A STUDY OF PRICING-BASED RELAYING COOPERATION IN WIRELESS AD HOC NETWORKS

by

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ABSTRACT OF THE THESIS

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Relaying cooperation in wireless ad hoc network has been studies for years. Through relaying cooperation, nodes can communicate with other nodes that are not in their communication range. However, because relaying packets costs extra resources of intermediate nodes, certain nodes may refuse to cooperate for saving own resources, especially when a network doesn't belong to a fixed infrastructure, such as wireless ad hoc network. Thus, to change the behavior of those *selfish* node, certain systems are proposed to stimulate the relaying cooperation. These systems are popularly classified as reputation-based system and pricing-based system. Three pricing-based strategies based on different key variables are proposed in this thesis. To evaluate the effectiveness of these strategies in terms of the equality of chances to participate in cooperation, a new fairness index named *centrality fairness* is proposed. By studying the behavior of nodes in static and dynamic topologies, edge node issues and importance of node mobility are discussed. With sufficient results from experiments, these pricing-based strategies are proved to be effective in static topology, and all of them can alleviate the effect from edge node issues. Eventually, the strategy using *utility ratio* as the key variable of the pricing adjustment is concluded to be the best strategy, which can provide

the best *centrality fairness* of a designated static network. Finally, to study the contributions of other parameters, such as pricing refresh rate (τ) and step size of pricing adjustment (Δ), several experiments are done with these parameters fine-tuned.

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A special thanks to my beloved wife, Ying Wang, who supported me throughout the writing of this thesis-patiently assisting with words of assurance and the much-needed letters of encouragement.

Dedication

This thesis is dedicated to my parents

RW Wang and Lulu Hu

who introduced me to the joy of engineering from birth,

enabling such a study to take place today.

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Chapter 1

Introduction

A wireless ad hoc network is a system involving a collection of nodes that do not belong to a fixed infrastructure. Every node in an ad hoc network is capable of both handling local transmissions, and supporting network functions like traditional routing. By utilizing the ability of routing and forwarding of packets offered by nodes nearby, a node pair can communicate even if they are not within each other's signal range. The help provided by relaying is a form of cooperation, which refers to "*a node's willingness to sacrifice resources(e.g., energy, bandwidth) for the benefit of other nodes in the network*" [1]. Because of cooperation, nodes not only can communicate with nodes that are beyond their signal range, but also reap the benefit of saving energy while communicating with other nodes by not having to increase transmit power to reach that node.

However, it may not be that all of the nodes in the network are cooperative. Initially, wireless ad hoc networks were developed for scenarios when all participants were members of the same organization or policy, and hence would naturally cooperate with each other. For example, in a military scenario, every node in the network would adhere to the orders issued by a commanding node, and would cooperate for the benefit of accomplishing the tactical mission. Later, wireless ad hoc networks were proposed for commercial use, such as in vehicular communications, where automobiles would transmit valuable information, for example traffic status updates and malfunction warnings, to friendly automobiles nearby. In the latter scenario, due to the lack of a singular infrastructure, it is important to note that nodes in commercial wireless ad hoc networks maybe *selfish* [2] in nature. Such nodes might hold the relay packets for the purpose of saving their own resources because the network is decentralized and resources are limited especially for mobile nodes.

Since relaying packets incurs both a real cost (energy and bandwidth) and an opportunity cost(in lost transmissions) [1], nodes may not sacrifice their resources to help others unless there are appropriate incentives. To stimulate cooperation in wireless ad hoc networks, additional mechanisms are needed. Several approaches to encourage this cooperation have already been studied, which can be roughly classified into reputation-based systems [3–5], and pricing-based systems [1, 6–12].

In reputation-based systems, nodes keep a record of the reputation of all or some of the nodes in the network. Based on the reputation records, these nodes judge the behaviors of other nodes and whether they will likely cooperate. Accordingly, they decide whether to cooperate with other nodes or not. In general, nodes will gain reputation for successful forwarding of packets, and lose reputation for rejecting a cooperation request or failing to deliver packets. One significant problem in reputation-based systems is that nodes of these systems must have good knowledge of the behaviors of all other nodes in the networks [3, 4], or that some neutral devices must be deployed in the network to monitor and offer an assessment of reputation information for every node in the network.

In pricing-based systems, incentives take the place of reputation. Nodes that take advantage of relaying cooperation must pay for the cooperation through incentives, and the intermediate nodes will agree to cooperate as long as the source node can afford the cost associated with relaying cooperation. Node reputation information is no longer required in pricing-based system, instead. Moreover, pricing-based systems are independent of the form of incentives, that is to say, incentives can be credits that are only valid within the network [7–10], or, can be a form of digital coin that has the real value outside the network [6, 11, 13–15]. The ability to attract more cooperation is very important for each node in pricing-based system, because if nodes want to send out more packets they must be able to afford the cooperation, while the only way for nodes to accumulate incentives is through cooperation and successfully relaying packets. As a result, understanding the role of pricing in the network is important as the cost associated with forwarding packets will have a direct impact on whether nodes will engage in cooperation, if they will be able to afford cooperation, and whether or not the underlying micro-economy running within the network will be stable enough to support persistent operations of the network. The goal of this thesis is to examine the problem of pricing and to explore a general strategy of adjusting prices in pricing-based network systems.

Beyond the problem of pricing control, a successful pricing-based system will face many challenges. First, certain measures are required to keep transactions (relaying cooperation) robust. Unlike reputation values, the incentives in pricing-based systems must be transported through networks to complete the relaying cooperation. It is necessary to have consistent regulations for preventing misbehavior as well as accidental events. For example, a selfish relay node that drops relay packets on purpose should not receive any incentive. Further, nodes should receive partial payment even though packets may be lost due to poor channel conditions, which are natural occurrences in wireless networks. We note that malicious behavior can exist, but in this thesis we are focusing on the scenario that nodes are assumed to be rational. The strategies of pricing adjustment mentioned above can also be viewed as a form of regulations. For instance, before deciding the path to use, the source node can collect the prices of intermediate nodes, and the path with lowest price can be adopted. Thus any node that is eager to cooperate can win its opportunity by offering a price lower than the price of other other nodes. As a result, nodes that are greedy, or desire to manipulate, the resources of other nodes can be regulated through pricing strategies. However, we note that pricing adjustment is a double-edeged sword. On one hand, lower pricing can attract more cooperation; on the other hand, it lowers the income resulting from an individual cooperation act, which may result in nodes running behind their expenses.

Another challenge exits because packets are relayed without trustworthiness guarantees. Security strategies for transactions are required to assure the confidentiality. Similar strategies are also used in Electronic Commerce applications [14, 16], but in a wireless environment, the existence of conventional central authority is no longer a reasonable approach, because traditional public key infrastructure (PKIs) or certificate authorities (CAs) are expensive to build and vulnerable to maintain. To be suitable for wireless ad hoc networks, the strategies must be off-line achievable and distributable. One choice is anonymous asymmetric fingerprinting, which has been popularly used in digital coin based systems [13–15, 17, 18] as a means to prevent illegally redistribution of coins because this technique does not require the owner to be present when using digital cash, which is a basic requirement for digital cash. Another good choice is identity-based cryptography (IBC) [19, 20]. In [9], an IBC is used in order to ensure that the confidentiality and authenticity of information exchange is not compromised. IBC is a new form of public key cryptography (PKC), whereby a node can generate the public key of another entity through its identity directly, so that the role of PKIs or CAs can be reduced. Although this thesis does not study security problems in networked communications, it is assumed that certain security strategies have already been set up in the environment.

Third, maintaining the fairness of the network is very important to keeping the network functional. This will be another focus of this thesis. There are various definitions of fairness based on different ways to view the operation of the network. For example, Jain's fairness index [21] is widely used to measure the fairness of throughput, and protocols that seek throughput fairness try to have every node in the network have the same share of throughput. However, due to the variable link quality in a wireless ad hoc network, it is hard to maintain the same share of bandwidth for every node, which makes Jain's fairness index not well-suited for wireless ad hoc networks. To adapt to this character of wireless ad hoc networks, a modified max-min fairness [12] and proportional fairness [22, 23] have been proposed. These two types of fairness are achieved if the node that spends the most resources, obtains the highest data rate in the network. Still, in systems that use these two types of fairness, a trustworthy central judge is required in calculating the fairness. To avoid the central authority, we take the viewpoint that the economic balance of incentives (or digital coins, if you will) in the network indicates the fairness of the network. As a result, the design of an incentivized network should strive to keep the amount of digital coins in each node's account to follow a budget balance that is neither too large nor too small. The reason for choosing economic balance as the indicator is because it is a parameter that's locally bound to each node, and it has a direct correlation with the number of packets that the node has relayed.

In this thesis, we focus on the fairness and robustness of the relaying cooperation system in wireless ad hoc networks. Towards this objective, we assume the security issues can be taken care of by some trustworthy agents, which are working between users and networks. Such an idea is similar to using controllers in Law Governed Interactions (LGI) [24–26] and is a common assumption in the area of electrical commerce [16] . Regulations for assuring the success of cooperation as well as related transactions are proposed, which are integrated with agents. Users can only call the functions offered by local agents, and have no way to redefine the functions or regulations. We also assume that all nodes are rational, which means nodes will not attack or exploit each other. With these assumptions, we build a pricing-based cooperation system over a wireless ad hoc network where we use digital coins as the incentive. In our system, only the agent can be the subject of a relaying cooperation involving actions, which includes sending/receiving packets, handling users' digital wallet, and exchanging digital coin for relaying cooperation. Digital coins are supposed to be initially obtained by the agent through a secure manner from the bank account of the identified user. Similar ideas can be found in pre-paid metro card or phone card with a micro-chip on it. In every relaying cooperation, all participants, who successfully relay the packets, will get the payment from the initiator. With our designed system, experiments have been performed on the ORBIT testbed to study the fairness of wireless ad hoc networks, where the fairness is defined as the economic balance of the network. We will define the network and hence the protocol as unfair for nodes in the networks if they have large differences in the amount of their budge of digital coins, while an effective strategy would keep the fairness by adjusting the price according to certain regulations, so that the balance of digital coins across the network is equitable.

The remainder of this thesis is organized as follows. Related work is discussed in

Chapter 2. In Chapter 3 we present our cooperation scheme and regulations in detail. We show the experiment results and discussions in Chapter 4 and summarize the thesis in Chapter 5.

Chapter 2

Background Knowledge and Related Works

In this chapter, we will discuss some background knowledge related to the techniques and tools that we are going to use in this thesis. The contents of this chapter are divided into four sections, the first section explains the issues involved in the relaying cooperation in wireless ad hoc network. In next two sections, we show two elementary tools for studying networks, which are centrality and fairness. The last section is an introduction of Law Governed Interactions (LGI), which is used as a guideline for presenting our regulations.

2.1 Relaying cooperation in wireless ad hoc network

2.1.1 Relaying cooperation and wireless ad hoc network

Relaying cooperation

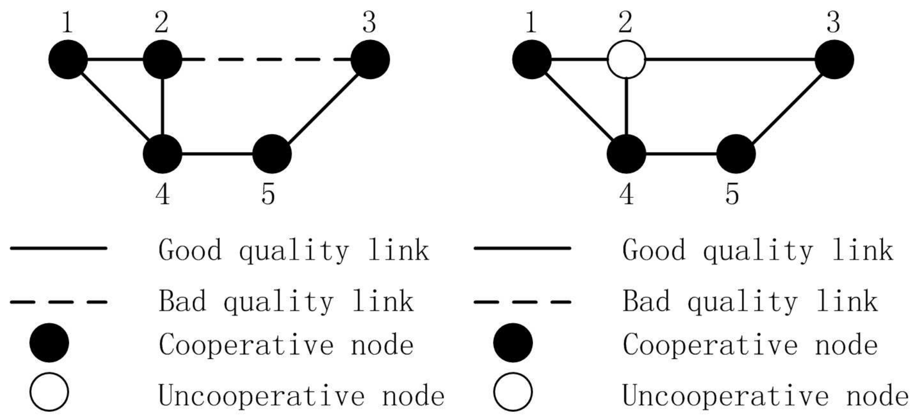
Traditional end-to-end transmission involves only one hop, which means one end node can only communicate with another end node within its signal range . However, there are many cases where nodes want to communicate with the others out of signal range, especially in wireless ad hoc networks. It is convenient to have some intermediate nodes help connect these two unrelated nodes together by offering delivery/forwording services. As a result, the idea of relaying cooperation is introduced, which implies that some intermediate nodes can help route packets to the destination for node pairs that cannot reach each other directly. There are many advantages for using relaying cooperation, such as that the energy consumption of the nodes can be reduced because the distance for each communication hop is reduced, or that interference with other nodes can be reduced.

Wireless ad hoc network

A wireless ad hoc network is a network that consists of many wireless nodes that are not designated to a predefined infrastructure. The wireless nodes in ad hoc networks can support not only basic transmissions, but also routing functions, just like traditional routers. However, due to the nature of the wireless medium, the connections are unstable and vulnerable to malicious attacks. Moreover, most wireless ad hoc networks are based on mobile nodes, and hence the issue of power consumption is very critical to the network. Therefore, many issues about security and power efficiency are related to the problem of relaying cooperation in wireless ad hoc network.

Relaying cooperation in wireless ad hoc networks

Relaying cooperation in wireless ad hoc networks involves more than merely accepting the request to forward packets and then relaying their packets, there are many other factors that are involved. In wireless ad hoc network, every node has the ability of relaying packets, so that it can accept the request of relaying packets. Thus, every source node that wants to send packets to another node beyond its signal range will face many choices for choosing its partners. To make a proper choice, a source node needs to compare the conditions of candidates that are meaningful to the nodes raising the requests. For example, transmission delay and pricing of cooperation may be factors to consider. Similarly, intermediate nodes also have many choices to face, such as choosing a source node to cooperate with, since many nodes in the network can issue cooperation requests simultaneously, yet that node may only be able to be involved in a few forwarding actions. In that case, the criteria for choosing partners are related to the bandwidth usage or power consumption of the node that will offer cooperation. To assure both source nodes and relay nodes can make a right decision, certain strategies are designed for every nodes in the network. The strategies are like laws for nodes to follow, so that nodes can behave themselves and compete with each other rationally.



