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Game Theory for Multi-hop Broadcast in Wireless Networks

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To my parents,
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and my beloved wife,
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Kurzfassung

Multi-Hop Broadcast-Übertragung ist eine wichtige Anwendung in drahtlosen Netzwerken. Sie kann u.a. zum Austausch von Dateien, zur Aktualisierung von Software oder zur Verteilung von Benachrichtigungen eingesetzt werden. Beim Multi-Hop Broadcast teilt ein Knoten des drahtlosen Netzwerks, der als Quelle agiert, seine Nachricht durch Multi-Hop Übertragung mit anderen Knoten. Aufgrund der Bedeutung des Energieverbrauchs in drahtlosen Netzwerken, wird in dieser Dissertation die Minimierung des Energieverbrauchs in Multi-Hop Netzwerken untersucht. Der Nachrichtenfluss von der Quelle zu den Empfängern kann als Baumdiagramm dargestellt werden, welches als Broadcast-Tree (BT) bezeichnet wird. Das entsprechende Problem, die Nachricht mit minimalem Energieaufwand im Netzwerk zu verbreiten, wird als Minimum-Power Broadcast-Tree (MPBT) Problem bezeichnet. Das MPBT-Problem ist NP-vollständig, was bedeutet, dass es sich vermutlich nicht effizient lösen lässt. Daher wurden viele zentralisierte und verteilte Algorithmen vorgeschlagen, die das MPBT-Problem approximieren. Verteilte Ansätze sind dabei in drahtlosen Netzwerken passender, weil die Verwaltung eines Netzwerks durch eine zentrale Steuereinheit nicht immer möglich ist.

Der primäre Fokus dieser Dissertation liegt auf der Entwicklung verteilter Algorithmen, die das MPBT-Problem angehen. Wenn das MPBT-Problem aus der Sichtweise eines verteilten Optimierungsproblems gesehen wird, muss jeder Knoten im Netzwerk eine eigene Rolle zur Bildung des BT spielen und Kommunikationsverbindungen zu anderen Knoten aufbauen. Dies kann passenderweise über Methoden der Spieltheorie modelliert werden, bei denen die Spieler miteinander um die Minimierung der eigenen Kosten konkurrieren. In dieser Dissertation wird ein Modell für das MPBT-Problem basierend auf Spieltheorie vorgeschlagen. In diesem Modell wählt jeder Knoten, der eine Nachricht empfangen möchte, einen anderen Knoten als entsprechenden Sendeknoten aus. In diesem Fall wird der sendende Knoten als Parent Node (PN) und der empfangende Knoten als Child Node (CN) bezeichnet. Eine solche Entscheidung erlegt dem gewählten PN eine Sendeleistung auf. Der Grundgedanke des Modells ist die Zuordnung von Kosten zu jedem CN in Abhängigkeit der auferlegten Sendeleistung an den von ihm gewählten PN, um durch Kostenminimierung an den CNs auch die Leistung im Netzwerk zu minimieren. Die Gesamtleistung, die von einem drahtlosen Sender benötigt wird, setzt sich aus (i) der benötigten Sendeleistung des Verstärkers zur Übertragung über die drahtlose Verbindung und (ii) die Schaltkreisleistung, die von den passiven Kommunikationshardwarekomponenten benötigt wird, zusammen. Die konventionellen Algorithmen für das MPBT-Problem beschränken sich meist auf die Minimierung der Leistung zur drahtlosen Übertragung, während das hier vorgestellte

Modell beide Leistungen berücksichtigt. Es wird gezeigt, dass die Schaltkreisleistung bemerkenswerten Einfluss auf die Netzwerkleistung hat.

Das modellierte Spiel ist ein nicht-kooperatives Kostenteilungsspiel. In einem solchen Spiel werden die Kosten der Nutzung eines PNs von allen CNs, die diesen PN wählen, über ein sogenanntes Kostenteilungsschema geteilt. Durch die Nutzung eines Kostenteilungsspiels, werden die CNs zum Zusammenschluss durch Bildung einer Multicast-Empfangsgruppe motiviert, um die Anzahl der notwendigen Übertragungen im Netzwerk zu reduzieren. Mehrere Kostenteilungsschemata und die jeweiligen Eigenschaften in Bezug auf die Performanz des erreichten BT sowie die Konvergenz hin zu einem Nash-Gleichgewicht (engl. Nash equilibrium, NE) werden diskutiert. Es wird gezeigt, dass mit dem Kostenteilungsschema des Deckungsbeitrags (engl. Marginal Contribution, MC) die Kostenminimierung der Knoten exakt auf die Minimierung des Energieverbrauchs im Netzwerk angepasst ist. Dies bedeutet, dass eine Reduzierung der Kosten an einem Knoten in der gleichen Reduzierung des Energieverbrauchs im Netzwerk resultiert und daher die globale Zielsetzung durch lokale Entscheidungen verbessert werden kann. Hieraus folgt, dass beim MC-Schema der optimale BT immer ein NE des Spiels darstellt. Neben dem MC-Schema werden noch die häufig verwendeten, Schemata der ausgeglichenen Kostenteilung (engl. Equal Share, ES) und des Shapley-Werts (engl. Shapley Value, SV) untersucht. Es wird gezeigt, dass (i) MC die besten Ergebnisse für die verteilte MPBT-Erzeugung liefert, (ii) das ES-Schema keine Konvergenz des Spiels zu einem NE garantiert und (iii) bei den ES- und SV-Schemata im Gegensatz zum MC-Schema lokale und globale Ziele nicht aufeinander angepasst sind, weshalb der optimale BT nicht notwendigerweise dem NE des Spiels entspricht.

Typischerweise ist beim MPBT-Problem ein CN beim Empfang von Daten vom PN abhängig, aber durch die Möglichkeit eines Broadcasts bei drahtloser Übertragung können die Signale mehrerer Sender an einem CN empfangen werden. Um Signale von mehreren sendenden Knoten im Netzwerk ausnutzen zu können, wird die Implementierung von Maximal-Ratio Combining (MRC) an den Empfangsknoten vorgeschlagen. Das vorgestellte spieltheoretische Modell wird zusätzlich erweitert und eine gemischt-ganzzahlig lineare Optimierung (engl. mixed integer-linear program, MILP) wird vorgeschlagen, so dass ein CN mehrere PNs auswählen und gleichzeitig die Sendeleistung der gewählten PNs bestimmen kann. Da ein CN bei einem solchen Ansatz die gesendeten Signale von mehreren PNs ausnutzen und akkumulieren kann, kann die benötigte Energie im Netzwerk zur Verbreitung von Nachrichten beachtlich reduziert werden.

Es ist allgemein bekannt, dass die Datenmenge in kommenden Netzwerkgenerationen vor allem durch Videoanwendungen bestimmt wird. Außerdem hängt gerade der Erfolg von Multi-Hop Broadcast für Videoanwendungen sehr stark von der Zusammenarbeit der Endnutzer ab. In dieser Dissertation wird daher das vorgestellte spieltheoretische Grundgerüst weiter auf Videostreaming in nutzerzentrierten Netzwerken (engl. User-Centric Networks, UCNs) optimiert. Es wird angenommen, dass das betrachtete Video mit der Scalable Video Coding (SVC) Technik kodiert ist. Ein SVC Video besteht aus mehreren Schichten, und es wird angenommen, dass jede Schicht des Videos über einen anderen BT verbreitet wird. Um eine bestimmte Videoqualität zu erhalten, muss ein Knoten dem entsprechenden BTs beitreten. Um den beitragenden Knoten einen Anreiz zu bieten nehmen wir an, dass empfangende Knoten als Belohnung einen sogenannten Token an die sendenden Knoten zahlen, der von der von den PNs verbrauchten Energie abhängig ist. Indem ein teilnehmender Knoten Tokens für das Weiterleiten von Videos sammelt, erhält er die Möglichkeit an einer größeren Anzahl BTs teilzunehmen und eine bessere Videoqualität zu erhalten. Bei Multi-Hop Broadcast haben in der Nähe der Quelle sitzende Knoten eine hohe Bedeutung für den Rest des Netzwerks. Um die Performanz zu erhöhen schlagen wir daher ein Verteilungsmodell vor, das speziell den Knoten nahe der Quelle höhere Belohnungen verspricht. Die Nutzenfunktion des vorgeschlagenen spieltheoretischen Modells berücksichtigt (i) die Bedeutung der Videoqualität für den Nutzer, (ii) die Kosten, die ein Nutzer zahlt, (iii) die Bereitschaft eines Nutzers, einen Beitrag zum Netzwerk zu leisten und (iv) die Belohnung, die ein Nutzer für das Weiterleiten von Videos an andere Nutzer erhält. Durch die Maximierung seiner Nutzenfunktion bestimmt ein Nutzer dafür gleichzeitig, wie vielen BTs er beitritt, den entsprechenden PN jedes BT und ob erhaltene Videos an andere Nutzer weitergeleitet werden sollen. Es wird gezeigt, dass das vorgestellte spieltheoretische Anreizmodell zu einer signifikanten Steigerung der wahrgenommenen Videoqualität bei den Nutzern bei gleichzeitiger Beibehaltung der Energieeffizienz des Netzwerks führt.

Abstract

Multi-hop broadcast is an important application in wireless networks. It can be employed for file sharing, software update, notification distribution, video streaming, etc. In a multi-hop broadcast, a node of a wireless network, as the source, shares its message with other nodes in a multi-hop fashion. Due to the importance of power management in wireless networks, in this dissertation, we study power minimization in multi-hop broadcast. In a multi-hop broadcast, the message flow from the source to the receivers can be modeled as a tree-graph, called the broadcast-tree (BT) and the problem of disseminating the message in the network with minimum-power is called the minimum-power broadcast-tree (MPBT) problem. The MPBT problem is NP-complete, meaning that a polynomial-time algorithm unlikely exists for it. Hence, many centralized and decentralized approximation algorithms are proposed in order to approximate the MPBT problem. Since managing the network traditionally from a centralized controller may not be always possible, decentralized approaches are more suitable to be employed in wireless networks.

The primary focus of this dissertation is on developing decentralized methods for tackling the MPBT problem. Seeing the MPBT problem from a decentralized optimization point of view, every individual node has to play its own role in forming the BT by establishing a communication link to another node. This can be suitably modeled by game theory, in which the players compete with each other in minimizing their own cost. In this dissertation, we first propose a game-theoretic model for the MPBT problem. In the proposed game, every node, in order to receive the message, chooses another node as its respective transmitting node. In this case, a receiving node and its respective transmitting node are called the child node (CN) and the parent node (PN), respectively. Such a decision by a CN imposes transmit power on its chosen PN. The key idea here is to assign a cost to every CN according to the power it imposes on its chosen PN so that the network power is minimized via cost minimization at the CNs. The total power required at a wireless transmitter consists of (i) the transmit power of the amplifier required for the transmission over a radio link and (ii) the circuitry power needed for passive communication hardware modules. The conventional algorithms for the MPBT problem mostly focus merely on the minimization of the power required for the radio link, but in our model, we take both powers into account and show that the circuitry power remarkably impacts the network power.

The game that we design is a non-cooperative cost sharing game. In such a game, via a so-called cost sharing scheme, the cost of using a PN is shared among the CNs that choose it. By employing a cost sharing game, the CNs are motivated to join together

and form a multicast receiving group and this reduces the number of transmissions in the network. We study several cost sharing schemes and discuss their properties in terms of the performance of the obtained BT and the convergence of the game to a Nash equilibrium (NE). It is shown that, with the marginal contribution (MC) cost sharing scheme, the cost minimization of the nodes is exactly aligned with the network power minimization. This means that cost reduction at a node results in the same reduction in the network power and hence, the global objective can be improved via local decision making. As a consequence, with MC, the optimum BT is always an NE of the game. Besides MC, we study equal-share (ES) and the Shapley value (SV) as two other widely-adopted budget-balanced cost sharing schemes. It is shown that (i) the MC performs the best for the decentralized MPBT construction, (ii) the equal-share (ES) scheme does not guarantee the convergence of the game to an NE for the MPBT problem and (iii) with budget-balanced cost sharing schemes, unlike for the MC, the local and global objectives are not aligned and hence, the optimum BT is not necessarily an NE.

Typically for the MPBT problem, a CN relies on one PN for receiving data, however, due to the broadcast nature of the wireless medium, the signals from multiple transmitters can be received at a CN. In order to exploit the signals transmitted by multiple transmitting nodes, maximal-ratio combining (MRC) is proposed to be employed at the receiving nodes. The proposed game-theoretic framework is further extended and a mixed integer-linear program (MILP) is proposed to find the global optimum solution. By the proposed algorithm a CN selects multiple PNs for itself and at the same time determines the transmit power of its chosen PNs. Since by such an approach a CN is able to exploit and accumulate the signals transmitted from multiple PNs, the required power for message dissemination in the network reduces.

It is known that video is the dominant application in the next generation of communication networks. Moreover, the success of multi-hop broadcast for video application depends highly on the collaboration of the end users. In this dissertation, the proposed game-theoretic framework is further optimized for video streaming in user-centric networks (UCNs). The considered video is assumed to be encoded by the scalable video coding (SVC) technique. An SVC video consists of several layers and in our work, it is assumed that every layer of the video is streamed by a separate BT. To receive a certain video quality, a node has to join the corresponding BTs. In order to provide an incentive for the PNs, we assume that the PNs are paid by their corresponding CNs via tokens. The payment depends on the energy consumed by the PNs. By collecting tokens in exchange for forwarding the video, a contributing node is able to receive a higher video quality. Further, in multi-hop broadcast, the contribution of the nodes who are located closer to the source is vital for the rest of the network. To address this issue, we propose a taxation mechanism that specifically provides higher rewards for the nodes closer to the source. The utility function of the nodes in the proposed game-theoretic model captures (i) the importance of video quality for the user, (ii) the cost the user pays, (iii) the willingness of the user for contribution to the network and (iv) the reward a user receives if it forwards the video to others. A user, by maximizing her utility function, simultaneously determines how many BTs she should join to, her corresponding PN for each BT, and if she should forward the received video to others. It is shown that the proposed game-theoretic incentive mechanism significantly improves the video quality perceived by the users while preserving the energy-efficiency of the network.

Contents

Chapter 1

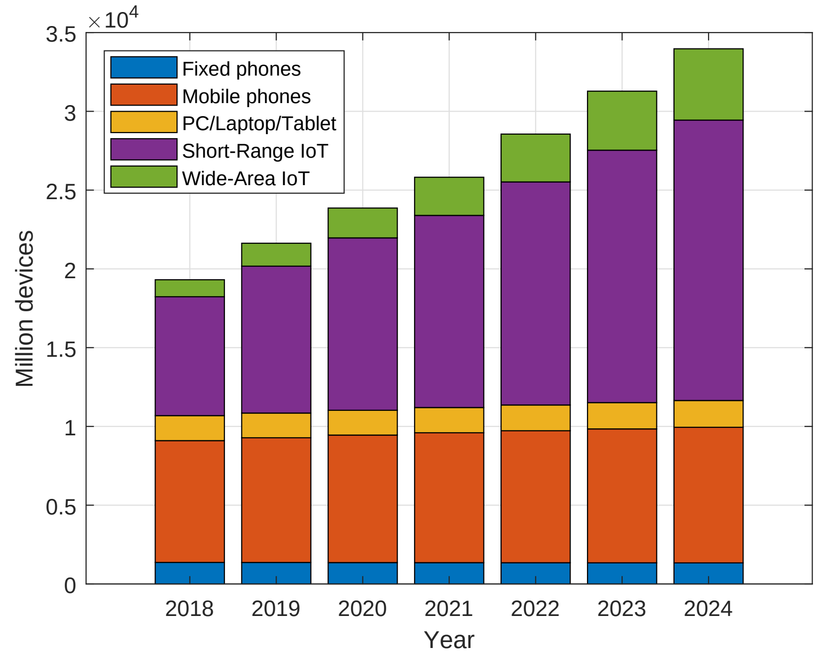
Introduction

1.1 Motivation

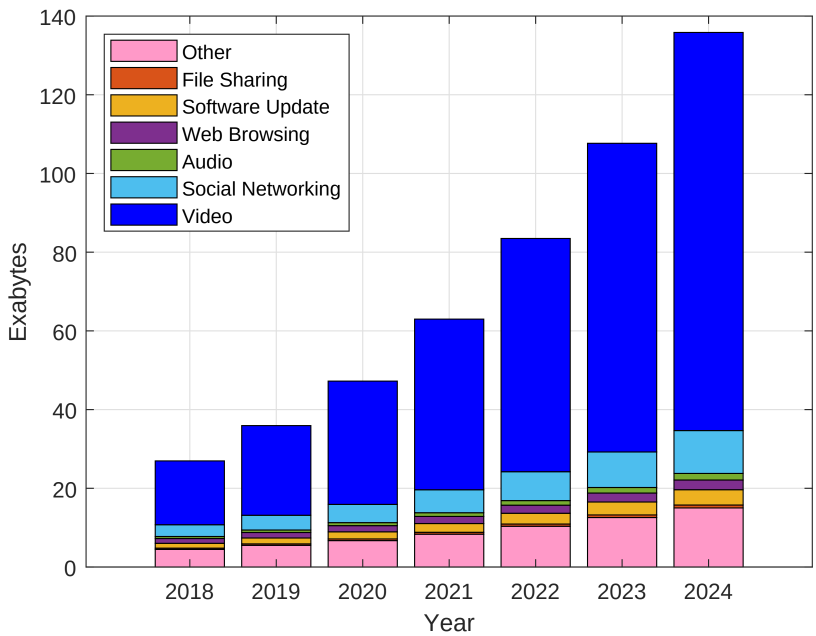
Wireless communications have experienced a rapid growth during the past years. First, the number of wireless-enabled devices has substantially increased due to their affordability and this made the wireless networks dense. The density of wireless networks is going to increase even more by emerging new applications such as the Internet of things (IoT), machine to machine (M2M) communications, etc., see Fig. 1.1.(a). Second, due to the advances in technology and design of chips, running complex signal processing algorithms is now feasible in low-cost devices. As a consequence, the data rate achieved by the end users has significantly increased. Nowadays, accessing bandwidth-hungry applications is feasible via hand-held devices. Video, as a bandwidth-hungry application, is currently the most popular application for the end users [Eri18]. According to a recent report by Ericson [Eri18], video applications, as shown in Fig. 1.1.(b), are expected to occupy around 74 percent of mobile data traffic by 2024 while this amount in 2018 was about 60 percent. Moreover, the volume of video traffic is going to increase from 16 Exabytes in 2018 to 101 Exabytes in 2024. In a nutshell, high density and video dominance are two main characteristics of the future generations of communication networks.

Given the limited and scarce wireless resources, meeting the expectations of the end users in future dense wireless networks is challenging. Multi-hop broadcast is envisioned as a technique for tackling this problem by improving the capacity of future communication networks [WWH+18]. With multi-hop broadcast, for instance, a user in a wireless network can share her already-cached content with other users in order to prevent the load on a centralized server [JHJ+17]. In another scenario, which is applicable to streaming of live events, one of the users of the network can receive the content from the base station, as the head of a group of nodes, and serve the other nodes [FASWK15]. This dissertation is centered around multi-hop peer-to-peer communication in wireless networks as an important communication technique for the future generations of communication networks.

In order to clarify the multi-hop broadcast transmission scheme, an illustrative example is provided in in Fig. 1.2 with one source S and multiple receivers. The source, as the



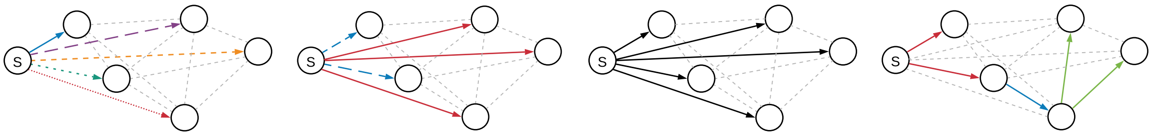
(a) Number of connected devices.



(b) Mobile data traffic for different applications.

Figure 1.1. The number of connected devices and the prediction of mobile data traffic for different applications by 2024 [Eri18].

transmitting node, has a common message for all the other nodes and can serve them by different transmission schemes. (a) Unicast: In unicast transmission, the source has just



(a) Unicast **(b)** Multicast **(c)** Broadcast **(d)** Multi-hop broadcast

Figure 1.2. Different transmission schemes for data dissemination. The arrows with similar color represent the transmission in the same time-slot.

one intended receiver in a time-slot. To serve all the receiving nodes, the source requires a dedicated time-slot for every receiver. (b) Multicast: In multicast transmission, more than one receiver is served by the source in a time-slot. (c) Broadcast: In a broadcast, all the nodes of the network receive the source's message in a single-hop transmission. Although the single-hop broadcast seems to be the simplest way as it requires only one transmission by the source in one time-slot, it has two main drawbacks. Firstly, it may not be energy-efficient as the transmit power required at a transmitter grows polynomially with respect to the distance between a transmitter and receiver. Secondly, due to physical limitations, a transmitting node has a limited coverage area and it may not be possible for it to cover all the receiving nodes in a single-hop transmission. A solution to this problem is using multi-hop broadcast, shown in Fig. 1.2.(d), by which some of the nodes of the network act as a relay and re-transmit the source's message. This approach not only improves the coverage area of the network, but also can help in network energy-efficiency [WNE02, vHE02]. The application of multi-hop broadcast ranges from IoT and sensor networks [WNE02, ZGC+15] to video streaming [ESS+13]. Usually, the goal in such networks is determined by the quality-of-service (QoS) constraints which, for instance, could be network throughput maximization [ZGC+15] or network energy minimization [MASW+15, MASK19, WNE02].

In a multi-hop broadcast, some of the nodes of the network, usually the ones in the middle, may need to act as re-transmitting nodes. Due to the critical role of energy efficiency in wireless networks, in this dissertation, we study the energy efficiency of multi-hop broadcast. The transmission flow from a source to the receiving nodes of the network, in a multi-hop broadcast, forms a tree-graph, rooted at the source, called the broadcast-tree (BT), in which every receiving node has a respective transmitting node. A receiving node an its respective transmitting node are called the child node (CN) and the parent node (PN), respectively. Numerous BTs can be constructed for multi-hop broadcast, however, they may be remarkably different in terms of the power they require for disseminating the source' message. The power of a BT, which is referred to as the network power, is the summation of the power required by the PNs of the network, including the source, for message transmission. The problem of finding the BT that requires the minimum power for disseminating the source's message is called the minimum-power broadcast-tree (MPBT) problem. It has been shown that the MPBT problem is NP-complete [Lia02]. This means that a polynomial-time algorithm to find the optimum BT unlikely exists and thus, an approximation algorithm is required. Although many approximation algorithms have been proposed for the MPBT problem, most of them are centralized heuristics [WNE02, vHE02, CFM13, HB09, HCF13, SB11]. The main drawback of the centralized algorithms is their dependency on a central entity. In fact, to run a centralized algorithm, the important properties of the network such as the channel quality between any two nodes must be collected by a central entity. The process of collecting the information, finding the broadcast-tree and informing the nodes of the network about how to construct the broadcast-tree is time-consuming and requires a high amount of overhead. More importantly, as the central entity plays a critical role, the network becomes vulnerable if the nodes lose their connection to the central entity. This makes decentralized algorithms, by which the nodes can construct an adaptive network, independent of a central entity, more suitable for the MPBT problem [AWB+19, FHK+16]. Hence, the *first challenge* for an energy-efficient multi-hop broadcast is having a simple yet efficient decentralized algorithm.

The primary focus of this dissertation is to develop decentralized methods for the MPBT problem which will be further optimized for video applications. Seeing the MPBT problem from a decentralized optimization point of view, every individual node has to play its own role in forming the BT by establishing a communication link to another node. This can be suitably modeled by game theory, in which the players of the game, here the nodes, are typically modeled as selfish agents seeking to minimize (maximize) their own cost (revenue). The key idea here is to assign a cost to every node according to its action. In our work, the action of a node is to choose another node in the network as its respective transmitting node in order to receive the source's message. As a consequence of its decision, a cost is assigned to the node based on the power it imposes on its chosen node. In a multicast transmission where multiple receiving nodes can benefit from a single transmission, the cost of transmission, here the power required at a transmitting node, can be shared among the receiving nodes. The game in which the goal of the players is to minimize their own cost, while the cost of using a resource or transmitting node is shared among the players who choose the same resource, is called a cost sharing game (CSG) [JM07, SLB08]. In CSG, the cost is shared among the users via a so-called *cost sharing scheme*. The Nash equilibrium (NE) is a suitable solution concept for such a game. At the NE, none of the nodes can change its action and be better-off while the action of the other nodes remains unchanged [SLB08].

It is well-known that the future generations of communication networks are highly human-centric in which the end users play a more active role. According to studies, energy (battery) consumption is one of the main concerns of mobile users [ASKJ$^+$19]. The energy consumption of the applications like video streaming is relatively high for the users who re-transmit the video. Unlike for the traditional networks where the system optimizer decides about the role of a node, in the future generations of communication networks the *end users* may decide whether to contribute to the network. Hence, it is critical to provide proper incentives for the users so that they will contribute to the network and forward the message to others. Such networks in which the end users play an active role and impact the performance of the network are called the user-centric networks (UCNs). In UCNs, network optimization without taking the users satisfaction into account is not feasible. Hence, multi-hop broadcast in UCNs is challenging and has to be studied.

The success of a technique like multi-hop transmission in a UCN depends highly on the users' willingness to contribute to the network [PPZ$^+$17]. For instance, in video streaming, the contribution of a user who is located closer to the source than the others, in forwarding the video, can determine the quality of the video received by other users. This brings us to the *second challenge*; the design of incentive mechanism for user's contribution. Studies show that users are reluctant to contribute to networks without receiving a proper reward [WAF$^+$16, FDGR$^+$14]. Unlike traditional networks where the users did not have many degrees of freedom in deciding on the behavior of their device in a network, thanks to the advances in software engineering and the popularity of smart devices, the level at which users nowadays interact with their devices significantly increased. The users are now able to simply set their personal preferences and determine their willingness to contribute to the network.

As an incentive for the contributing users, payment via virtual currency or tokens has been proposed and developed by researchers during the past two decades as one of the best candidates to be used in UCNs [BH03, IGHT14a, IGHT14b, CGFH17]. Although virtual currency is a promising tool for providing incentives for the users in UCNs, two important issues need to be answered in adopting such an approach. First, the number of tokens a receiver has to pay to its transmitting node has to be related to the energy consumption of the transmitter. Second, the way that the cost is shared among the receiving users in a multicast transmission has to be fair. A common goal in such scenarios is to minimize the total costs the users pay in order to receive the video, called the *social cost*.

While the first two challenges are independent of the application, there are other issues that need to be further considered specifically for video applications. In a video streaming scenario, the user's satisfaction regarding the video quality is critical. One of the main drawbacks of the existing video streaming algorithms is that they treat the users as a homogeneous set. Typically these approaches target a certain level of QoS for everyone and ignore the preference of *individual users* [ESS+13, HGL11]. In reality, besides the willingness to contribute, each user of the network, depending on different parameters such as the content of the video, user's age, size of the device's screen, etc., may have a different preference regarding the video quality. Hence, the *third challenge* is to incorporate the preferences of individual users in our decentralized BT construction used in video streaming.

