        } END if

        set currState = i

} END While

RETURN P
```

Figure 4: Optimal Cost Algorithm

FREE_BANDWIDTH ( )

{

INPUT: Nodes X, Y,T, ..Z

OUTPUT: Bandwidth B

$$B(XYT \ldots \ldots Z) \min (\min (\min (free\_slots(X), free\_slots(Y)), free\_slots(T)) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots free\_slots(Z))$$

// X, Y, T and Z are the nodes in the Network

// $free\_slots(X)$ represents the available bandwidth slots at a given node

RETURN B

}

Figure 5: Free Bandwidth Algorithm

FREE_BANDWIDTH algorithm returns the available free bandwidth over a route on which our algorithm operates. Here X, Y…….Z are the nodes in the route and $free\_slots(X)$ determines the available free slots at a given node. The minimization function is used to determine the available free bandwidth in a route (Each slot defines each KB of Bandwidth available).

6. CONVERGENCE OF THE OPTIMAL POLICY ALGORITHM

To identify the convergence of the algorithm, we describe a procedure that labels the peers or states recursively. The main idea is to label each peer as {reached, unreached}. This is a boolean level of labeling every peer of a state. Initially, all the states will be labeled unreached. When the game starts, we begin labeling each state as {reached} such that the game terminates when the goal state is labeled {reached}. The game follows only the states that are unreached so that the algorithm avoids the formation of loops and reaches the goal state in finite time. Let $p_1, p_2 \dots\dots.. p_n$ be the peers in the M-P2P network and $x_1, x_2 \dots\dots.. x_n$ be the states of these peers, after the set of routes are identified from source to the destination. The game starts at state x_i and will be in one of the states say, x_i after a time t. We define the convergence of the algorithm, if it satisfies the following conditions

1) All the states are labeled {reached} or
2) If the game reached the state x_i, the goal state

Since we play the game on the set of routes identified we observe that, the game always ends in the goal state.

7. SIMULATION

We built a simulation environment in Java to study the performance by conducting experiments on the Incentive based routing protocol (IRP) described in Section 4 and comparing it to the Shortest Path Dynamic source routing (SP-DSR) [2] protocol.

The simulation area is approximately 1000 X 600 m^2 and it can afford a range of 30 to 150 peers in the network. The maximum connection distance between any two peers is 100 m. The queries are randomly generated and it is done at an average of 5 queries per second. The maximum bandwidth between any two peers is 128 kbps and 8 kbps being the minimum. The simulator also provides a graphical user interface to adjust the location of peers manually or automatically.

The movement of the nodes is handled by implementing the random way point model (RWP) [3]. In RWP, each node moves along a zig zag line from one way point to the other. The random way points are uniformly distributed over the given area and all the nodes tend to converge at the center.

But this type of model has some common problems. When we take the average speed of a node, it tends to decay over a period of time and eventually approaches zero. RWP chooses a destination and speed for a node randomly and independently, and the node will keep moving at that speed until it reaches that destination

Table 7.1: Simulation Parameters

Parameter	**Range**
Simulation area	1000 X 600 m^2
Number of peers	30 ~ 150
Maximum connection distance	100 m
Bandwidth between peers	8 ~ 128 Kbps
Queries generated per sec	5

. A common problem arises when a node moves very slowly for a given long destination which it reaches after a very long time, which increases simulation time. To overcome such a problem, we have used a slight variation of RWP in which we consider a new parameter, time. To overcome the average speed decay problem, we randomly choose speed which is uniformly distributed in the interval $[1, V_{max})$ instead of $(0, V_{max})$ used previously. This ensures that the average speed does not tend to zero.