(a) An example for always bad connection (b) An example for always rejection

Figure 2.1: Different scenarios of bad connection in (a) and (b)

2.1.2 Relaying cooperation systems

Initially, wireless ad hoc networks were designed for military use, so that every node in the network would obey the command from an unique officer, and cooperate without argument. However, it is unreasonable to force a node to cooperate in a heterogeneous and commercial network, which might involve nodes from different infrastructures. Further, even if the node accepts the request to relay packets, there is no reason to believe the cooperation is efficient or trustworthy. In some circumstances, the traditional attributes, like estimated delivery time and hop count, are not good enough to assist nodes making right choices. For example, in Figure 2.1(a), node1 wants to communicate with node3 using the relaying cooperation of node2 or the involvement of both node4 and node5. Based on a shortest path protocol, the path through node2 is the best choice. However, node2 may have a long delay in order to communicate with node3. In this case, problem can easily be solved if link quality is introduced. There are other cases, like the one in Figure 2.1(b), where node2 may always reject a request to cooperate, which is a form of misbehavior. It is also quite unfair for node4 to always sacrifice its resources for others, just because another node does not want to cooperate. This can only be solved if certain measures are taken by node1 and node4 to recognize this bad behavior, and suppress it.

To regulate the relaying cooperation in networks and assist nodes in making decisions, various systems based on an assortment of criteria have been designed. Most of them can be classified into two categories: reputation-based systems and pricing-based systems. We now provide more detail about these two categories, and describe the associated literature.

Reputation-based systems

In reputation-based systems, nodes monitor others' behaviors throughout the entire process of relaying cooperation, and assign *grade* according to the observations. The grade of each node is called reputation in the system. The basic idea is that nodes will get an increment in their grade for completing a relay cooperation, and will get a decrement for rejecting requests or cheating in cooperation. It is analogous to building a credit history in the real world, where a higher reputation implies a more reliable history and this is used as a suggestion for more trustworthiness in future activities. A reputation-based system is designed to choose the nodes with highest reputation to cooperate with, and accordingly abandon or disregard the uncooperative nodes. This strategy takes effect when choosing the path for relaying packets, such as in a routing protocol. In previous research work, some metrics have been introduced as the criterions for assessing reputation in networks. For example, Sonja Buchegger [3] proposed a reputation-based system named CONFIDANT , where nodes observe the transmission activities of their neighbors to recognize the misbehaved events, and try to keep the misbehavior away from relaying cooperation. Marti [27] proposed a similar system in which nodes use a "watchdog" mechanism to detect malicious nodes, and avoid them in routing the relay packets. Haijin Yan used a *cooperation coefficient* [4], which is a numerical measure of a given node's contribution to and consumption from the network. Urpi proved that reputation-based systems can be modeled by using Bayesian game theory in [2]. However, these strategies can only help a node to make decisions, not offer a way to compensate the relay nodes for the extra resources they used while relaying packets.

Pricing-based systems

For relaying cooperation without incentives, like the reputation-based systems mentioned above, no matter how the strategy is designed, cooperation always consumes the resources of relay nodes without compensation. Such sacrifices may not be accepted by some nodes that really value their resources, e.g. a form of selfishness [2]. To stimulate cooperation, incentives are required to compensate the loss of resources. Incentives may not be directly related to real money, but it must be something valuable in the network, so that even selfish nodes would consider cooperating to earn the incentives.

In pricing-based systems, incentives are used to stimulate relaying packets. Nodes in such systems gain micro-payments (or credits) for relaying packets, and they can use the payments (or credits) to send their own packets when relaying cooperation is needed. Buttyan and Hubaux proposed a credit-based system in [10], which uses probability payment. Such an approach is like a lottery: the source node just send credits along with the packet, and intermediate nodes can take credits from the packet as long as it receives the 'winning ticket', which is also given by the source node randomly. In [7], another approach is proposed for credit-based systems whereby the pricing for relaying each packet is governed by the length of the packet. This approach typically leads to a loss for long route relaying, but yields a profit for short route relaying. Naveen Shastry and Raviraj and S.Adve proposed a simple pricing game that can stimulates cooperation [1], where the source nodes only consider maximizing their utilities. Peter Marbach and Ying Qiu used an iterative algorithm for the nodes to adapt the price [6]. However, none of these approaches consider the fact that nodes will likely have budget constraints. That is to say, even nodes at the edge of the network, which suffer from having small chances of taking part in cooperation, do not need to worry about spending out their savings, which might cause them to become unable to send their own packets through relaying cooperation.

In this thesis, we provide the construction of a pricing-based system, and use the system to explore how would the nodes behave while having constraints in their budgets, and explore what can be utilized to achieve a better performance under that constrain.

2.2 Network centrality

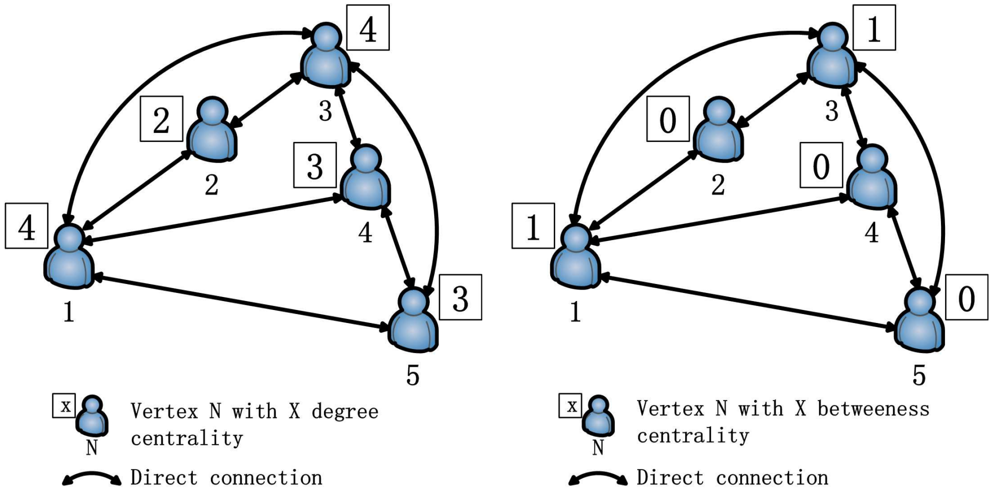
Centrality index is introduced to describe relative importance of a vertex in the graph structure. It is also widely used in measuring the relative importance of a given node in a network, since it concerns issues such as network resilience. Nodes with higher centrality usually have higher probability to communicate with other nodes, therefore, these nodes are more likely to be invited to take part in activities, like relaying cooperation. As a result, centrality is a very useful attribute to help in choosing nodes for efficient relaying cooperation, and regulating the behaviors in the network. Four measures of centrality are widely used in network analysis: degree centrality, betweenness centrality, closeness centrality and eigenvector centrality. Here we introduce two most popular ones, degree centrality and betweenness centrality.

2.2.1 Degree centrality

Degree centrality is defined as the number of connections with other vertices (or adjacent edges) that a given vertex has, which is also called degree in a graph structure. In [28], the mathematical definition of degree centrality is given as below (eq.2.1):

$$d(i) = \sum_{j} m_{ij}, \tag{2.1}$$

where $m_{ij} = 1$ if nodes i and j has connection, and $m_{ij} = 0$ if the connection does not exist. An example is given in Figure 2.2(a), where the numbers in boxes are degree centralities of specific vertices of the network. Such degree information is often of interest in social network analysis, and roughly indicates the relationship between two human beings. For directed networks, such as friendship graphs, degree centrality is separated into two parts, called indegree centrality and outdegree centrality; these two parts can be referred to as popularity and gregariousness respectively. However,



(a) An example for degree centrality (b) An example for betweenness centrality

Figure 2.2: Comparison of degree centrality and betweenness centrality

degree centrality can only emphasize the local information, which is not sufficient when studying the global effects of a node in a network. For example, such problems exist in the scenarios of fast recovery from network attacks.

2.2.2 Betweenness centrality

Betweenness centrality is another measurement of centrality that involves studying how many shortest paths between two vertices exist via the given one. Contrary to degree centrality, betweenness centrality has a global sense of the importance of given vertex. It tells us how many paths will become longer when a certain vertex is removed on purpose or becomes dead by accident. It is also interesting to note that the behaviors of a node with high betweenness centrality can have a control on the participating interactions. Such a scenario is very similar to the problem of relaying cooperation in communication networks. In fact, intermediate nodes with high betweenness centrality are more efficient in delivery of packets because they have more choices of possible paths. Theoretically, betweenness centrality is very useful for estimating behaviors of nodes and in deciding the best partner to choose in cooperation. One common definition of betweenness centrality index is given in [29] as (eq.2.2):

$$C_b(n_i) = \sum_{j}^{n} \sum_{k}^{n} \frac{g_{jk}(n_i)}{g_{jk}}, j < k, \tag{2.2}$$

where $g_{jk}(n_i)$ is the number of shortest paths between selected node pair j and k that pass node i, and g_{jk} is the number of all shortest paths between selected node pair j and k. Freeman also proposed two other definitions for betweenness-based centrality measure [29], one of them extend the betweenness centrality measure by considering the number of points in the graph, and the other takes an alternative view of centrality, which implies the dominance of one point in the graph. Figure 2.2(b) shows the betweenness centralities of the same network that was previously used in the example for degree centrality. As we can see, although vertex2 is different from vertex3 and vertex4 in degree centrality, the betweenness centrality for all of them are zeros. That means all three of these vertices have nothing to do with others' relationship, no matter how many connections they have.

Although betweenness centrality can globally describe the importance of nodes in the network, the calculation of betweenness centrality needs a complete description of all of the connections in a given network, which makes it impossible for a single node to compute based on information that is only locally available. We will introduce a new definition of centrality in Chapter 3, which is a revised version of betweenness centrality that can be achieved based on local information.

2.3 Fairness

Fairness in a network is related to how much of a fair share of the resources, such as bandwidth, timeslots, etc., that a node receives in the network. Just like in real society, a network system with fairness maintained is optimized for a sustainable operation. It is very hard to measure the fairness with a general approach, because different measures of fairness focus on different attributes of the system, and most of them involve tradeoffs. Several popular definitions of fairness are listed below:

2.3.1 Total capacity fairness

To maximize the sum of data rates of all data flows is the purpose of this measure of fairness. Jain's fairness index [21] is a very popular tool to show how fairness of data rate (throughput) can be allocated in a network, which was first proposed to measure the throughput fairness of a network. The fairness index actually measures the "equality" of the resources allocated to users, that is to say, if all users get the same share of the resources, the fairness index reaches its maximum, which is equal to 1.

The definition of Jain's fairness index is showed below (eq.2.3):

$$f(x) = \frac{\left[\sum_{i=1}^{n} x_i\right]^2}{\sum_{i=1}^{n} x_i^2}, \tag{2.3}$$

where x_i is the resources allocated to the node i. An extension of total capacity fairness that maximizes a weighted sum of data rates wireless network is proposed in [30]. Jain gave the definition of this general weighted fairness in [30] as following (eq.2.4):

$$a_i = \lambda_i + \frac{w_i(B - \lambda)}{\sum_{j=1}^{n} w_j}, \tag{2.4}$$

where

a_i = general weighted fair allocation for connection i

B = excess bandwidth to be shared among candidate connections

w_i = predetermined weight associated with the connection i

λ_i = minimum cell rate of candidate connections i

λ = sum of minimum cell rate of candidate connections

n = number of candidate connections

In this definition, only excess bandwidth is allocated proportional to predetermined weights. However total capacity fairness, which is a throughput based fairness, has been shown to be unsuitable for wireless networks because it can report high values of unfairness in wireless when transmission power tends to infinity [22].

2.3.2 Max-min fairness

Conventional max-min fairness is defined by flow rate, which is referred to end-to-end transmission rate of a flow. The approach is that the minimum data rate requirement of flows is firstly maximized, and then the second lowest data rate requirement is maximized, and so on. This criterion is suitable for wired networks, since flows in wired networks do not contend against each other for the resource, which is the link bandwidth. However, in wireless networks, the effect of intra-flow contention and unequal channel capacity [12] cause efficiency problems with max-min fairness.

2.3.3 Proportional fairness

Proportional fairness was first introduced by Kelly [31] as an alternative to max-min fairness. The aim of proportional fairness is to balance fairness and efficiency of the network. This is achieved by allocating an optimal data rate to each of the data flows, which is inversely proportional to its resource consumptions. In [22], B. Radunovic and J.-Y. Le Boudec numerically showed that proportional fairness of rates can achieve a better trade-off between fairness and efficiency than max-min fairness in multi-hop wireless networks.

In our thesis, we will use economic balance to indicate the fairness of the network. Details of this fairness are introduced in Chapter 3, but the basic idea is that fairness is achieved when every node has the same share of the total amount of incentives in a network, assuming we start with a fixed total amount of incentives, and allow the networked system to communicate for a period of time to achieve the steady-state. The reason we use this fairness is because it is a parameter locally bound to each node, and it has a direct correlation with the number of packets that the node has relayed.

2.4 Law governed interaction (LGI)

2.4.1 Introduction of LGI

LGI was first introduced by N.H. Minsky [24]; it is a mechanism for exchanging messages that allows an open group of distributed agents to interact under designed policies. The agents are software blocks written in arbitrary languages, and the structure of them are unlimited. The only requirement for communications between agents is that the messages as a language used in communications should be constrained by designed laws, we call it $\mathcal{L}$-messages. This unique requirement ensures that agents of the same group can communicate with each other, by the same group here it means being able to use the $\mathcal{L}$-messages that comply with same laws in communications. Besides agents, the LGI mechanism makes a strict separation between policies and a set of policy independent executors, called controllers. It is an essential property of LGI that the controllers are implemented to ensure the policies be executed strictly by following involved laws. Each law consists of many basic elements, which are called rules. These rules are usually described by a pseudo-code in event-condition-action form:

$$\mathbf{UPON} \quad e \quad \mathbf{IF} \quad c \quad \mathbf{DO} \quad [o], \tag{2.5}$$

where e is an event, c is an optional condition, and o is the set of primitive operations. That means, actions $[o]$ should be executed if the condition c is true when event e happens. The involved events and primitive operations can be represented by following notations:

(a) send(m): a "sent" event, representing the case that a message m is sent from an agent to a destination, which is not specified here,

(b) arrived(m): a "arrive" event, representing an arrival of a message m at the home agent,

(c) forward(m): an "forward" action, representing that the controller forwards the message m from the agent to the destination defined by sent event, which is not specified here,

(d) acceptMessage(m): an "accept" action, representing that the controller gives the permission to accept the arrived message m, An example of law $\mathcal{ST}$ is provided as pseudo-code in Table 2.1. This law is defined by two event-condition-action rules. Each rule starts with an index and ends with a comment. First rule $\mathcal{R}1$ only allows the special component called *mgr* to send the message *setTime(k)*, which is to set the remote clock to *k*. By second rule $\mathcal{R}2$, when the message *setTime(k)* arrives at its destination, the agent sets its local parameter *localTime* to received value *k*. Through this law $\mathcal{ST}$, the action to set up a remote clock is locally constrained by designed rules.