1.2 State-of-the-art

1.2.1 Minimum-power Multi-hop Broadcast

In this section, we review the state of the art for the MPBT problem. The MPBT problem has been studied by researchers extensively during the past two decades [WNE02, vHE02, CFM13, HB09, HCF13, SB11, MP09, CSS03, RVF08, KMG08, CK13, CCLE+07]. NP-completeness of the MPBT problem can be shown by reducing the Steiner tree problem to it [Lia02]. The approximation algorithms proposed for the MPBT are usually not able to find the optimum BT, especially when the number of nodes in the network is large, but they can find a low-power BT in polynomial-time.

A well-known heuristic called the broadcast incremental power (BIP) algorithm is proposed in [WNE02]. The BIP algorithm is a centralized greedy heuristic. To build a BT, it starts from the source and iteratively connects the nodes to the source or to the other nodes already connected to the BT. Considering the transmit power of the nodes which are already connected to the BT, in each iteration, the node which requires the minimum incremental transmit power is chosen as the new node to connect to the BT [WNE02]. The ratio of the worst case performance of an algorithm and the optimum solution, here in terms of the required power for the BT, is called the approximation ratio of the algorithm. It has been shown in [WCLF02] that the approximation ratio of the BIP algorithm is constant and independent of the number of nodes. Since the BIP algorithm fails in exploiting the benefit of multicast transmission in the wireless medium, the authors of [WNE02] further propose a procedure called sweeping in order to improve their algorithm. We refer to the BIP algorithm along with the sweeping procedure as the BIPSW algorithm. When the BT is initialized by the BIP algorithm, the BIPSW prunes the links to the nodes which can be covered by other transmitting nodes and prevents unnecessary transmissions. Other heuristics based on minimum spanning tree [vHE02, CFM13], ant colony optimization [HB09], particle swarm optimization [HCF13], and genetic algorithm [SB11] have also been proposed during the past years for the MPBT problem which all are centralized and may perform better than the BIP algorithm at the expense of a higher complexity.

As stated before, a centralized approach is not suitable for dense and crowded future wireless networks as controlling every single device via a central entity may not be feasible. Hence, decentralized algorithms [RVF08, MP09, CSS03], by which the nodes construct the BT just based on their local information, are a better choice for real-world implementations. Since in a decentralized algorithm the nodes update their action independently, to find a valid tree-graph as a BT, the algorithm may require to be initialized to restrict the decisions of the nodes. The authors of [RVF08] suggest an algorithm called the broadcast decremental power (BDP) which first initializes the BT by a centralized algorithm (Bellman-Ford), and then, every node changes its respective transmitting node if the change leads to a lower transmit power. A decentralized algorithm is also suggested in [CSS03], but it requires the geographical position of all the nodes of the network at every single node. Decentralized approaches for the MPBT problem have received less attention, and in general, lack a good performance compared to the centralized ones.

Game theory, as a powerful mathematical tool, has been widely used for designing games for distributed optimization [MW13a, CCLE+07, CK13, MASW+15] or resource sharing in competitive situations [BLSS16, HMR17]. For instance, the authors of [KMG08] exploit a potential game to control the topology and maintain the connectivity of a multi-hop wireless network. Their proposed approach does not consider multicast transmission and requires the information from several hops to be collected at every single node. Using game theory to establish a network is known as *network creation game* [vTW07] [CLL15]. In such games, the elements of the game are designed in a way that when the game is played by rational players, the decisions made by them are in favor of the desired objective from the game designer's perspective. CSG is a suitable model for network creation. Using a CSG, the nodes are motivated to form multicast receiving groups and choose a common transmitting node. This can lead to network power reduction by reducing the number of transmissions. The cost that needs to be paid by the members of the coalition has to be shared among them via a so-called cost sharing scheme. Different cost sharing schemes, each with different properties in terms of implementation difficulties or convergence to an NE, can be employed within a CSG . The authors of [SA11] studied some of the schemes that can be used for multicast receiving group formation for a single-hop transmission.

An important class of sharing schemes for CSGs is the class of budget-balanced schemes

[GMW14,CRV10,DMRS08]. A cost sharing scheme is budget-balanced if the sum of the cost allocated to each of the receiving nodes of a multicast transmission is equal to the transmit power of the transmitting node. One of the widely-adopted budget-balanced schemes is the Equal-share (ES) scheme in which the cost is simply shared equally among the nodes. Due to difficulties of designing a decentralized approach to the MPBT problem, simplified versions of this problem have also been studied in the literature which we call the minimum-transmission BT (MTBT) and the minimum fixed-power BT (MFPBT) problems. In the MFPBT problem, the nodes have fixed but not necessarily equal transmit powers while in the MTBT problem, the transmit powers of the nodes are not only assumed to be fixed but also *equal* for all the nodes. In fact, the MTBT problem is a special case of the MFPBT problem and both of them are simplified versions of the MPBT problem. The ES cost sharing scheme has been employed in [CK13] and [CCLE+07] for the MTBT and MFPBT problems, respectively. The algorithm in [CK13] is called game-based broadcast-tree construction (GBBTC) algorithm and the authors, by assuming a fixed transmit power at the nodes, minimize the number of transmissions in the network as a way to minimize the network power.

The GBBTC algorithm studied in [CK13] has three main drawbacks. Firstly, it does not perform power control at the transmitting nodes. Secondly, the cost sharing scheme employed in [CK13], which is ES, does not guarantee the convergence of the state of the BT to an NE. In fact, as we will show in Chapter 4, to ensure the convergence to an NE when using the ES cost sharing scheme, the power control feature at the nodes cannot be exploited and a fixed transmit power must be used instead. Indeed, the application of the proposed approach in [CK13] is limited to the MFPBT problem with fixed transmit power at the nodes. Thirdly, to find a valid tree-graph as BT, GBBTC in [CK13] requires initialization.

Besides addressing these drawbacks in our proposed algorithm, we use a power model for the nodes which is more realistic than the models commonly used in the literature [WNE02, vHE02, MP09, CSS03, CFM13, HB09, HCF13, RVF08, SB11, KMG08, CK13, CCLE+07]. Our proposed cost model consists of both the transmit power for the radio link and the circuitry power of a transmitting node as the total power required at a transmitting node. Here, the circuitry power is referred to the power required for proper operation of passive modules in a wireless transmitter, such as, digital-to-analog converter (DAC), mixer, etc. While most of the existing works ignore the circuitry power of wireless devices and just focus on the power required for the radio link, the circuitry power imposed on a transmitter has a significant impact on the energy consumption in a wireless network [AGD+11]. In practice, not only the circuitry power is not negligible compared to the transmit power required for the radio links, but also it can dominate when the distance between the transmitter and receiver is short

Table 1.1. Comparison between different algorithms proposed for the MPBT problem.

	BIPSW [WNE02]	BDP [RVF08]	MFPBT [CCLE+07]	GBBTC [CK13]	[MY04]	This work
Decentralized	×	✓	✓	✓	×	✓
Transmit power control	✓	✓	×	×	✓	✓
Circuitry power consideration	×	×	×	×	×	✓
Different max. transmit power	✓	✓	✓	×	✓	✓
Without initialization phase	×	×	✓	×	✓	✓
Diversity combining	×	×	×	×	✓	✓

[CGB05, WHY06]. For instance, if the network is dense, having a single-hop broadcast would be more energy-efficient than having multiple short hops. Note that the impact of circuitry powers cannot be seen as a fixed value on top of the result obtained by an algorithm that ignores the circuitry power. In fact, as we will show, taking the circuitry power into account may significantly change the structure of the BT and having an algorithm that captures both the device's circuitry power and radio link power jointly in BT construction is of high importance.

Note that in all the aforementioned works, every receiving node chooses just one transmitting node for itself. Exploiting direversity combining and receiving the message from multiple transmitting node has not been explored much. The authors of [MY04] propose a heuristic algorithm using the maximal ratio combining (MRC) technique. The proposed algorithm is centralized and the central controller chooses multiple nodes in the network, including the source, as transmitting nodes and the receiving nodes combine the signal received from multiple transmitters. Besides being centralized, the algorithm in [MY04] does not consider the circuitry power of the transmitters in network power optimization. Table 1.1 compares our work with the main algorithms discussed in this section.

1.2.2 Multi-hop video streaming in user-centric networks

In this section, we introduce the state of the art in incentive mechanism design and multi-hop video streaming, applicable to the UCNs discussed in Section 1.1. As stated earlier, video applications occupy most of the traffic in today's communication networks and addressing the ever-growing user requirements in such networks is challenging. Prior research on multimedia transmission over wireless networks has mostly focused the QoS constraints [BCN15, DHV14], while there has been a shift in recent years towards the quality of experience (QoE) as a more suitable metric for performance evaluation of multimedia contents [CWZ15] via measures like the mean opinion score

(MOS) [QPSV17] or pseudo-subjective quality assessment (PSQA) [DHV14]. Unlike QoS that focuses on objective parameters of a network, such as throughput, energy or delay, QoE is subjective and mainly reflects the user satisfaction. For example, in [QPSV17] the authors use a PSQA [MR02] to target maximization of the mean opinion score (MOS) of the users, by minimizing the packet loss in an ad hoc network with lossy links. The authors of [DHV14] propose an algorithm for peak-signal-power to noise-power ratio (PSNR) maximization in a hybrid network composed of cellular and wireless Ad Hoc network, such that some users of the Ad Hoc network are chosen by a cellular network as gateways for video delivery to other users. Although the networks studied in [DHV14] [QPSV17] are multi-hop, the algorithms are centralized and the incentive mechanism has not been addressed.

Despite a variety of works on QoE-based network optimization, the consideration of the *individual* user preferences has been largely ignored. Researchers have recently started taking this point into account, e.g., in video caching [LM17] or content offloading [PPZ+17]. The most relevant work to our present work is [PPZ+17] where the authors consider the willingness of the users in helping each other for data offloading. In their work, users form different groups based on their content preferences and share the content with inter-group and intra-group users at different sharing probabilities to maximize the offloading gain. The model presented in [PPZ+17] depends on probabilistic decisions, while in a video application, we need to optimize the network based on users' deterministic preferences. Moreover, the proposed approach does not address the incentive mechanism issue.

Clearly, the success of a user-centric network depends on the contribution of the users for which a variety of incentive mechanisms have been proposed. These approaches are either based on tit-for-tat [PL13], reputation [RZZS15], taxation [HGL11] or payment via virtual currency [IGHT14a]. The tit-for-tat is simple but has a limited application [ZZSF11]. In reputation-based mechanisms, a node cannot ask the other nodes for relaying her message if her reputation is lower than a threshold. She needs to help others and obtain positive reputation [ZZSF11]. In [HGL11], a taxation mechanism has been proposed for video streaming in a wired peer-to-peer network in which the users experience a higher download rate if they transmit to a higher number of nodes.

The main drawback of the existing incentive mechanisms is that they try to balance the incoming and outgoing QoS measures for a node, like the download and the upload rates [HGL11]. As mentioned earlier, in a tree structure, the contributions of different nodes have different impacts on the service quality the users experience even if they receive and forward the same number of packets. In one of the early works on incentive mechanisms in tree-based multi-hop transmission in [LL05], the authors propose a simple reward function by which a given forwarding user is rewarded based on the *number of nodes* that rely on her contribution for receiving data. Although in this way the nodes closer to the source receive a higher reward, the proposed solution can just be applied to a pre-constructed network via an access point. Moreover, it ignores the level of resource consumption at the nodes. In this dissertation, we will address how the contributing users can be rewarded according to the energy they spend and the impact of their contribution on the network.

1.3 Open issues

In this section, considering the prior works, we describe the main questions that will be answered in this dissertation.

In this dissertation, we first focus on the energy efficiency of multi-hop broadcast in wireless networks with one source and multiple receivers. The aim is to disseminate the packets, available at the source, to all the nodes with minimum power. The network is managed in a decentralized way such that the set of transmitters and their corresponding receivers have to be found without the help of a central entity. To this end, every node chooses a respective transmitting node, including the source, from which it receives the intended message. The nodes can repeatedly change their chosen transmitting node until the convergence which is a point at which none of the nodes changes its decision. The major questions that arise here are as follows.

Q1. How can a decentralized algorithm for the MPBT problem be designed with guaranteed convergence?

Q2. How can one address the energy-efficiency in a decentralized way with better performance compared to the conventional heuristics?

Q3. How can one develop an algorithm by which the nodes exploit the multicast transmission in decentralized construction of the BT?

Q4. What is the best/worst case performance of the designed decentralized algorithm compared to the global optimum?

Q5. How can one find the network's optimum structure?

Most of the existing algorithms for the MPBT problem merely focus on minimization of the power required for the radio link. However, in practice, there exist other passive modules inside a wireless transmitter like DAC, mixer, etc., which all require energy for proper operation. When the energy efficiency of the network as a whole is the goal, one should also consider the circuitry power required for other modules, which leads to the following open issue.

Q6. How to design a decentralized algorithm that takes both the circuitry power and the radio link power jointly into account for network formation? How much does such a design improve the energy efficiency of the network?

We assume the contributing users receive tokens in exchange for their contributions. The tokens are sent from the receiving nodes to transmitting nodes. We design our mechanism for decentralized network formation using CSG. In multicast transmission where multiple nodes can benefit from a single transmission, the cost, or indeed, the number of tokens that needs to be paid from the multicast receiving nodes to the transmitting node, have to be shared among the receivers. This arises the following question.

Q7. What is a fair payment and how to address fairness in cost sharing? Is it possible to guarantee the convergence of a decentralized algorithm while addressing the fairness issue?

Since there may be multiple transmitting nodes in the network, a CN can exploit maximal ratio combining (MRC). Using MRC, instead of choosing one PN, a CN can combine the signals transmitted by multiple PNs to decode the intended message. This can reduce the network power and the following questions arise.

Q8. How can one exploit MRC in multi-hop broadcast in a decentralized manner?

Q9. Is it possible to address the fairness and the convergence of a decentralized algorithm for the MPBT problem while exploiting MRC?

Obviously, the aforementioned questions are related to the BT construction for the MPBT problem and are independent of the application. Now, there is a need for further optimization regarding video streaming over a BT. There exist several open questions as follows.

Q10. How can such a decentralized algorithm be customized for an application like video streaming? How can one design an incentive mechanism for user collaboration for video streaming?

Q11. How should the video layers, that result in different video qualities, be distributed in order to maximize the QoE of the users?

Q12. How to incorporate the individual user preferences in decentralized video streaming?

Q13. Since the contribution of the users closer to the source is vital for the network, how to reward the contributing users according to the impact of their contribution on the network and not merely based on the energy they consume for others?

1.4 Contributions and dissertation overview

In this section, an overview of the dissertation is provided. The section summarizes the main contributions of the dissertation given the questions raised in the previous section.

In Chapter 2, an overview of game theory as the main mathematical tool for designing and analyzing our decentralized algorithm is presented. The categories of games and the mathematical techniques used for their analysis are introduced. We further focus on CSG as the main class of game considered through this dissertation. Different cost sharing schemes and the relevant theorems are discussed.

Chapter 3 describes the system model that we consider in this dissertation. The parameters and terminologies used in this dissertation are defined. In addition to the system model, a medium access control (MAC) scheme using which the nodes can access the channel and construct the BT in a decentralized ways is described.

In Chapter 4, our decentralized game theoretic approach for BT construction is presented. Questions Q1. to Q7. are addressed in this chapter. Given the system model described in Chapter 3, in this chapter, a game-theoretic algorithm is proposed for the MPBT problem. The designed game is a potential game for which the convergence of the state of the BT is always guaranteed (Q1.). The proposed model takes the circuitry power of the transmitting nodes into account in addition to the power required for the signal amplification (Q6.). The results are shown to be significantly better than the existing approaches in term of the network power (Q2.). In order to benefit from multicast transmission, the proposed game is designed based on the CSG by which the CNs share the cost if they choose a common PN (Q3.). The marginal contribution (MC), the equal-share (ES) and the Shapley value (SV) are studied as the main cost sharing schemes in this chapter and the MC is shown to have the best performance for the MPBT problem. Further, it is shown that in UCNs where the fairness in cost sharing is critical, SV is the best to be employed. The SV not only guarantees the convergence of the BT, but also is the fairest cost sharing scheme (Q7.). We analyze the performance of the game via measures called the price of stability (PoS) and the price of anarchy (PoA), respectively (Q4.). In addition, a mixed integer linear program (MILP) is provided for finding the optimum BT, which serves as a benchmark for our decentralized algorithm (Q5.). Finally, in this chapter, a MAC scheme for decentralized construction of the BT is studied.

In Chapter 5, the model proposed in Chapter 4 is further extended and the MRC technique is employed at the receiving nodes. This chapter answers questions Q8. and Q9. of the previous section. The CNs in this chapter are allowed to choose multiple PNs. Instead of relying on one PN, a CN combines the signals transmitted by multiple PNs. In addition, the CNs determine the transmit power by which their chosen PNs have to transmit the message (Q8.). The proposed approach addresses network energy efficiency and social cost minimization via the MC and the SV cost sharing schemes, respectively. It is shown that the MRC-based game via both the MC and the SV cost sharing schemes converges to an NE (Q9.). The results in this section show that, exploiting MRC can significantly improve the network energy efficiency and the social cost. Further in this section, an MILP is provided for finding the optimum network configuration.

In Chapter 6, we specifically optimize our decentralized framework for video streaming in UCNs. To address Q10. raised in the previous section, we propose a framework for joint video quality adaptation and overlay network creation in a multi-hop wireless network based on the CSG presented in Chapter 4. The order of distributing the layers is according to the impact of the video layer on the QoE of the users as well as the data rate that a video layer requires for transmission (Q11.). In our model, a utility function is designed for each user that captures the preferences of the user concerning the video quality she wishes to obtain and her preferred level of contribution to the network (Q12.). The decision of the user, concerning the video quality she receives as well as her transmit power for forwarding the video, is determined via utility function maximization. An incentive mechanism is proposed by which the contributing users are paid based on the energy they consume for forwarding the video. Further, a taxation mechanism is proposed that captures the impact of the contribution of a user for the network and pays the user accordingly (Q13.). The optimum tax rate is discussed and it is shown that the proposed incentive and taxation mechanisms improve the video quality perceived by the users while preserving the network energy efficiency.

Chapter 7 concludes the dissertation and discusses the open problems.

Chapter 2

Overview of game theory

2.1 Introduction

Game theory models and studies the interactions among self-interested entities with a set of mathematical tools. The entities are independent and each aims to maximize its own benefit in a competitive environment. Competition among selfish agents has been discussed in the field of economics long before the modern game theory, for instance, Cournot [Cou38] and Bertrand [Ber83] introduced models for finding the strategy of firms in duopoly markets. Game theory, as a mathematical discipline, was formally introduced by John von Neumann in his paper titled "Zur Theorie der Gesellschaftsspiele" in 1928 [vN28] and later in the book with Morgenstern titled "Theory of Games and Economic Behavior" published in 1944 [vNM44].

During the past decade, there has been significant growth in employing game theory for tackling the problems related to communication networks. This is mainly due to the importance of multi-user networks and distributed control for future generations of communication networks. In this chapter, we review game theory and present the relevant definitions an the results that we use throughout this dissertation. Classically, game theory is divided into two categories of non-cooperative and cooperative games. In Section 2.2, we formally introduce the categories of games, their components and the mathematical techniques used for their analysis. We first start with non-cooperative games in Section 2.2.1. Then, we present the cooperative game in Section 2.2.2. We summarize the important aspects of cooperative game theory which will be used later in this dissertation. Then, in Section 2.3.2, we specifically focus on non-cooperative cost sharing games, as the main class of games which will be used in our work, and discuss their properties in more details.

2.2 Categories of games

2.2.1 Non-cooperative games

Non-cooperative games, also known as a strategic games, are characterized by:

- A finite set $\mathcal{P} = \{1, \ldots, N\}$ of players.
- An action set $\mathcal{A}_i$ for each player $i \in \mathcal{P}$.
  Let $a_i \in \mathcal{A}_i$ be the action, or strategy, of player i. Then, the action profile of the game is shown by $\boldsymbol{a} = (a_1, \ldots, a_N) \in \mathcal{A}$ in which $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_N$ is the joint action set of the game. The action profile of the game can also be denoted by $\boldsymbol{a} = (a_i, \boldsymbol{a}_{-i})$ in which $\boldsymbol{a}_{-i}$ represents the actions of all the players except player i.
- A utility function u_i that assigns a real value to player $i \in \mathcal{P}$ depending on the action profile of the game as $u_i(a_i, \boldsymbol{a}_{-i}) : \mathcal{A} \to \mathbb{R}$.

The non-cooperative game is then formally shown by the tuple $G := (\mathcal{P}, (\mathcal{A}_i)_{i\in\mathcal{P}}, (u_i)_{i\in\mathcal{P}})$. The game is called finite if $\mathcal{A}_i$ is finite for all $i \in \mathcal{P}$.

Definition 2.1. ***(Best response function)****: The set valued function $\mathcal{B}_i(\boldsymbol{a}_{-i})$ is called the best response function of player i and defined as [OR94]*

$$\mathcal{B}_i(\boldsymbol{a}_{-i}) := \left\{ a_i \in \mathcal{A}_i \middle| u_i(a_i, \boldsymbol{a}_{-i}) \geq u_i(a_i', \boldsymbol{a}_{-i}), \forall a_i' \in \mathcal{A}_i \right\}. \tag{2.1}$$

As the name suggests, the best response function finds the best action that player i can take given the actions of the other players, i.e., $\boldsymbol{a}_{-i}$. Based on the definition of the best response function in (2.1), a player of the game deterministically chooses an action among its action set. This also called a *pure strategy* game. In contrast, in a *mixed strategy* game, the players randomly choose their action.

Definition 2.2. ***(Mixed strategies)****: Given a (pure strategy) non-cooperative game $G := (\mathcal{P}, (\mathcal{A}_i)_{i\in\mathcal{P}}, (u_i)_{i\in\mathcal{P}})$, a mixed strategy game is defined by the tuple $G := (\mathcal{P}, (\Sigma_i(\mathcal{A}_i))_{i\in\mathcal{P}}, (\tilde{u}_i)_{i\in\mathcal{P}})$ in which $\Sigma_i(\mathcal{A}_i) := \{\sigma_i(a_i) | a_i \in \mathcal{A}_i\}$ is a probability distribution of player i over its action set $\mathcal{A}_i$ with $\sum_{a_i\in\mathcal{A}_i} \sigma_i(a_i) = 1$. The joint mixed strategy set of the game that indicates the space of the game is defined as $\Sigma = \Sigma_1 \times \cdots \times \Sigma_N$. The mixed strategy profile of the game is shown by $\boldsymbol{\sigma} = (\sigma_1, \ldots, \sigma_N)$. Further, the expected utility $\tilde{u}_i$ of player i defined as [OR94]*

$$\tilde{u}_i(\boldsymbol{\sigma}) = \sum_{\boldsymbol{a}\in\mathcal{A}} u_i(\boldsymbol{a}) \left(\prod_{j\in\mathcal{P}} \sigma_j(a_j) \right). \tag{2.2}$$

Clearly, a pure strategy game is a special case of a mixed-strategy game in which the probability of choosing one of the actions in $a_i \in \mathcal{A}_i$ is equal to 1. Throughout this dissertation, we merely focus on pure strategies.

One of the most widely-used solution concepts in game theory, used for analysis of the game and prediction of player's behavior is the Nash equilibrium (NE).

Definition 2.3. ***(Nash equilibrium (NE))****: An action profile $\boldsymbol{a}^* \in \mathcal{A}$ is an (a pure) NE of the game G if*

$$u_i(a_i^*, \boldsymbol{a}_{-i}^*) \geq u_i(a_i, \boldsymbol{a}_{-i}^*), \quad \forall i \in \mathcal{P}, a_i \in \mathcal{A}_i. \tag{2.3}$$

Given the definition of the best response function in (2.1), an NE, defined in Definition 2.3, can also be seen as a fixed-point of the best-response function. More precisely, an action profile $\boldsymbol{a}^* \in \mathcal{A}$ is an NE for which $a_i^* = \mathcal{B}_i(\boldsymbol{a}_{-i}^*), \forall i \in \mathcal{P}$ [OR94].

Roughly speaking, an NE is an action profile $\boldsymbol{a}^*$ for which none of the players has an incentive to unilaterally deviate from the action profile $\boldsymbol{a}^*$, given the actions of other players. Note that there may exist another action profile, say $\boldsymbol{a}'$, resulting in a higher utility for player i, that is, $u_i(\boldsymbol{a}') > u_i(\boldsymbol{a}^*)$, but moving from the action profile $\boldsymbol{a}^*$ to $\boldsymbol{a}'$ needs more than one player to change their actions. This is in contradiction to the definition of non-cooperative games in which the players take their action independently and selfishly. Hence, given $\boldsymbol{a}_{-i}^*$, player i must stick to action a_i^* in order to prevent her loss. Since, based on Definition 2.3, this situation holds for all the players, nobody can unilaterally deviate from $\boldsymbol{a}^*$ to improve her utility. John Nash[1] was the first who introduced such a notion as an equilibrium point in a non-cooperative game, and stated the following theorem.

Theorem 2.1. ***(Existence of NE)****: Every finite non-cooperative game has at least one (mixed-strategy) NE [Nas50].*

Remark 2.1. *Although according to Theorem 2.1, the existence of a mixed-strategy NE is guaranteed in any finite game, the existence of a pure NE depends on the properties of the game and needs to be investigated as a crucial question.*

A non-cooperative game can either be played as a one-shot game, also known as a stage game, or a repeated game. In a one-shot game, the players can take actions either simultaneously or iteratively, depending on the design of the game. As the names suggest, in simultaneous games, the players know the action set of other players along with the utilities corresponding to each action profile in advance. In fact, the full information of the game is available for the players and the players have to take one action (in a pure strategy game), out of their action set, simultaneously. The prisoners dilemma is a well-known example of a one-shot simultaneous game [OR94]. In contrast, in an iterative games, also known as a dynamic games, the players take

[1]He won the *Nobel Memorial Prize in Economic Sciences* in 1994 for his contributions to the analysis of equilibria in the theory of non-cooperative games.

actions one after another by observing the previous actions taken by the other players. In such games, a common approach for the players is to employ the best-response dynamics that we will discuss in Section 2.2.1.2. Unlike for the one-shot games, in a repeated game, the game will be played among the players for more than one round. The game in a single stage of a repeated game could be either one-shot or iterative. The analysis of repeated games is different from one-shot games. When the game is repeated multiple times, the best action in a one-shot game may not be the best move in the long run.

2.2.1.1 Potential games

The concept of potential games was first introduced by Monderer and Shapley in their seminal paper [MS96]. In potential games, the strategy of the players and the outcome of the game can be analyzed and predicted using a global function, called the potential function. Such property makes potential games a strong tool for distributed optimization [MW13a], resource allocation [ME12] and mechanism design [MASW+15].

Definition 2.4. ***(Potential game)****: A game G is an exact (finite) potential game [MS96] if there exists a (finite) real-valued function $\Phi : \mathcal{A} \to \mathbb{R}$, called the potential function, such that for every $i \in \mathcal{P}$, $a_i, a_i' \in \mathcal{A}_i$,*

$$u_i(a_i', \boldsymbol{a}_{-i}) - u_i(a_i, \boldsymbol{a}_{-i}) = \Phi(a_i', \boldsymbol{a}_{-i}) - \Phi(a_i, \boldsymbol{a}_{-i}). \tag{2.4}$$

$\Phi(a_i', \boldsymbol{a}_{-i})$ can also be denoted by $\Phi(\boldsymbol{a})$.