The formation of the node cluster (Broker architecture) is handled by implementing a Connected Dominating Set (CDS) [11] model. Several algorithms for the CDS formation have been discussed in [1]. We have used Steiner tree based CDS construction to define Broker nodes in the network. As discussed in Section 3.1 all the nodes connected to these Broker Nodes are the Access Point Nodes and all the other nodes are classified as Non Broker Nodes

The effectiveness of the protocol can be evaluated by performing experiments on the network. The network is divided into clusters of various sizes. Each cluster will have three types of nodes Non Broker Node, Access Point Node and the Broker Node, which acts as the cluster head. A randomly selected node from one of the clusters requests a service in the network and the service is processed using the proposed Game theoretic approach.

7.1 PERFORMANCE EVALUATION

The results are studied to analyze the metrics such as bandwidth usage, response time, average hop count and energy utilization and compare these metrics with those of Dynamic Source Routing (DSR) [2] protocol.

7.1.1 Average response time vs. Number of peers: We define response time as the time required to successfully find an optimal route from source to the destination. We perform the experiment by increasing the number of peers in the network from 30 to 150. Figure 6 shows the plot of average response time against the number of peers. We observe that as the number of peers' increases, the performance of our protocol gets better compared to the shortest path DSR due to the presence of the broker peer architecture that uses less number of nodes in processing a request.

Initially when the size of the network is small, we see that, both the protocols works equally better. When the size of the network increases, a slight decrease in the response time is observed in our protocol compared to DSR. This is due to the performance of the broker peer architecture, which uses lesser number of peers in processing the request. This experiment shows that the response time in our protocol is decreased compared to DSR.

Figure 6: Average response time with increasing number of peers in the network

Considering the scenario of finding multiple maximal disjoint paths to the destination, we observe that IRP for multi paths still performs better compared to split multipath routing (SMR). There is a slight increase in the response time observed compared to IRP for single optimal route as finding maximal disjoint paths costs time over finding all the routes.

7.1.2 Average hop count vs. increasing number of peers: Hop Count is defined as the number of hops a packet takes, starting from the source peer to reach the destination peer. We increase the hop count as the packet reaches each intermediate peer on its way to the destination. Figure 7 shows the comparison between the hop counts by Incentive based routing protocol (IRP) and DSR with the increase of the number of peers in the network.

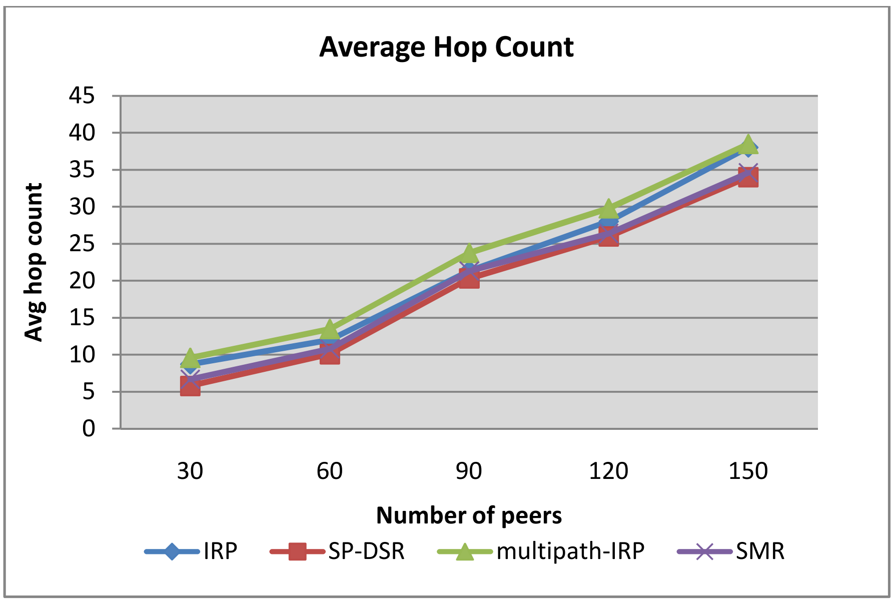

Figure 7 : Average Hop Count with increasing number of peers in the network

From the Figure 7, we observe that the average hop count for IRP is little high compared to the DSR. Though not a significant difference is observed, the difference is because of the incorporated QoS factors in finding the route. A slight increase in the average hop count is observed because of the argument that, minimizing the hop-count maximizes the distance traveled by each hop, which is likely to minimize signal strength and maximize the loss ratio.