Table 2.1: A pseudo-code representation for the example law $\mathcal{ST}$ of Set Time

$\mathcal{R}1.$	**UPON** sent(setTime(k)) **IF** sender=mgr **DO** [forward(setTime(k))] *If message setTime(k) is sent, and the mgr is the sender, this message is forwarded to its destination.*
$\mathcal{R}2.$	**UPON** arrived(setTime(k)) **DO** [localTime=k; acceptMessage(setTime(k))] *Triggered by the arrival of message setTime(k), the variable localTime is set to value k, and the message is accepted by the actor.*

2.4.2 Elements of LGI

The LGI system consists of four main elements: agents, controllers, control-state, and laws, as illustrated in Figure 2.3. All controllers maintain the control-state $\mathcal{CS}$, which is a set of attributes for the given agent that connects to the controller. Controllers have the same copies of the laws $\mathcal{L}$ for every group. Both agents and controllers are independent of policies, so that a given agent can join different policies simultaneously. However, agents are expected to be responsible for being familiar with the laws that used by policies, because laws are enforced by controllers which are also separated from agents, and cannot be violated by any agent, even one who does not know the law.

2.4.3 Electronic-commerce with LGI

Electronic-commerce(e-commerce), which is the core subject of online transaction, is being adopted because of its efficiency compared to the conventional commercial activities. Such efficiency highly requires secure policies that can be viewed as the

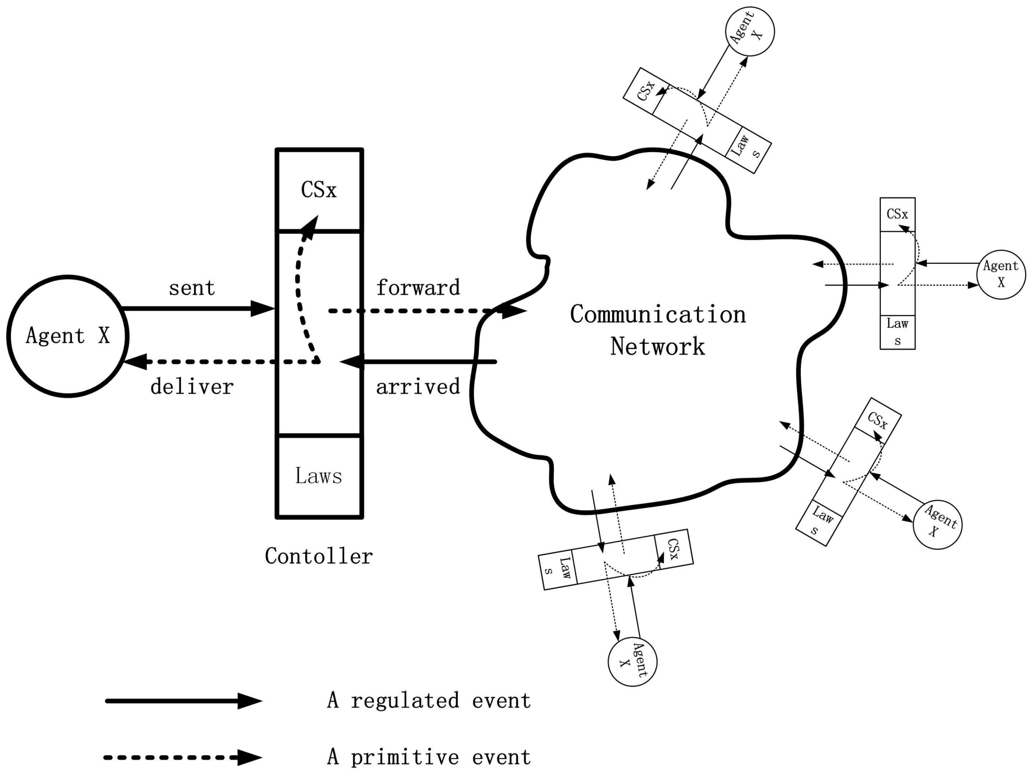


Figure 2.3: LGI model

contracts between clients and merchandisers involved in the transactions. A commercial policy may face various issues. For example, it is necessary to prevent digital coins used as currency from being duplicated, or it may be desirable to ensure the privacy of the clients or merchandisers being protected. Unfortunately, there is no universal policy that can solve all such issues. Traditional commercial activities may contain many policies focusing on different issues, and further there are many implementations of the various policies involved in electronic commerce. However, due to the flexibility of e-commerce, the deployment of these implementations are very vulnerable to malicious manipulation as participants of a transaction can easily modify their interface to make high profit. In recent research, LGI was proposed to be used for e-commerce, the policies in e-commerce can easily be defined and deployed by combining certain predefined laws. With the help of LGI, different policies can be adopted by a single agent in different commercial activities. Further, agents are forced to follow the laws by the policy independent trusted controllers. Examples of

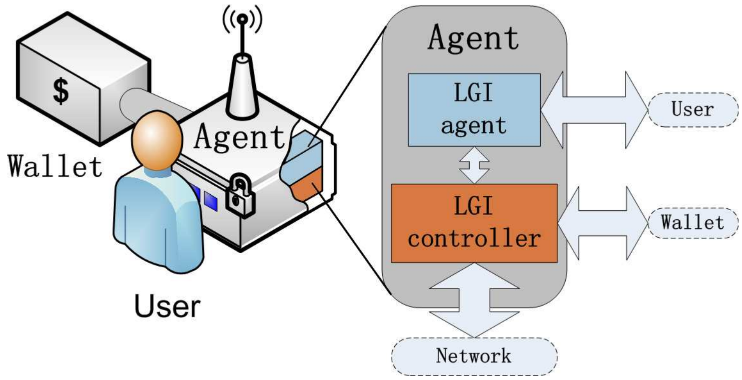


Figure 2.4: Detail structure of a single agent

e-commerce applications implemented by LGI can be found in [26, 32, 33].

In this thesis, we are going to use digital coins as the incentives to stimulate relaying cooperation, which we view as electronic commercial activities. The required commercial policies can be conveniently implemented by using LGI defined agents and controllers. As showed in Figure 2.4, a designed "Agent" consists of a LGI agent and a LGI controller, inside which the LGI agent is supposed to be ruled by the LGI controller. The "Agent" can be thought as a black box to users, so that users cannot make any malicious change to the controller. A new object called "Wallet" is proposed in this thesis for the purpose of storing digital coins and recording transactions. The "Wallet" can only be operated by the corresponding user's agent via a controller. This makes the "Wallet" also separate from users, agents and policies, which means it is protected by the controller from illegal usages of digital coins.

Chapter 3

System Description

In this chapter, we are going to introduce our pricing-based relaying cooperation. First, several definitions are provided to introduce the system. Then the assumptions for the system and experiments are listed. Finally, we introduce our strategies of pricing adjustment.

3.1 Definitions

3.1.1 Task

In this thesis, a task is defined as a selected node transmitting a certain number of packets to another selected node during specific time period. We denoted a task by $\mathcal{T}_k(ID_s, ID_d, P_k, \mathcal{T}_k)$, where ID_s and ID_d are ID of source and destination respectively, P_k is the number of packets to be transmitted, and $\mathcal{T}_k$ is the time period designed for the task $\mathcal{T}_k$.

3.1.2 Local centrality

We define the local centrality as the number of cooperation that a node has taken during the specific time period, denoted by $\mathcal{C}_i$, where i indicates the ith node of the network. To complete the definition, we first define the indicator function of node i for kth task as following:

$$S_i^k = \begin{cases} 1, & \textit{node } i \textit{ cooperates in task } k \\ 0, & \textit{node } i \textit{ does not cooperate in task } k \end{cases} \tag{3.1}$$

Hence the local centrality of ith node can be calculated by the equation showed below.

$$\mathcal{C}_i = \sum_{k=1}^{N_{total}} S_i^k, \tag{3.2}$$

where the N_{total} is the total number of tasks.

3.1.3 Centrality fairness

Following the introduction of local centrality, we can define the fairness of a network as the statistical variance of the local centralities of every node in the system at a particular instant, which is shown in (eq. 3.3).

$$F_n = Var(\mathcal{C}_n), \tag{3.3}$$

Since it stands to reason that the more *evenly* distributed are the chances to participate in network tasks, the more fair the network is, then smaller values of centrality fairness implies that max fairness exists in the network.

3.1.4 Local utility ratio

We defined the local utility ratio of a node as the times the node has taken part in the cooperation to the times it has requested for cooperation, denoted by U_i which is shown below.

$$U_i = \frac{n_i}{r_i}, \tag{3.4}$$

where n_i is the number of cooperation events that the ith node has participated, and r_i is the number of requests that the ith node has issued.

3.1.5 "Agent" and "Wallet"

Previously in 2, we mentioned that we will use LGI structured "Agent" in this thesis as the motivational framework for building and enforcing electronic commerce policies related to network cooperation. The "Agent" is a program integrated with each node,

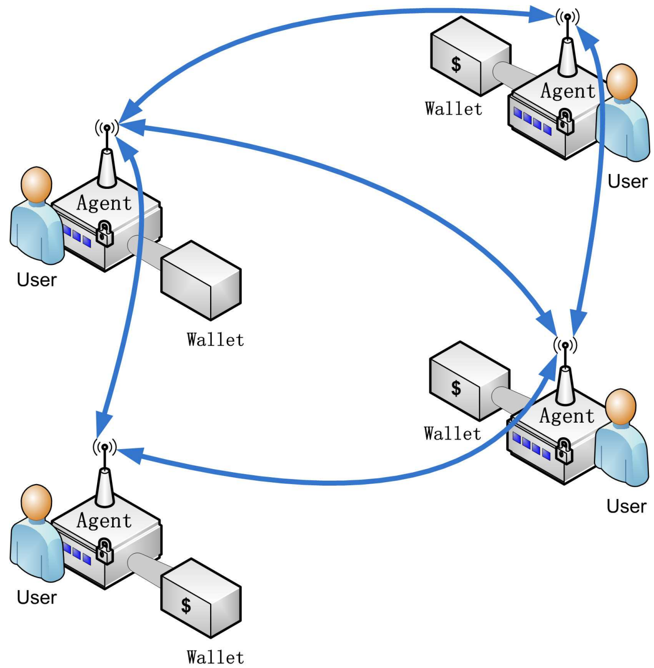


Figure 3.1: An illustration of "Agents"

as corresponds to the depiction of LGI shown in Figure 2.3. In addition to managing policies, the "Agent" executes the pricing adjustment strategies for the user it attaches to, and acts as a trustworthy third party between user and the network, or, user and his money account called "Wallet" in the system. It is also the responsibility of an "Agent" to guarantee the success and the security of each task it takes part in. All the abilities of "Agents" are bounded by regulations called laws in LGI, which are software building blocks provided by controllers inside the "Agents". As shown in Figure 3.1, the "Agents" work between users and networks, which indicates that only "Agents" can actually complete the tasks, and hence access the "Wallets" of particular users as well.

The "Wallet" is an isolated object with available actions: "Deposit" and "Withdraw". It is only authorized to the "Agent" that serves the same owner of the "Wallet", and all transactions are recorded. None of the users can directly access the "Wallet", not even the transaction records. We adopted this design to eliminate possible misbehavior to the "Wallet", such as illegal duplication of digital coins.

3.1.6 Balance and digital coin

This thesis uses balance B_i to indicate the amount of incentives held in the "Wallet" of node i. The incentives used in the thesis are digital coins, which in the system are representatives of real money. Initially, real money is withdrew from the bank in the form of digital coins by the "Agent", and deposited to the corresponding "Wallet". In fact digital coins can also be redeemed via "Agents" if users want to, the redeemed cash can be consumed outside the network, or deposited to the banking account.

As the most important character of digital coins, off-line anonymous transaction is the reason why digital coins are used in our system. Doing transactions without the attendance of users is very convenient for a distributed system, for example the pricing-based relaying cooperation system in wireless ad hoc network.

3.1.7 Fairness

Unlike other systems, we are not going to use throughput or other physical attributes of communications to evaluate the fairness of the network. Instead, fairness is defined as the economic balance of the network in our system. That is to say, the system achieves its best fairness when the balance is equitably distributed across the nodes of the network (after the network has been working for a certain amount of time).

3.1.8 Incentives and pricing

Our incentives are defined as digital coins, which are initially deposited into each node's account. The total amount of incentives are fixed, the only way to earn the incentive in the system is through the relaying of packets. Hence the pricing of cooperation is the key weapon for fighting for fairness in this economic environment: whichever path has the lowest price for relaying cooperation will win the competition, and the nodes on the path will benefit from winning the competition.

3.2 Assumptions

Here, we list the assumptions for the system and experiments we had in this thesis.

- Each user will attach to only one “Agent”, and one “Wallet”.
- Certain amount of incentives are initially deposited to every “Wallet”, and each “Wallet” does not have a limitation an the maximum balance it can hold.
- The only way to collect incentives in the system is to relay packets for other nodes; the only way to lose incentives in the system is to transmit packets via some intermediate nodes.
- The minimum denomination of digital coins, which we use as incentives, is 1 coin, and the value of the digital coin is same for every node of the system.
- Although the incentives are redeemable, the total amount of incentives in the whole system is assumed to be fixed. That is to say, users are assumed not to redeem their incentives during any experiment.
- Users are the ones who give orders to “Agents”. They are all assumed to be well-behaved in the system, which means no malicious activities exist.
- The “Agents” used in the system are assumed to be trustworthy and unbreakable, thus any security related or privacy related issues are taken care of by “Agents”.
- The environment of wireless communication is assumed to be stable, no interference exists during any transaction. Thus, there is no packet loss in our experiments. This was a necessary simplification for this preliminary analysis.
- For every task, incentives are assumed to be paid for each relayed packet. Such assumption can guarantee that the intermediate nodes will receive compensation for their relaying cooperation.
- In our experiments, the communication pairs are selected randomly for each task, so that every node has an equal chance to be a source node or a destination node.
- To prevent interference and to make the experimental results clear, we assume that the system will have only one task at a time, and every communication task is assumed to last for the same length of time.

3.3 Strategies of pricing adjustment

Strategies of pricing adjustment are categorized according to the three modes for different control variables used in the strategies. We compare the results of the experiments using different pricing adjustment modes to find the strategy that can achieve the best fairness for the network. Later, we will fine tune the parameters of the chosen mode to achieve an optimum results. In the pricing adjustment modes, we describe the pricing in terms of pricing rate r_n^k, which is the unit price of the kth node for relaying per packet at time n. The price P_n^k of node k for one packet can be calculated with following equation.

$$P_n^k = r_n^k * \nu_i, \tag{3.5}$$

where ν_i is the number of bytes for one packet in ith task. As a default, the pricing rate r_n^k is refreshed every 10 seconds, this time interval τ is also a very important control variable which will be showed in Chapter 4.