Theorem 2.2. *Every potential game has at least one pure NE.*

Proof. It is straightforward to verify this theorem. As shown in in Fig. 2.1, let $\mathcal{A}$ be the (continuous) action space and $\Phi(\boldsymbol{a})$ be the potential function value of $\boldsymbol{a} \in \mathcal{A}$. Further, let $\boldsymbol{a}^* = \operatorname{argmax}_{\boldsymbol{a}\in\mathcal{A}} \Phi(\boldsymbol{a})$ be the point that maximizes the potential function. Suppose that $\boldsymbol{a}^*$ is not an NE. Then, there exists at least one player who can deviate from $\boldsymbol{a}^*$ to increase its utility. Based on the definition of potential games, such a deviation increases the potential function as well. This is in contradiction to our first assumption that $\boldsymbol{a}^*$ maximizes the potential function. Note that the point that maximizes the potential function could also be a local optimum. $\square$

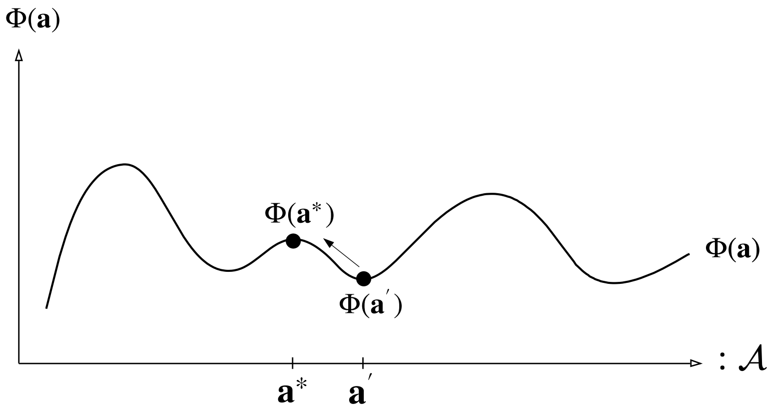


Figure 2.1. The value of a potential function for two different action profiles. The action space in this figure is assumed to be continuous.

2.2.1.2 Best-response dynamics

Although potential games answer to a key question in game theory, that is, the existence of a pure NE for the game, another important question that needs to be answered here is how one can find an NE.

Definition 2.5. ***(Best-response dynamics)****: The best-response dynamics, also known as finite improvement path, is a strategy of playing a game in which every player iteratively best-responds to the action taken by other players as [Rou16]*

$$a_i^* = \underset{a_i \in \mathcal{A}_i}{\operatorname{argmax}}\, u_i(a, \boldsymbol{a}_{-i}). \tag{2.5}$$

Proposition 2.1. *In every potential game, the best-response dynamics converges to the NE [Rou16].*

Proof. The proof is similar to the proof given for Theorem 2.2. The players iteratively update their action, and each action increases the potential function. Since the potential function is finite, this process stops at an action profile which is an NE. □

2.2.1.3 Performance measures

In a game with multiple NEs, the quality of each NE may differ in terms of the value they provide for the players. One of the common measures for quantifying the quality of an NE is the so-called social welfare.

Definition 2.6. ***(Social welfare):*** *The social-welfare of a non-cooperative game G is defined as*

$$\mathrm{SW}(G) = \frac{1}{N}\sum_{i\in\mathcal{P}} u_i(a_i, \boldsymbol{a}_{-i}). \tag{2.6}$$

The social welfare, in general, is a function of the utilities of the players in the game. It can also be defined without normalization in (2.6) as $\mathrm{SW}(G) = \sum_{i\in\mathcal{P}} u_i(a_i, \boldsymbol{a}_{-i})$ or even $\mathrm{SW}(G) = \min_{i\in\mathcal{P}} u_i(a_i, \boldsymbol{a}_{-i})$ [SLB08]. In the latter case, the performance of the game is measured via the minimum utility experienced by the players of the game at an NE.

When the objective in the game is cost minimization, rather than utility maximization, the social cost is used as the measure, defined similarly to the social welfare.

Definition 2.7. ***(Social cost):*** *Denoting by $c_i(a_i, \boldsymbol{a}_{-i})$ the cost of player i in the game, the social cost is defined as*

$$\mathrm{SC}(G) = \frac{1}{N}\sum_{i\in\mathcal{P}} c_i(a_i, \boldsymbol{a}_{-i}). \tag{2.7}$$

As stated earlier, the NEs may have different qualities concerning the value they bring for the players. This is also the case in potential games. Although in such games the best-response dynamics is guaranteed to reach an NE, the quality of the NE reached by the best-response dynamics may heavily depend on the starting point (starting action profile) of the game. More precisely, as shown in Fig. 2.1, depending on the initial $\boldsymbol{a} \in \mathcal{A}$ and its corresponding $\Phi(\boldsymbol{a})$, improvement of $\Phi(\boldsymbol{a})$ may lead to a different (local) maximum and consequently, result in a different $\boldsymbol{a}^*$. To evaluate the efficiency of an NE, the price of anarchy (POA) and the price of stability (PoS) are used as measures.

Definition 2.8. ***(POA and PoS):*** *Let $\mathcal{E}(G)$ be the set of NEs of the game G and $\mathcal{G}$ denote the set of all possible games G. Let $f(\boldsymbol{a})$ be the objective function of the game and $\mathrm{OPT}^{\max}$ represents its maximum value. The PoA and the PoS of the game G are defined, respectively, as [SLB08]*

$$\mathrm{PoA}(\mathcal{G}) := \inf_{G\in\mathcal{G}} \quad \frac{\mathrm{OPT}^{\max}_{\mathrm{a}\in\mathcal{A}} \quad f(\boldsymbol{a})}{\min_{a\in\mathcal{E}(G)} f(\boldsymbol{a})}. \tag{2.8}$$

and

$$\mathrm{PoS}(\mathcal{G}) := \inf_{G\in\mathcal{G}} \quad \frac{\mathrm{OPT}^{\max}_{a\in\mathcal{A}} \quad f(\boldsymbol{a})}{\max_{a\in\mathcal{E}(G)} f(\boldsymbol{a})}, \tag{2.9}$$

A common choice for $f(\boldsymbol{a})$ is the social welfare or the social cost function defined in Definition 2.6. When the objective in the game is to *minimize* the cost function f, the PoA, and the PoS are defined as

$$\mathrm{PoA}(\mathcal{G}) := \sup_{G\in\mathcal{G}} \quad \frac{\max_{a\in\mathcal{E}(G)} f(\boldsymbol{a})}{\mathrm{OPT}^{\min}_{\mathrm{a}\in\mathcal{A}} \quad f(\boldsymbol{a})}, \tag{2.10}$$

and

$$\mathrm{PoS}(\mathcal{G}) := \sup_{G\in\mathcal{G}} \quad \frac{\min_{a\in\mathcal{E}(G)} f(\boldsymbol{a})}{\mathrm{OPT}^{\min}_{\mathrm{a}\in\mathcal{A}} \quad f(\boldsymbol{a})}, \tag{2.11}$$

respectively.

2.2.2 Cooperative games

2.2.2.1 Definition

In cooperative games, also known as coalitional games, the players of the game can join together in order to form a coalition. Unlike for the non-cooperative game that focuses on the actions that result in an equilibrium, in cooperative games, the goal is to find the combinations of the users who benefit by forming a coalition, given the payoff (or utility) assigned to them in the coalition they form. The payoff of a player in a coalition is determined by a payoff allocation scheme which is a share of the *value* generated by the coalition. An important point here is that in both cooperative and non-cooperative games, the players are independent and self-interested, and decide rationally to maximizes their own utility.

In a cooperative game, the coalition formed by *all the players* of the game is called the *grand coalition* of the game [SLB08]. Clearly, a grand coalition is formed if all the players of the game are better-off by joining together. If one of the players of the game refuses to join the grand coalition, then it is called that the grand coalition of the game is not stable. Classically, in cooperative games, the central question is how to share the generated value in order to have a stable grand coalition, rather than what coalitions $\mathcal{S} \subseteq \mathcal{P}$ will be stable [SLB08]. The cooperative games that focus on the former problem are also known as canonical cooperative games [SHD+09].

A cooperative game is characterized by

- A finite set $\mathcal{P} = \{1, \ldots, N\}$ of players.

- A value function that shows the value generated by the coalition $\mathcal{S} \subseteq \mathcal{P}$, denoted by $v(\mathcal{S})$.

A cooperative game is formally shown by the tuple $(\mathcal{P}, v)$ and the payoff of player i in coalition $\mathcal{P}$ is denoted by $\psi_i(\mathcal{P}, v)$.

2.2.2.2 The core

A critical problem in cooperative games is how the value generated by a coalition has to be shared among the members. In fact, one has to find the properties that a payoff allocation scheme needs to satisfy in order to guarantee a stable grand coalition. The answer is that the grand coalition is stable if the payoff allocation is in the *core* of the cooperative game. The core is defined as follows:

Definition 2.9. ***(Core)**: Let x_i be the payoff allocated to player i in the grand coalition and $v(\{i\})$ denote the value generated by a single player i if it does not join any coalition. The payoff allocation $\boldsymbol{x} \in \mathbb{R}^N$ lies in the core of a cooperative game $(\mathcal{P}, v)$ if and only if it satisfies the following conditions [SLB08]*

- ***Efficiency:*** $$\sum_{i\in\mathcal{P}} x_i = v(\mathcal{P}) \tag{2.12}$$
- ***Group rationality:*** $$\forall \mathcal{S} \subseteq \mathcal{P}, \sum_{i\in\mathcal{S}} x_i \geq v(\mathcal{S}). \tag{2.13}$$

Roughly speaking, a payoff allocation results in a stable grand coalition if (i) it shares the whole generated value among its members, and (ii) given a sub-coalition $\mathcal{S} \subseteq \mathcal{P}$, the aggregated payoff allocated to the members of $\mathcal{S}$ in the grand coalition must not be less than the value generated by the sub-coalition out of the grand coalition.

Note that the group rationality condition in (2.13) also includes the individual rationality, meaning that the allocated payoff to a single player must not be less that the value that the player can generate alone, i.e., $\forall i \in \mathcal{P}, x_i \geq v(\{i\})$.

Remark 2.2. *The notion of core is analogues to the notion of NE from non-cooperative games.*

Both NE and core concepts describe the situations in which none of the players is better off by deviating from the equilibrium or leaving the coalition, respectively. One can even conclude that the notion of the core is stronger than the notion of NE. An NE guarantees the stability of a game with respect to a single player. This means that there is no single player who can unilaterally deviate from the equilibrium and benefit from such an action. Instead, the core states that there is no incentive for leaving the grand coalition not only for a single player, but also for any arbitrary coalition of the players $\mathcal{S} \subseteq \mathcal{P}$ [SLB08].

The core of the game is actually obtained by solving the linear feasibility problem using the constraints in (2.12) and (2.13). A linear feasibility problem is a linear optimization problem in which the objective is not important. It focuses merely on finding the feasible region of the problem given the constraints. Note that, depending on the constraints, the feasible region of a cooperative game may be empty.

Remark 2.3. *A cooperative game may have an empty core.*

Similar to a non-cooperative game that may not possess a pure NE, a cooperative game may also have an empty core. The non-emptyness of a cooperative game has to be verified. Further, not every payoff allocation scheme falls inside the core of a cooperative game. There are various ways for payoff allocation in cooperative games, for instance equal-share [SLB08], the Shapley value [Sha53], Nucleolus allocation [Sch69], Egalitarian allocation [PS78], etc. In the next section we will take a closer look at the Shapley value as we will use it in the rest of this dissertation for our game-theoretic algorithm design.

2.2.2.3 Shapley value

The Shapley value (SV) was first introduced by Loyd Shapley[2] in 1953 [Sha53]. It is one of the most prominent approaches for payoff allocation in cooperative games.

Definition 2.10. *According to the SV, the payoff allocation to player i in coalition $\mathcal{P}$ is calculated by*

$$x_i := \psi_i(\mathcal{P}, v) = \sum_{\mathcal{S} \subseteq \mathcal{P} \setminus \{i\}} \frac{|\mathcal{S}|!\, (|\mathcal{P}| - |\mathcal{S}| - 1)!}{|\mathcal{P}|!} (v(\mathcal{S} \cup \{i\}) - v(\mathcal{S})). \tag{2.14}$$

Roughly speaking, the SV of a player is the average of her marginal contribution to all sub-coalitions $\mathcal{S} \subseteq \mathcal{P}$ when player i is not a member of $\mathcal{S}$. The SV in (2.14) is equivalent to the following: Let $o := (i_1, \ldots, i_{k-1}, i_k, \ldots i_N)$ be an ordering (permutation) based

[2] He won the *Nobel Memorial Prize in Economic Sciences* in 2012 for his contributions to the theory of stable allocations and the practice of market design.

Table 2.1. Calculating the SV of the players in the grand coalition of the Example 2.1.

o	$\tilde{v}_o(\{1\})$	$\tilde{v}_o(\{2\})$	$\tilde{v}_o(\{3\})$
1,2,3	2	5	3
1,3,2	2	4	4
2,1,3	4	3	3
2,3,1	1	3	6
3,1,2	3	4	3
3,2,1	1	6	3
x_i :	2.17	4.17	3.66

on which the players in $\mathcal{P}$ join the coalition. We define the contribution of player i who has the k-th position in the ordering o as

$$\tilde{v}_o(i_k) = v(\{i_1, \ldots, i_{k-1}, i_k\}) - v(\{i_1, \ldots, i_{k-1}\}). \tag{2.15}$$

In other words, $\tilde{v}_o(i_k)$ finds the marginal contribution of player i_k to the coalition formed by the players who join the coalition prior to player i_k given the ordering o. Let $\mathcal{O}$ be the set of all orderings with $|\mathcal{O}| = N!$. Then the SV of player i in (2.14) is equivalent to [Mad08]

$$x_i = \frac{1}{N!} \sum_{\mathcal{O}} \tilde{v}_o(i), \qquad o \in \mathcal{O}. \tag{2.16}$$

Illustrative Example 2.1. *Suppose that a coalition is formed by* $\mathcal{P} = \{1, 2, 3\}$. *The value generated by each of the individual players and different sub-coalitions are given by:* $v(\{1\}) = 2$, $v(\{2\}) = 3$, $v(\{3\}) = 3$, $v(\{1, 2\}) = 7$, $v(\{1, 3\}) = 6$, $v(\{2, 3\}) = 9$, $v(\{1, 2, 3\}) = 10$. *We find the SV of each of the players using* (2.16)*. All the possible orders by which the players can join together and form the grand coalition are gathered in Table 2.1. In this table, the first column represents the order of joining the coalition by the players 1, 2 and 3. The columns on the right side show the contribution of each player to the coalition according to the ordering o. The last row takes an average over the contributions of each player based on* (2.16).

2.2.2.4 Fairness

The main question that the concept of the core answers is the characterization of payoff vectors that lead to a stable grand coalition. Such a payoff allocation is not unique. The question that arises here is how fair is the allocated payoff. A payoff allocation vector is fair if it satisfies the axioms of fairness. Before introducing the axioms of fairness, we present the following definitions [SLB08].

Definition 2.11. ***(Interchangeable Players)***: *Players i and j are interchangeable if they contribute the same amount to every coalition $\mathcal{S} \subseteq \mathcal{P} \backslash \{i, j\}$. That is, $v(\mathcal{S} \cup \{i\}) = v(\mathcal{S} \cup \{j\})$.*

Definition 2.12. ***(Dummy player)***: *A player i is dummy if it does not contribute to any coalition. In other words, the value generated by a dummy player alone is equal to the value generated by every coalition $\mathcal{S}$ that the player joins, i.e., $v(\mathcal{S} \cup \{i\}) = v(\{i\})$.*

We now define the axioms of fairness in payoff allocation.

Definition 2.13. ***(Axioms of fairness)***: *In a cooperative game $(\mathcal{P}, v)$, the payoff allocation $\boldsymbol{x} \in \mathbb{R}^N$ is fair if it satisfies the following axioms [SLB08]:*

- ***Symmetry:*** *If players i and j are interchangeable, then $x_i = x_j$ for any v.*
- ***Dummy player:*** *If player i is a dummy player, then $x_i = v(\{i\})$.*
- ***Additivity:*** *Let v_1 and v_2 be two value functions and $v_1(\mathcal{S})$ and $v_2(\mathcal{S})$ be the value of coalition $\mathcal{S} \subseteq \mathcal{P}$. The payoff allocation scheme is additive if $\psi_i(\mathcal{P}, (v_1 + v_2)) = \psi_i(\mathcal{P}, v_1) + \psi_i(\mathcal{P}, v_2)$ in which the characteristic function $v_1 + v_2$ on the set $\mathcal{S} \subseteq \mathcal{P}$ is defined by $(v_1 + v_2)(\mathcal{S}) = v_1(\mathcal{S}) + v_2(\mathcal{S})$.*

Theorem 2.3. *The SV is the only payoff allocation scheme that satisfies the axioms of fairness, defined in Definition 2.13 [OR94].*

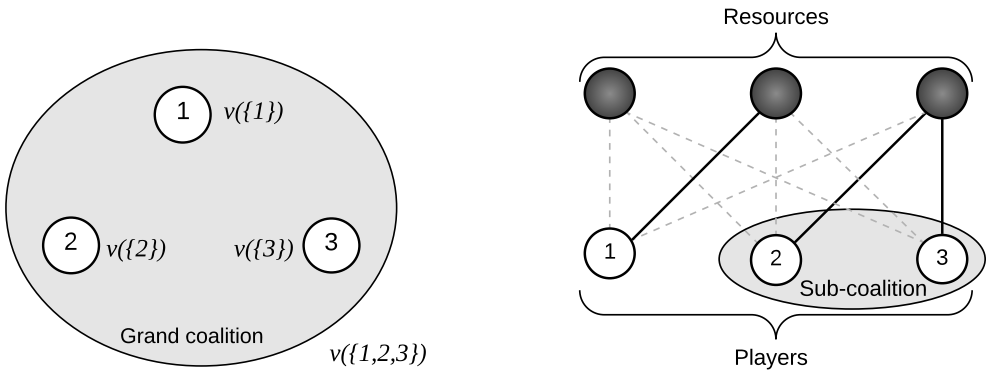
Finally, note that, even if the SV provides a fair approach in allocating the value of a coalition, it does not address the stability of the coalition. To have a stable grand coalition, the payoff allocation must be in the core which, in general, is not the case with the SV.

2.3 Non-cooperative cost sharing games

2.3.1 Introduction

A new class of games within the category of non-cooperative games, called non-cooperative cost sharing games or simply *cost sharing games*, has attracted significant attentions during the past decade due to its applications in distributed control [KM06], distributed optimization [LM13], mechanism design [Rou16] and network formation [vTW07]. The term *cost sharing* here comes from the specific setup of the game. In cost sharing games, the players are to choose a resource from the set of resources available to them. A resource could be a road, a public good, an internet service provider, etc. Since the players who share a common resource will impose a cost on resource providers, the cost of using the resource is shared among the players who choose the same resource. Cost sharing games have elements from both non-cooperative and cooperative games. Similar to the definition of a non-cooperative game, a (non-cooperative) cost sharing game is defined by a tuple $G := (\mathcal{P}, (\mathcal{A}_i)_{i\in\mathcal{P}}, (c_i)_{i\in\mathcal{P}})$ in which c_i is the cost of player i. While the game is non-cooperative, the cost sharing scheme c is defined similarly to the payoff allocation from the cooperative games. In fact, based on the decision of the players, a cost is shared among the players who take the same action depending on the value that those players generate. Here, the goal of the players is to minimize their own cost by joining the best coalition given the cost sharing scheme. The solution concept from cooperative games, like the core, is not applicable here, and instead, the concept of NE is commonly used in this context.

The difference between the cooperative games and the cost sharing games is interpreted as follows. As shown in Fig. 2.2.(a), in a cooperative game, each player is assumed to generate a value even if she does not join any coalition. In such games, we study the conditions (payoff allocation schemes) that provide incentives for *all* the players to join together and form the grand coalition. In contrast, a cost sharing game is a non-cooperative game. In cost sharing games, the players who take the same action are treated as a grand coalition although they may be a subset of the set of players. For instance, players 2 and 3 in in Fig. 2.2.(b). A cost sharing scheme shares the cost among the players according to the cost imposed on the resource provider by the players who choose the same resource. In other words, in cooperative games, the decision of a player i is either to choose the grand coalition or opt-out and generate its fixed value alone, that is, $\mathcal{A}_i = \{\emptyset, \mathcal{P}\}$. In a cost sharing game, in contrast, a player i has to choose one of the resources out of the set of available resources $\mathcal{D}$, i.e., $\mathcal{A}_i \subseteq 2^{\mathcal{D}}$. Note that, in both cooperative and cost sharing games, the actions of the players are assumed to be discrete.



(a) Cooperative game

(b) Non-cooperateive cost sharing game

Figure 2.2. Difference between the cooperative and non-cooperative cost sharing games.

2.3.2 Cost sharing for multicast transmission

2.3.2.1 Definition

Let $p(\mathcal{P})$ be the price of using a resource by coalition $\mathcal{P} = \{1, \ldots, N\}$, defined as

$$p(\mathcal{P}) = \max_{i \in \mathcal{P}} p(\{i\}), \tag{2.17}$$

in which $p(\{i\})$ is the price of using the resource when a single player i uses it, called the singleton price of player i. Note that the price function here is equivalent to the value function from cooperative games.

The multicast transmit power of a wireless transmitter satisfies the property of the function in (2.17). In a unicast transmission, the transmit power of the transmitting node is equal to power required for serving the single receiver, that is the singleton price $p(\{i\})$. In a multicast transmission, the transmit power of a transmitter is equivalent to the maximum of the powers required for serving every individual receiver. In order words, as shown in Fig. 2.2.(a), the unicast and the multicast transmit powers are, respectively, equivalent to the singleton and the grand coalition values of a cooperative game with one resource in which the value function is determined by (2.17).

2.3.2.2 Cost sharing schemes

In this section, we present a few cost sharing schemes that can be used for finding the cost share of each user $i \in \mathcal{P}$ in using a resource under the assumption in (2.17)

[SA11, GMW14]. Without loss of generality, let us assume that the singleton prices for using the resource can be sorted as

$$p(\{1\}) \leq p(\{2\}) \leq \cdots \leq p(\{N\}). \tag{2.18}$$

- **Equal-share (ES):** The ES simply splits the price among the players, that is,

$$c_i^{\mathrm{ES}} = p(\{N\})/N \qquad \forall i \in \mathcal{P}. \tag{2.19}$$

- **Highest cost allocation (HC):** With the HC, the player with the highest singleton price pays the whole price of using the resource while the others pay nothing, i.e.,

$$c_i^{\mathrm{HC}} = \begin{cases} p(\{N\}) & i = N \\ 0 & \text{otherwise.} \end{cases} \tag{2.20}$$

- **Incremental cost allocation (IC):** With the IC, every player is assigned the marginal contribution she has over the player who appears before her in the list given in (2.18). That is,

$$c_i^{\mathrm{IC}} = p(\{i\}) - p(\{i-1\}), \qquad \forall i \in \mathcal{P}, p(\{0\}) = 0. \tag{2.21}$$

- **Marginal contribution (MC)** Using the MC, the cost of all the players is zero expect the one who has the highest singleton price as

$$c_i^{\mathrm{MC}} = \begin{cases} p(\{N\}) - p(\{N-1\}) & i = N \\ 0 & \text{otherwise.} \end{cases} \tag{2.22}$$

- **Shapley value (SV):** With the assumption of (2.17), the SV of a player is given by [LO73]

$$c_i^{\mathrm{SV}} = \sum_{n=1}^{i} \frac{p(\{n\}) - p(\{n-1\})}{N+1-n}. \tag{2.23}$$

Remark 2.4. *The MC scheme in* (2.22) *is equivalent to*

$$c_i^{\mathrm{MC}} = p(\mathcal{P}) - p(\mathcal{P}\backslash\{i\}) \qquad \forall i \in \mathcal{P} \tag{2.24}$$

meaning that the cost share of player i is the difference in the generated price with and without player i in $\mathcal{P}$.

2.3.2.3 Relevant definitions and results

In this section, we presents the important definitions and results that we use later in this dissertation.

Lemma 2.1. *Suppose that singleton price of all the players in $\mathcal{P}$ is equal to* p. *Then, the SV acts similar to the ES and assigns an equal cost to every player $i \in \mathcal{P}$.*

Proof. We use (2.16) to prove. When $p(\{i\}) = \mathrm{p}$, $\forall i \in \mathcal{P}$, a player i has a positive contribution if it joins the coalition as the first member. In such a case, the total number of permutations by which the other players can join the grand coalition is $(N-1)!$. This means that a player $i \in \mathcal{P}$ has a positive contribution equal to p for $(N-1)!$ times and zero contribution for the rest of the cases. Then, according to (2.16), her cost is given by

$$c_i^{\mathrm{SV}} = \frac{1}{N!}\left((N-1)!\mathrm{p}\right) = \mathrm{p}/N = c_i^{\mathrm{ES}} \qquad \forall i \in \mathcal{P}. \tag{2.25}$$

$\square$

Definition 2.14. ***(Budget-balanced cost sharing scheme)****:* *A cost sharing scheme is budget-balanced if the summation of the costs allocated to the players is equal to the price of using the resource, i.e., if*

$$\sum_{i \in \mathcal{P}} c_i^{\mathrm{BB}} = p(\mathcal{P}). \tag{2.26}$$

Remark 2.5. *The notion of budget-balancedness of a cost sharing scheme is equivalent to the notion of efficiency of a payoff allocation scheme from cooperative games defined in* (2.12)*.*

Remark 2.6. *The cost sharing schemes introduced in this section are all budget-balanced except for the MC. Although the MC is not budget-balanced, we will show the benefits of using it in Chapter 4. It should also be noted that the HC and the MC may not be a true cost sharing scheme as they do not share the cost among the players. This case is even worse with the MC as it may allocate zero cost to all the players. The term cost allocation scheme may describe them better, however, for the sake of consistency we refer to all of them as cost sharing schemes. ES and SV are two of the widely-adopted budget-balanced schemes in the field of CSGs and are known to be fair depending on the application [ADK+04, MMAS+16].*

Definition 2.15. ***(Cross-monotonicity)****:* *A cost sharing scheme c is cross-monotone if*

$$c_i(\mathcal{S} \cup \{k\}) \leq c_i(\mathcal{S}) \qquad \forall k \in \mathcal{P} \backslash \mathcal{S}. \tag{2.27}$$

In other words, a cost sharing scheme is cross-monotone if the costs of the players who are in a coalition do not increase if the size of the coalition expands.

Observation 2.1. *All the cost sharing schemes discussed in Section 2.3.2.2 are cross-monotone.*

Proof. It is straightforward to see that the MC, the HC, and the IC are cross-monotone. The SV is also cross-monotone. Let $i \in \mathcal{S}$. If a node k joins $\mathcal{S}$, then, the denominator of (2.23) reduces as the number of players increases from $|\mathcal{S}|$ to $|\mathcal{S}|+1$. Further, the nominator of (2.23) in this case either decreases or remains unchanged. It decreases if $p_{i-1,r} < p_{k,r} \leq p_{i,r}$ and remains unchanged otherwise. In both cases, the cost of the players in $\mathcal{S}$ decreases when the number of players using the resource expands. This means that the SV is a cross-monotone function.