Even if the best route is a minimum hop-count route, in a dense network there may be many routes of the same minimum length, with widely varying qualities; the arbitrary choice made by most minimum hop-count metrics is not likely to be the best. As IRP selects the route based on the price calculated over several parameters that include signal strength, transmission power and receiving power, and a low cost route is always selected, the route may contain more number of hops with less cost compared to that of DSR which may contain minimum hops with a high cost. When multiple paths are selected in IRP, since more than a single path is used in routing the packets to the destination, the average hop count in multipath IRP, SMR[9] increases compared to IRP and SP-DSR.

7.1.2.1 Average Hop Count vs. Number of requests: Figure 8 shows a graph of average hop count plotted against the number of requests in a network. The experiment is conducted over a network of size 60 with the increasing number of requests. The readings are taken for every 10 requests. The irregularity of the graph is due to the randomness in the query generation.

The graph for average hop count for the increasing number of requests shows a slight difference in the hop count as the number of requests increases. Thus, we conclude that increasing the number of requests from 20 to 120 only increase the hopcount by about one and hence, the method scale well with increasing the number of requests.

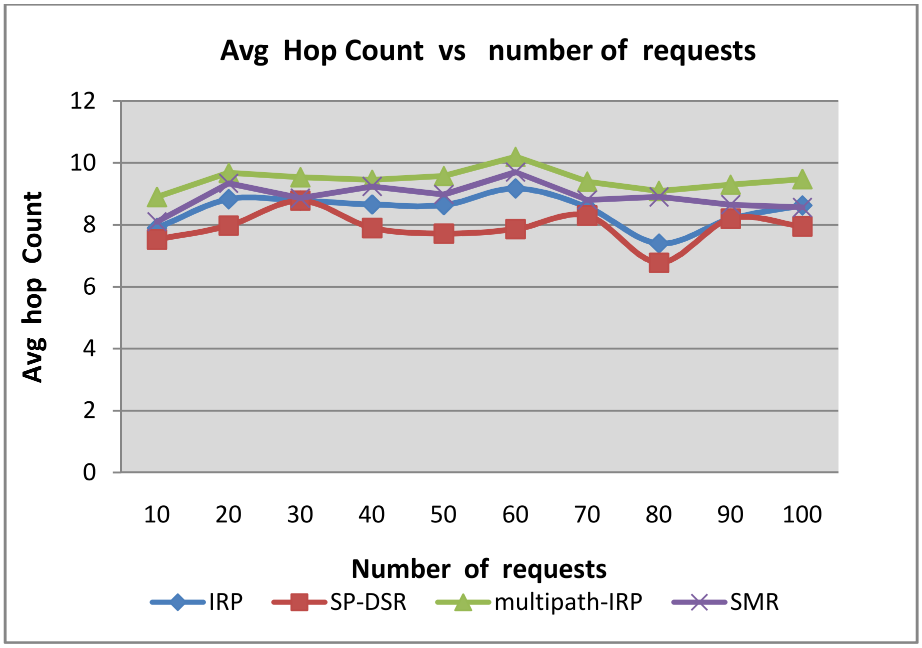

Figure 8 : Average Hop Count with increasing number of requests

7.1.2.2 Path Optimality: We define path optimaility as the difference between the number of hops a packet took to reach its destination and the length of the shortest path that physically existed through the network when the packet was originated.

Figure 9 shows the scatter graph pointing the differences in the hop count of both the protocols. The readings are taken for a network of size 60 while increasing the number of requests. Each point on the graph shows the difference between the hop counts of IRP and DSR.