- Mode 1: Savings control mode, where the "Agent" decides whether to adjust the current pricing rate (r_n^k) or not by observing the savings of digital coins in the account of each node. If the current balance is larger than the previous balance, this node increases the charge rate, otherwise, it reduce the charge rate, we set the effective region of r_{n-1^k} is $0.6 \leq r_{n-1}^k < 1$ to prevent the pricing adjustment being too aggressive. The pricing rate for node k can be calculated as following:

$$r_n^k = r_{n-1}^k + \frac{B_n^k - B_{n-1}^k - \gamma_B^k}{\left|B_n^k - B_{n-1}^k - \gamma_B^k\right|} * \Delta, \quad 0.6 \leq r_{n-1}^k < 1, \tag{3.6}$$

  where B_n^k is the balance of node$k$ at time n, and γ_B^k is the threshold for the difference of balance of node$k$, which has the default value of 0.

- Mode 2: Centrality control mode, where the "Agent" decide whether to adjust the pricing or not by observing the local centrality of each node previously defined. If the current centrality is larger than the previous saved centrality for γ_C^k, this node will increase the charge rate, otherwise, it will reduce the charge rate. The effective region for r_{n-1} is $0.6 \leq r_{n-1}^k < 1$. The pricing rate update is calculated as follows:

$$r_n^k = r_{n-1}^k + \frac{C_{n-1}^k - C_n^k - \gamma_C^k}{\left|C_{n-1}^k - C_n^k - \gamma_C^k\right|} * \Delta, \quad 0.6 \leq r_{n-1}^k < 1, \tag{3.7}$$

where C_n^k is the local centrality of node k at time n, and γ_C^k is the threshold for the difference in the centrality of node k, which has a default value of 0.

- Mode 3: Ratio control mode, where the "Agent" decides whether to adjust the pricing or not by observing the local utility ratio U_i introduced in chapter2 (eq. 3.4). If the ratio is larger than γ_R^k, this node increases the charge rate, otherwise, it reduces the charge rate. The effective region of r_{n-1} is the same as mode 1 and mode 2. The update for γ_n^k is as follows:

$$r_n^k = r_{n-1}^k + \frac{U_k - \gamma_U^k}{\left|U_k - \gamma_U^k\right|} * \Delta, \quad 0.6 \leq r_{n-1}^k < 1, \tag{3.8}$$

where U_k is the local utility ratio of node k at time n, and γ_U^k is the threshold for the local utility ratio of node k, which has a default value of 1.

3.4 Pricing-based cooperation in LGI

We assume the pricing-based cooperation system that we proposed is implemented using LGI to achieve the security. The interactions involved in cooperation can be roughly divided into two parts: first part is to choose partners for cooperation, which is a preparation for the cooperation; second part is to accomplish the cooperation with selected partners. For the first part, there are three stages: a) request for help; b) answer with prices; c) compare received prices and make a decision. The request of cooperation will be sent out to all the neighbors from the source node, if any neighbor can directly reach the destination, it will answer with his price for this single hop relaying cooperation, otherwise, the request will be handed over to this particular node's neighbors. In the latter scenario, the total price for relaying through each intermediate node will be added together and sent back to the source node that issued the request. Finally, the source node will receive one or more than one answers for his request, a decision will be made based on the total price included in the received message. The second part is the exchange of messages between nodes. This topic is a normal issue in communications, and we don't explain the details in this thesis. These interactions mentioned above are restricted by laws that are analogous to the pseudo-codes shown in the Table (3.1). Note that these pseudo-codes are just a fragment of the laws of the pricing-based cooperation system, there are many other laws required in the whole pricing-based cooperation system, such as $\mathcal{WH}$ for Wallet Handling, which is for handling all the actions related to "Wallet".

Table 3.1: A fragment of the law of pricing-based cooperation

$\mathcal{R}1.$	**UPON** send(taskRequest, dest_addr) **DO** [forward(taskRequest, dest_addr, req_id)] *Triggered by the message (taskRequest, dest_addr), the message will be forwarded to all its neighbors with an id of request for preventing duplication.*
$\mathcal{R}2.$	**UPON** arrived(taskRequest, dest_addr, req_id) **IF** req_id=/=last_req **DO** [acceptMessage] *When receiving the message (taskRequest, dest_addr, req_id), if the request received last time has different id, accept the message, otherwise, ignore the message.*
$\mathcal{R}3.$	**UPON** send(acceptRequest, req_id) **IF** isReachable=True **DO** [forward(acceptRequest, req_id, localprice] **IF** isReachable=False **DO** [price=localprice+nextprice; forward(acceptRequest, req_id, price] *The message (acceptRequest, req_id) is forwarded to the node that sends out the request of cooperation with the localprice for relaying cooperation, only if the destination of this relaying task is reachable. Otherwise, the price forwarded to the requesting node is the sum of localprice and the nextprice offered by next cooperative node.*
$\mathcal{R}4.$	**UPON** arrived(acceptRequest, req_id, p) **IF** (req_id=my_req) AND (p<=localbalance) **DO** [acceptMessage] **IF** req_id=/=my_req **DO** [newprice=localprice+p; forward(acceptRequest, req_id, newprice)] *When the message (accepRequest, req_id, p) arrives, if this is the sender of the request and the offered price is affordable, accept the message, else if this is not the sender of the request, forward the message with updated price to the node that sends out the request.*

Chapter 4

Experimental Results and Aenalysis

This chapter includes three parts. First, we are going to present experiments that will illustrate the different behaviors that nodes in static topologies and dynamic topologies exhibit respectively. Second, we will show the best strategy to use to keep the network fair. Finally, we will fine tune the parameters for the best strategy of pricing adjustment to find a set of parameters that can achieve the best fairness for a given network. The experiments that we are going to introduce are all listed in Table 4.1, and details will be given later through corresponding sections.

4.1 Part I: Experiments with static and dynamic topologies

4.1.1 Importance of topologies

The topology of a network indicates the relationships between nodes of the network, which also has an impact on the fairness of the network. Due to the limitation of geographical positions or energy consumption, it is almost impossible for every node to have connections with all other nodes. This provides opportunities for relaying cooperation. However, different topological and operational settings may cause nodes having extremely different opportunities to participate in relaying cooperation. Just as we mentioned in the previous chapter, the limited incentives (budget) of each node will soon be spent if the node has an isolated position in the network, e.g. is at the edge of the network. Thus, topology is the most important character in determining the fairness of a network.

In general, topologies can be divided into two categories, static topologies and dynamic topologies. In the former, topologies do not change or seldom change, so

Table 4.1: List of the experiments presented in this thesis

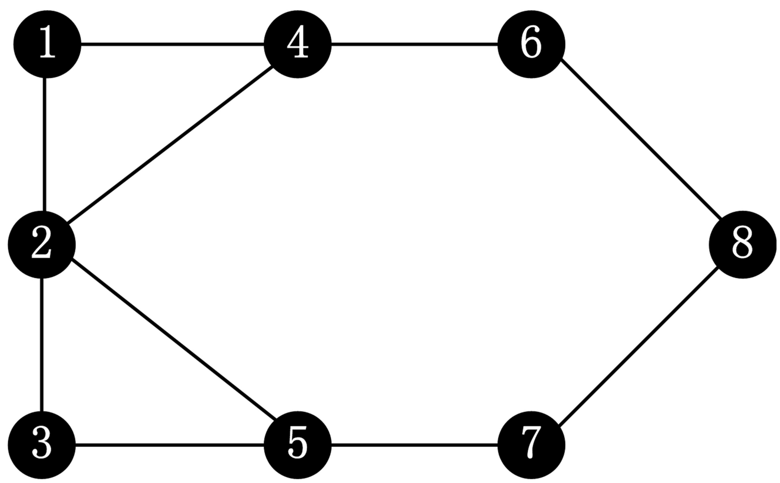
Part I			
Exp. index	Topologies	Strategies	Parameters
1	Static $S1$	Strategy mode1	$\tau = 10s$ $\gamma_*^k = 0$ $\Delta = 0.1$
2	Static $S2$	Strategy mode1	
3	Dynamic $D1$	Strategy mode1	
4	Dynamic $D1$	Strategy mode1	
Part II			
5	New dynamic N1	Strategy mode1	$\tau = 10s$ $\gamma_*^k = 0$ $\Delta = 0.1$
6	New dynamic N1	Strategy mode2	
7	New dynamic N1	Strategy mode3	
Part III			
Exp. index	Topologies	Strategies	Parameters
8	New dynamic N1	Strategy mode1,mode2,mode3	$\tau = 0.1s, 30s, 60s, 120s$ $\gamma_B^k = 0$ $\Delta = 0.1$
9	New dynamic N1	Strategy mode1,mode2,mode3	$\tau = 60s$ $\gamma_B^k = 0$ $\Delta = 0.00125, 0.4$
10	New dynamic N1	Strategy mode1,mode2,mode3	$\tau = 30, 60s$ $\gamma_B^k = \pm 10P_{n-1}^k$ $, 10P_{n-1}^k / 10P_{n-1}^k$ $\Delta = 0.00125$

nodes won't have a chance to pursue more opportunities to relay packets. In the latter, topologies can often change by means of node mobility. Nodes with bad initial position can easily change their situation by moving towards the center of the network, which will provide more opportunities to relay packets. We did many experiments to study the behavior of nodes for both categories of topologies. The experiments are set up as follows.

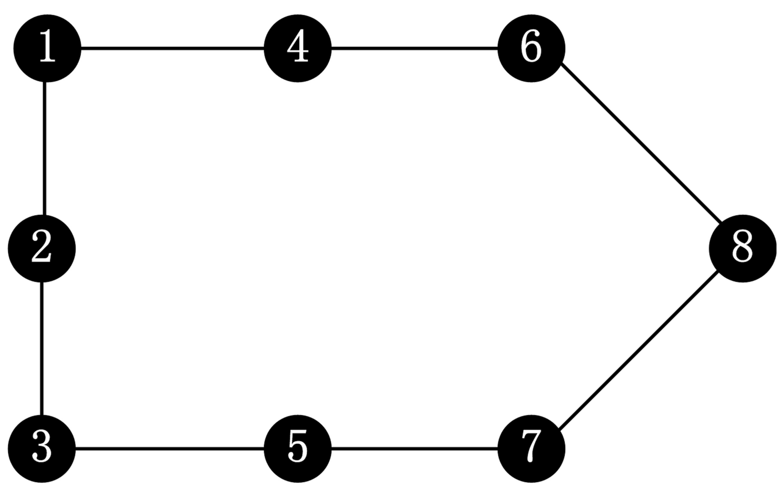
4.1.2 Experiment setup

Static topology

Two static topologies, topology $S1$ (Figure 4.1(a)) and topology $S2$ (Figure 4.1(b)) are studied in this thesis. Both topologies have 8 nodes and the same geographical positions for the nodes, but the connections for node2 are slightly different. This small difference makes node1 and node3 have very different opportunities to relay packets in the two topologies. Details of the setup for these two topologies are given below:



(a) Static topology S1



(b) Static topology S2

Figure 4.1: Static topologies used in the thesis

- Parameters:

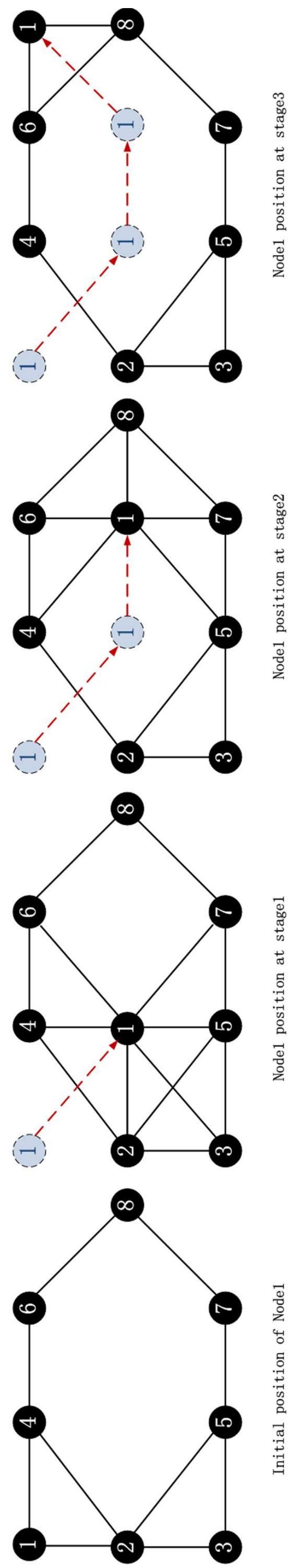
- Number of nodes (K): 8
- Number of tasks included (N_{total}): 600
- Types of tasks: all relaying
- Initial amount of digital coins (B_{init}): 3000000
- Initial pricing rate (r_{init}): 1/Byte
- Seconds of per task: 2 s/7.5 s (transmission only/total)
- Length of per packet (ν_i): 800 Bytes
- Task logging rate: 10 times/s
- Strategy of pricing adjustment: none

- Short comment: In topology $S1$, node2 has connections with node4 and node5, which makes shortcuts that bypass node1 and node3. That is to say, any task that needs cooperation will ignore node1 and node3, because they can never offer a price for relaying packets better than 0 for direct connections. While in topology $S2$, node2 only has connections with node1 and node3, and tasks that need cooperation may choose node1 and node3 as the intermediate node.

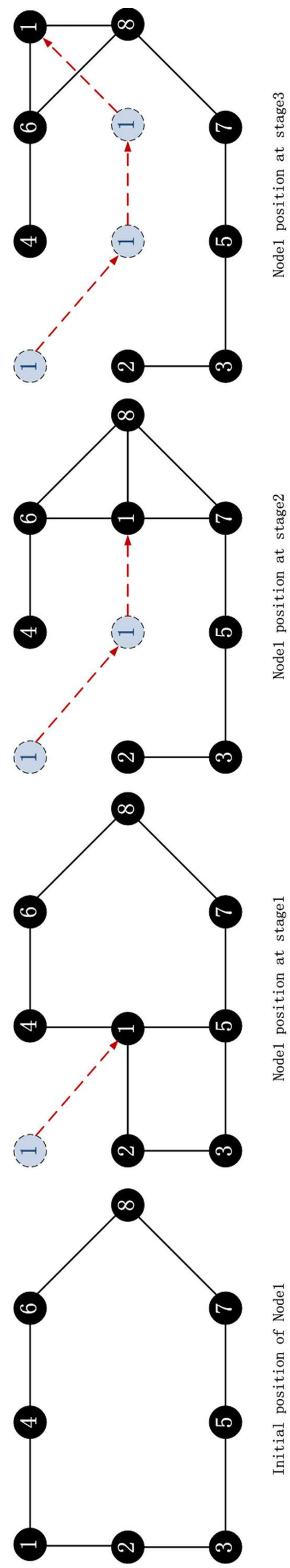
Dynamic topology

Two dynamic topologies are used in this thesis, topology $D1$ (Figure 4.2(a)) and $D2$ (Figure 4.2(b)). These two topologies are derived from the static topologies $S1$ and $S2$. As the pictures show, node1 is traveling through the network for three stages. With the help of mobility, a node can easily increase the number of connections in the network by moving towards the center of the network. For the same reason, opportunities to participate in relaying cooperation also vary according with the changes of relative geographical position of node1.