The ES is not cross monotone. Suppose $\mathcal{P} = \{1\}$ and $p_{1,r} = 1$. Then, $c_1^{\text{ES}}(\mathcal{P}) = 1$. Now assume that player 2 joins the coalition with $p_{2,r} = 3$. The cost of player 1 in the new coalition, according to the price function in (2.17) and the ES cost sharing scheme in (2.19), increases as

$$c_1^{\text{ES}}(\mathcal{P} \cup \{2\}) = \max\{3, 1\}/2 = 1.5 > c_1^{\text{ES}}(\mathcal{P}) = 1. \tag{2.28}$$

$\square$

Chapter 3

System and network models

3.1 Introduction

In this chapter, the system and the network models that we consider in this dissertation will be introduced. We start by introducing the multicast transmission in wireless networks in Section 3.2. Then, we express the conditions required to construct a BT and finally, formulate the MPBT problem. In Section 3.3 we propose a MAC scheme to be used by the nodes for decentralized construction of the BT. Parts of this model have been published by the author of this dissertation in [MASW+15, MASL+15, MAHK16]. Here in this section we describe the basic system model. In the next chapters, we will extend the system model where needed.

3.2 Transmission model and network power

In this section, we introduce the main properties of the system model that we use during the rest of this dissertation. We first start by modeling the transmit power of the nodes. We present a model that captures both powers required for radio link and circuitry power at a transmitting node for a successful transmission. The MPBT problem will also be formally defined.

In this dissertation, we consider a network composed of $N + 1$ wireless nodes with random locations in a two-dimensional plane; a source S and a set $\mathcal{P}$ of N receiving nodes. The nodes in $\mathcal{P}$ are interested in receiving the source's message. We denote the set of all the nodes of the network by $\mathcal{Q} = \mathcal{P} \cup \{\mathrm{S}\}$. Every node is equipped with an omnidirectional antenna and has a *transmit* power constraint $p_j^{\max}, j \in \mathcal{Q}$, and hence, its coverage area is limited. In a transmission from a transmitting node $j \in \mathcal{Q}$ to a receiving node $i \in \mathcal{P}$, nodes j and i are called the PN and the CN, respectively. The transmitting nodes transmit either by multicast or unicast. It should be remarked that, although the antenna broadcasts the message omnidirectionally, we refer to the transmission as unicast or multicast, when a PN has one or more than one intended receivers as its CNs, respectively. As stated in Chapter 1, the transmission flow from a source to the receiving nodes of the network forms a tree-graph called the BT. In this

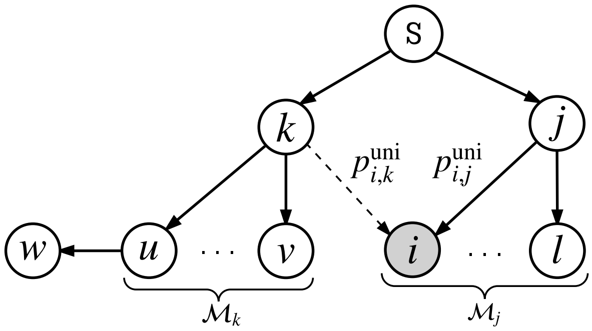


Figure 3.1. A sample network and BT. The solid arrows show the transmission from PNs to CNs and the dashed arrow represents a possible link that can be established for CN i if it chooses PN k.

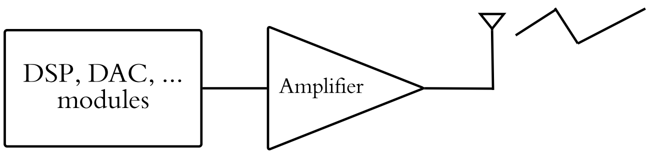


Figure 3.2. Structure of transmission modules in a transmitter.

chapter, we assume that in a BT, every node has one PN, but a PN may have one or more than one CN in case of unicast or multicast transmission, respectively. The set of CNs of PN j is denoted by $\mathcal{M}_j$ and the number of CNs of a PN is denoted by M_j. Fig. 3.1 shows an instance of a BT. In this network, some of the nodes of the network act as PN. Note that every node, except the source, is a CN in this network as it will be assigned to a PN. For instance, in Fig. 3.1 node j is a PN of node i while it is a CN of node S too. If a node $j \in \mathcal{P}$ does not forward the message of the source to any other node, then, $\mathcal{M}_j = \varnothing$.

A general structure of the transmission modules in a wireless transmitter is shown in Fig. 3.2. The total power required at a transmitting node consists of two main parts. The first part is the power required for the modules that mainly prepare the signal for transmission, such as, base-band signal processing (DSP) unit, DAC and power amplifier [CGB05]. We refer to the power required for these modules as the *circuitry* power of the node required for transmission and denote it by $p_j^{\text{ct}}, \forall j \in \mathcal{Q}$. The second part is the power that has to be spent by a transmitter to amplify the signal, referred to as the *transmit* power of a node. As mentioned before, the circuitry power of a wireless device is not negligible compared to the transmit power and may even dominate it if the distance between the transmitter and the receiver is short [CGB05]. Hence, we assume that every node $j \in \mathcal{Q}$ has a total power budget of $p_j^{\text{ct}} + p_j^{\max}$. While the circuitry power of a transmitter can be assumed as a fixed value, the transmit power needed at a transmitting node j for amplifying the signal depends on the channel quality between the transmitter and its receivers in $\mathcal{M}_j$ and thus, it is denoted by $p_j^{\text{Tx}}(\mathcal{M}_j)$ with $p_j^{\text{Tx}}(\mathcal{M}_j) \leq p_j^{\max}$. The *total* power required at *node* j for transmission to its CNs in $\mathcal{M}_j$ is

$$P_j^{\text{Tx}}(\mathcal{M}_j) = p_j^{\text{ct}} + p_j^{\text{Tx}}(\mathcal{M}_j). \tag{3.1}$$

We refer to the PN of CN i as a_i such that $a_i = j, j \in \mathcal{Q}\backslash\{i\}$ and $\boldsymbol{a} = (a_1, \ldots, a_N)$ represents a vector whose elements are the PNs of each of the nodes in $\mathcal{P}$. For the sake of notational convenience, we use $P_j^{\text{Tx}}(\boldsymbol{a})$ instead of $P_j^{\text{Tx}}(\mathcal{M}_j)$, when required. Note that in our model, where every CN has one PN, we omit the circuitry power required for message reception as it does not affect the energy-efficiency of the network. In other words, circuitry power required for receiving data, usually a fixed value, is needed at every node that aims to receive the message from its single PN and this energy does not depend on the network topology. It should be remarked that the reception circuitry power will be considered in our model studied in Chapter 5 where a node may have more than one PN. In fact, as we will show, in such a case the reception circuitry power of a CN varies depending on the number of PNs that serve it.

The power p_j^{out} of the signal emitted from the antenna of a transmitter j depends on the efficiency of its power amplifier, denoted by η_j with $0 < \eta_j < 1$, as is given by [WHY06]

$$p_j^{\text{out}} = \eta_j p_j^{\text{Tx}}. \tag{3.2}$$

For the message reception, a threshold model is considered which means, a minimum signal-to-noise ratio (SNR), denoted by γ^{th}, is required at a CN for successful reception of the message transmitted from its PN. In other words, the bit-error rate is assumed to be negligible considering γ^{th}. Hence, we assume that the statistical properties of the channel remain invariant during the data transmission. Let $g_{i,j}$ be the average channel gain between the PN j and the CN i. By treating interference as noise and denoting their joint power at the receiver i as σ^2, the SNR of the signal received by CN i is given by

$$\gamma_{i,j}(p_j^{\text{out}}) = \frac{p_j^{\text{out}} g_{i,j}}{\sigma^2}. \tag{3.3}$$

Based on the minimum required SNR γ^{th} at CN i, and using (3.2) and (3.3), the transmit power needed at a transmitting node j for transmission to a receiving node i is given by

$$p_{i,j}^{\text{need}} = \frac{\gamma^{\text{th}} \sigma^2}{\eta_j g_{i,j}}. \tag{3.4}$$

Notice that $p_{i,j}^{\text{need}}$ takes the efficiency of the power amplifier of the transmitting node into account.

Due to the transmit power constraint, a node $j \in \mathcal{Q}$ can be a PN of node i if the power required for the link between the nodes j and i is less than $p_j^{\max}$. The set of neighboring nodes of node i is denoted by $\mathcal{N}_i$ and defined as

$$\mathcal{N}_i = \left\{ j \,\middle|\, j \in \mathcal{Q}, p_{i,j}^{\text{need}} \leq p_j^{\max} \right\}. \tag{3.5}$$

It is assumed that every node knows the channel gains of the links to its neighboring nodes. We specifically denote the unicast transmit power required for the link between node j and its neighboring node i by $p_{i,j}^{\text{uni}}$. In other words, $p_{i,j}^{\text{uni}} = p_{i,j}^{\text{need}}$, if $j \in \mathcal{N}_i$, see Fig. 3.1. The transmit power of a PN j is calcualted by

$$p_j^{\text{Tx}}(\mathcal{M}_j) = \max_{i \in \mathcal{M}_j} \left\{ p_{i,j}^{\text{uni}} \right\}. \tag{3.6}$$

Considering the circuitry power of PN j, the total power required for a unicast transmission at PN j is

$$P_{i,j}^{\text{uni}} = p_j^{\text{ct}} + p_{i,j}^{\text{uni}}. \tag{3.7}$$

In case of multicast transmission, where a parent node j has multiple CNs, the total required power at a PN j in (3.1) is given by

$$P_j^{\text{Tx}}(\boldsymbol{a}) = P_j^{\text{Tx}}(\mathcal{M}_j) = \begin{cases} p_j^{\text{ct}} + p_{i,j}^{\text{Tx}}(\mathcal{M}_j) = \max\limits_{i \in \mathcal{M}_j} \left\{ P_{i,j}^{\text{uni}} \right\} & \text{if } \mathcal{M}_j \neq \varnothing \\ 0 & \text{if } \mathcal{M}_j = \varnothing \end{cases}. \tag{3.8}$$

Observation 3.1. *Since the multicast transmit power in* (3.8) *is determined by the highest required unicast power, it holds the property of the function* p *in* (2.17) *discussed in Section 2.3.2.*

Finally, the *total* required transmit power in the *network* for message dissemination among all the nodes, simply termed the *network transmit power*, is calculated by

$$P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}) = \sum_{j \in \mathcal{Q}} P_j^{\text{Tx}}(\boldsymbol{a}). \tag{3.9}$$

It should be remarked that the message flow from the source to the nodes must result in a tree-graph, rooted at the source without any cycle. When a cycle occurs in a graph, a part of the network loses its connections to S. We define the route of a node as the set of the nodes which are on the route from S to node i, including node i, and denote it by $\mathcal{R}_i$. For instance, $\mathcal{R}_w = \{\text{S}, k, u, w\}$ for the BT given in Fig. 3.1. The route of S is set to $\mathcal{R}_\text{S} = \{\text{S}\}$. If node i chooses PN j, $\mathcal{R}_i$ can be simply found as

$$\mathcal{R}_i = \mathcal{R}_j \cup \{i\}. \tag{3.10}$$

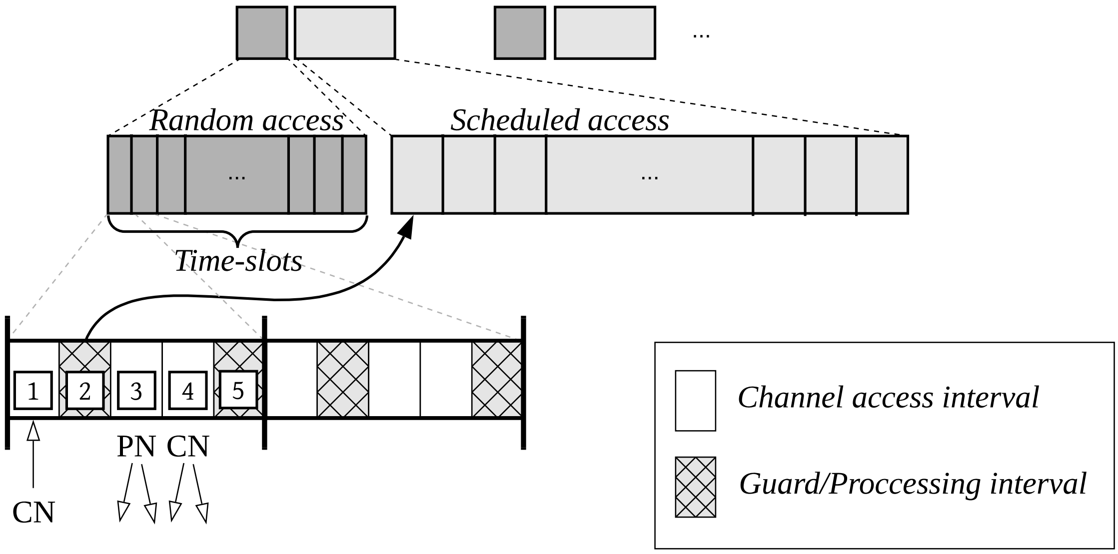


Figure 3.3. Channel access scheme.

The network-wide objective, which is also referred to as the *global objective*, is to minimize the network power defined in (3.9) such that every receiving node in $\mathcal{W}$ receives the source's message from a node $j \in \mathcal{Q}\backslash\{i\}$ and has the source in its route as

$$\begin{aligned} &\underset{\{\mathcal{M}_j\}_{\forall j \in \mathcal{Q}}}{\text{minimize}} && \textstyle\sum_{j\in\mathcal{Q}} P_j^{\mathrm{Tx}}(\mathcal{M}_j) \\ &\text{subject to:} && \forall i \in \mathcal{P}\ \exists! j \in \mathcal{Q}\backslash\{i\} : i \in \mathcal{M}_j, \mathrm{S} \in \mathcal{R}_j \quad . \end{aligned} \tag{3.11}$$

Since every node $i \in \mathcal{W}$ is allowed to choose one PN and the source must be in the route of the PN, i.e., $\mathrm{S} \in \mathcal{R}_j$, the constraints above results in a tree-graph.

3.3 Medium access control

Since the channel in this network is shared among the users, a proper MAC protocol needs to be run in the network to provide access for every node. In our work, any decentralized channel access scheme suitable for multi-hop communications can be employed. For instance, a single, time-slotted channel can be used that consists of two sections, the first section as random access and the second section as scheduled access. The first section is contention-based and used for signaling message exchanges while the transmissions by the PNs are carried out during the scheduled access section. Such a model has been studied and adopted by standards during the past years [ROGLA06, TSMW15, 3GP10].

Fig. 3.3 shows a model for channel access. In this model, the random access channel (RACH) phase, i.e., the first phase, is divided into several time-slots, each divided into five main intervals. Let us assume that a node i decides to access the channel in the random access phase in time-slot s. Node i sends its request to node j in the first interval of time-slot s, shown by $\boxed{1}$. In $\boxed{2}$, node j, as a PN, reserves a time-slot for its transmission in the scheduled section. Then, in $\boxed{3}$ it broadcasts a message to inform its neighboring nodes about the reserved time-slot in the scheduled section as well as other information which is required for the algorithm to run. The required information depends on the cost sharing scheme used in the network which we discuss in the next section. In the interval $\boxed{4}$, the CN i informs its neighboring nodes about its new PN. Finally, $\boxed{5}$ is a guard interval which can also be used for other nodes to process the information they receive in $\boxed{3}$ and $\boxed{4}$ from the nodes i and j. Clearly, if node j had already been chosen as a PN by other nodes, it does not require to reserve a new time-slot.

In our model, a node accesses the channel at most once in a RACH phase. The random access section is prone to collision, and a collision occurs if two or more nodes use *the same time-slot* in the RACH phase for sending their requests. In this case, the nodes have to retry accessing the channel in the next round of the RACH phase. The collision probability depends on the number of nodes, the number of slots in a RACH phase and the frequency of access. It will be shown in the next chapter that, by a proper design of the MAC mechanism, one can keep the average number of nodes which face a collision significantly low. It is important to remark that in this dissertation, we do not focus on random channel access optimization. Moreover, to have a fair comparison with the existing works, through the rest of this dissertation we abstract from the collision probability and measure the performance of our new scheme separately. We assume that the possible collisions impact the performance of our work and the existing works in a comparable way. Indeed, in this work, given a random channel access method for multi-hop networks, we propose a decentralized algorithm that finds an energy-efficient BT for data dissemination during the scheduled access section.

Since such a channel access scheme requires time synchronization at the nodes, it is common to use the clock of the source as a reference clock. The synchronization can be done via a dedicated time-slot in a hop by hop manner from the source toward the leaves of the BT [WCS11]. We assume that synchronization in the network is attained. It should also be noted that, although the signaling messages impose additional energy consumption on the network, we assume that the imposed energy is negligible compared to that required for the actual data dissemination.

Chapter 4

Energy-efficient multi-hop broadcast: Single transmitter per user

4.1 Introduction

In this chapter, we propose a novel decentralized approach for BT construction in wireless networks. Given the system model that we discussed in the previous chapter, in this chapter, we propose an algorithm based on a cost sharing game for the MPBT problem. Parts of this chapter have been originally published by the author in [MASW+15, KLM+15, MASK19]. In Section 4.2, we first introduce our game-theoretic model for the problem and the components of the game. We propose using MC for the MPBT problem and will show that it performs the best in comparison to the SV and the ES. For UCNs where the fairness is important, we employ SV and ES as budget-balanced cost sharing schemes. A budget-balanced cost sharing scheme is fair from a transmitter point of view, however, the way the cost of transmission is shared among the receivers is also critical. We will show that not only the SV is fair, both from the transmitter and the receivers' perspectives, but also unlike ES it always results in convergence to NE.

The model that we propose takes the circuitry power of the transmitting nodes into account in addition to the power required for the signal amplification. As we will show, such a model results in a significant improvement over the existing approaches. In Section 4.2.2, we discuss the properties of our proposed cost sharing scheme in comparison to the ES and the SV schemes, discussed in Section 2.3.2.2, in terms of the convergence of the game to an NE, the overhead information required for implementation, etc.

The performance bounds of the game will be discussed in Section 4.2.3 concerning the PoS and the PoA, which were introduced in Section 2.2.1.3. Implementation notes and how the algorithm has to be run in practice will be addressed in Section 4.2.5. Section 4.2.4 evaluates the performance the proposed RACH scheme discussed in Section 3.3. We show that by a proper design, the probability of collision in the network can be kept very low. Section 4.3 provides a centralized model for finding the MPBT based on a mixed-integer linear program (MILP). The centralized solution with the MILP serves as a benchmark for our algorithm. In Section 4.4, we provide the simulation results of our algorithm and finally, Section 4.5 provide a summary of this chapter.

4.2 Decentralized approach with cost sharing games

4.2.1 Definition

In this section, we propose a non-cooperative cost sharing game for the MPBT problem. As stated before, in a decentralized approach for the MPBT problem, every individual node has to play its own role in forming the BT by establishing a communication link to another node. Game theory is a suitable mathematical tool to design a framework within which the nodes can act independently and form the BT. The proposed game is an iterative (dynamic) game such that at every iteration t, one of the nodes of the network takes one of its possible actions from its action set. The elements of the game are as follows:

- **Players:** A set $\mathcal{P} = \{1, \dots, N\}$ of non-cooperative and rational nodes, that is, all the nodes in the network except the source.
- **Action:** Choosing another node $j \in \mathcal{Q} \backslash \{i\}$ as a PN. The action of a node i is denoted by $a_i \in \mathcal{A}_i^{(t)}$ in which $\mathcal{A}_i^{(t)}$ is the action set of player i at iteration t. The action profile of the game is shown by $\boldsymbol{a} = (a_1, \dots, a_N) \in \mathcal{A}^{(t)}$ in which $\mathcal{A}^{(t)} = \mathcal{A}_1^{(t)} \times \cdots \times \mathcal{A}_N^{(t)}$ is the joint action set of the game at iteration t.
- **Cost function:** The cost of a node is obtained based on a cost sharing scheme defined as $c_i(a_i, \boldsymbol{a}_{-i}) : \mathcal{A}^{(t)} \to \mathbb{R}^+ \cup \{0\}, \forall i \in \mathcal{P}$ in which $\mathbb{R}^+$ represents the positive real numbers.

The non-cooperative dynamic game G^{OPN} in which the every node chooses one PN for itself is defined formally by the tuple $G^{\text{OPN}} := (\mathcal{P}, \{\mathcal{A}_i\}_{i \in \mathcal{P}}, \{c_i\}_{i \in \mathcal{P}})$. The total power required in the network depends on the action profile of the game, i.e., which nodes are chosen as the PNs. We denote the action profile corresponding to the optimum BT by $\boldsymbol{a}^{\text{opt}}$. We further show the cost of node i in case of choosing PN j as $c_i(j, \mathcal{M}_j)$ since the cost just depends on the set of the nodes who choose the same PN. Moreover, $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$ denotes an update in the action profile of the game from $\boldsymbol{a}$ to $\boldsymbol{a}' = (a_i', \boldsymbol{a}_{-i})$ when node i updates its action from a_i to a_i'. The game G^{OPN} is a child-driven game, that is, a node as a child selects another node in its neighboring area as its PN. The action set of a node has to be defined in a way to ensure that no cycle occurs in different iterations of the game. Based on the definition, a cycle occurs in a rooted tree when a node $i \in \mathcal{P}$ connects to one of its descendants [Die06]; The descendants of a node $j \in \mathcal{Q}$ are all the nodes who have the node j on their route to S. A cycle occurs if node j chooses one of its descendants as its PN, for instance in Fig. 3.1, if node k chooses node w as its PN. Denoting the route of a node j at iteration t by $\mathcal{R}_j^{(t)}$, we define the action set of a node $i \in \mathcal{P}$ at iteration t as all the neighboring nodes of node i except its descendants as

$$\mathcal{A}_i^{(t)} = \left\{ j \,\middle|\, j \in \mathcal{N}_i, \mathrm{S} \in \mathcal{R}_j^{(t-1)}, i \notin \mathcal{R}_j^{(t-1)} \right\} \tag{4.1}$$

in which $\mathrm{S} \in \mathcal{R}_j^{(t-1)}$ indicates that node j, in order to be a PN of node i, must be connected to the BT. For the sake of simplicity, in the rest we omit the time indicator t in $\mathcal{A}^{(t)}$.

In order to benefit from the broadcast nature of the wireless channel, the cost of the nodes should be defined in a way to motivate the CNs to form a multicast group and choose a common PN. Moreover, the circuitry power of a transmitting node must also be considered in the cost model. The cost function in this game is defined based on the MC principle (cf. Section 2.3.2.2) as

$$c_i^{\mathrm{MC}}(j, \mathcal{M}_j) = P_j(\mathcal{M}_j) - P_j(\mathcal{M}_j \backslash \{i\}), \qquad i \in \mathcal{M}_j \tag{4.2}$$

in which $\mathcal{M}_j \backslash \{i\}$ represents the set of CNs of PN j except the CN i. Roughly speaking, the cost of node i is the difference in the total power required at node j with and without node i. Based on (4.2), a positive cost is assigned to the CN that requires the highest unicast transmit power from PN j while the cost assigned to the other CNs in $\mathcal{M}_j$ is zero. The game G^{OPN} with the MC, defined in (4.2), as its cost function is called the CSG-MC.

To illustrate the cost model in (4.2), let us assume that node i and node l require the highest and the second highest unicast powers from PN j, respectively, see Fig. 3.1. In this case, the cost assigned to the CN i using (4.2) is given by

$$c_i^{\mathrm{MC}}(j, \mathcal{M}_j) = p_j^{\mathrm{ct}} + p_{i,j}^{\mathrm{uni}} - \left(p_j^{\mathrm{ct}} + \max_{h \in \mathcal{M}_j \backslash \{i\}} \{p_{h,j}^{\mathrm{uni}}\} \right) = p_{i,j}^{\mathrm{uni}} - p_{l,j}^{\mathrm{uni}}. \tag{4.3}$$

In this case, either $i \in \mathcal{M}_j$ or $i \notin \mathcal{M}_j$, the circuitry power is consumed at PN j as it must serve the CN l. Therefore, no *additional* power, here the circuitry power, is imposed on PN j by CN i and hence, the circuitry power of PN j does not appear in the cost assigned to the CN i. Moreover, if we assume that the CN i is the only CN of the PN j, then based on (4.2), the cost of CN i contains the circuitry power of PN j, i.e., $c_i^{\mathrm{MC}}(j, \mathcal{M}_j) = p_j^{\mathrm{ct}} + p_{i,j}^{\mathrm{uni}}$, as $\max_{h \in \mathcal{M}_j \backslash \{i\}} \{p_{h,j}^{\mathrm{uni}}\} = 0$. In other words, since in a unicast both transmit and circuitry powers are imposed on the PN j by the CN i, the circuitry power appears in the cost assigned to the CN i as well as the transmit power. Therefore, depending on the structure of the BT and the transmission scheme (unicast or multicast), the cost model in (4.2) treats the circuitry power intelligently. It keeps or removes the circuitry power from the cost of receiving nodes to prevent establishing a new unicast transmission or motivate the nodes to form a multicast receiving group and reduce the number of transmissions, respectively. Whether joining a multicast group is better than establishing a unicast connection is decided by the node based on its cost function.

We employ the best response dynamics (BRD) for game G^{OPN}, cf. Section 2.2.1.2). The best response of player i, which is also here referred to as the *local objective*, is defined as

$$a_i = \operatorname*{argmin}_{j \in \mathcal{A}_i} \quad c_i(j, \mathcal{M}_j), \qquad \forall i \in \mathcal{P}. \tag{4.4}$$

Finally, we consider the NE as the solution concept of our game, defined in (2.3). When cost minimization is the objective of the nodes, the NE is defined as

$$c_i(a_i^*, \boldsymbol{a}_{-i}^*) \leq c_i(a_i, \boldsymbol{a}_{-i}^*), \quad \forall i \in \mathcal{P}, a_i \in \mathcal{A}_i. \tag{4.5}$$

While with the BRD, only one node is allowed to update its action in a time-slot, it is possible to enable multiple simultaneous actions per time-slot. In [ZVP+11], a randomized distributed algorithm is introduced by which the game can be viewed as a time homogeneous Markov Chain with finite number of states in which each NE represents an absorbing state. This will ensure convergence to an absorbing state with probability 1, even with simultaneous updates. Although by such a design the game converges to an NE, the complexity of the game increases, especially for designing rules for preventing the occurrence of loop in the BT.

4.2.2 Convergence of the game and discussion

In this subsection, we discuss the properties of the game described in the previous subsection. We first show that the game converges to an NE. Then we discuss the properties of the game.

Definition 4.1. *Let* $\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} f := f(\boldsymbol{a}') - f(\boldsymbol{a})$ *be the change in the function* f *when* $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$*. The local objective in* (4.4) *is said to be aligned with the global objective in* (3.11) *if for every* $i \in \mathcal{P}$, $\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} c_i < 0$, *then,* $\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} P_{\mathrm{net}}^{\mathrm{Tx}} < 0$*. They are also said to be exactly aligned if* $\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} c_i = \underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} P_{\mathrm{net}}^{\mathrm{Tx}}$.