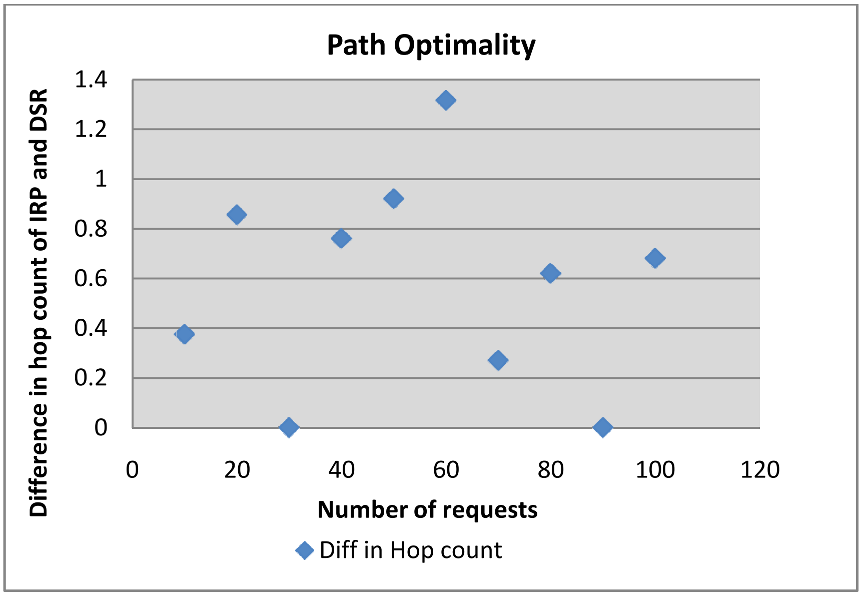

Figure 9 : Difference between the number of hops to reach the destination and the length of the shortest path that physically existed through the network (IRP vs DSR)

Let *d* denote the difference between the shortest path and the length of the optimal route actually taken by the packet. A difference of 0 means that the packet has taken a shortest path. While a difference greater than 0 means that it has taken a path longer than the shortest path i.e. it took extra hops to reach the destination. Figure 9 shows the average value of *d* between IRP and SP-DSRand Figure 10 shows the average value of *d* between multipath IRP and SMR. We observe that most of the points fall in the range [0,1]. This means that the optimal route taken is close to the shortest path. As the network size is increased we expect a slight increase in the range. This plot helps in understanding the ability of the routing protocol to efficiently use the network resources in finding the optimal path despite a slight variation in the hop count.

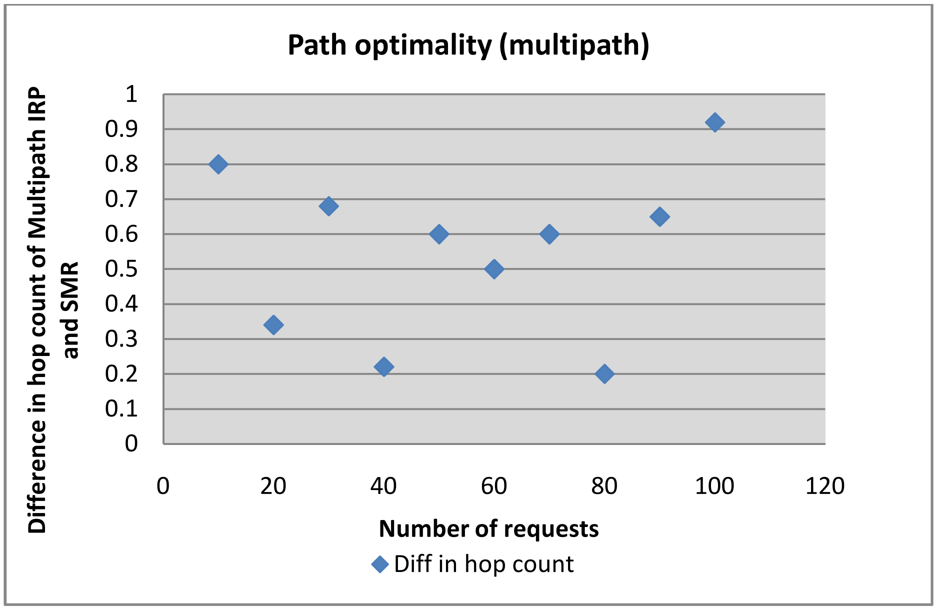

Figure 10 : Difference between the average number of hops in multiple paths to reach the destination and the average length of the shortest paths that physically existed through the network (multipath-IRP vs SMR)

7.1.3 Available Bandwidth vs. Number of requests: We define available bandwidth between any two nodes (or over the path) as the set of available free slots between them.