- Parameters:
  - Number of nodes (K): 8
  - Number of tasks included (N_{total}): 600



(a) Dynamic topology D1



(b) Dynamic topology D2

Figure 4.2: Dynamic topologies used in the thesis

  - Types of tasks: all relaying
  - Initial amount of digital coins (B_{init}): 3000000
  - Initial pricing rate (r_{init}): 1/Byte
  - Seconds of per task: 2 s/7.5 s (transmission only/total)
  - Length of per packet (ν_i): 800 Bytes
  - Task logging rate: 10 times/s
  - Strategy of pricing adjustment: none

- Short comment: Starting from static topology $S1$ mentioned earlier, topology $D1$ has node1 moving through the network. With the movement, the betweenness centrality of node1 changes accordingly, and the chances of being invited to a relaying cooperation change with the centrality. In topology $D2$, node1 has the same traveling route as it has in $D1$, but certain shortcuts are removed from $D1$, just as it is in static topology $S2$. We will see in the following chapter that the fairness of this network is better than the others. The reason for this is because initially there are no shortcuts that can bypass node1 and node3, and later the node can move to even better positions.

4.1.3 Results and analysis

Limitation of the static topology

First, we will show the results of the experiments under topology $S1$ and topology $S2$, where node1 has totally different economic abilities in these two topologies, although the difference between the topologies is very small. In topology $S1$, node1 is bypassed by the direct connection between node2 and node4, this makes node1 isolated from any relaying cooperation, similarly for node3. No matter what price for relaying packets node1 offers, it is always more expensive than a direct connection without paying between node2 and node4. In Figure 4.3, the solid line with circle and rectangle indicate the balance of node1 in topology $S1$ and topology $S2$ respectively. The balance for node1 in topology $S2$ doesn't drop as fast as it does in topology $S1$.

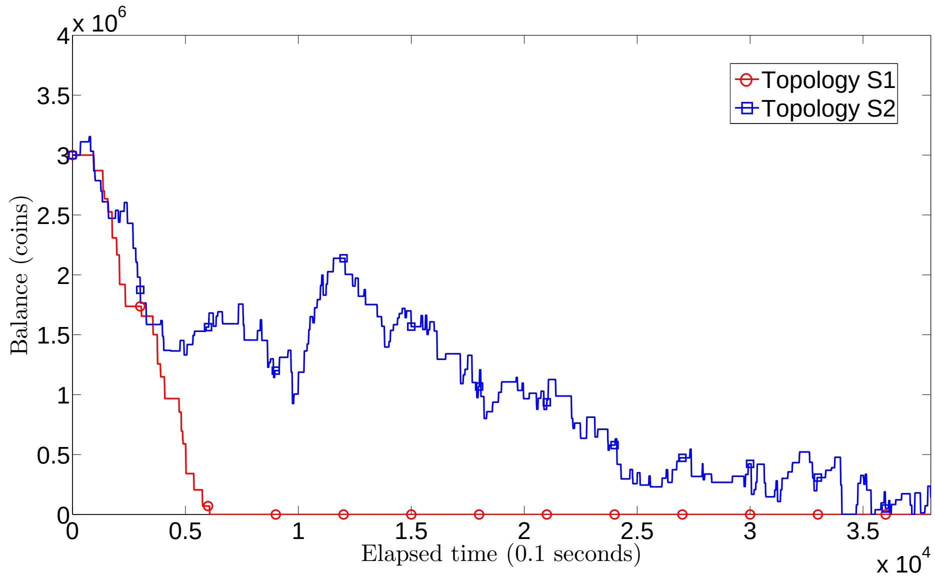


Figure 4.3: A comparison of balance of node1 between static topology $S1$ and S2

In fact, it even has some increments during the experiment. These increments allow node1 to survive longer in the network, which is a mission impossible for node1 in the topology $S1$. However, because of the static property, all static topologies will eventually face the problem that the edge nodes become isolated and eventually unable to participate. It is also the aim of this thesis to alleviate this difficulty in some ways.

Second, if we take a look at the Figure 4.4, which is the comparison of fairness for these two scenarios, we will find that topology $S2$ does have better centrality fairness than topology $S1$. In addition, we can also find the correlation between the distribution of local centrality and cumulative balances through this experiment (Figure 4.5). Note that the value in Figure 4.5 are collected at the end of the experiment, however this correlation exists throughout the experiment. It is clear that the distribution of digital coins in the network follows the distribution of local centralities, which has been proposed as a conclusion of [8]. With all the comparisons given above, we can further conclude that, for a long running experiment, the topology impacts the behaviors of nodes within the network, and a node's balance has a direct correlation with its local centrality.

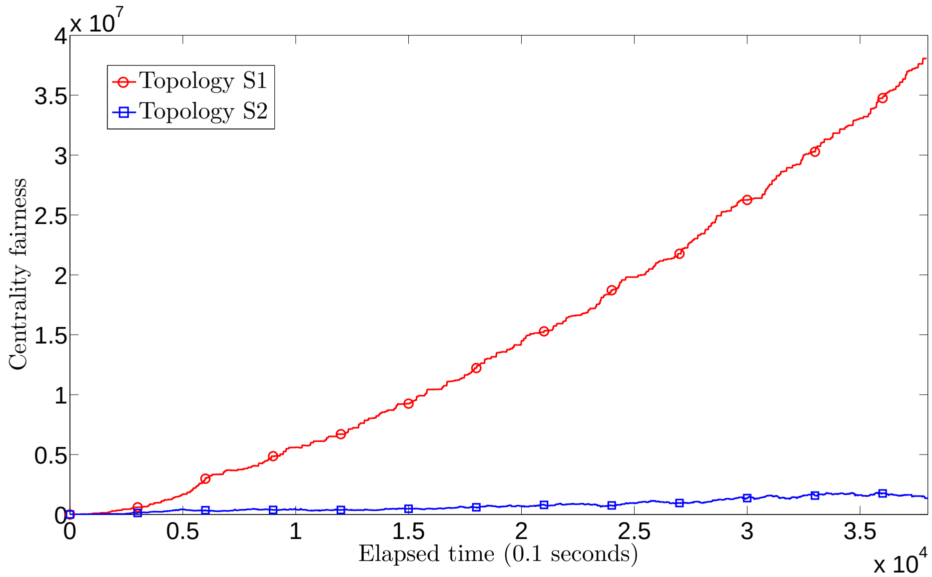
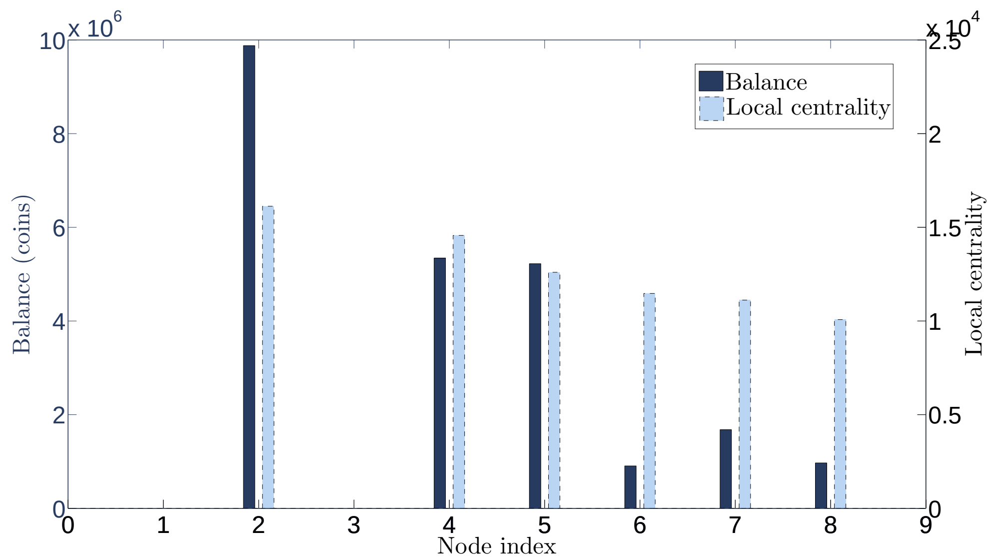


Figure 4.4: A comparison of fairness between static topologies $S1$ and S2

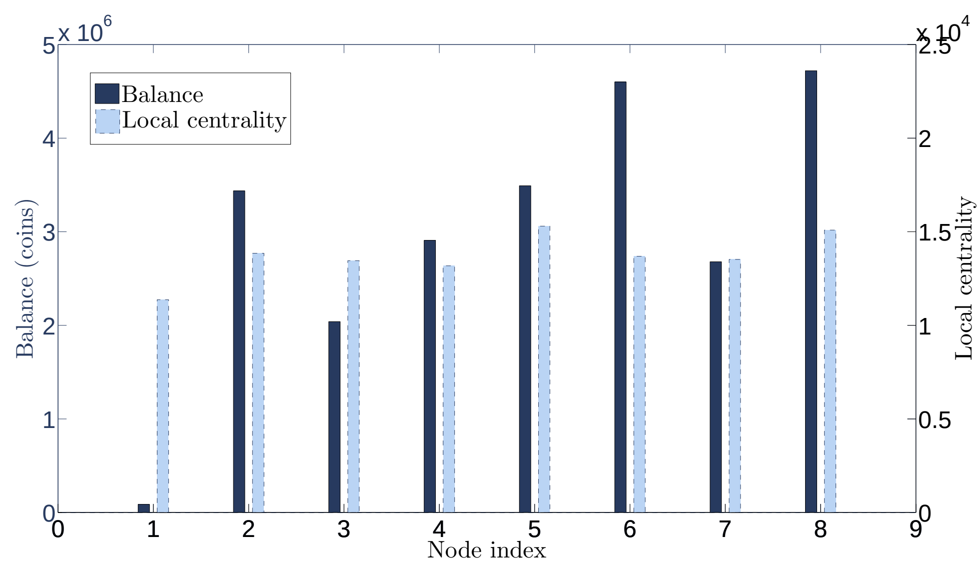
Mobility creates chances for economic opportunity

In Figure 4.6, we compare the cumulative balance of node1 in the static topology $S1$ and the dynamic topology $D1$, the centrality fairness of these two scenarios are also given in Figure 4.7. The cumulative balance of node1 in topology $S1$, which is indicated by the red line in Figure 4.6, goes all the way down to zero at time around $1200s$, while the cumulative balance of node1 in topology $D1$ indicated by the blue line stops dropping and keeps increasing after around $1100s$. Obviously, node1 in topology $D1$, benefitting from its mobility, not only has a moderate speed of decrement in its limited balance, but even earns a great fortune after the node changes its position. When node1 moves towards the center of the network, more connections are available, which leads to more chances to participate in cooperation. This significant change is because as that node travels through the network, the topology changes, which changes the node's local centrality and creates opportunities to participate in possible cooperation.

The comparison of centrality fairness showed in Figure 4.7 further presents a clear picture of the difference between the dynamic topology and the static topology. The dynamic topology $D1$ with a flat line of centrality fairness, has better fairness than



(a) Comparison for topology S1



(b) Comparison for topology S2

Figure 4.5: A comparison between balance and centrality for static topology $S1$ and S2

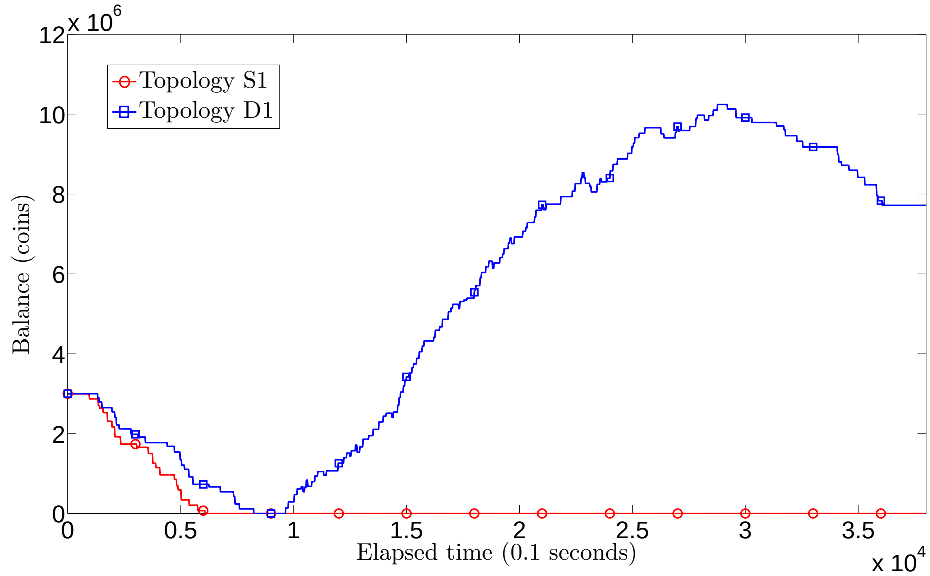


Figure 4.6: Balance of node1 in different topologies for static $S1$ and dynamic D1