Theorem 4.1. *The game G^{OPN} with the proposed MC cost sharing scheme is an exact potential game with the potential function*

$$\Phi(\boldsymbol{a}) = \sum_{j \in \mathcal{Q}} P_j^{\mathrm{Tx}}(\boldsymbol{a}). \tag{4.6}$$

Proof. According to the definition of a potential game in (2.4) and using (4.2) and (4.6), we have to show that

$$\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} c_i^{\mathrm{MC}}(\boldsymbol{a}) = \underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} \Phi(\boldsymbol{a}) \tag{4.7}$$

in which $c_i^{\mathrm{MC}}(\boldsymbol{a})$ and $\Phi(\boldsymbol{a})$ are defined in (4.2) and (4.6), respectively. Let us assume that $a_i = j$ and $a_i' = k$ and $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$, see Fig. 3.1. With such a transition, just PN j and PN k will be affected among the PNs in the network. Thus, the network transmit power, here the potential function of the game, can be written as

$$\Phi(\boldsymbol{a}) = \sum_{j \in \mathcal{Q}} P_j^{\mathrm{Tx}}(\boldsymbol{a}) = P_j^{\mathrm{Tx}}(\mathcal{M}_j) + P_k^{\mathrm{Tx}}(\mathcal{M}_k) + \sum_{m \in \mathcal{Q}\backslash\{j,k\}} P_m^{\mathrm{Tx}}(\mathcal{M}_m). \tag{4.8}$$

The cost of node i when $i \in \mathcal{M}_j$ is given by

$$c_i^{\mathrm{MC}}(j, \mathcal{M}_j) = P_j^{\mathrm{Tx}}(\mathcal{M}_j) - P_j^{\mathrm{Tx}}(\mathcal{M}_j\backslash\{i\}), \tag{4.9}$$

and the cost assigned to node i when it joins PN k is

$$c_i^{\mathrm{MC}}(k, \mathcal{M}_k \cup \{i\}) = P_k^{\mathrm{Tx}}(\mathcal{M}_k \cup \{i\}) - P_k^{\mathrm{Tx}}(\mathcal{M}_k). \tag{4.10}$$

The potential function in (4.8) when $a_i' = k$ is given by

$$\Phi(\boldsymbol{a}') = P_j^{\mathrm{Tx}}(\mathcal{M}_j\backslash\{i\}) + P_k^{\mathrm{Tx}}(\mathcal{M}_k \cup \{i\}) + \sum_{m \in \mathcal{Q}\backslash\{j,k\}} P_m^{\mathrm{Tx}}(\mathcal{M}_m). \tag{4.11}$$

Then, using (4.8), (4.9), (4.10), (4.11) we have

$$\begin{aligned}\underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} \Phi(\boldsymbol{a}) &= P_k^{\mathrm{Tx}}(\mathcal{M}_k \cup \{i\}) - P_k^{\mathrm{Tx}}(\mathcal{M}_k) - P_j^{\mathrm{Tx}}(\mathcal{M}_j) + P_j^{\mathrm{Tx}}(\mathcal{M}_j\backslash\{i\}) \\ &= \underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} c_i^{\mathrm{MC}}(\boldsymbol{a})\end{aligned} \tag{4.12}$$

Hence, given the potential function in (4.6) we always have $= \underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} c_i^{\mathrm{MC}}(\boldsymbol{a}) = \underset{\boldsymbol{a}\to\boldsymbol{a}'}{\Delta^i} \Phi(\boldsymbol{a})$.

□

Corollary 4.1. *If the cost of the nodes is defined based on the MC, the local objective in the game G^{OPN} is exactly aligned with the global objective defined in* (3.11).

Corollary 4.2. *The BRD converges to a pure NE for the game G^{OPN}.*

Proof. Since the game G^{OPN} is an exact potential game, it possesses a pure NE [MS96]. When a node updates its action in order to reduce its cost, based on Theorem 4.1 the same reduction occurs in Φ. As Φ, i.e., the network transmit power, is bounded from below, after some iterations the game G^{OPN} reaches a state at which none of the nodes can further reduce its own cost given the action of other nodes. □

Remark 4.1. *Although reaching an NE in a finite number of iterations is guaranteed by using BRD, its convergence rate is exponential in the worst case. Nevertheless, the average convergence rate of the BRD is $O(N)$ [DG16] which is acceptable for practical scenarios.*

Theorem 4.2. *Using MC, $\boldsymbol{a}^{\mathrm{opt}}$ is always an NE of the game G^{OPN}.*

Proof. Recall that $\boldsymbol{a}^{\mathrm{opt}}$ is the action profile of the game associated with the optimum BT. Let us assume that $\boldsymbol{a}^{\mathrm{opt}}$ is not an NE. Therefore, based on the definition of NE, at least one of the nodes of the network can update its action to reach a lower cost. As shown in Theorem 4.1, reduction in the cost of a node results in the same reduction of Φ, that is, the network transmit power. This is a contradiction as the BT of $\boldsymbol{a}^{\mathrm{opt}}$ is optimum. □

Remark 4.2. *Let $p^{\mathrm{uni}}_{0,j} = 0 \leq p^{\mathrm{uni}}_{1,j} \leq \cdots \leq p^{\mathrm{uni}}_{i,j} \leq \cdots \leq p^{\mathrm{uni}}_{M_j,j}$, be the sorted individual unicast powers imposed on PN j by its CNs. The cost of the i-th CN based on the SV (cf.* (2.23)*) is given by*

$$c_i^{\mathrm{SV}}(j, \mathcal{M}_j) = \sum_{n=1}^{i} \frac{P^{\mathrm{uni}}_{n,j} - P^{\mathrm{uni}}_{n-1,j}}{M_j + 1 - n}. \tag{4.13}$$

in which $P^{\mathrm{uni}}_{n,j}$ is defined in (3.7)*.*

Remark 4.3. *Given the definition of the ES cost sharing scheme in* (2.19)*, the cost of a node i in this game is obtained by*

$$c_i^{\mathrm{ES}}(j, \mathcal{M}_j) = P_j^{\mathrm{Tx}}(\mathcal{M}_j)/M_j, \quad \forall i \in \mathcal{M}_j. \tag{4.14}$$

Note that $c_i^{\mathrm{ES}}(j, \mathcal{M}_j)$ does not necessarily depend on the individual unicast power of the link from the CN i to its PN j.

Remark 4.4. *According to Definition 2.14, a budget-balanced cost sharing scheme in this game satisfies*

$$\sum_{i \in \mathcal{M}_j} c_i^{\mathrm{BB}}(j, \mathcal{M}_j) = P_j^{\mathrm{Tx}}(\mathcal{M}_j) \tag{4.15}$$

in which $c^{\mathrm{BB}}(.)$ denotes a budget-balanced cost sharing scheme like the SV or the ES.

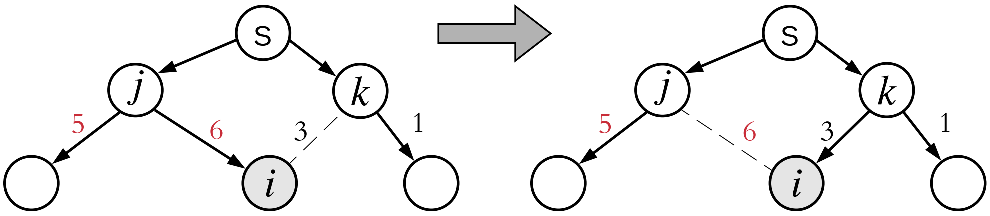


Figure 4.1. With ES and SV the optimum BT may not be an NE of the game (Transition $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$).

Theorem 4.3. *For both ES and SV, there exists at least one instance in which* $\mathbf{a}^{\text{opt}}$ *is not an NE.*

Proof: We provide an instance in Fig. 4.1 for which the optimum action profile is not an NE for the ES and the SV. In this instance, using the ES, node i updates its action from $a_i = j$ to $a'_i = k$ to reduce its cost from $(p^{\text{c}}_j + 6)/2$ to $(p^{\text{c}}_k + 3)/2$. Assuming $p^{\text{c}}_j = p^{\text{c}}_k$, this action reduces the cost of node i by 1.5 units while at the same time, it deviates from the optimum action profile ($\mathbf{a}$) and increases the network transmit power by 1 unit, that is, from $P^{\text{Tx}}_{\text{net}}(\mathbf{a}) = P^{\text{Tx}}_{\text{S}}(\{j,k\}) + p^{\text{c}}_j + 6 + p^{\text{c}}_k + 1$ to $P^{\text{Tx}}_{\text{net}}(\mathbf{a}') = P^{\text{Tx}}_{\text{S}}(\{j,k\}) + p^{\text{c}}_j + 5 + p^{\text{c}}_k + 3$. Using the SV defined in (4.13) also leads to the same conclusion as node i reduces its cost from 3.5 to 2.5 by the same action. ■

Remark 4.5. *Although for the instance provided in Fig. 4.1 both the ES and the SV are not able to reach the optimum configuration, the instances for which* $\boldsymbol{a}^{\text{opt}}$ *is not an NE may be different ones for the ES and the SV.*

We now discuss how can one verify if a budget-balanced cost sharing scheme is not able to reach the global optimum in general.

Remark 4.6. *Let node i change its action from $a_i = j, a_i \in \mathbf{a}$ to $a'_i = k, a'_i \in \mathbf{a}'$ under a given budget-balanced cost sharing scheme c^{BB}. Then, $\boldsymbol{a}^{\text{opt}} \in \mathcal{A}$ cannot be guaranteed to be an NE for the C^{BB} if one can find $\boldsymbol{a}$ and $\boldsymbol{a}'$ for which the following holds:*

$$\underset{\mathbf{a}\to\mathbf{a}'}{\Delta^i} \sum_{m\in\mathcal{M}_k\cup\mathcal{M}_j\setminus\{i\}} c^{\text{BB}}_m > -\underset{\mathbf{a}\to\mathbf{a}'}{\Delta^i} c^{\text{BB}}_i. \tag{4.16}$$

This can be shown as follows. Using Remark 4.4 and by a summation over all the nodes $j \in \mathcal{Q}$, for a budget-balanced cost sharing scheme one can write

$$\sum_{j\in\mathcal{Q}} \sum_{i\in\mathcal{M}_j} c^{\text{BB}}_i(j,\mathcal{M}_j) = \sum_{j\in\mathcal{Q}} P^{\text{Tx}}_j(\mathcal{M}_j). \tag{4.17}$$

The left side of (4.17) *represents the total payment received by the PNs* $j \in \mathcal{Q}$ *which is equal to the cost paid by the CNs* $i \in \mathcal{W}$*, i.e.,* $\sum_{i \in \mathcal{W}} c_i^{\text{BB}}(\mathbf{a})$*. Thus,* (4.17) *is equivalent to*

$$\sum_{i \in \mathcal{W}} c_i^{\text{BB}}(\mathbf{a}) = \sum_{j \in \mathcal{Q}} P_j^{\text{Tx}}(\mathbf{a}). \tag{4.18}$$

By expanding the left side of (4.18) *and re-arranging it, the cost of node* i *is given by*

$$\begin{aligned} c_i^{\text{BB}}(\mathbf{a}) &= \sum_{j \in \mathcal{Q}} P_j^{\text{Tx}}(\mathbf{a}) - \sum_{m \in \mathcal{W} \setminus \{i\}} c_m^{\text{BB}}(\mathbf{a}) \\ &= P_{\text{net}}^{\text{Tx}}(\mathbf{a}) - \sum_{m \in \mathcal{W} \setminus \{i\}} c_m^{\text{BB}}(\mathbf{a}) \end{aligned} \tag{4.19}$$

in which $P_{\text{net}}^{\text{Tx}}(\mathbf{a})$ *is defined in* (3.9)*. Since in transition from* $a_i = j$ *to* $a'_i = k$*, only the PNs* j *and* k *and their CNs are affected, then using* (4.19) *we get*

$$\begin{aligned} \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} c_i^{\text{BB}} &= \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} P_{\text{net}}^{\text{Tx}} - \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} \sum_{m \in \mathcal{W} \setminus \{i\}} c_m^{\text{BB}} \\ &= \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} P_{\text{net}}^{\text{Tx}} - \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} \sum_{m \in \mathcal{M}_k \cup \mathcal{M}_j \setminus \{i\}} c_m^{\text{BB}}. \end{aligned} \tag{4.20}$$

Since $\mathbf{a} \xrightarrow{i} \mathbf{a}'$ *implies that* $\underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} c_i^{\text{BB}} < 0$*, based on* (4.20)*,* $\underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} P_{\text{net}}^{\text{Tx}} < \underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} \sum_{m \in \mathcal{M}_k \cup \mathcal{M}_j \setminus \{i\}} c_m^{\text{BB}}$ *which does not necessarily indicate* $\underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} P_{\text{net}}^{\text{Tx}} < 0$*. More precisely, based on* (4.20)*, if the condition in* (4.16) *is met, then,* $\underset{\mathbf{a} \to \mathbf{a}'}{\Delta^i} P_{\text{net}}^{\text{Tx}} > 0$*. Roughly speaking, according to* (4.16)*, if the increase in the sum of the costs of the CNs in* $m \in \mathcal{M}_k \cup \mathcal{M}_j \setminus \{i\}$ *is higher than the reduction that CN* i *experiences in its cost, then the network transmit power increases by* $\mathbf{a} \xrightarrow{i} \mathbf{a}'$*.*

Hence, if one finds an instance of the network for which (4.16) *holds, then, the cost of a CN and the network transmit power are not aligned under* c^{BB} *and deviating from an action profile* $\mathbf{a} \in \mathcal{A}$ *does not, in general, result in network transmit power reduction. Since* $\mathbf{a}^{\text{opt}} \in \mathcal{A}$*, the global optimum cannot be guaranteed to be an NE for* c^{BB}*.*

If our proposed game, that employs the MC cost sharing scheme, reaches to the global optimum at some iteration, the network never leaves the optimum point which is a result of Theorem 4.2. Based on Theorem 4.3, this is not necessarily true if a budget-balanced cost sharing scheme is used.

We further discuss the instances of networks provided in Fig. 4.1 and Fig. 4.2 where node i updates its action to reduce its cost according to a budget-balanced cost sharing

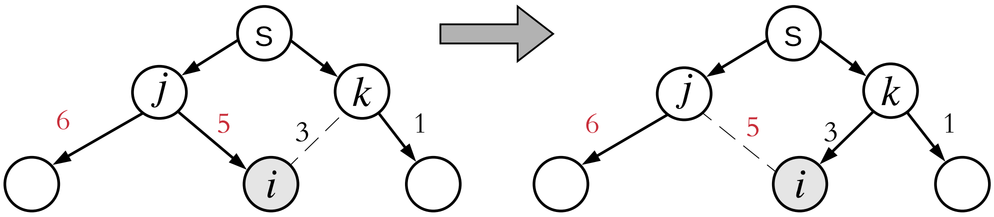


Figure 4.2. With IC the optimum BT may not be an NE of the game (Transition $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$).

Table 4.1. Changes in the network transmit power and the cost of node i in Fig. 4.1 and Fig. 4.2 due to $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$ with $p_j^{\mathrm{ct}} = p_k^{\mathrm{ct}}$ and $\tilde{P} := P_{\mathrm{S}}^{\mathrm{Tx}}(\{j,k\}) + p_j^{\mathrm{ct}} + p_k^{\mathrm{ct}}$.

Scheme	Fig.	$c_i(\boldsymbol{a})$	$c_i(\boldsymbol{a}')$	$P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a})$	$P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a}')$	$\Delta^i_{\boldsymbol{a}\to\boldsymbol{a}'} c_i^{\mathrm{BB}}$	$\Delta^i_{\boldsymbol{a}\to\boldsymbol{a}'} P_{\mathrm{net}}^{\mathrm{Tx}}$
ES	4.1	3	1.5	$\tilde{P}+7$	$\tilde{P}$ +8	-1.5	+1
SV	4.1	3.5	2.5	$\tilde{P}$ +7	$\tilde{P}$ +8	-1	+1
HC	4.1	6	3	$\tilde{P}$ +7	$\tilde{P}$ +8	-3	+1
IC	4.2	5	2	$\tilde{P}$ +7	$\tilde{P}$ +9	-3	+2
MC	4.1	1	2	$\tilde{P}$ +7	$\tilde{P}$ +8	+1	+1

scheme while its action increases the network transmit power. The cost sharing schemes and the corresponding values, that is, the cost of node i before and after the transition as well as the network transmit power, are gathered in Table 4.1. All the cost sharing schemes used in this table have been introduced in Section 2.3.2.2. For instance, using the HC scheme in Fig. 4.1, node i updates its action from $a_i = j$ to $a_i' = k$ to reduce its cost from $p_j^{\mathrm{ct}} + 6$ to $p_k^{\mathrm{ct}} + 3$. Assuming $p_j^{\mathrm{ct}} = p_k^{\mathrm{ct}}$, this action reduces the cost of node i by 3 units while at the same time, it deviates from the optimum action profile $\boldsymbol{a}$ and increases the network transmit power by 1 unit, that is, from $P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a}) = P_{\mathrm{S}}^{\mathrm{Tx}}(\{j,k\}) + p_j^{\mathrm{ct}} + 6 + p_k^{\mathrm{ct}} + 1$ to $P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a}') = P_{\mathrm{S}}^{\mathrm{Tx}}(\{j,k\}) + p_j^{\mathrm{ct}} + 5 + p_k^{\mathrm{ct}} + 3$. Note that the condition in (4.16) holds in this case. It should also be remarked that by employing the MC in the example given in Fig. 4.1, node i does not change its action since such an action increases its cost from 1 to 2.

In the rest of this chapter, we further investigate the properties of ES and SV in comparison to MC.

Lemma 4.1. *A necessary condition of a budget-balanced cost sharing scheme to guarantee the existence of an NE is cross-monotonicity [MW13b].*

Recall that, according to Definition 2.15, a cost function is cross-monotone if the cost

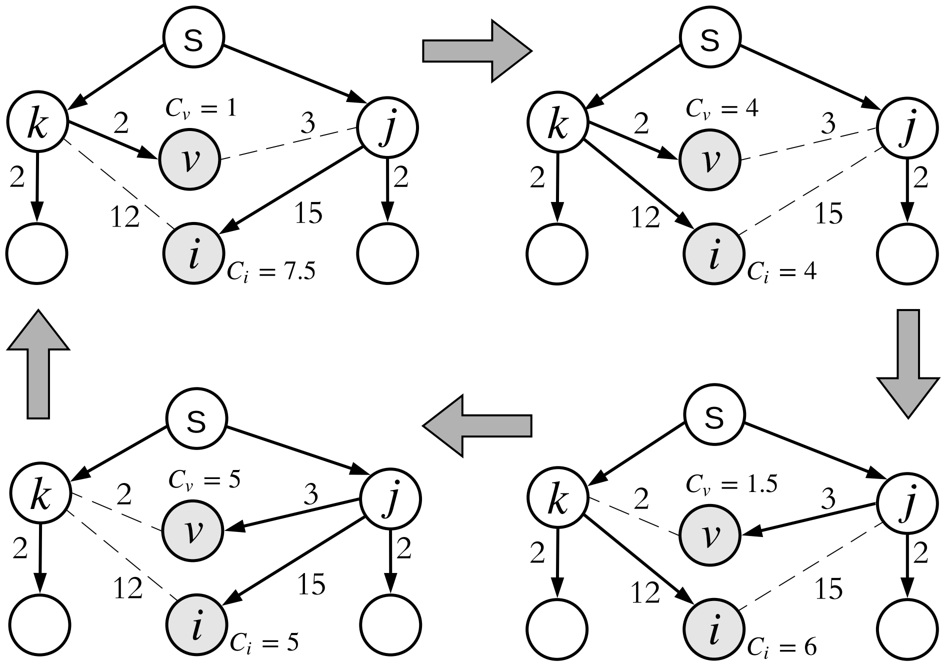


Figure 4.3. The ES scheme for the MPBT problem does not guarantee the convergence.

of the CNs of a PN does not increase when a new node joins the PN. This property for the convergence of the game is intuitive. When the cost is not cross-monotone, when a new node joins a multicast group, the other nodes leave the group if their cost increases and this may result in instability.

Theorem 4.4. *The ES does not guarantee the existence of an NE for the MPBT problem.*

Proof. It is easy to see that based on Definition 2.15, the ES is not cross-monotone and hence, based on Lemma 4.1 the convergence to an NE is not guaranteed. Moreover, we provide an instance of the network in Fig. 4.3 for which the ES scheme does not lead to an NE. In this figure, updating the action at node i increases the cost of node v and vice versa. Hence, the nodes i and v iteratively update their actions and the game G^{OPN} does not converge. The costs of node i and v are provided in the figure for different states of the BT. □

Lemma 4.2. *When the power of a PN j is fixed and independent of $\mathcal{M}_j$, the cost assigned to a CN by the SV is equal to the one assigned by the ES, i.e.,* $c_i^{\text{ES}}(j, \mathcal{M}_j) = c_i^{\text{SV}}(j, \mathcal{M}_j), \forall i \in \mathcal{M}_j$.

Proof. With fixed $P_j(\mathcal{M}_j)$, the contribution of every CN in $\mathcal{M}_j$ on the transmit power of PN j is equal and can be assumed as $P_{i,j}^{\text{uni}} = P_j(\mathcal{M}_j), \forall i \in \mathcal{M}_j$. Using (4.13) for

$i = 1$ we have $c_1^{\mathrm{SV}}(j, \mathcal{M}_j) = P_j(\mathcal{M}_j)/M_j$. Since the other nodes do not change the total transmit power of PN j, then, $P_{i,j}^{\mathrm{uni}} = P_{i-1,j}^{\mathrm{uni}}, \forall i > 1$. Therefore, $c_i^{\mathrm{SV}}(j, \mathcal{M}_j) = c_1^{\mathrm{SV}}(j, \mathcal{M}_j), \forall i \in \mathcal{M}_j$. □

Remark 4.7. *Note that for the MTBT problem where the transmit powers are all equal and fixed (and their values do not matter), the ES shares the cost as* $c_i^{\mathrm{ES}}(j, \mathcal{M}_j) = 1/M_j$.

Lemma 4.3. *A non-cooperative CSG with SV scheme is a potential game for which an NE always exists [MS96, GMW14].*

Theorem 4.5. *The ES guarantees the existence of an NE for the MFPBT (and MTBT) problem.*

Proof. As stated in Lemma 4.2, the ES scheme is a special case of the SV when the contributions of the CNs are assumed to be equal. This is the case for the MFPBT problem where the transmit power of a PN, regardless of the individual unicast powers required for the links to its CNs, is fixed. Hence, using the ES for the MFPBT problem can be seen as a special case of the MPBT problem with the SV scheme. Since based on Lemma 4.3, the SV guarantees the existence of an NE for the MPBT (and MFPBT) problem, the ES does so for the MFPBT problem. □

Note that, based on Definition 2.15, the ES is cross-monotone for the MFPBT problem and fulfills the necessary condition in Lemma 4.1.

Remark 4.8. *The implantation of different cost sharing schemes differs in terms of the information overhead they require. The ES is the simplest one since a node, to calculate its cost, just requires knowing the number of CNs in a multicast receiving group. With MC, every node needs to know the highest and the second highest unicast powers required by the CNs of a PN. Finally, the SV imposes the highest overhead on the network. To calculate the cost using the SV, a node must know the unicast power required of every individual CN in a multicast group.*

The information required for decision making has to be transmitted in a neighboring area by every node as overhead information via a broadcast channel. Table 4.2 summarizes the properties of the different cost sharing schemes. The comparison in terms of overhead is relative.

In conclusion, based on what has been discussed and using Table 4.2, we can find that the MC has two main advantages over the SV for the MPBT problem. Firstly, with MC, unlike SV or any other budget-balanced cost sharing scheme, $\boldsymbol{a}^{\mathrm{opt}}$ is always an

Table 4.2. Properties of different cost sharing schemes.

	MC	SV	ES	HC	IC
Convergence for MPBT	yes	yes	no	yes	yes
Convergence for MTBT/MFPBT	yes	yes	yes	yes	yes
Is $\boldsymbol{a}^{\mathrm{opt}}$ always an NE?	yes	no	no	no	no
Overhead	medium	high	low	low	high

NE. Secondly, the required overhead information for MC is lower than that of the SV. This becomes more important when the size of the multicast receiving group increases. Note that here we do not consider the ES for the MPBT problem due to the lack of convergence guarantee.

4.2.3 Performance bound

In this section, we study the performance of our algorithm using the PoA and the PoS measures defined in (2.10) and (2.11), respectively. We provide an instance of a network for which the proposed game theoretic algorithm may converge to a bad NE. This will be a lower bound for the worst case performance of our algorithm.

Theorem 4.6. *The PoS of the proposed game with MC is lower bounded by* $\Omega(N^{(\alpha-1)})$.

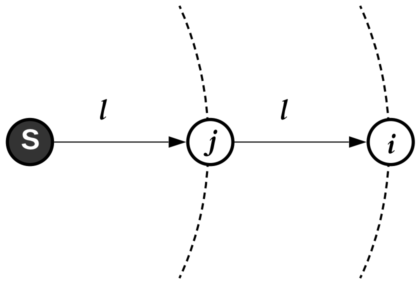
Proof. Based on Theorem 4.2, $\boldsymbol{a}^{\mathrm{opt}}$ is always an NE of the game G^{OPN}, thus, $\mathrm{PoS}(\mathcal{G}^{\mathrm{OPN}}) = 1$. □

Remark 4.9. *With a budget-balanced scheme for the MPBT problem, based on Theorem 4.3,* $\mathrm{PoS}(\mathcal{G}^{\mathrm{OPN}}) > 1$.

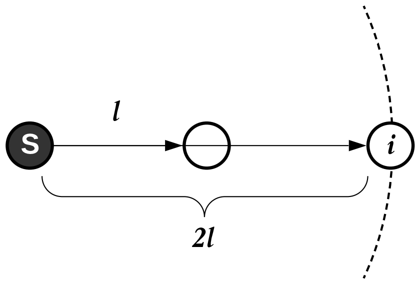
Theorem 4.7. *The POA of the game* G^{OPN} *with MC is lower bounded by* $\Omega(N^{(\alpha-1)})$.

Proof. In this section, we provide a lower bound for the PoA of our game, mentioned in Theorem 4.7. We find an instance of an NE for which the network transmit power compared to the global optimum is bad. We assume a path-loss model for the channel with the path-loss exponent α, $2 < \alpha < 6$. Thus, the channel gain between the nodes i and j can be represented as $g_{i,j} \propto 1/(\tilde{l}_{i,j})^{\alpha}$ in which $\tilde{l}_{i,j}$ is the distance between them. Using Eq. (3.4), the maximum transmit power is given by

$$p_j^{\max} = \frac{\gamma^{\mathrm{th}}\sigma^2\,(l^{\max})^{\alpha}}{\eta_j} \tag{4.21}$$



(a) Unicast transmissions with $P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_1)$.



(b) Broadcast with $P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_2)$.

Figure 4.4. Different schemes for transmission.