Figure 11 shows the available bandwidth over the path to destination, varying the network of sizes 30, 45 and 60. The readings were taken for 11^{th}, 21^{st} and so on requests. Initially the requests are randomly generated with a difference of 10 queries ranging from 10 to 50 in the network of varying size and the readings for 11^{th}, 21^{st}, and so on requests are taken. The plot shows that initially there is dip in the bandwidth available, this is because of the increase in the number of requests utilizing the bandwidth. However, as more and more requests gets satisfied faster, more bandwidth becomes available to process additional requests. Hence, we observe a rise in the available bandwidth later on with increase in the number of requests.

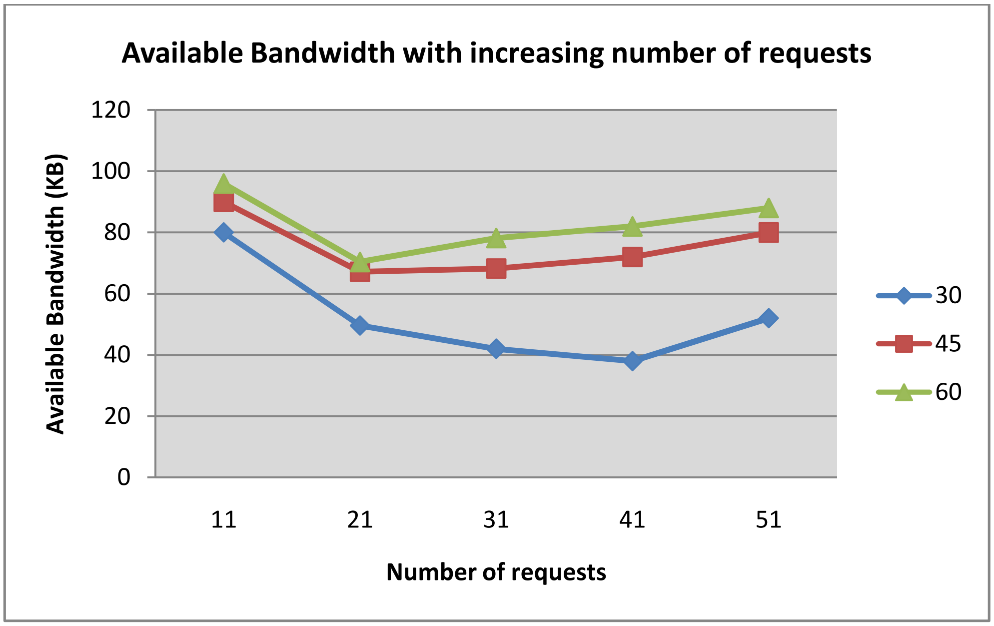

Figure 11 : Available Bandwidth with increasing number of requests

Figure 12 shows the readings of the available bandwidth for 11^{th}, 21^{st}, so on requests in the network of varying size for multi path IRP. Comparing the graph of figure 12 with that of figure 11, we observe that more bandwidth is available for multi path IRP than that of IRP for single route. This is because of the presence of multiple routes to the destination. Hence, we can infer that multi path IRP performs better compared to the IRP in terms of available bandwidth.