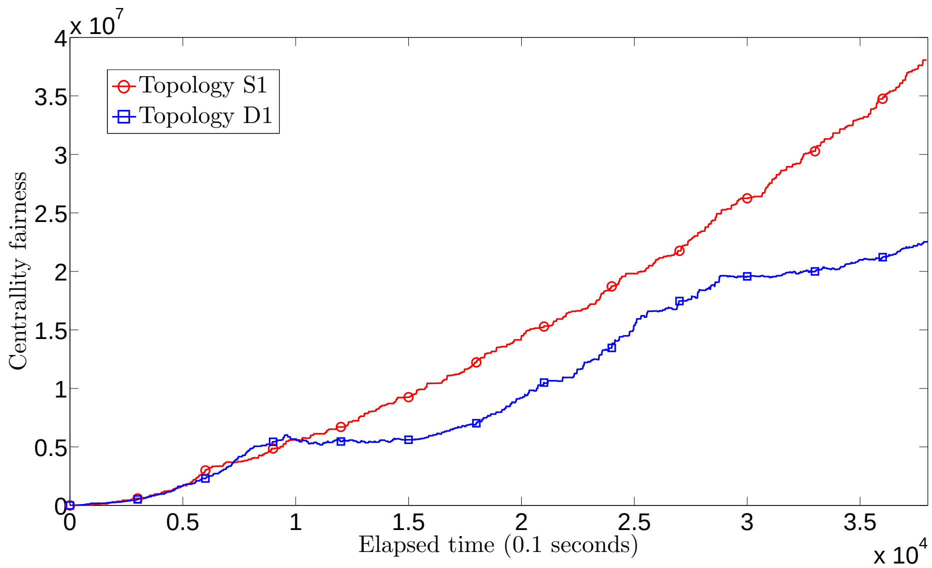
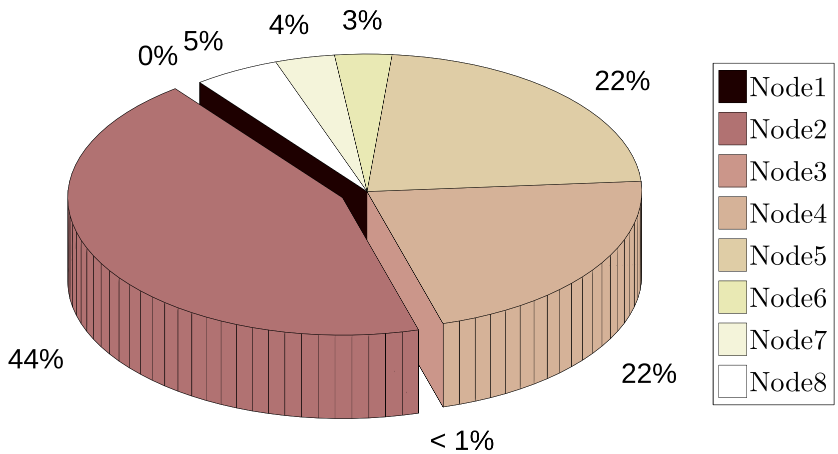
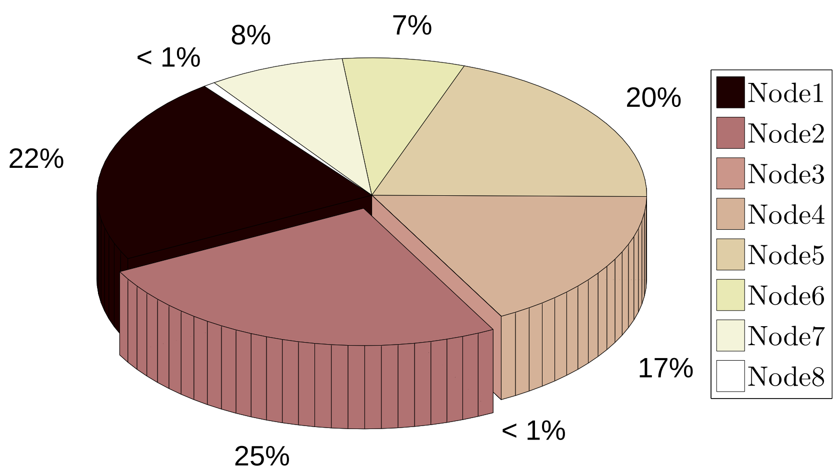


Figure 4.7: A comparison of centrality fairness of topologies $S1$ and $D1$



(a) Balances of nodes in topology S1



(b) Balances of nodes in topology D1

Figure 4.8: A comparison of balances of nodes in different topologies

another topology $S1$ does, and, as a result, topology $D1$ has an even distribution of digital coins after the completion of the experiment(Figure 4.8), comparing to the topology $S1$. The remaining balance of node1 grew up to 22% in topology $D1$, which was 0% in topology $S1$. This great change of cumulative balance makes node1 able to afford more tasks that will need cooperation.

4.2 Part II: Experiments for pricing adjustment modes

The previous section proves that topologies strongly affect the fairness of networks and a node's ability to earn digital coins. A network with dynamic topology may provide more fairness than a network with static topology. However, if the static topology is given, is that possible to improve the fairness of the network without forcing nodes moving around? The answer is yes. In this part we are going to show experiments involving different strategies for pricing adjustment, in hopes to find a best one that should have the best ability to keep the fairness of a static network. In Table 4.2, we again list three modes mentioned in Chapter 3. We will see that, although all of the results show the same trend of changes in balances, the strategy based on balance is the one we are looking for.

Table 4.2: Strategies of pricing adjustment

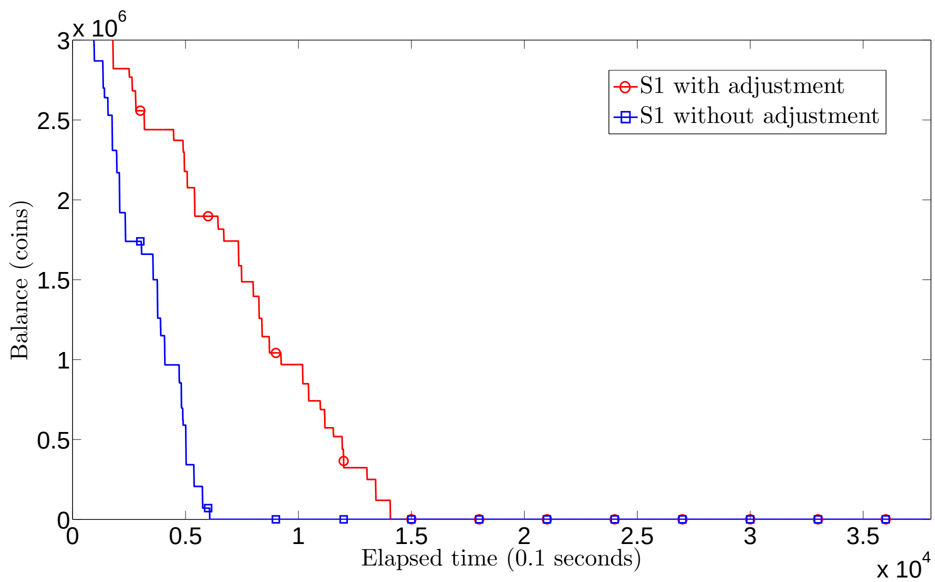
Mode Index	**Mode Name**	**Equations**
1	Savings control	$r_n^k = r_{n-1}^k + \frac{B_n^k - B_{n-1}^k - \gamma_B^k}{\lvert B_n^k - B_{n-1}^k - \gamma_B^k \rvert} * \Delta, \quad 0.6 \le r_{n-1}^k < 1$
2	Centrality control	$r_n^k = r_{n-1}^k + \frac{C_{n-1}^k - C_n^k - \gamma_C^k}{\lvert C_{n-1}^k - C_n^k - \gamma_C^k \rvert} * \Delta, \quad 0.6 \le r_{n-1}^k < 1$
3	Ratio control	$r_n^k = r_{n-1}^k + \frac{U_k - \gamma_U^k}{\lvert U_k - \gamma_U^k \rvert} * \Delta, \quad 0.6 \le r_{n-1}^k < 1$

4.2.1 Effectiveness of pricing adjustment

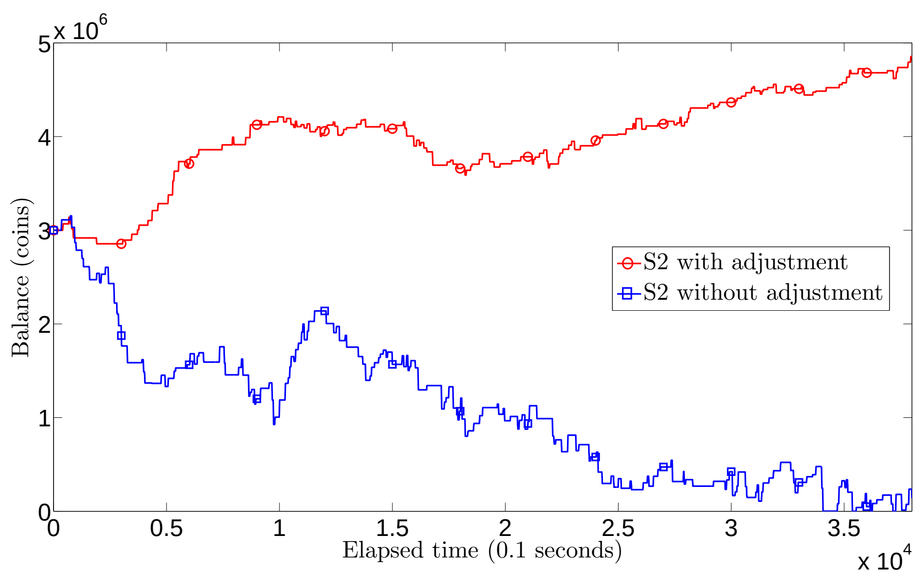
We are going to present the effectiveness of using the strategies of pricing adjustment in this section. The topologies that we use for experiments are all static topologies, so that we can focus our study on the contribution of different strategies of pricing adjustments. The static topologies $S1$ and $S2$ used in this part are the same topologies that were used in previous experiments, as well as the setups, except that we will add some scenarios using different strategies of pricing adjustment.

Before studying different strategies, we notice an interesting phenomenon in Figure 4.9, where we provide the comparison of node1's balance in two static topologies with the scenario using or not using pricing adjustment. We note that, compared to the result from static topology $S2$ (Figure 4.9(b)), the trends of node1's balance in static topology $S1$ (Figure 4.9(a)) improved only a little after applying the strategy of pricing adjustment. The same conclusion can be drawn from Figure 4.10, which is the comparison of centrality fairness in these two topologies that involved with or without pricing adjustment. This difference in the effectiveness of using pricing adjustment is caused by the static topology itself, which is the same reason that node1 and node3 don't earn money in static topology $S1$. As a result, because no strategy can provide a price less than nothing, it is impossible for any strategy of pricing adjustment to significantly improve a node's ability of earning incentives if that node is bypassed by shortcuts. In fact, the slight improvement of node1's balance in Figure 4.9(a) is just a side effect of the pricing adjustment, which is caused by the decrement of the other nodes' prices for relaying packets during the competition of pricing.

There is one more conclusion for Figure 4.9(b). The huge difference in balance after using pricing adjustment in static topology $S2$ indicates that a pricing adjustment does affect the ability to earn incentives in some topologies. As long as a node in the network is not bypassed, there will be a price given by the pricing adjustment that can make the node win a role in cooperation. We can argue that if there exists a lower boundary for pricing adjustment to guarantee profits from cooperation, and if there are only decrements in the pricing adjustment, the static topology will lead the price all the way down to this boundary. It is even worse if every node has the same lower boundary, because when the prices converge to the same boundary, the prices are logically fixed, so that the strategies of pricing adjustment become no longer effective. To deal with this issue, we can either choose different lower boundaries for different nodes, or include the increment operation in the strategies. The former is not practical, since it is like manually defining a weight value for each connection without

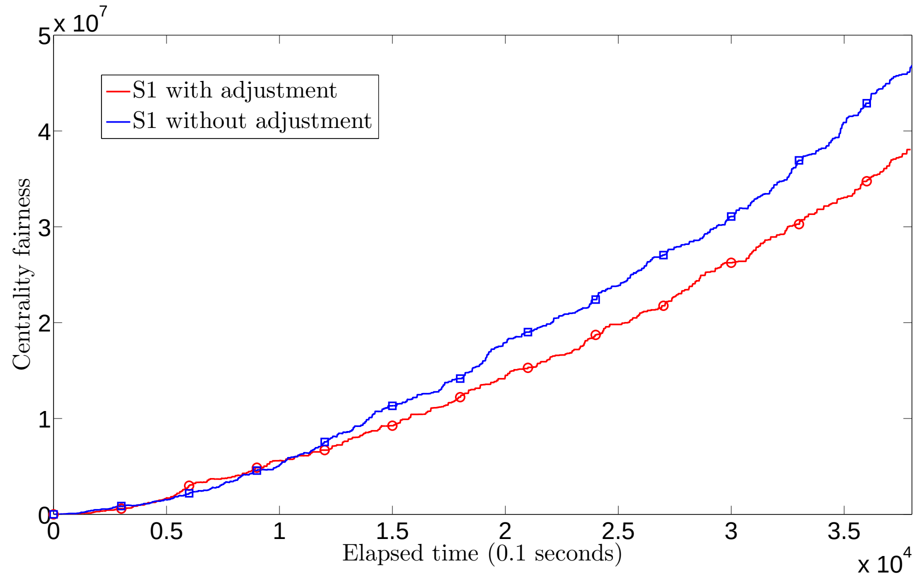


(a) Balance of node1 in topology S1(with or without pricing adjustment)

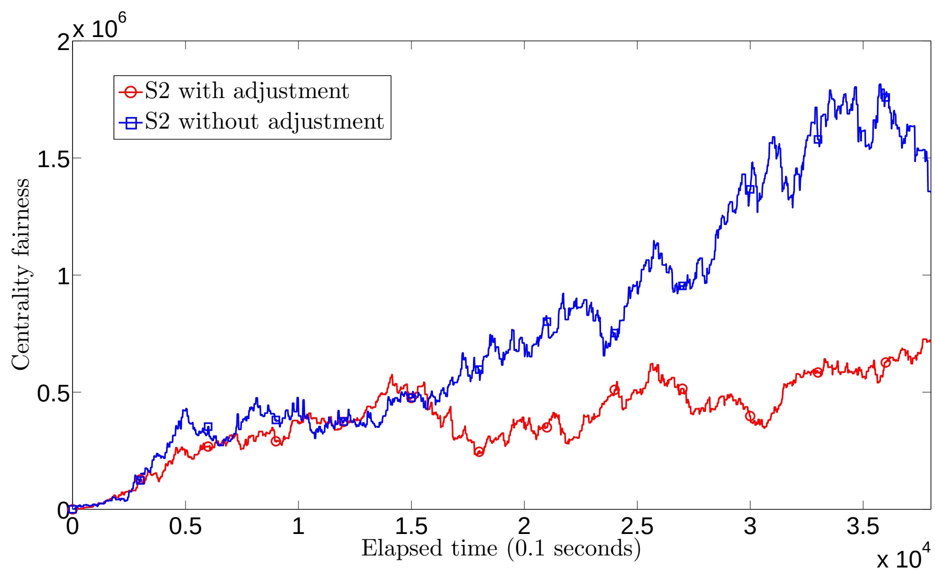


(b) Balance of node1 in topology S2(with or without pricing adjustment)

Figure 4.9: A comparison of node1's balance in topology S1 and S2 for different scenarios that involved with or without pricing adjustment



(a) Fairness of node1 in topology S1(with or without pricing adjustment)



(b) Fairness of node1 in topology S2(with or without pricing adjustment)

Figure 4.10: A comparison of node1's balance in topology S1 and S2 for different scenarios that involved with or without pricing adjustment

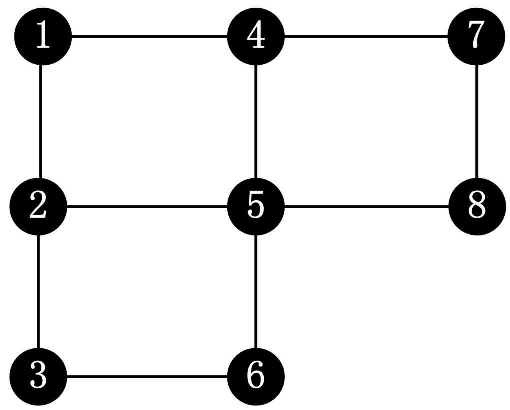


Figure 4.11: A new static topology for testing strategies of pricing adjustment

any reason. As a result, we choose the latter, and we note that it is possible to set different thresholds for the operations of increasing and decreasing prices in pricing adjustment strategies.