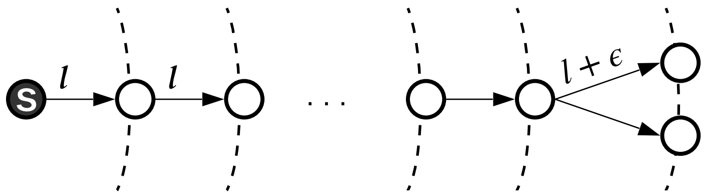
in which $l^{\max}$ is the largest possible distance between the PN j and its CN. For the sake of convenience, in this section, we normalize the unicast power of the links to $p_j^{\max}$ in (4.21) so that the transmit power between nodes i and j can be represented as $p_{i,j}^{\text{uni}} = (l_{i,j})^\alpha$ with $l_{i,j} = \tilde{l}_{i,j}/l^{\max}$ and $0 \leq l_{i,j} \leq 1$. Moreover, the maximum transmit power is given by $p^{\max} = 1$. Further, we assume that $p_j^{\text{ct}} = p^{\text{c}}, \forall j \in \mathcal{Q}$. We now find a topology for which the game-theoretic algorithm may converge to a bad NE. Let the nodes of the network be evenly distributed on a line as shown in Fig. 4.4 and Fig. 4.5 and $l = 1/N$. We first express the following lemma.

Lemma 4.4. *In Fig. 4.4,* $P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_1) \leq P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_2)$ *if* $p^c \leq 1 - 1/2^{(\alpha-1)}$.

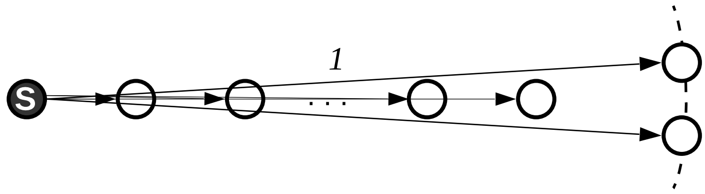
Proof. With $N = 2$ we have $l = 1/2$. Hence, $P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_1) \leq P_{\text{net}}^{\text{Tx}}(\boldsymbol{a}_2)$ implies $2(p^c + l^\alpha) \leq p^c + (2l)^\alpha$. This is valid if $p^c \leq 1 - 1/2^{(\alpha-1)}$. $\square$

Lemma 4.5. *Let* $\boldsymbol{a}_1$ *be the action profile corresponding to a BT formed merely by unicast transmissions and let* $\boldsymbol{a}_2 \in \mathcal{A}\backslash\{\boldsymbol{a}_1\}$ *be the action profile corresponding to the BT with a single-hop broadcast. Similar to Lemma 4.4, one can show that for every* $N \geq 2 \in \mathbb{N}$*, we have* $P^{\text{net}}(\boldsymbol{a}_1) \leq P^{\text{net}}(\boldsymbol{a}_2)$ *if* $p^{\text{c}} \leq \left(1 - 1/N^{\alpha-1}\right)/(N-1)$.

Let us assume that the condition in Lemma 4.5 holds. Then, given $\epsilon \to 0$, the BT in Fig. 4.5.(a) is the optimum configuration while the BT in Fig. 4.5.(b) is an NE. The



(a) Optimum BT with the action profile $\boldsymbol{a}_1$.



(b) A bad instance of NE with the action profile $\boldsymbol{a}_2$

Figure 4.5. The Optimum BT and a bad instance of NE.

PoA given the action profiles $\boldsymbol{a}_1$ and $\boldsymbol{a}_2$ is obtained by

$$\mathrm{PoA}(G^{\mathrm{OPN}}) = \frac{P^{\mathrm{net}}(\boldsymbol{a}_2)}{P^{\mathrm{net}}(\boldsymbol{a}_1)} = \frac{1 + p^{\mathrm{c}}}{N\left(1/N^{\alpha} + p^{\mathrm{c}}\right)}. \tag{4.22}$$

The PoA in (4.22) is maximized when when $p^{\mathrm{c}} \to 0$. Thus, a lower bound of the PoA is $\Omega(N^{(\alpha-1)})$. □

Remark 4.10. *The PoA of the game G^{OPN} with ES scheme for the MPBT problem is bounded by $O(\sqrt{N}\log^2 N)$ [CCLE+07].*

The PoA of the game G^{OPN} with SV scheme remains open.

4.2.4 Analysis of RACH for MAC

In this section, we analyze the performance of the proposed RACH scheme suggested in Section 3.3. We find the probability of collision in this network and discuss the number of slots required so that the nodes can access the channel at least once and choose their PNs.

We consider a RACH consisting of s time-slots. Every node $i \in \mathcal{P}$ randomly and uniformly chooses one of the slots in order to access the channel and send its request.

Theorem 4.8. *The probability of collision in the RACH phase with s slots and N nodes is equal to $1 - \frac{{}_s\mathrm{P}_N}{s^N}$ in which ${}_s\mathrm{P}_N$ is the number of s-permutations of N.*

Proof. We first find the probability of a collision-free access. Clearly, there will be no collision with one node. The probability of a collision-free access with two nodes accessing the channel, as the second node has $s-1$ choices out of s, is given by $(s-1)/s = 1 - 1/s$. Similarly, a collision-free access with three nodes is obtained by $(1-1/s)\,(1-2/s)$. By induction, the probability of a collision-free access with N nodes is calculated by

$$\begin{aligned}
\bar{\rho}_{\text{col}} &= \left(\frac{s-1}{s}\right)\left(\frac{s-2}{s}\right)\dots\left(\frac{s-N+1}{s}\right) \\
&= \frac{(s-1)(s-2)\dots(s-N+1)}{s^{(N-1)}} \\
&= \frac{s}{s}\frac{(s-1)(s-2)\dots(s-N+1)}{s^{(N-1)}}\frac{(s-N)!}{(s-N)!} \\
&= \frac{s!}{s^N(s-N)!} = \frac{{}_N\mathrm{P}_s}{s^N}.
\end{aligned} \tag{4.23}$$

The probability of collision is then given by $\rho_{\text{col}} = 1 - \bar{\rho}_{\text{col}}$. □

Theorem 4.9. *Let N be the number of nodes that randomly and uniformly access a RACH consisting of s slots. Then, the average number n_{col} of the nodes that experience a collision is given by $n_{\text{col}} = N(1-(1-\frac{1}{s})^{(N-1)})$.*

Proof. We start by finding the probability of collision for a given node. As mentioned before, the probability of a collision-free access for two nodes is equal to $1-1/s$. A given node does not have a collision with any other nodes in $\mathcal{P}\backslash\{i\}$ with probability $(1-1/s)^{(N-1)}$. Since there are N nodes in the network, the expected number of nodes that successfully choose a time-slot (experience no collision) is obtained by $N\,(1-1/s)^{(N-1)}$. Finally, the average number of nodes that experience a collision is equal to

$$n_{\text{col}} = N - N\,(1-1/s)^{(N-1)} = N(1-(1-\frac{1}{s})^{(N-1)}). \tag{4.24}$$

□

Fig. 4.6 and 4.7 show the probability of collision in the network and the average number of nodes that experience a collision in a RACH consisting of s time-slots, respectively. As can be seen, the probability of collision, even if $N << s$ is high, however, as shown in Fig. 4.7 the number of nodes that face a collision is expected to be relatively low. This means that the number of nodes that needs to retry accessing the RACH will significantly reduce over consecutive RACH phases.

Lemma 4.6. *(Binomial approximation): $(1+x)^k \approx 1 + kx$ if $|x| < 1$ and $|kx| << 1$.*

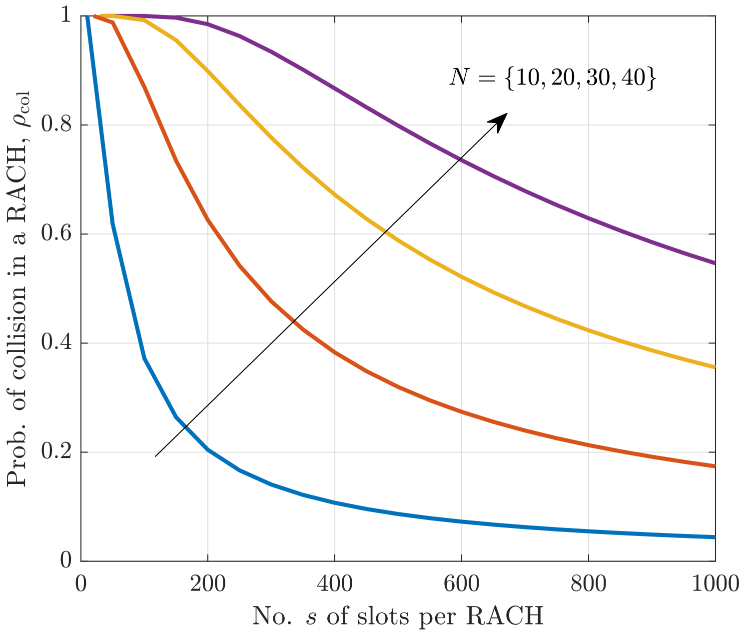


Figure 4.6. Probability of collision in a RACH for different number s of slots and for different number N of nodes.

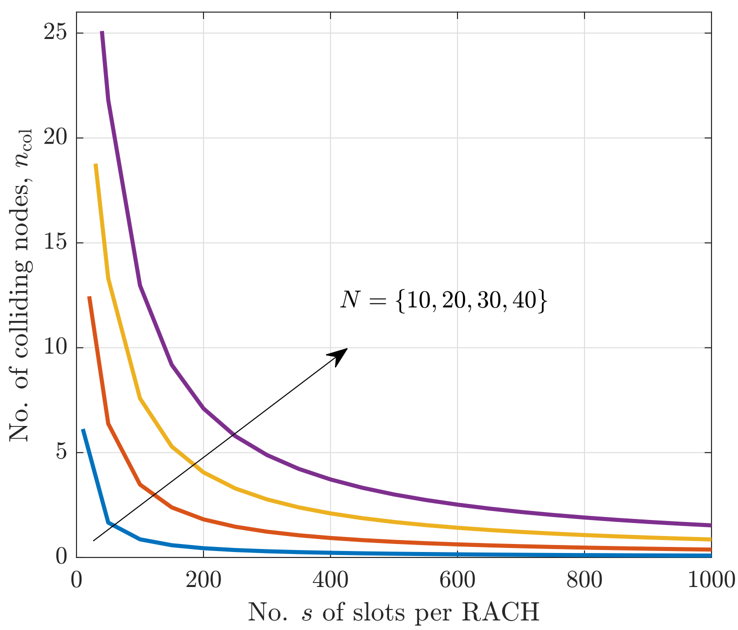


Figure 4.7. Number of colliding nodes in a RACH for different number s of slots and for different number N of nodes.

Corollary 4.3. *Using Lemma 4.6 in Theorem 4.9 and assuming* $N >> 1$ *and* $N/s <<$ 1, *we can approximate* $(1 - 1/s)^{(N-1)}$ *by* $1 - N/s$. *Therefore,* (4.24) *can approximated* *by*

$$\tilde{n}_{\text{col}} \approx N(1-(1-\frac{N}{s})) = N^2/s. \tag{4.25}$$

Note that, the number of collisions merely depends on the number of nodes and the number of available time-slots.

Observation 4.1. *Given* (4.24) *and* (4.25)*, we always have* $\tilde{n}_{\text{col}} \geq n_{\text{col}}$.

Proof. If $\tilde{n}_{\text{col}} \geq n_{\text{col}}$, then,

$$\begin{aligned} N(1-(1-\frac{N}{s})) - N(1-(1-\frac{1}{s})^{(N-1)}) &\geq 0 \\ (1-\frac{1}{s})^{(N-1)} &\geq 1-\frac{N}{s}. \end{aligned} \tag{4.26}$$

According to the Bernoulli's inequality, we always have

$$(1-\frac{1}{s})^{(N-1)} \geq 1-\frac{N-1}{s}, \tag{4.27}$$

and, since $1-\frac{N-1}{s} > 1-\frac{N}{s}$, the statement in (4.26) is always true. □

One can conclude from Observation 4.3 that $\tilde{n}_{\text{col}}$ in (4.24) is an upper bound for the actual value of n_{col} in (4.25).

Assumption 4.1. *We assume that the nodes in the network randomly and uniformly access a RACH consisting of s time-slots. Further, if a collision occurs, that is, if more than one node chooses the same time-slot for accessing the channel, the colliding nodes back-off and access the channel in the next round of RACH phase. More precisely, if a collision occurs in the r-th round of RACH phase, $r \geq 1$, the colliding nodes back off, and, retry accessing the channel during the next round of RACH phase within the time-slots $[rs+1,(r+1)s]$, see Fig. 3.3.*

Theorem 4.10. *Let us assume that the nodes aim at accessing the RACH successfully only for once. This means that, the nodes, after a successful access, do not access the channel anymore. Considering $N << s$ and according to Assumption 4.1, the average number $\bar{r}$ of the rounds required so that all the nodes access the RACH successfully is upper-bounded by*

$$\bar{r} \leq 1 + \log\left(\frac{\log(s)}{\log(s/N)}\right). \tag{4.28}$$

Proof. Let $\tilde{n}_{\text{acc}}^{(r)}$ and $\tilde{n}_{\text{col}}^{(r)}$ be the approximated number of nodes that aim at accessing the channel at round r of RACH phase and the approximated number of colliding nodes in the r-th round of the RACH phase, respectively. Clearly, the number of nodes that try to access the channel at the beginning of the r-th round of RACH, for $r \geq 2$, is equal to the number of colliding nodes at the end of the previous round, i.e.,

$$\tilde{n}_{\text{acc}}^{(r)} = \tilde{n}_{\text{col}}^{(r-1)}. \tag{4.29}$$

In the first round of RACH we start by $\tilde{n}_{\text{acc}}^{(1)} = N$ and, based on Corollary 4.3, the number of colliding nodes is given by $\tilde{n}_{\text{col}}^{(1)} \approx N^2/s$. A number $\tilde{n}_{\text{acc}}^{(2)} \approx N^2/s$ of the nods access the channel in the second round of RACH again which results in $\tilde{n}_{\text{col}}^{(2)} \approx N^4/s^3$. Using induction, the number of colliding nodes at the r-th round of RACH phase is obtained by

$$\tilde{n}_{\text{col}}^{(r)} \approx \frac{N^{2^r}}{s^{(2^r-1)}}. \tag{4.30}$$

The average number $\bar{r}$ of rounds required so that all the nodes access the channel once is upper-bounded by the round for which we have $\tilde{n}_{\text{acc}}^{(\bar{r})} \leq 1$. By setting $\tilde{n}_{\text{acc}}^{(\bar{r})} \leq 1$ we get

$$\begin{aligned}
N^{2^{(\bar{r}-1)}} &\leq s^{2^{(\bar{r}-1)}-1} \\
2^{(\bar{r}-1)} \log N &\leq (2^{(\bar{r}-1)} - 1) \log s \\
2^{(\bar{r}-1)} (\log N - \log s) &\leq - \log s \\
2^{(\bar{r}-1)} &\leq \frac{-\log s}{\log N - \log s} \\
\bar{r} - 1 &\leq \log \left(\frac{-\log s}{\log N - \log s} \right) \\
\bar{r} &\leq 1 + \log \left(\frac{\log(s)}{\log(s/N)} \right).
\end{aligned} \tag{4.31}$$

□

Fig. 4.8 shows the average number of colliding nodes over different rounds of RACH. In this figure, we set $s = 10N$ and $N \in \{10, 30, 50, 70, 90\}$. This figure shows both the simulation results and the approximation given in (4.30) which are fairly close. As expected, although collisions occur in the first round of RACH, the number of collisions in the second round would be very close to zero. Further, we observe that in Fig. 4.8, the gap between the approximation and the simulation in the first round of RACH increases when N becomes larger. The reason is the error of the approximation given

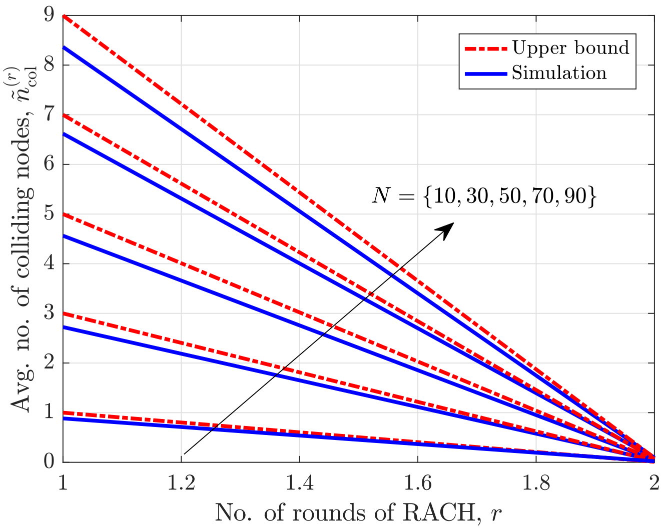


Figure 4.8. Average number of nodes that experience a collision in different rounds of RACH phases.

in (4.25). Let $k = N/s$, then, δ as the approximation error is calculated as

$$\begin{aligned}\delta &= \left|N(1-(1-\frac{1}{s})^{(N-1)}) - N(1-(1-\frac{N}{s}))\right| \\ &= N\left|1-\frac{N}{s}-(1-\frac{1}{s})^{(N-1)}\right| \\ &= N\left|1-k-\underbrace{(1-\frac{1}{s})^{(N-1)}}_{\approx 1-\epsilon}\right|, \end{aligned} \tag{4.32}$$

that shows the error scales with N.

Fig. 4.9 shows the average number of rounds required for successful channel access by all the nodes, assuming $s = 10N$. We depict the result obtained by simulation, as well as the approximation provided in (4.31). We observer that, when the number of nodes is less than 60, less than two rounds of RACH are required, on average, so that all the nodes access the channel once.

Remark 4.11. *In practice, in designing a MAC scheme for the proposed data-dissemination algorithm, one can assume that during the first $\bar{r}$ rounds of RACH, the nodes are allowed to have just one successful channel access. This way, and based on Fig. 4.9, the initial BT can be formed with a few iterations. The nodes are allowed to update their action in any of the next RACH phases without any limitations, however, one attempt per RACH phase is allowed. Since the number of nodes that need to update their action is a fraction of the total number of nodes, based on Fig. 4.8, the number of nodes that may face a collision is expected to be significantly low.*

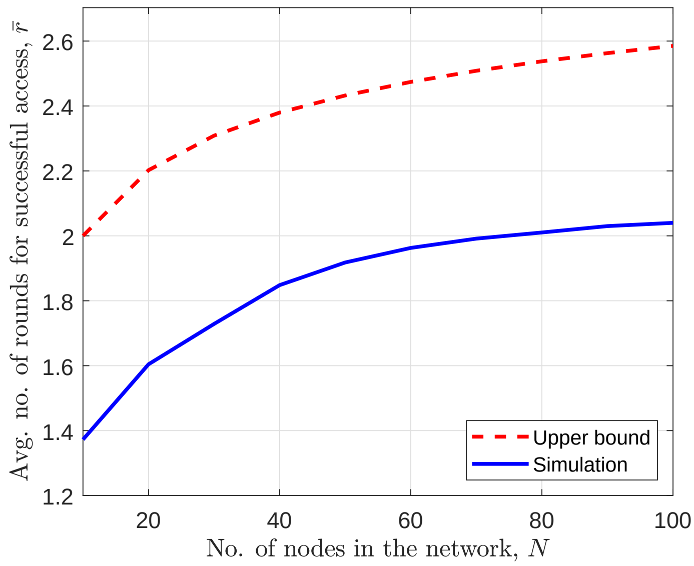


Figure 4.9. Average number of rounds required until all the nodes access the channel once.

4.2.5 Implementation notes

In this section, we explain how the proposed algorithm can be implemented in a decentralized way. Using a so-called HELLO message is necessary to implement the proposed algorithm. When a node, as a source, has a message to disseminate in the network, it broadcasts HELLO messages to inform its neighboring nodes. In fact, every node after joining the broadcast-tree transmits the HELLO message to inform its neighboring nodes. A HELLO message contains the node's ID along with other necessary information required for constructing the network. A node can obtain the required unicast power of the link to its neighboring nodes by measuring the strength of the received HELLO message [SL06].

After receiving the HELLO messages, a node finds its initial PN by solving (4.4) and sends a JOIN message to its chosen PN. As stated in (3.10), the route of a node i to S, i.e., $\mathcal{R}_i$, if node i chooses PN j can be simply found as

$$\mathcal{R}_i = \mathcal{R}_j \cup \{i\}.$$

This means that, when a CN i chooses PN j, it can simply add its ID to $\mathcal{R}_j$ to find its own route to the $\mathcal{S}$. When the node i joins the PN j and later on, receives a HELLO message from a node k resulting in a lower cost than that of the PN j, it sends a LEAVE message to the PN j and sends a JOIN message to the new PN k.

In order to solve (4.4) and consequently find its PN, every node needs to know the highest and the second highest unicast powers required by its CNs. Therefore, a PN has to also add this information into its HELLO message. The action set of a node in the game can also be found by using (3.10) in (4.1). To summarize, the HELLO message of a node $j \in \mathcal{Q}$ contains:

- Node's ID: j
- Circuitry power: p_j^{ct}
- The route to the source: $\mathcal{R}_j$
- Cost sharing scheme-specified information:
  - MC: The highest and the second highest unicsat powers of the links to its CNs in $\mathcal{M}_j, j \in \mathcal{Q}$
  - SV: The unicsat power of *all* the links to its CNs in $\mathcal{M}_j, j \in \mathcal{Q}$
  - ES: The highest unicast power of the links to its CNs in $\mathcal{M}_j, j \in \mathcal{Q}$ along with the number of CNs, i.e., M_j.

4.3 Centralized approach with mixed integer linear program (MILP)

In this section, we model the MPBT problem of (3.11) as an MILP. This approach is employed in the paper published by the author in [MASK19]. The provided MILP mainly finds the optimum value of the network transmit power by finding the nodes that should act as transmitting nodes as well as their transmit power. It does not determine the structure of the optimum BT. We first provide the MILP for the MPBT problem and then propose an algorithm by which the structure of the optimum BT can be found based on the solution of the MILP. Before providing the MILP formulation, we define the following vectors and variables and, later in this section, explain them by a toy example:

- Transmission vector: the transmission vector is used to determine whether a node $j \in \mathcal{Q}$ acts as a transmitting node or not. Moreover, in case that node j is a transmitting node, it determines the CN of PN j that requires the highest unicast power. The transmission vector is defined as $\boldsymbol{t}_j = [t_{1,j}, \ldots, t_{N,j}]^{\mathrm{T}}, j \in \mathcal{Q}$

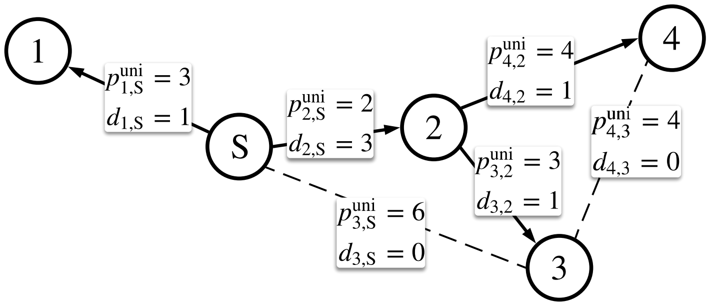


Figure 4.10. A sample BT from S to four other nodes. The numbers on the links show the required unicast powers, $p^{\text{uni}}_{i,j}$, and the downstream values, $d_{i,j}$.

as an $N \times 1$ vector such that $t_{i,j} \in \{0, 1\}$ and $t_{i,j} = 1$ if and only if node i is the CN of PN j that requires the highest unicast power among all nodes in $\mathcal{M}_j$. Moreover, $\sum_{i \in \mathcal{N}_j} t_{i,j} \leq 1$. If node j is a transmitter, then $\sum_{i \in \mathcal{N}_j} t_{i,j} = 1$, otherwise $\sum_{i \in \mathcal{N}_j} t_{i,j} = 0$.

- Reachability vector: it determines that if a node $i \in \mathcal{P}$ is a CN of PN j with highest required unicast power, given $P^{\text{Tx}}_j = p^{\text{uni}}_{i,j}$, which of the other nodes in $\mathcal{P}$ fall inside the coverage area of PN j (without imposing additional transmit power on PN j). It is defined as $\boldsymbol{r}_{i,j} = [r^{(1)}_{i,j}, \dots, r^{(l)}_{i,j}, \dots, r^{(N)}_{i,j}]$ as a $1 \times N$ binary vector for all $j \in \mathcal{Q}$ and $i, l \in \mathcal{P}$. The l-th entry of $\boldsymbol{r}_{i,j}$ is equal to 1 if $p^{\text{uni}}_{l,j} \leq p^{\text{uni}}_{i,j} = p^{\text{Tx}}_j, \forall i \in \mathcal{P}$. Since a node does not transmit to itself, then, $r^{(l)}_{i,i} = 0, \forall i, l \in \mathcal{P}, r^{(j)}_{i,j} = 0, \forall i, j \in \mathcal{P}$. Reachability matrix $\boldsymbol{R}_j = [\boldsymbol{r}^{\text{T}}_{1,j}, \dots, \boldsymbol{r}^{\text{T}}_{N,j}]^{\text{T}}, j \in \mathcal{Q}$ is an $N \times N$ binary matrix with $\boldsymbol{r}_{i,j}$ the reachability vector.

- Downstream value: the downstream value $d_{i,j}$ is defined for the link between any two nodes j and i in $\mathcal{Q}$ and shows the total number of nodes in the network that rely on the transmission from PN j to CN i for receiving the source's message.

Since the outcome of the MILP must be a tree graph rooted at the source, i.e., $\text{S} \in \mathcal{R}_i.\forall i \in \mathcal{P}$, as also exploited in [CK13], three conditions for the downstream have to be met. Firstly, the source node cannot be in the downstream of any other node as it is not a CN for other PNs. Secondly, the number of downstream nodes of the source node must be equal to N, as the whole network is connected to the source, either directly or indirectly. Finally, the difference between the sum of the downstream values of the links coming in and going out of a node in $\mathcal{P}$ must be equal to 1.