7.1.4 Energy utilization in the network: Energy utilization is defined as the amount of battery power, transmission power and reception power a node uses in processing a request. As we define our price based on these parameters in VC price function (defined in Section 4.1), we infer that energy utilized in processing a request to be the cost observed along the path. Hence we plot energy in terms of virtual currency derived from the VC price function.

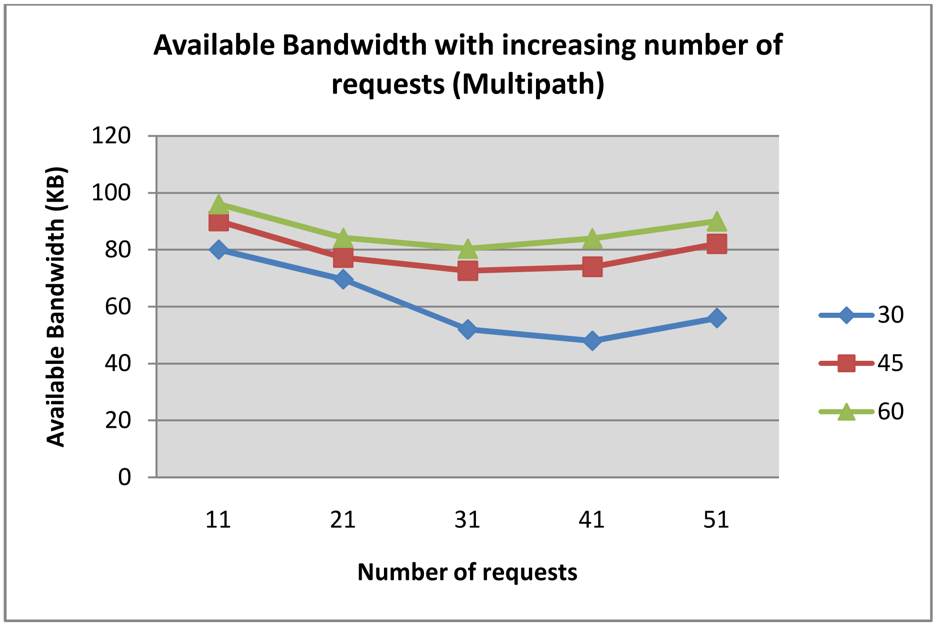

Figure 12 : Available Bandwidth with increasing number of requestsfor Multipath IRP

Figure 13 shows the graph to read the energy utilized in the network to process a request. The readings are taken by increasing the number of peers in the network ranging 30 to 150. As IRP focuses on finding the low cost path compared to DSR, we observe that the graph of IRP lies below the shortest path DSR. Initially when the network size is small, the difference in the energy is less. But, as the network size is increased we see that IRP performs efficiently in terms of energy utilization as the focus is on finding the low cost route in terms of cost unlike SP-DSR which focuses on finding a path with minimum hops which may cost higher.

Considering the multi paths for IRP and SMR, we observe that there is slight increase in the energy utilization compared to the previous models. This is because of the fact that multiple routes are considered from source to the destination. This increases the average cost to the destination, which results in the increase of energy.