4.2.2 Experiment setups

A new static topology

To present the effectiveness of different strategies better, we introduce a new topology (Figure 4.11), which doesn't have shortcuts for nodes in the network and the node5 in the center of the network will have more chances to participant in cooperation. We will see that the ability to earn incentives is suppressed for the node in the center of the network, and an opposite effect exists for the nodes at the edge of the network, when the strategies of pricing adjustment are applied.

Common setups for the experiments with different strategies:

- Parameters:
  - Number of nodes (K): 8
  - Number of tasks included (N_{total}): 600
  - Types of tasks: all relaying
  - Initial amount of digital coins (B_{init}): 3000000
  - Initial pricing rate (r_{init}): 1/Byte

- Seconds of per task: 2 s/7.5 s (transmission only/total)
- Length of per packet (ν_i): 800 Bytes
- Task logging rate: 10 times/s
- Strategy of pricing adjustment: Mode1, 2 and 3
- Pricing refresh rate (τ): 1 time/10 s
- Pricing adjustment step size (Δ): 0.1

• Short comment: Node1, 3, and 7 have the worst positions, comparing to other nodes. Node5 is in the center of the network which has the most connections of the network. Node 2 and 4 although are not in the middle of the network, they both have more connections than Node1, 3 and 7 has. Two left node6 and 8 are having slightly better because they have direct connection to the center node5, which makes them logically close to the center of the network.

Different setups for strategies (Table 4.3):

Table 4.3: Different values for strategies

Parameter	**Mode1**	**Mode2**	**Mode3**
γ_+[1]	0	1	1
γ_-[2]	0	1	1

We try to keep all the strategies used in this experiment in a comparable manner, as a result we choose similar values for the parameters within each strategy. It is the effectiveness of different strategies themselves that we are looking for in this experiment. We will test different combinations of the parameters in experiments of Part III to see the effectiveness of every parameter.

[1]Threshold for taking increasing step

[2]Threshold for taking decreasing step

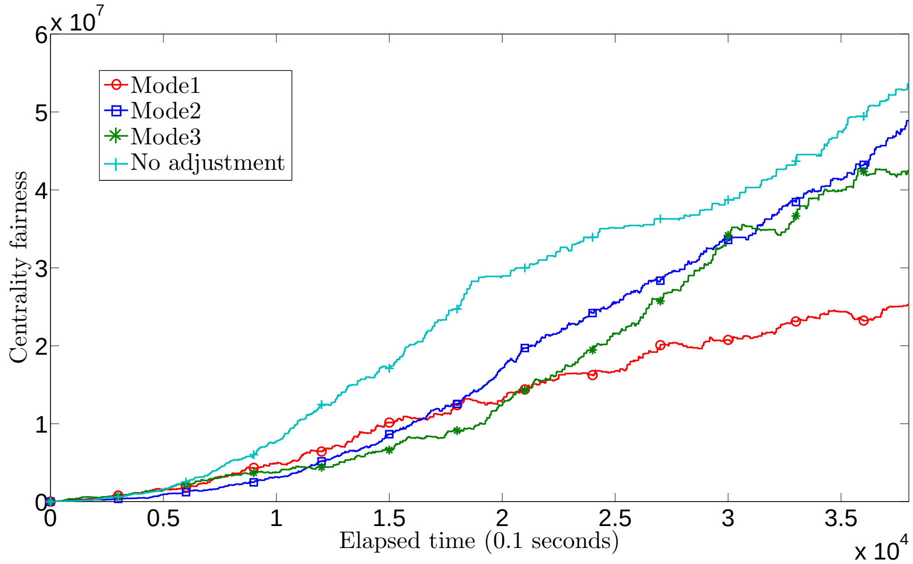


Figure 4.12: A comparison of different strategies of pricing adjustment in centrality fairness

4.2.3 Results and analysis

We compare the centrality fairness of network topology $N1$ with all listed strategies of pricing adjustment shown above, the result of which is shown in Figure 4.12. It is obvious that the red line with the most flat trend is the fairest strategy, where the local balance of a node is used as the key in adjusting the local price of relaying cooperation.

We also observe that the distributions of balances shown in Figure 4.13 are not really clear enough to distinguish the differences between each strategy. In Figure 4.13, The large bars separated in rows represent the same total amount of digital coins existing in the network with different strategies of pricing adjustment. From bottom to top, the large bars denotes the scenarios with Mode 1, Mode 2, Mode 3 and without adjustment (Mode 4), respectively. Each large bar consists of small blocks with different colors, which represent the balances of different nodes of the network. The thickness of each colored block indicates the amount of a node's digital coins. By showing these five subplots we present the comparison of the distributions of balances at five selected time instances (every 769 seconds). One interesting discovery is that, although Mode 1 is concluded to be the fairest strategy according to its flat trend of

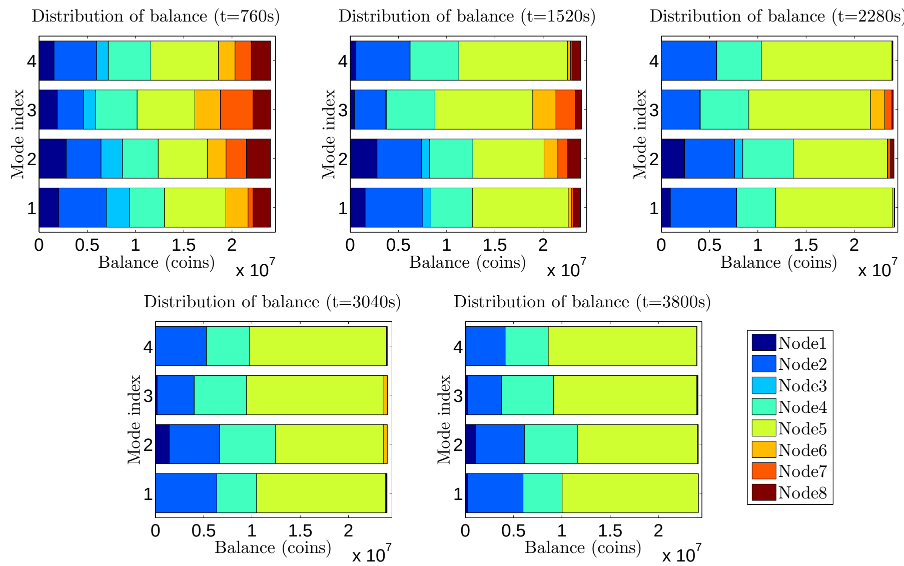


Figure 4.13: A comparison of different strategies of pricing adjustment in balance

centrality fairness, the distributions of balances show little difference between each mode. It can be observed that the distributions of balance of different scenarios start to converge in the subplot 3 of Figure 4.13. Only Mode 2 and 3 still have over 4 significant portions of balances in the subplot of subplot 3, and this difference is hard to tell in subplot 4.

Another observation is that we compare the life time of nodes for different scenarios, which is the time during that nodes can complete tasks without stopping for cumulating incentives. Benefiting from strategies, nodes at the edge can keep activate and send more packets in the scenarios with pricing adjustment than they do in the scenarios without pricing adjustment. This phenomenon can be easily observed from Figure 4.14, which shows the counts of the packets sent by node1 versus the elapsed time. The light green line representing the scenario without pricing adjustment increases very slowly after 2000 seconds elapsed, and the other three lines for scenarios with pricing adjustment keep the same speed of increasing till the end of the experiment. The amount of packets sent by node1 in the experiments varied from 4200 to 10000 in the scenario without pricing adjustment and with strategy mode 1, respectively, which is a 138% increment in all. However, the result still shows very little differences between the scenarios using different modes of strategies.

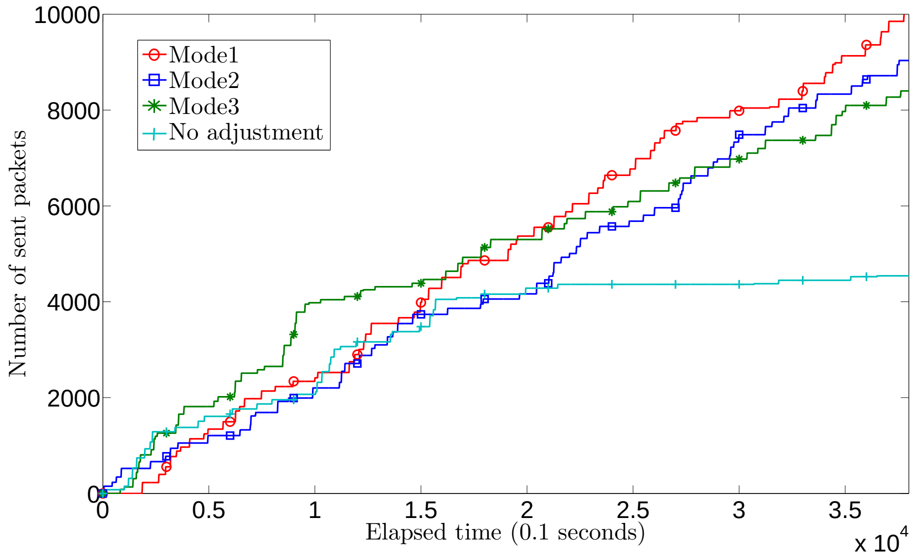


Figure 4.14: A comparison of different strategies of pricing adjustment in number of packets sent by nodes

We conclude for this section that although the strategy mode 1 that use local balance as the key of controlling local price has good centrality fairness in the comparison. Neither the distribution of balance, nor the life time of nodes shows that these three strategies of pricing adjustment have big difference between each other. In next section, We will keep testing these three strategies with different combinations of parameters to see which will be the best.

4.3 Part III: Experiments for optimum fairness of a network

Previous section shows that there is no big difference between different strategies, except that the mode 1 achieves the best centrality fairness of the network among all the scenarios. We will do more experiments in this section to fine tune the parameters in the strategies. These parameters include the pricing refresh rate (τ), adjustment step size (Δ), and thresholds for adjusting prices (γ_+, γ_-).

4.3.1 Experiment setups

Like previous setups for experiment, we provide the common setups for every experiment as follows:

- Parameters:
  - Number of nodes (K): 8
  - Number of tasks included (N_{total}): 600
  - Types of tasks: all relaying
  - Initial amount of digital coins (B_{init}): 3000000
  - Initial pricing rate (r_{init}): 1/Byte
  - Seconds of per task: 2 s/7.5 s (transmission only/total)
  - Length of per packet (ν_i): 800 Bytes
  - Strategy of pricing adjustment: Mode1, 2 and 3
- Short comment: Topology is the same as the one used in previous experiments. The results are compared with each other and the result from the scenario without pricing adjustment.

The detail setups for different scenarios are shown below:

Table 4.4: Different values for nodes

Scenario	**Index of experiment**	τ	Δ	γ_+	γ_-
Mode 1, Mode 2, Mode 3	1	1s	0.1	0	
	2	30s	0.1	0	
	3	60s	0.1	0	
	4	120s	0.1	0	
	5	30s/60s[3]	0.4	0	
	6	30s/60s	0.00125	0	
	7	60s	0.1	1.1	
	8	60s	0.1	0.9	
	9	60s	0.1	1.1	0.9

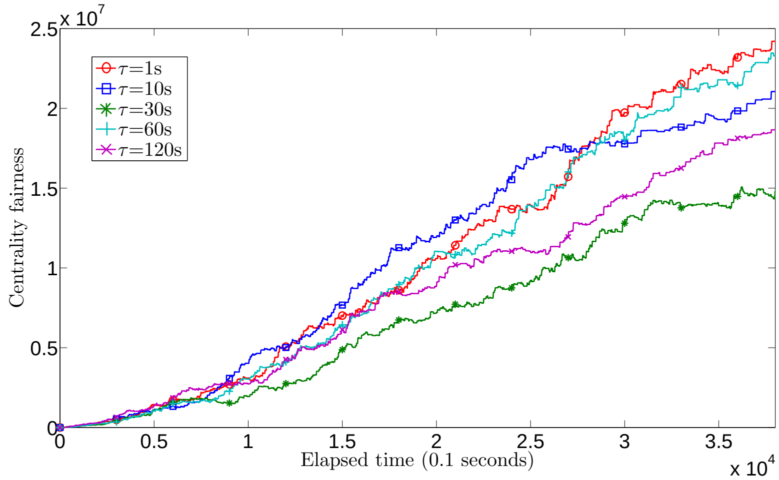
[1]Depends on the mode.