We explain the defined vectors and matrices in detail using the illustration shown in Fig. 4.10. In the BT of Fig. 4.10, the source node multicasts the message to node 1 and node 2. Then, node 2 forwards the message to nodes 3 and 4. $p^{\text{uni}}_{i,j}$ required between any two nodes i and j and $d_{i,j}$ of the link are also shown in Fig. 4.10. As can be seen, the downstream values of the links between the source and nodes 1 and 2 are equal to $d_{1,\mathrm{S}} = 1$ and $d_{2,\mathrm{S}} = 3$, respectively. Therefore, $d_{1,\mathrm{S}} + d_{2,\mathrm{S}} = 4$, that is, the total number of downstream nodes of S is equal to the total number of receiving nodes in $\mathcal{P}$. The difference between the downstream values coming to and going out of node 2, as an intermediate node, is 1, i.e., $d_{2,\mathrm{S}} - (d_{3,2} + d_{4,2}) = 1$. This is also true for the nodes which do not forward the message. Variables $t_{i,j}$ and $d_{i,j}$ are to be found by the MILP for all $i, j \in \mathcal{Q}$, while $\boldsymbol{R}_j$ can be obtained based on the unicast power required between the nodes. Based on the unicast power for each link shown in Fig. 4.10, the reachability matrix for S is given by

$$\boldsymbol{R}_\mathrm{S} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}. \tag{4.33}$$

The entries of the last row in (4.33), i.e., $\boldsymbol{r}_{4,\mathrm{S}}$, are all zero as node 4 and S are no neighbors, that is, node 4 cannot be reached by S due to the power constraint at S. It can be seen in (4.33) that $\boldsymbol{r}_{1,\mathrm{S}} = [1, 1, 0, 0]$, that is, $r_{1,\mathrm{S}}^{(1)}$ and $r_{1,\mathrm{S}}^{(2)}$ are equal to 1. Recall the entries of $\boldsymbol{r}_{i,j}$ show the nodes that can receive the message from PN j without additional transmit power at node j if the transmit power of node j is equal to $p_{i,j}^{\mathrm{uni}}$. This shows that if the source node transmits to node 1, then, node 2 can also receive the source's message by a multicast transmission without additional transmit power. In order to find which of the nodes of the network are covered by PN j based on its transmission, we define $\boldsymbol{y}_j = [y_{1,j}, \ldots, y_{N,j}]^\mathrm{T}$ as

$$\boldsymbol{y}_j = \boldsymbol{R}_j^\mathrm{T} \boldsymbol{t}_j. \tag{4.34}$$

More precisely, $\boldsymbol{y}_j$ is equal to one of the reachability vectors of node j depending on its transmission matrix $\boldsymbol{t}_j$. In the BT shown in Fig. 4.10, $\boldsymbol{t}_\mathrm{S} = [1, 0, 0, 0]^\mathrm{T}$. Using (4.33) and (4.34), we have $\boldsymbol{y}_\mathrm{S} = \boldsymbol{r}_{1,\mathrm{S}}^\mathrm{T} = [1, 1, 0, 0]^\mathrm{T}$.

The MILP for the MPBT problem is provided in (4.35).

$$\min_{t_{i,j}} \quad \sum_{j\in\mathcal{Q}, i\in\mathcal{N}_j} t_{i,j} P^{\text{uni}}_{i,j} \tag{4.35a}$$

s.t.

$$\sum_{i\in\mathcal{N}_j} t_{i,j} = \begin{cases} 1 & j = \text{S} \\ \leq 1 & j \in \mathcal{P} \end{cases} \tag{4.35b}$$

$$\sum_{i\in\mathcal{N}_j} (d_{i,j} - d_{j,i}) = \begin{cases} N & j = \text{S} \\ -1 & j \in \mathcal{P} \end{cases} \tag{4.35c}$$

$$d_{i,j} \leq N y_{i,j} \qquad \forall j \in \mathcal{Q}, \forall i \in \mathcal{N}_j \tag{4.35d}$$

$$t_{j,j} = 0 \qquad \forall j \in \mathcal{P} \tag{4.35e}$$

$$t_{i,j} \in \{0,1\}, d_{i,j} \geq 0, d_{i,j} \in \mathbb{R} \qquad \forall i \in \mathcal{P}, j \in \mathcal{Q}. \tag{4.35f}$$

$P^{\text{uni}}_{i,j}$ in (4.35a) is defined in (3.7). Eq. (4.35b) expresses that the source node must be a transmitter while the other nodes $j \in \mathcal{P}$ are not necessarily a transmitter. The constraints in (4.35c) and (4.35d), as stated before, guarantee that the resulting tree is a BT rooted at the source. The values of $y_{i,j}$, found by (4.34), are used in (4.35d) to find the downstream values of the links between the nodes. Eq. (4.35d) represents the constraint on the downstream values. More precisely, $y_{i,j} = 0$ in (4.35d) indicates that, for a given $\boldsymbol{t}_j$, node i cannot be covered by node j and the downstream value of the link between the nodes j and i must be zero, that is, $d_{i,j} = 0$.

Finally, it should be mentioned that the proposed MILP can also be used for the MFPBT and the MTBT problems [CCLE+07, CK13], however, due to the fixed transmit power, the number of constraints for the MFPBT problem will be much lower than that of the MPBT problem. In fact, since every node has only two choices, that is, whether to transmit or not, there will be only a reachability vector for the nodes and no reachability matrix.

By the solution of the MILP, a node $j \in \mathcal{Q}$ is a transmitting node if $\sum_{i\in\mathcal{N}_j} t_{i,j} = 1$ and its transmit power is equal to $p^{\text{Tx}}_j = p^{\text{uni}}_{i,j}$ if $t_{i,j} = 1$. As a node can be covered by multiple transmitting nodes in the network, an algorithm is required to find the set $\mathcal{M}_j$ of each PN $j \in \mathcal{Q}$ in the optimum BT as well as the route $\mathcal{R}_i$ of every receiving node in $\mathcal{P}$. To this end, we suggest Algorithm 1. In this algorithm, using the solution of the MILP and starting from the source, node $i \in \mathcal{P}$ is a CN of node j if $y_{i,j} \neq 0$ and node i has not been already connected to the BT. The set $\mathcal{C}$ in this algorithm refers to the set of nodes which are connected to the BT. This set at first contains S and the algorithm is run until all the nodes of the network are added to this set. The algorithm

Algorithm 1 Constructing the optimum BT

$\mathcal{C} = \{\mathrm{S}\}$, $\mathcal{V} = \varnothing$
while $\mathcal{Q} \setminus \mathcal{C} \neq \varnothing$ **do**
  for each node $j \in \mathcal{C} \setminus \mathcal{V}$ **do**
    $\mathcal{V} = \mathcal{V} \cup j$
    if $y_{i,j} \neq 0, i \in \mathcal{N}_j, i \notin \mathcal{C}$ **then**
      $\mathcal{M}_j = \mathcal{M}_j \cup \{i\}$
      $\mathcal{R}_i = \mathcal{R}_j \cup \{i\}$
      $\mathcal{C} = \mathcal{C} \cup \{i\}$
    end if
  end for
end while

visits the nodes one by one to see if based on the solution of the MILP, a given node must be a PN of other nodes or not. In this algorithm, the set of visited nodes by the algorithm is given by $\mathcal{V}$. The number of binary variables that have to be determined with the proposed MILP are N binary variables for the source and, as $t_{j,j} = 0$ and $t_{\mathrm{S},j} = 0$, a number $N-1$ of binary variables for each of the N nodes in $\mathcal{P}$. Thus, the total number of binary variables for the proposed MILP is $N + N(N-1) = N^2$.

4.4 Performance analysis

4.4.1 Simulation Setup

For simulation, a 250m×250m area is considered in which the coordinate of a node is determined by (x, y) with x and y as independently and uniformly distributed random variables in the interval [0, 250]. The total number of nodes varies between 10 and 50. The simulation results are based on the Monte-Carlo method and in each simulation run, one of the nodes in the network is randomly chosen as the source. The channel is based on the path-loss model. Let $l_{i,j}$ and l_0 be the distance between nodes i and j and a reference distance, respectively. Then, by considering η as the path loss exponent and λ as the signal wavelength, the power gain of the channel between nodes i and j is defined as

$$g_{i,j} = \left(\frac{\lambda}{4\pi l_0}\right)^2 \left(\frac{l_0}{l_{i,j}}\right)^\eta \tag{4.36}$$

During the simulation, we set $\lambda = 0.125$m, $l_0 = 1$m and $\eta = 3$. Moreover, using [CGB05], we assume uniformly distributed random values for $p_j^{\max} \in [150, 250]$ mW and $p_j^{\mathrm{ct}} \in [50, 100]$ mW and $\eta_j = 0.3$ for all $j \in \mathcal{Q}$. The minimum SNR for successful

Table 4.3. Parameters used through the simulation.

Parameter	Value
$p_j^{\max}$	$\in [150, 250]$ mW
p_j^{ct}	$\in [50, 100]$ mW
σ^2	-90 dBm
γ^{th}	10 dBm
λ	0.125m
l_0	1
α	3

decoding is set to $\gamma^{\mathrm{th}} = 10$ dB and the noise power is assumed to be $\sigma^2 = -90$ dBm. We compare our algorithm with the conventional centralized and decentralized algorithms. The benchmarks of our algorithm are the optimum solution of the MILP, explained in Section 4.3, and the BIPSW [WNE02], the BDP [RVF08] and the GBBTC [CK13] algorithms which are discussed in Section 1.2 and Section 4.2.2. It should be noted that the result obtained for the MFPBT problem using the ES scheme will be similar to that of GBBTC for the MTBT problem, on average. Hence, we just use the GBBTC algorithm representing both. The results for the network transmit power for all the algorithms are normalized to the average of the maximum power budget of the nodes denoted by $\bar{P}^{\max}$, i.e., $\bar{P}^{\max} = \mathbb{E}_{j\in\mathcal{Q}}[p_j^{\mathrm{ct}} + p_j^{\max}]$. The normalized network transmit power is then denoted by $P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a}) = P_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a})/\bar{P}^{\max}$ in which $\hat{P}_{\mathrm{net}}^{\mathrm{Tx}}(\boldsymbol{a})$ is defined in (3.9). The simulations are carried out in MATLAB[1] and the optimization problems of (6.34) and (6.35) are solved using CVX[2] [GB14, GB08] along with Gurobi.[3].The simulation parameters are collected in Table 4.3

It should be noted that we apply no changes to the benchmark algorithms. For instance, in terms of the circuitry power, the benchmarks ignore it and we also implement them in this way. After constructing the BT by those algorithms, we consider the circuitry powers in calculating the actual network transmit power. Modifying those algorithms in a proper way to consider the circuitry power is out of the scope of our work. Furthermore, we aim to emphasize on the impact of the circuitry power which has been largely ignored by the existing algorithms and to show that the BT resulting from those algorithms are not efficient.

[1]http://mathworks.com/
[2]http://cvxr.com/cvx/
[3]http://www.gurobi.com/

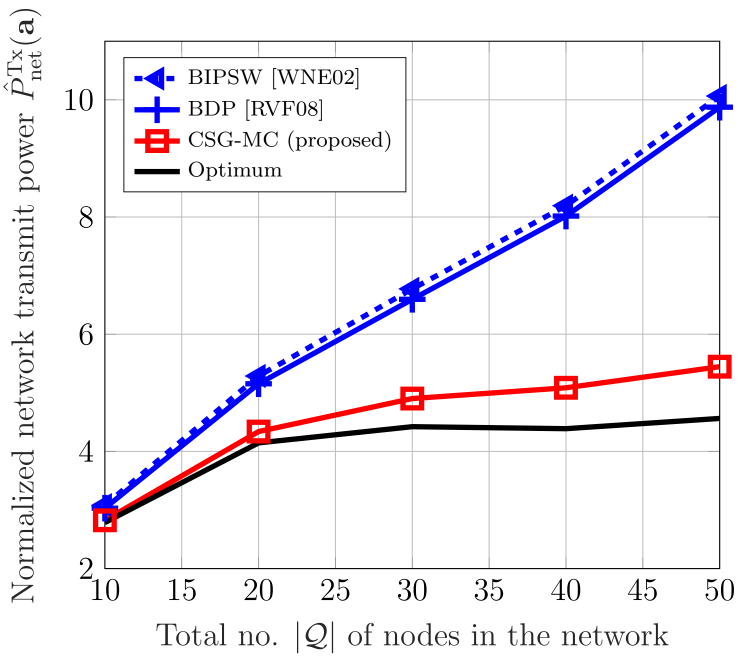


Figure 4.11. Normalized network transmit power versus the number of nodes for different algorithms.

4.4.2 Results

Fig. 4.11 compares the normalized network transmit power $\hat{P}^{\mathrm{Tx}}_{\mathrm{net}}(\boldsymbol{a})$ versus the number of nodes for different algorithms for the MPBT problem. The benchmark algorithms, except the MILP, do not consider the circuitry power during the BT construction. As can be observed, our proposed algorithm outperforms other benchmark algorithms. The main reason is that our algorithm, besides the transmit power, considers the amount of circuitry power of the nodes and adapts the BT based on that. In a dense network, the effect of the circuitry power on the network transmit power is significant. In our algorithm, by increasing the number of nodes, the network transmit power first starts increasing and then tends to saturate. When the number of nodes in the network increases, the distances between the nodes and consequently the transmit powers required between the nodes reduce. Despite the fact that the required transmit powers reduce, the number of transmitting nodes in the network increases and since each transmitting node imposes a fixed power on the network, which is not negligible, the network transmit power increases. When the network becomes dense, the number of transmitting nodes required to cover the whole network, as well as the network transmit power, remains roughly the same.

Fig. 4.12 compares the three main cost sharing schemes discussed in this chapter, that

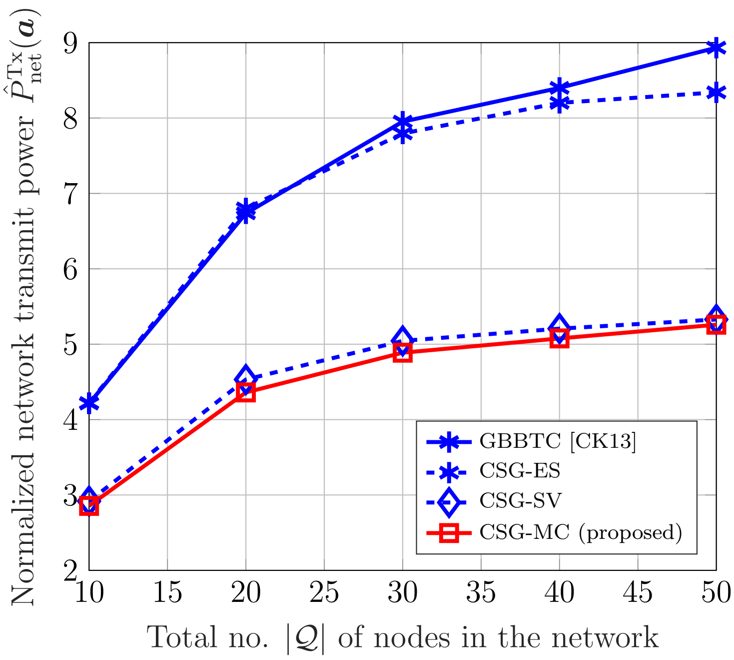


Figure 4.12. Comparison between different cost sharing schemes for multi-hop broadcast.

is, the MC, the SV, and the ES in terms of the total normalized network transmit power versus the number of nodes in the network. We replace the MC cost sharing scheme in CSG-MC with SV and ES and refer to them as the CSG-SV and the CSG-ES, respectively. Due to the lack of convergence guarantee with the ES scheme, the transmit power of the nodes for the CSG-ES, as well as for the GBBTC, are assumed to be fixed and equal to 200 mW. In this experiment, all the algorithm, except the GBBTC, consider the circuitry power in BT construction. In fact, the only difference between GBBTC and CSG-ES is that GBBTC relies merely on the transmit power. There are two main observations in Fig. 4.12. First, performing power control at the nodes and taking the circuitry power into account, which is the case for the CSG-MC and CSG-SV, significantly improves the energy-efficiency of the network. For instance, in a network with $|\mathcal{Q}| = 40$, the normalized network transmit power obtained by CSG-MC is $\hat{P}^{\mathrm{net}}(\boldsymbol{a}) \simeq 5$. This number for the GBBTC (and also for BIPSW in Fig. 4.11) is more than 8 which means that the BT obtained by our algorithm requires around 40% less energy. The second observation is that the MC performs slightly better than the SV. This observation is in accordance with Theorems 4.2 and 4.3. Aside from the performance, the information overhead required for the MC is much lower than that of the SV and this makes the MC the best choice for such a network. Although the transmit power of the nodes is fixed for both the GBBTC and the CSG-ES, the network transmit power with CSG-ES is less than that of the GBBTC. This is because, unlike

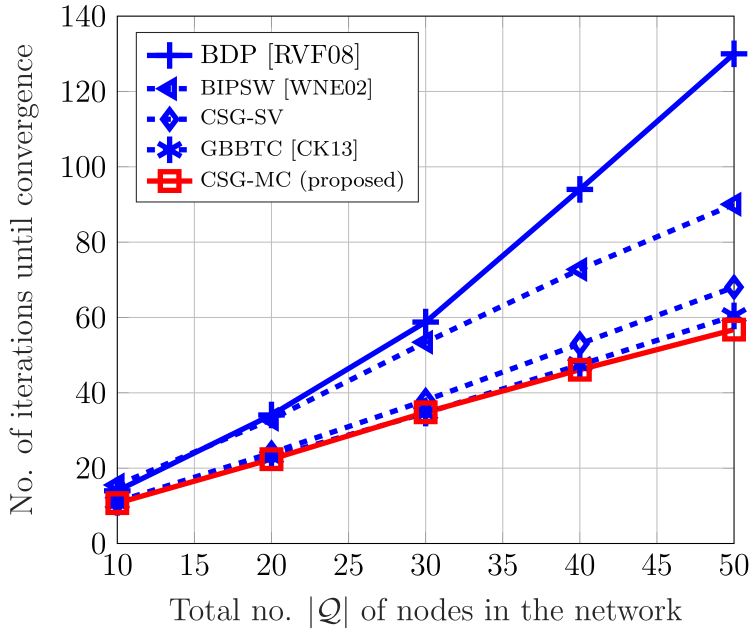


Figure 4.13. Number of iterations required for algorithms to converge.

the GBBTC, the CSG-ES considers the circuitry power in the BT formation and thus, a smaller number of nodes act as PN.

In Fig. 4.13, we depict the number of iterations required for each of these algorithms to converge. The number of iterations of an algorithm can also represent its time complexity. As can be observed, the CSG-MC algorithm requires the lowest number of iterations among all. Moreover, the SV-based CSG requires a higher number of iterations than the MC-based CSG. This difference stems from the way these algorithms share a cost among the receiving nodes of a multicast group. With MC, the cost of all CNs except one of them is zero, and hence, the CNs have no incentive to change their PN. In contrast, the cost of the CNs with SV is always a positive value and the CNs may have an incentive for updating their action and finding a PN with lower cost. Moreover, the number of iterations required for all algorithms, except for the BDP, increases almost linearly. The non-linear time complexity of BDP stems from the Bellman-Ford algorithm with which the BDP needs to be initialized.

To show how the circuitry power affects the structure of the BT, Fig. 4.14 shows the average number of PNs in the network versus the total number ($|\mathcal{Q}|$) of nodes and for different values of the circuitry power. It actually shows the average number of transmissions that will be carried out in the network. The set $\mathcal{T}$ of the PNs in the network is defined as $\mathcal{T} = \{j | p_j^{\mathrm{Tx}} > 0, j \in \mathcal{Q}\}$ where $|\mathcal{T}|$ represents the number of PNs. As can be seen, when the circuitry power increases, the number of PNs in the

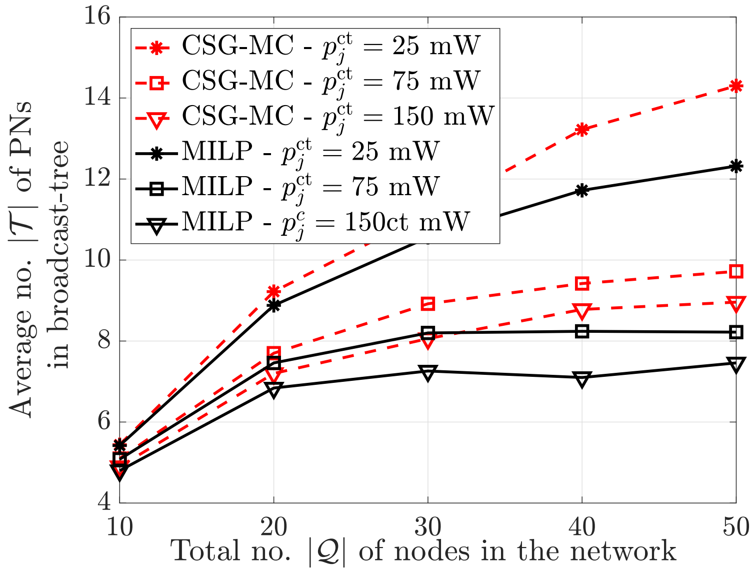
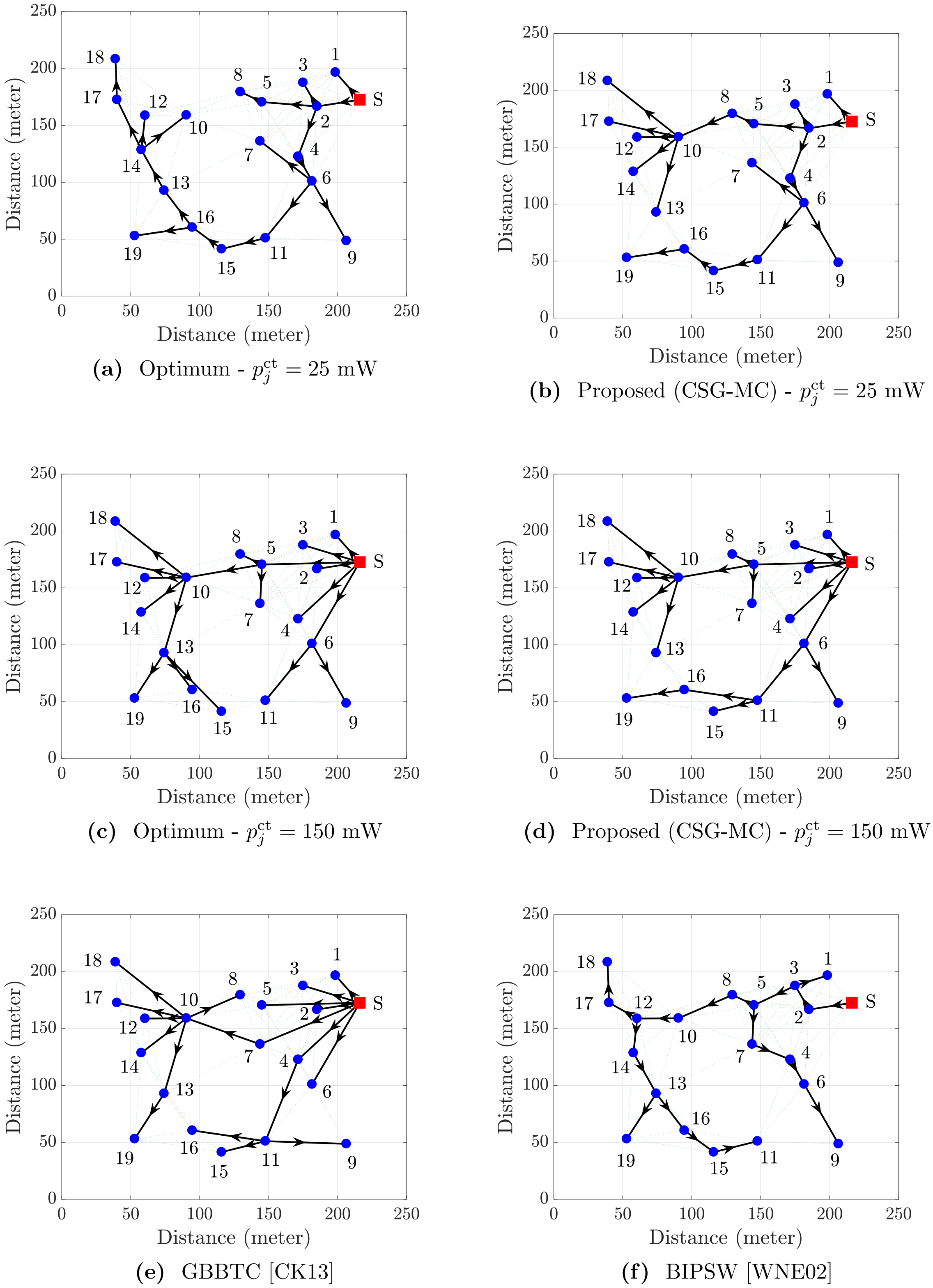


Figure 4.14. Average number of PNs (transmitting nodes) in the network for different total number of nodes.

network decreases. In this case, our proposed algorithm, as well as the MILP, exploit multicast transmission to reduce the network transmit power by reducing the number of transmissions. For instance, when $|\mathcal{Q}| = 30$ and the average value of the circuitry power is $\mathbb{E}_{j\in\mathcal{Q}}[p_j^{\text{ct}}] = 25$ mW, the BT, constructed by our algorithm, consists of roughly $|\mathcal{T}| = 11$ PNs, which means, every PN has 2.75 CNs on average. When the average circuitry power is $\mathbb{E}_{j\in\mathcal{Q}}[p_j^{\text{ct}}] = 150$ mW, the number of PNs becomes $|\mathcal{T}| = 8$, that is, 3.75 CNs on average for every PN.

Finally, to have a better insight about how the algorithms construct the BT, a realization of the network with $|\mathcal{Q}| = 20$ nodes is presented in Fig. 4.15. In this figure, the BT is constructed with four algorithms; the optimum BT in Fig. 4.15 (a) and 4.15 (c) based on the centralized MILP approach along with the Algorithm 1 explained in Section 4.3, the proposed decentralized game theoretic algorithm in Fig. 4.15 (b) and 4.15 (d), the GBBTC [CK13] in Fig. 4.15 (e) and the centralized BIPSW [WNE02] in Fig. 4.15 (f). In this experiment, to show the impact of the circuitry power on the BT construction, the MILP and CSG-MC algorithms are run for two different values of the average circuitry power, that is, $p_j^{\text{ct}} = 25$ mW in Fig. 4.15 (a) and Fig. 4.15 (b), and $p_j^{\text{ct}} = 150$ mW in 4.15 (c) and 4.15 (d) which is assumed to be the same for all the nodes $j \in \mathcal{Q}$. Recall that the GBBTC and BIPSW ignore the circuitry power. In Fig. 4.15 the nodes with just one outgoing link represent the PNs that transmit via unicast while multiple outgoing links show a multicast transmission. For instance, in the obtained BT in Fig. 4.15 (f), node 2 receives the message from the source by a



(a) Optimum - $p_j^{\mathrm{ct}} = 25$ mW

(b) Proposed (CSG-MC) - $p_j^{\mathrm{ct}} = 25$ mW

(c) Optimum - $p_j^{\mathrm{ct}} = 150$ mW

(d) Proposed (CSG-MC) - $p_j^{\mathrm{ct}} = 150$ mW

(e) GBBTC [CK13]

(f) BIPSW [WNE02]

Figure 4.15. BT resulting from different algorithms in a 250m×250m area with $|\mathcal{Q}| = 20$.

unicast transmission and sends it to its CN, i.e., node 3, again by a unicast. Node 3 then forwards the message to its CNs, node 1 and 5, via multicast. In Fig. 4.15 (f), we first find that the BIPSW constructs the BT mostly with short hops including many unicasts. This is because the BIPSW relies merely on minimizing the transmit powers. For the given instance, BIPSW requires 14 transmissions in total where 11 of these transmissions are via unicast. In contrast to BIPSW, the GBBTC in Fig. 4.15 (e), due to the fixed transmit power of the nodes, tends to form large multicast groups to reduce the number of transmissions.