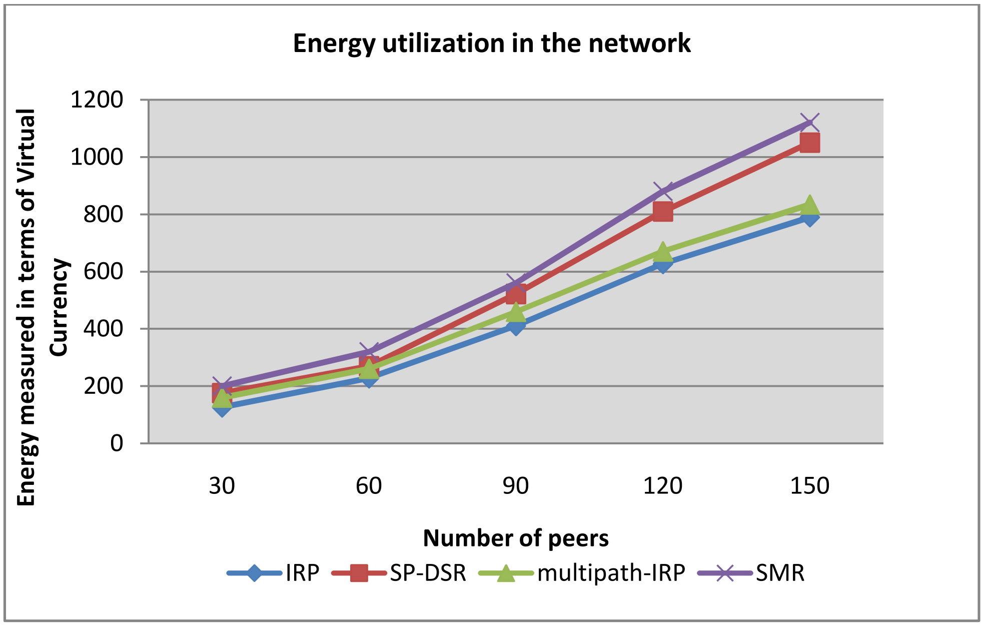

Figure 13 : Energy utilization in the network

8. CONCLUSIONS AND FUTURE WORK

In this paper, we propose an economic approach for finding an optimal cost routing which uses the cost calculated over the resource parameters such as transmission power and receiving power (directly proportional to battery power available) as an incentive to forward the data while discovering a route. A Game theory based approach is used in selecting an optimal route over the set of possible routes identified, which in addition, takes into consideration the QoS factors such as the bandwidth available, service capacity, and the link reliability in calculating for the transition probabilities to select the next hop peer in the path. This works in conjunction with the proposed broker-based peer architecture which helps in selecting the next hop nodes in the path while minimizing the number of hops in doing so.

Our simulation study validates that IRP is an effective approach to find an optimal low cost route compared to the shortest path DSR for the average response time, average hop count, path optimality, available bandwidth and energy utilization in the network, and IRP proves to perform better for all the metrics though a slight difference is observed while studying the average hop count.

As a future work, we will try to select the QoS factors based on the kind of service processed and therefore, we will customize the route discovery process.

9. REFERENCES

[1] J. Blum, M. Ding, A. Thaeler, and X. Cheng, Connected Dominating Set in Sensor Networks and MANETs, Handbook of Combinatorial Optimization (Editors D.-Z. Du and P. Pardalos), pp. 329-369, 2004, Kluwer Academic Publisher

[2] J. Broch, D. Jhonson, and D. Maltz, Dynamic Source Routing in Ad Hoc Wireless Networks, in Mobile Computing, edited by Tomasz Imielinski and Hank Korth, Chapter 5, pp. 153-181, Kluwer Academic Publishers, 1996.

[3] C. Bettstetter, G. Resta, P. Santi, The Node Distribution of the Random Waypoint Mobility Model for Wireless Ad Hoc Networks, IEEE Trans. on Mobile Computing, Vol. 2, n.3, pp. 257-269, July-Sept. 2003.

[4] Douglas S. J. De Couto, Daniel Aguayo, John Bicket, and Robert Morris, A High-Throughput Path Metric for Multi-Hop Wireless Routing, Proceedings of the 9th ACM International Conference on Mobile Computing and Networking (MobiCom '03), pp. 134-146, San Diego, California, September 2003.

[5] K. Chen and K. Nahrstedt, iPass: An Incentive Compatible Auction Scheme to Enable Packet Forwarding Service in MANET, in Proceedings of 24th IEEE International Conference on Distributed Computing Systems (*ICDCS)*, Japan, March 2004.