4.3.2 Results and analysis

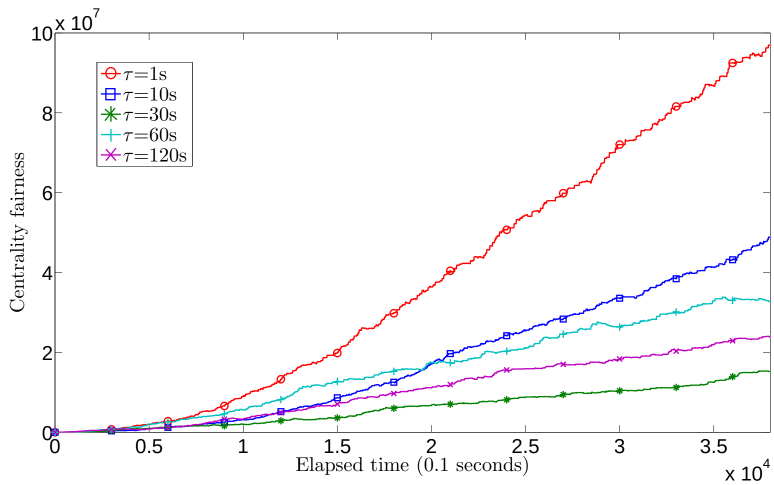
First we change the time intervals τ between each pricing check, this change also affects the minimum time intervals between two pricing adjustments. We choose the values for τ as 1s, 10s, 30s, 60s and 120s, and test them in all three modes. The results of the experiments are shown in Figure 4.15. After comparing the results, we conclude that the minimum time interval between two pricing adjustments has little effect to Mode 1, but for Mode2 and Mode3, the centrality fairness is obviously changed with the increment of the time interval τ. There are also differences between the best case for each mode in these tests: both Mode 1 and Mode 2 has its best centrality fairness when τ equals to 30s, but Mode 3 has its best centrality fairness when τ equals 60s.

Second, based on the best cases for different τ in different mode, we do experiments by tuning the step size of pricing adjustment as listed in Table 4.4. We expect to see that the smaller step size may cause better performance in pricing adjustment, because when the source node considers its partners in cooperation, the differences between total offered prices from different paths are not limited to any small value, which can be even one digital coin. So that candidate nodes can win the pricing competitions with lower costs, eventually, this can lead the nodes working for longer time.

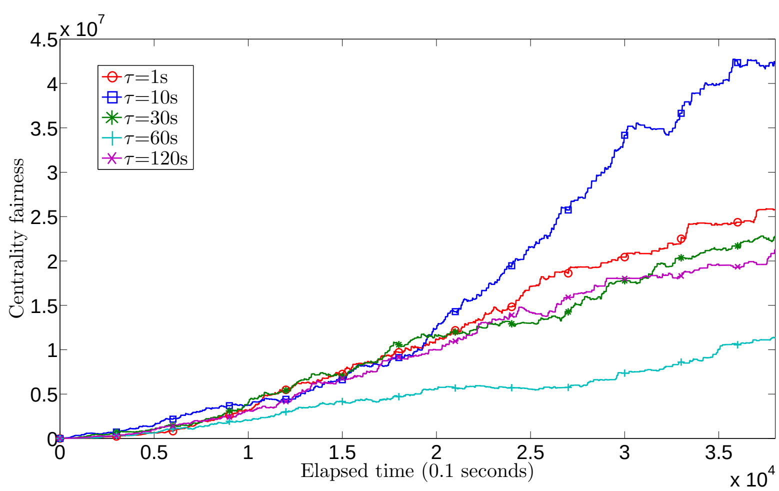
However, the experimental results shown in Figure 4.16 illustrate that all three strategies achieve their best centrality fairness respectively when the step size is set to 0.1. One possible reason for this is because centrality fairness cannot reflect the effects of changing step size Δ, since the step size can only lower the cost of winning each pricing competition and improve the life time nodes. We compare the results from different combinations of step size Δ and refresh time interval τ for each pricing adjustment strategy in Figure 4.17, from which we can conclude that Mode 3 is the best strategy to control the pricing adjustment. Further more, we do experiments for different pricing adjustment thresholds (γ_+,γ_-). To illustrate the effects of changing pricing adjustment thresholds, we simply show the experimental results of Mode 3, which is previously concluded to be the best strategy of pricing adjustment. The



(a) Mode 1

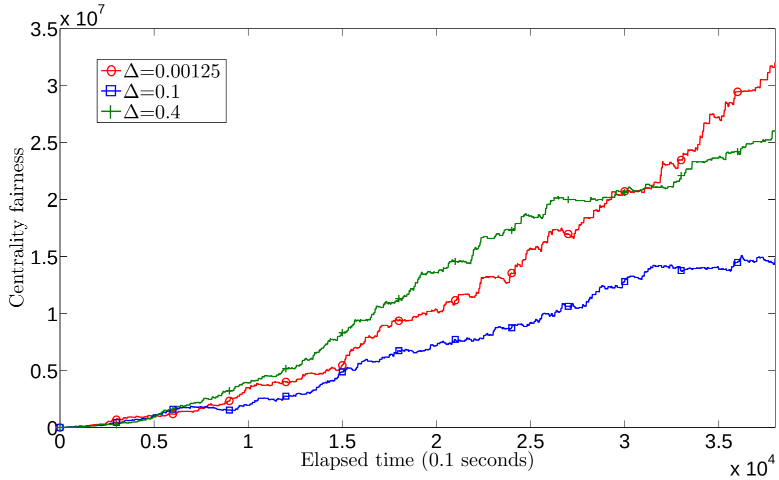


(b) Mode 2

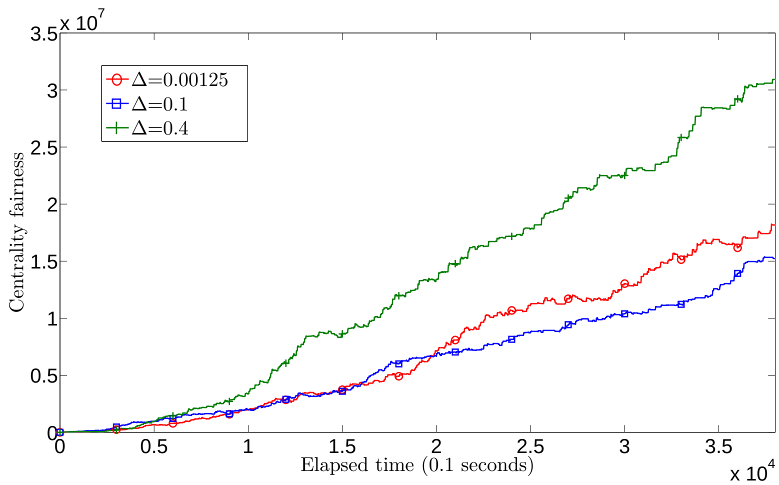


(c) Mode 3

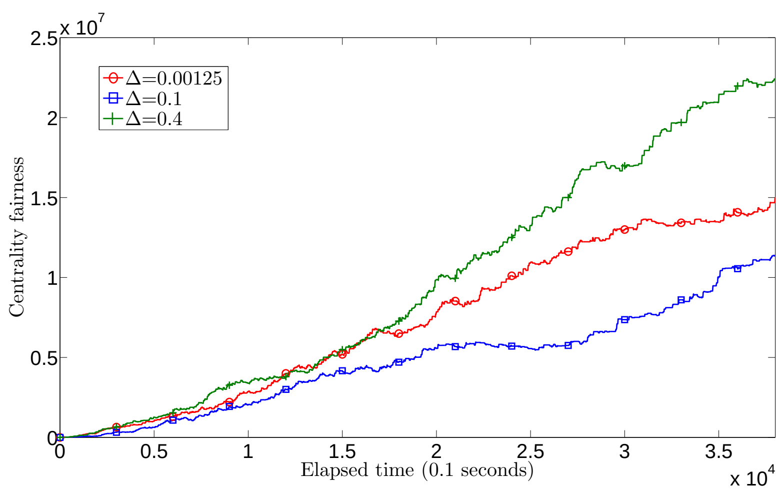
Figure 4.15: A comparison of centrality fairness for different τ values in Mode 1, Mode 2, and Mode 3



(a) Mode 1



(b) Mode 2



(c) Mode3

Figure 4.16: A comparison of centrality fairness for different Δ values in Mode 1, Mode 2 and Mode 3

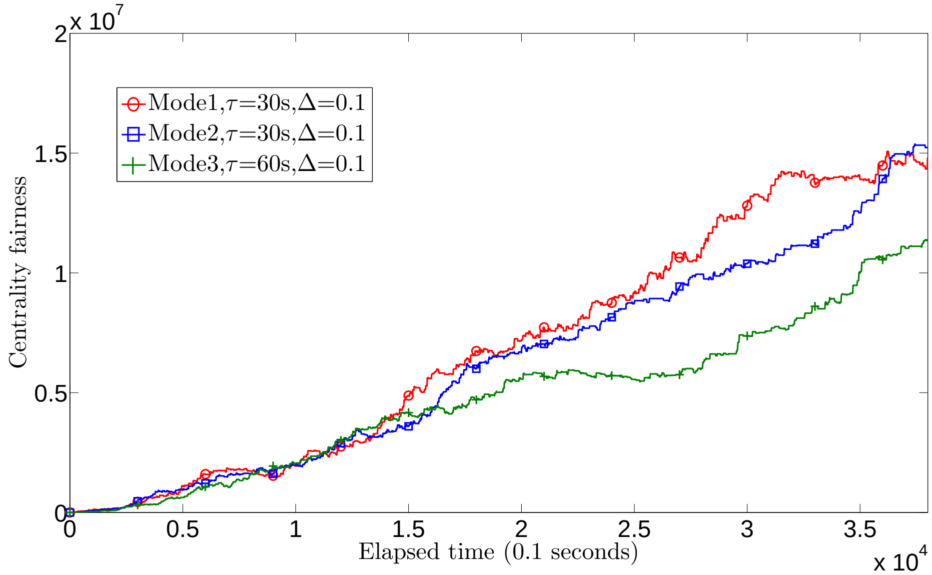


Figure 4.17: A comparison of centrality fairness for the best combinations of parameters of three strategies

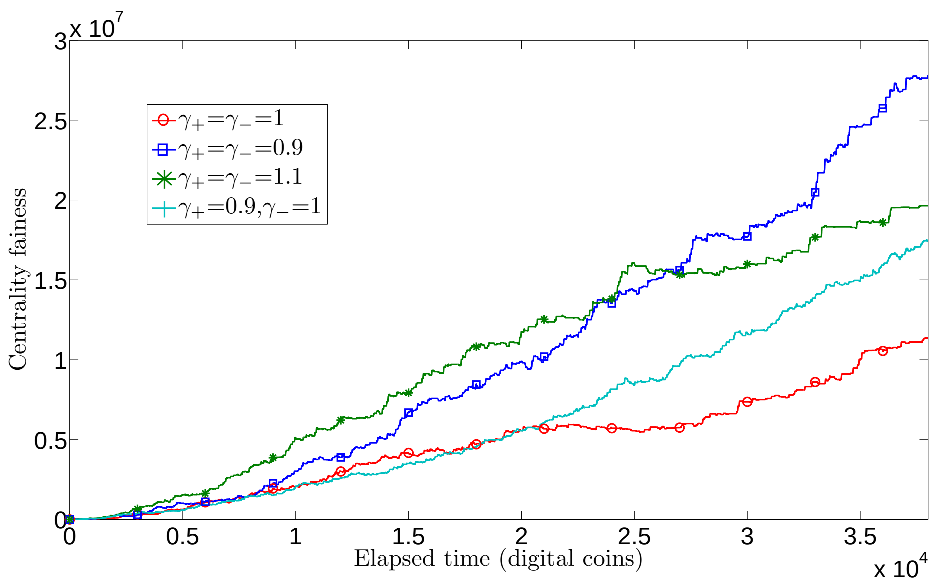


Figure 4.18: An experiment with different choices for pricing adjustment threshold γ_+ and γ_-

values of pricing adjustment thresholds are chosen as they were given in Table 4.4, and the results are provided in Figure 4.18. Apparently, the results for both increment and decrement adjustment thresholds set to 0.9 and 1.1 are not good enough to compete with the one that has the threshold set to 1. One possible reason for this is because the pricing adjustment can be viewed as a consequence of participating or not participating in the cooperation that is initialized by randomly picked communication pairs. To achieve the best centrality fairness, differences between centrality of nodes should be maintained as close as no difference. Since every node cannot be aware of the centrality of other nodes, the best way to build a balanced network is to keep a balance between the time for using and gaining digital coins, which is using the threshold (ratio) of 1 in the strategy.

Chapter 5

Conclusion and Future work

We illustrated the basic behavior of nodes in relaying cooperation for both a static topology and a dynamic topology involving our pricing-based cooperation system. We also observed the importance of the geographical position of a node in terms of the centrality. It is also illustrated in the thesis that static topologies always suffer from edge node issues when payments are exchanged for cooperation, which lead edge nodes spending their digital coins while having less chance to earn income through cooperation than other nodes. By studying the variation of nodes' centrality defined as centrality fairness in the thesis, we can easily tell the differences between networks in terms of their opportunities for participating in cooperation. The importance of node mobility is also illustrated in the thesis. With the mobility, a node can have its cooperation activity vary significantly according to the change of this node's geographical position in the network. This is considered to be the most effective way to solve the issue of edge nodes. However, there is an alternative way to alleviate the issue of edge nodes: we have shown that with a pricing adjustment strategy, we can improve the centrality fairness of a static network, and further we can also improve the life time of edge nodes to participate in cooperation. Finally, we studied the parameters of the pricing adjustment strategies, and made fine-tunes to the parameters to achieve even better results of the fairness. We found that the pricing refresh rate (τ) doesn't affect the Mode 1 very much, which monitors a node's local balance of digital coins for the purpose of adjusting prices; but for the other two modes, which use local centrality and local utility ratio respectively as the control variable in the adjustments of prices, they were impacted by the pricing refresh rate a lot. We also found that the optimum refresh rate for each strategy is not the same:

Mode 1 and Mode 2 achieves the best fairness when the refresh rate is set to 30 seconds, but Mode 3 achieves its best fairness when the refresh rate is 60 seconds. Through the experiments we performed, we conclude that the best one of the three pricing adjustment strategies we designed used a node's utility ratio as the control variable to adjust the prices for relaying packets. Finally, we studied the effectiveness of changing the step size (Δ) and thresholds (γ_+,γ_-). We found that Δ equal to 0.1 exhibited the best centrality fairness, not the smallest step size 0.00125, which makes the minimum amount of digital coins in exchange is 1 coin. Finally we note that the pricing adjustment threshold can also impact the centrality fairness, but precisely how it works is still under study.

There are many questions still left open in this topic, such as how does the parameter change the behavior of nodes in the network, and what is the economic relationship between nodes in the networks. According to the experimental results shown in the thesis, the parameters don't work separately, that is to say, it is the combination of parameters that impacts the performance of each strategy. To find the right combination of parameters, a good stochastic model should be built for the system, since the experiments are based on randomly chosen communication pairs for each task. The economic environment actually hasn't been well modeled in this thesis, which should be another interesting problem in microeconomics. One possible way to look at this system is through game theory, since every node is trying to win the chance to participate in every task. Still, this will need a new mathematical model to describe the system in economic terms.

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