[6] Sajal K. Das, Haitao Lin and Mainak Chatterjee**,** An Econometric Model for Resource Management in Competitive Wireless Data Networks, IEEE Network Magazine, vol. 18, No. 6, Nov/Dec 2004, pp. 20-26.

[7] http://en.wikipedia.org/wiki/Friis_transmission_equation

[8] Herbert Gintis, Game Theory Evolving, A Problem-Centered Introduction to Modeling Strategic Interaction, Princeton University Press, 2000. ISBN 0-691-00942-2, 0-691-00943-0. pp. 532

[9] S. J. Lee and M. Gerla. Split Multipath Routing with Maximally Disjoint Paths in Ad Hoc Networks, In Proceedings of the IEEE ICC, pages 3201-3205, 2001. http://citeseer.ist.psu.edu/lee01split.html

[10] C.R. Lin, C. Liu, An on-demand QoS routing protocol for mobile ad hoc networks, GLOBECOM ’00, Vol. 3, pp. 1783–1787, 20th Annual Joint Conference of the IEEE Computer and Communications Societies, Anchorage, 2001 (Infocom 2001)

[11] Y. Li, S. Zhu, M. T. Thai, and D.-Z. Du, Localized Construction of Connected Dominating Set in Wireless Networks, NSF International Workshop on Theoretical Aspects of Wireless Ad Hoc, Sensor and Peer-to-Peer Networks (TAWN04), Jun. 2004.

[12] Anirban Mondal, Sanjay Kumar Madria, Masuru Kitsuregawa, Research Issues in Economic Models for Mobile P2P Computing, 4th PDMST07 workshop along with DEXA 2007, Germany, pp. 809-813.

[13] Shamik Sengupta and Mainak Chatterjee**.** Designing Auctions Mechanism for Dynamic Spectrum Access, in ACM/Springer Mobile Networks and Applications (MONET), Special issue on Cognitive Radio Oriented Wireless Networks and Communications, 2008.

[14] Rüdiger Schollmeier, Ingo Gruber, Michael Finkenzeller Routing in Mobile Ad Hoc and Peer-to-Peer Networks. A Comparison, in proceedings of Networking 2002. International Workshop on Peer-to-Peer Computing, Pisa, Italy, May 19-24, 2002

[15] Theodre L. Turocy and Bernard von stengel's, Game Theory (2002), in Encyclopedia of Information Systems, Volume 2. San Diego, Elsevier Science (USA), pages 403-420.

[16] W. Wang, M. Chatterjee and K. Kwiat, An Economic Approach to Hierarchical Routing in Resource Rationed Ad Hoc Networks, World of Wireless, Mobile and Multimedia Networks, (WoWMoM) 2007, IEEE International Symposium on a 18-21 June 2007 Page(s):1 - 8

[17] Whalen. J.S, Kenney. J, Finding maximal link disjoint paths in a multigraph, Global Telecommunications Conference, 1990, and Exhibition, Communications: Connecting the Future, GLOBECOM '90., IEEE , vol., no., pp.470-474 vol.1, 2-5 Dec 1990

VITA

Anil Jade was born in Nalgonda, India on February 18, 1983. He completed his Bachelor of Engineering in Information Technology at Chaitanya Bharathi Institute of Technology in Hyderabad, India in May, 2004. Anil started his Master of Science program with the Computer Science Department at Missouri University of Science & Technology (UMR earlier) in Fall, 2006. His areas of interest include Economic Models and Routing in Mobile P2P networks.

He worked with Dr. Sanjay Kumar Madria in his area of interest. During his research, he designed and developed an Economic Incentive Based Routing Protocol Incorporating QoS factors in Mobile P2P Networks. He completed his research under Dr. Sanjay Kumar Madria and received his Master of Science Degree in August of 2008.