Our proposed algorithm, as well as the optimum MILP-based BT, are flexible. When the circuitry power is very low, the obtained BTs, similar to that obtained by the BIPSW, will be constructed by short hops and the unicast transmission is used relatively more often. For instance, with $p_j^c = 25$ mW, the BT constructed by our algorithm in Fig. 4.15 (b) contains 10 transmissions including 6 unicasts. With the optimum MILP algorithm in Fig. 4.15 (a), 11 transmissions are needed with also 6 unicasts. When the circuitry power increases to $p_j^c = 150$ mW, in the same network, the number of transmissions with our algorithm becomes 6 including 1 unicast (Fig. 4.15 (d)), while, the optimum BT (Fig. 4.15 (c)) consists of 5 transmissions, all via multicast. In fact, when the circuitry power, as a fixed term that affects the total transmit power of a node, dominates the transmit power, our proposed algorithm as well as the MILP, tend to exploit the multicast transmission. In other words, it adapts itself depending on the value of the circuitry power.

4.5 Summary

In this chapter, a non-cooperative cost sharing game with MC cost sharing scheme has been proposed for the MPBT problem in multi-hop wireless networks. MC, SV and ES cost sharing schemes are studies and we showed that MC is the best cost sharing scheme for MPBT problem. The proposed game has been shown to be a potential game with guaranteed convergence. The game is designed in a way that the potential function of the game is equal to the total power required in the whole network. We have shown that, the MC cost sharing scheme is the scheme for which the optimum BT is always an NE of the game. Besides, the information overhead required for it is relatively low. These two properties make it the best choice among the cost sharing schemes for the MPBT problem in terms of both performance and required information overhead.

We have shown that in designing games for decentralized optimization, the elements of the game such as the cost function, and the action sets have to be designed in a way to guarantee that the individual local behavior of the players is desirable from the global system point of view. In the MPBT problem, the MC cost sharing scheme satisfies such a critical condition, that is, the MC-based cost function of the nodes and the network transmit power are exactly aligned, while the budget-balanced cost sharing schemes, including the ES and the SV, do not. We further showed that the ES does not guarantee the convergence of the algorithm to an NE for the MPBT problem. To overcome this problem of the ES, the PNs in the network have to transmit with a fixed transmit power, regardless of the unicast power of the links to their corresponding CNs. Although by doing so, the algorithm will be guaranteed to converge, it is in contrast to the the network-wide goal, that is, the energy efficiency. Unlike many of the existing algorithms, our proposed model not only captures the circuitry power of a device together with its transmit power, but also the nodes in our algorithm are able to perform transmit power control. We also discussed a MAC scheme for decentralized broadcast-tree construction and studied the probability of collision and the number of time-slots required for the nodes for accessing the shared channel. We demonstrated that the proposed algorithm and the considered power model significantly improve the network energy-efficiency.

Chapter 5

Energy-efficient multi-hop broadcast: Multiple transmitters per user

5.1 Introduction

In this chapter, we extend the model we studied in the previous chapter and exploit the MRC combining diversity. Using MRC, a CN is able to combine the signals transmitted by multiple PNs in order to achieve the minimum SNR required for decoding the message. This can help in reducing the transmit power required at a given PN for serving a CN, and consequently, can help in reducing the power required for data dissemination. We showed in Section 4.2.2 that the MC cost sharing performs better than the other cost sharing schemes for the MPBT problem. Besides, among the budget-balanced cost sharing schemes, the SV is fair and also guarantees the convergence of the game for the MPBT problem. Hence, here we extend our model of the previous chapter for the MC-based and the SV-based cost sharing games to exploit MRC. Parts of this chapter have been originally published by the author in [MASL+15, MMAS+16].

The rest of this chapter is organized as follows: Since a CN is now able to have multiple PNs, in Section 5.2 we extend the system model, discuss the MAC scheme, and formulate the problem. The MRC-based decentralized game-theoretic approaches with the MC and the SV cost sharing schemes are provided in Section 5.3.2 and 5.3.3, respectively. In Section 5.4, we present an MILP formulation for finding the global optimum of our problem. Simulation results are provided in Section 5.5 and finally, Section 5.6 concludes the chapter.

5.2 System model extension and problem formulation

5.2.1 Power model and MAC scheme

The system model in this chapter is based on the one presented in Chapter 3 . Since in this chapter, we assume that the CNs can choose multiple PNs, the system model needs to be extended. In this network, every node $i \in \mathcal{P}$ chooses its PNs as well as the transmit power with which they should transmit the message for node i. By accumulating the SNRs of the signals received from the chosen PNs, the CN can successfully decode the message if the accumulated SNR is at least γ^{th}. The requested power of CN i from its PN j is denoted by $p_{i,j}^{\text{req}}$. We define the *action* of a node i in this network as the set of tuples composed of the PNs that the node chooses along with the corresponding requested powers

$$\boldsymbol{a}_i = \left\{(j, p_{i,j}^{\text{req}})|j \in \mathcal{A}_i, p_{i,j}^{\text{req}} \in [0, p_j^{\max}]\right\}, \tag{5.1}$$

in which $\mathcal{A}_i$ is the action set of the CN i. We further define the set of actions of all the nodes as

$$\boldsymbol{a} := \{\boldsymbol{a}_i|i \in \mathcal{P}\}. \tag{5.2}$$

Even thought with MRC a CN is able to accumulate the signals transmitted from the PNs which are not in its neighboring area, we restrict the action set of the CN to the nodes in its neighboring area. This is because overhead information needs to be transmitted in practice between a PN and a CN in order to find the multicast receiving group, the cost of the CNs, etc., and this implies that the PN must be in the neighboring area of the CN. The action set of node i in this section is defined as the set of neighboring nodes of node i whose distance from the source, in terms of the number of hops, is not larger than that for node i. More precisely, it is defined as

$$\mathcal{A}_i = \{j|j \in \mathcal{N}_i, h_j \leq h_i, h_j \neq \infty\} \tag{5.3}$$

in which h_j is called the hop-rank of node $j \in \mathcal{Q}$, representing the number of hops from the source to node j. Denoting by $\mathcal{W}_i \subseteq \mathcal{A}_i, \mathcal{W}_i \neq \emptyset$ the set of PNs of CN i, the hop-rank of CN i is obtained by

$$h_i = \max_{j \in \mathcal{W}_i} \{h_j\} + 1, \qquad \forall i \in \mathcal{P}, \tag{5.4}$$

which indicates that the hop-rank of a node depends on the maximum of the hop-ranks of its PNs. *Initially*, we set $h_{\text{S}} = 0$ and $h_i = \infty$ for all $i \in \mathcal{P}$. Based on the definition of the action of a node in (5.1), we observe that each action contains two sub-actions. We call them the PN set and the power request set of node i and define them as

$$\mathcal{W}_i = \left\{j|p_{i,j}^{\text{req}} > 0, j \in \mathcal{A}_i\right\} \tag{5.5}$$

and

$$\boldsymbol{p}_i^{\text{req}} = \left\{p_{i,j}^{\text{req}}|p_{i,j}^{\text{req}} > 0, j \in \mathcal{A}_i\right\}, \tag{5.6}$$

respectively. The number of PNs chosen by CN i is denoted by $W_i = |\mathcal{W}_i|$. Fig. 5.1 shows a sample network in which $\mathcal{W}_i = \{l, j\}$. From the perspective of a transmitting node $j \in \mathcal{Q}$, we define the set of its CNs as

$$\mathcal{M}_j = \left\{i \,\middle|\, p_{i,j}^{\text{req}} > 0, \forall i \in \mathcal{N}_j\right\}. \tag{5.7}$$

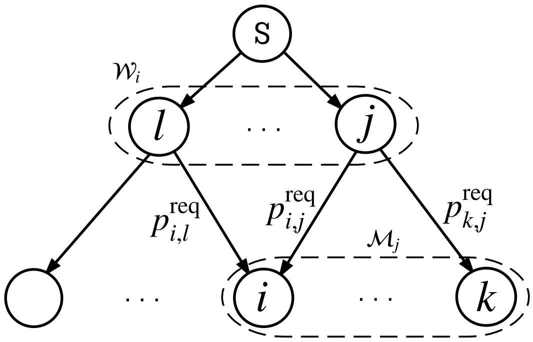


Figure 5.1. A sample network. In this network, node i decides to be served by more than one PN, that is, nodes l and j.

We further denote the set of power requests *received* by node j from its neighboring nodes as $\boldsymbol{p}_j^{\mathrm{rcv}} = \left\{p_{i,j}^{\mathrm{req}} | i \in \mathcal{M}_j\right\}$ and $\boldsymbol{p}_{-i,j}^{\mathrm{rcv}} := \boldsymbol{p}_j^{\mathrm{rcv}} \backslash \left\{p_{i,j}^{\mathrm{req}}\right\}$ represents the $\boldsymbol{p}_j^{\mathrm{rcv}}$ without the power request of CN i. The total transmit power of a PN j in the network is then given by

$$P_j^{\mathrm{Tx}}(\boldsymbol{a}) := P_j^{\mathrm{Tx}}(\boldsymbol{p}_j^{\mathrm{rcv}}) = \begin{cases} p_j^{\mathrm{ct}} + \max\limits_{i \in \mathcal{M}_j} \left\{p_{i,j}^{\mathrm{req}}\right\}, & \text{if } \mathcal{M}_j \neq \emptyset \\ 0 & \text{otherwise} \end{cases} \tag{5.8}$$

in which p_j^{ct} is the circuitry power required for transmission.

We assume that the CNs exploit the MRC technique and constructively combine the signals received from different PNs. Using MRC, the aggregated SNR experienced by CN i is calculated by

$$\gamma_{i|_{\mathrm{MRC}}}^{\mathrm{req}}(\boldsymbol{p}_i^{\mathrm{req}}) := \gamma_{i,1}^{\mathrm{req}}(p_{i,1}^{\mathrm{req}}) + \gamma_{i,2}^{\mathrm{req}}(p_{i,2}^{\mathrm{req}}) + \cdots + \gamma_{i,W_i}^{\mathrm{req}}(p_{i,W_i}^{\mathrm{req}}) = \sum_{j \in \mathcal{W}_i} \frac{p_{i,j}^{\mathrm{req}} g_{i,j}}{\sigma^2}, \tag{5.9}$$

where $\gamma_{i,j}^{\mathrm{req}}(p_{i,j}^{\mathrm{req}})$ is defined in (3.3). Note that $g_{i,j}$ in (5.9) represents the average value of the channel gain assuming that the statistical properties of the channel does not change. We further assume that a node knows the average channel gains between itself and the other nodes in its proximity.

The channel access scheme adopted for our MRC-based multi-hop broadcast approach is similar to the one suggested for the single-PN case in Fig. 3.3. In MRC-based multi-hop broadcast, as shown in Fig. 5.2, when a CN chooses multiple PNs, each of the selected PNs need to reserve a time-slot for their transmission in the scheduled section. Moreover, each PN needs to inform its neighboring nodes about the new CN that joined it. In the example shown in Fig. 5.2, the CNs can choose up to three PNs and the corresponding time-slots of the PNs for updating their neighboring nodes are represented by $\boxed{3}$, $\boxed{4}$ and $\boxed{5}$.

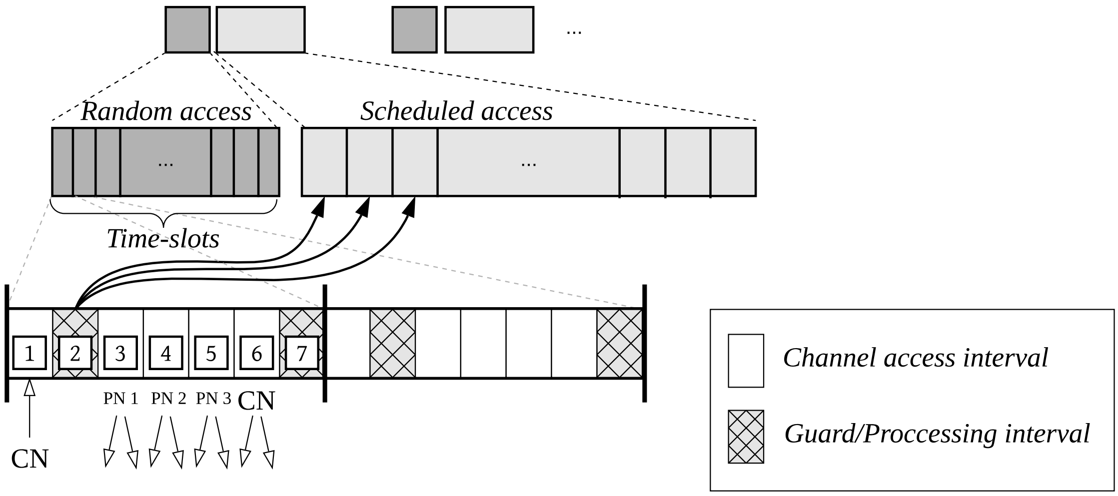


Figure 5.2. Channel access for multi-hop broadcast with MRC and three PNs.

In order to maximize the SNR received at a CN, the received signal from each of its PNs must be ideally combined.

Remark 5.1. *Let* $\boldsymbol{y}_i = [y_{i,1}, y_{i,2}, \ldots, y_{i,W_i}]^\intercal$ *denote the received signal vector at CN i transmitted by its chosen PNs. From the physical layer perspective,* $\boldsymbol{y}_i$ *is modeled as*

$$\boldsymbol{y}_i = \boldsymbol{h}_i x + \boldsymbol{n}_i, \tag{5.10}$$

in which

- x *is the transmitted symbol by the PNs of CN* i*,*
- $\boldsymbol{h}_i = [h_{i,1}, h_{i,2}, \ldots, h_{i,W_i}]^\intercal$ *is the vector of channel coefficients of the links between CN* i *and its PNs,*
- $\boldsymbol{n}_i = [n_{i,1}, n_{i,2}, \ldots, n_{i,W_i}]^\intercal$ *is the noise vector considered as AWGN.*

The reconstructed signal at CN i *is then obtained by* $\hat{y} = \boldsymbol{w}_i \boldsymbol{y}_i$ *in which* $\boldsymbol{w}_i = [w_{i,1}, w_{i,2}, \ldots, w_{i,W_i}]$ *is the combining vector that combines the signals received from the PNs. The MRC provides the highest SNR for the received signal* $\hat{y}$*, given in* (5.9)*, if* $\boldsymbol{w}_i = k\boldsymbol{h}_i^\intercal$ *in which* k *is a constant [PS08].*

One of the main differences between the network power model in this section and that proposed in Section 3.2 is the difference in the reception power of the nodes. In the previous section, every CN was allowed to choose only one PN and consequently would receive the signal transmitted by its PN in one time-slot of the the scheduled section.

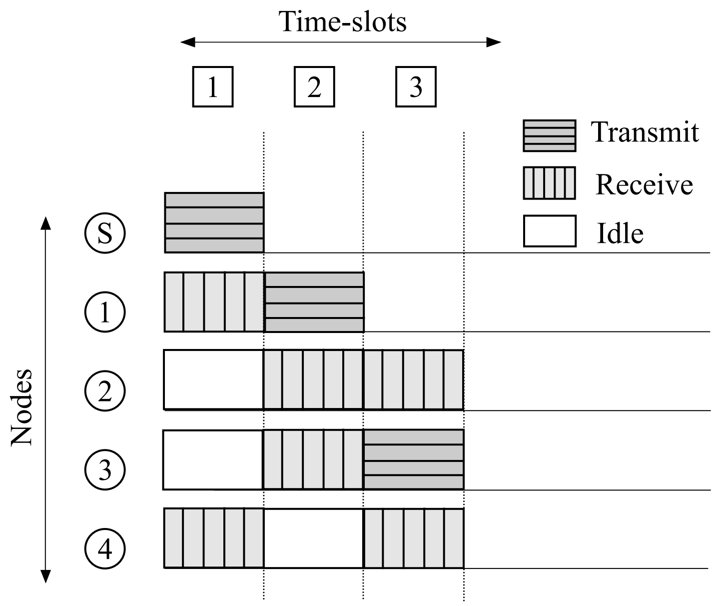


Figure 5.3. Transmission and reception in different time-slots in the scheduled section of the channel access. A node can receive its message in multiple slots.

In fact, the circuitry power required for receiving the message is equal for every node and therefore, could be omitted in network power optimization. In other words, in the previous chapter, to optimize the network power, one could merely focus on the transmit power of the nodes, composed of the power of the radio link and the circuitry power required for transmission.

Unlike the previous section, here, a node may need to receive the messages from its PNs in multiple time-slots. Hence, depending on the number of PNs that a CN chooses, the reception power and consequently the energy it requires to consume over multiple time-slots changes. This issue is further illustrated in Fig. 5.3. In this Figure, for instance, node 1 receives its message from the source in time-slot $\boxed{1}$ and acts as a PN in the next time-slot. Node 3 receives the message from node 1 , transmitted in time-slot $\boxed{2}$ and acts as a transmitter in time-slot $\boxed{3}$. Node 2, in order to receive the message, accumulates the signals received from node 1 and node 3 in time-slots $\boxed{1}$ and $\boxed{3}$, respectively. Node 4, similar to node 2 receives its message in more than one time-slot, from nodes S and 3 in time-slots $\boxed{1}$ and $\boxed{3}$. In this example, nodes 2 and 4 receive the message in two time-slots and the circuitry power they require for message reception is more than the case of receiving it from one PN, like nodes 1 and 3. Since the circuitry power required for message reception at a node may vary depending on the decision of the node, it must be considered in our problem.

The reception power of a CN i is calculated by

$$P_i^{\mathrm{Rx}}(\boldsymbol{a}) = W_i p_i^{\mathrm{cr}}, \tag{5.11}$$

in which p_i^{cr} is the circuitry power of node i for message reception. Using (5.8) and (5.11), the *total power* required at a node in this network for both message transmission and reception is then given by

$$\begin{aligned} P_j^{\mathrm{tot}}(\boldsymbol{a}) &= P_j^{\mathrm{Rx}}(\boldsymbol{a}) + P_j^{\mathrm{Tx}}(\boldsymbol{a}) \\ &= W_j p_j^{\mathrm{cr}} + \mathbb{1}_j(\mathcal{M}_j)\left(p_j^{\mathrm{ct}} + \max_{i\in\mathcal{M}_j}\left\{p_{i,j}^{\mathrm{req}}\right\}\right) \end{aligned} \tag{5.12}$$

in which $\mathbb{1}_j(\mathcal{M}_j)$ is an indicator and equals 1 if node j acts as a transmitting node and serve the CNs in $\mathcal{M}_j$. It is formally defined as

$$\mathbb{1}_j(\mathcal{M}_j) = \begin{cases} 1 & \text{if } \mathcal{M}_j \neq \emptyset \\ 0 & \text{otherwise.} \end{cases} \tag{5.13}$$

5.2.2 Problem formulation

Before formulating the problem, we first present the following definitions:

Definition 5.1. ***(Network power):*** *Let $P_j^{\mathrm{tot}}(\boldsymbol{a})$ be the total power that node $j \in \mathcal{Q}$ requires in this network. The total network power is defined by*

$$P_{\mathrm{net}}^{\mathrm{tot}}(\boldsymbol{a}) := \sum_{j\in\mathcal{Q}} P_j^{\mathrm{tot}}(\boldsymbol{a}). \tag{5.14}$$

Definition 5.2. ***(Node's Cost):*** *We define by $C_i^f(\boldsymbol{a})$ the total cost that a node i pays to its chosen PNs under the cost sharing scheme f as*

$$C_i^f(\boldsymbol{a}) := C_i^f(\boldsymbol{p}_i^{\mathrm{req}}) = \sum_{j\in\mathcal{W}_i} c_i^f(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) \tag{5.15}$$

in which $c_i^f(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}})$ is the cost paid from node i to its PN j given the requested powers $p_{i,j}^{\mathrm{req}}$ and $\boldsymbol{p}_{-i,j}^{\mathrm{rcv}}$.

Definition 5.3. ***(Social cost):*** *Let $C_i^f(\boldsymbol{a})$ be the cost that a node $i \in \mathcal{P}$ pays for receiving the message under the cost sharing f. The social cost of a network formed by the nodes in $\mathcal{P}$, denoted by $\mathrm{SC}(\boldsymbol{a})$, is defined as [SLB08]*

$$\mathrm{SC}(\boldsymbol{a}) := \sum_{i\in\mathcal{P}} C_i^f(\boldsymbol{a}). \tag{5.16}$$

As discussed earlier, we consider two different scenarios in this network. The objectives in each of the scenarios are defined as follows.

Scenario 1 (Energy minimization): The objective in this scenario is formally defined as

$$\textbf{OBJ-1:} \quad \underset{\{\boldsymbol{a}_i\}_{i\in\mathcal{P}}}{\text{minimize}} \quad P_{\text{net}}^{\text{tot}}\left(\{\boldsymbol{a}_i\}_{i\in\mathcal{P}}\right) \tag{5.17}$$

$$\text{subject to:} \quad \forall i \in \mathcal{P}\ \exists\{j\} \subseteq \mathcal{Q}\backslash\{i\} : i \in \mathcal{M}_j, h_i \leq h_j \tag{5.18}$$

$$\gamma_{i|_{\text{MRC}}}^{\text{req}}(\boldsymbol{p}_i^{\text{req}}) \geq \gamma^{\text{th}}. \tag{5.19}$$

Note that **OBJ1** is similar to the objective defined in (3.11). Unlike (3.11) where the nodes are allowed to have just one PN ($\exists! j \in \mathcal{Q}\backslash\{i\}$), here the nodes can have multiple PNs ($\exists\{j\} \subseteq \mathcal{Q}\backslash\{i\}$). The constraint in (5.19) guarantees that node i is able to decode the message transmitted by its PNs.

Scenario 2 (Social cost minimization): In this scenario, we aim to find the minimum cost required to be paid by the receiving nodes of the network for obtaining the message. Since in this scenario we assume that the forwarding nodes of the network are sensitive to incentives, we focus on the class of budget-balanced cost sharing schemes, cf. Definition 2.14. We define the network wide objective for the second scenario as:

$$\textbf{OBJ-2:} \quad \underset{\{\boldsymbol{a}_i\}_{i\in\mathcal{P}}}{\text{minimize}} \quad \text{SC}\left(\{\boldsymbol{a}_i\}_{i\in\mathcal{P}}\right) \tag{5.20}$$

$$\text{subject to:} \quad \forall i \in \mathcal{P}\ \exists\{j\} \subseteq \mathcal{Q}\backslash\{i\} : i \in \mathcal{M}_j, h_i \leq h_j \tag{5.21}$$

$$\sum_{i\in\mathcal{M}_j} c_i^f(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}}) = P_j^{\text{Tx}}(\boldsymbol{a}) \tag{5.22}$$

$$\gamma_{i|_{\text{MRC}}}^{\text{req}}(\boldsymbol{p}_i^{\text{req}}) \geq \gamma^{\text{th}} \tag{5.23}$$

The condition in (5.22) guarantees that the employed cost sharing scheme is budget-balanced.

5.3 MRC-based decentralized approach with CSG

5.3.1 Game-theoretic model

In this section, we propose a decentralized approach for Scenarios 1 and 2 discussed in the previous section and find the decision of the nodes in each scenario.

We propose a decentralized approach via a cost sharing game. The MRC-game with multiple PNs defined in this section is an extension of the case of a single-PN defined in 4.2. The properties of the game with MRC, denoted by G^{MPN}, is summarized as follows:

- **Players:** The finite number of nodes in $\mathcal{P}$.

- **Action:** The action of a node $i \in \mathcal{P}$ is defined in (5.1) as a set of tuples that determines the PN set and power request set of the node, defied in (5.5) and (5.6), respectively. The PN set of CN i is formally defined as $\mathcal{W}_i \in 2^{\mathcal{A}_i} \backslash \{\emptyset\}$ and the joint PN set of the game is given by $\mathcal{W} = \bigtimes_{i \in \mathcal{P}} \mathcal{W}_i$, in which $2^{\mathcal{A}_i}$ and $\bigtimes$ represent the power set of $\mathcal{A}_i$ and the Cartesian product, respectively. We further define the joint request set of the game as $\mathcal{P}^{\mathrm{req}} = \bigtimes_{i \in \mathcal{P}} \boldsymbol{p}_i^{\mathrm{req}}$.

- **Cost function:** Assigns a real-valued cost to every node $i \in \mathcal{P}$ as $C_i(\boldsymbol{a}) : (\mathcal{W}, \mathcal{P}^{\mathrm{req}}) \to \mathbb{R}^+$. The cost function is defined in (5.15).

Remark 5.2. *As a result of Theorem 4.1 and as we discussed in Section 4.2.2 we employ the MC cost sharing scheme for the first scenario where we aim at network energy minimization. For the second scenario, we adopt the SV due its fairness and budget-balancedness. In the rest of this section, we denote the two cost sharing schemes as* $c^f(.) \in \{c^{\mathrm{MC}}(.), c^{\mathrm{SV}}(.)\}$.

Theorem 5.1. *The* G^{MPN} *with* $c^{\mathrm{MC}}(.)$ *and* $c^{\mathrm{SV}}(.)$ *converges to an NE.*

Proof. We have shown in Section 4.2.2 that the game G^{OPN} in which the nodes can choose one PN is a potential game for which the convergence of the game to an NE is guaranteed. Let $\underset{(j)}{\Delta^i} c_i^f$ be the difference in the cost of node i with respect to PN j after it changes its decision. Since G^{OPN} is an exact potential game, then, $\underset{(j)}{\Delta^i} c_i^f = \underset{(j)}{\Delta^i} \Phi$ in which Φ is the potential function of the game when the nodes are allowed to choose one PN. Let $\mathcal{W}_i$ and $\mathcal{W}_i'$ be the sets of old and new PNs of CN i and $\underset{\mathcal{W}_i \to \mathcal{W}_i'}{\Delta^i} C_i^f$ be the change in the cost of node i when it changes its PNs from $\mathcal{W}_i$ to $\mathcal{W}_i'$. Since the cost function in G^{MPN}, defined in (5.15), is linearly separable with respect to the cost paid by a CN to each of its chosen PNs, we can write

$$\begin{aligned}
\underset{\mathcal{W}_i \to \mathcal{W}_i'}{\Delta^i} C_i^f &= \underset{\mathcal{W}_i \to \mathcal{W}_i'}{\Delta^i} \sum_{j \in \mathcal{W}_i \cup \mathcal{W}_i'} c_i^f(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}}) \\
&= \sum_{j \in \mathcal{W}_i \cup \mathcal{W}_i'} \underset{(j)}{\Delta^i} c_i^f \\
&= \sum_{j \in \mathcal{W}_i \cup \mathcal{W}_i'} \underset{(j)}{\Delta^i} \Phi \\
&= \underset{(j)}{\Delta^i} \sum_{j \in \mathcal{W}_i \cup \mathcal{W}_i'} \Phi \\
&= \Delta \Phi', \qquad (5.24)
\end{aligned}$$

which shows that the game is still an exact potential game with a new potential function $\Phi' = \sum_{j \in \mathcal{W}_i \cup \mathcal{W}_i'} \Phi$. □

5.3.2 Marginal contribution cost sharing scheme

In this section, we propose a decentralized approach for the problem in (5.17) using the MC, aiming at network energy minimization. According to (4.2), the cost of node i, based on the MC, is defined as the power imposed by CN i on the network, including the power imposed on the chosen PNs and its own circuitry power, as

$$\begin{aligned}
C_i^{\text{MC}}(\boldsymbol{a}) &= P_i^{\text{Rx}}(\boldsymbol{a}) + \sum_{j \in \mathcal{W}_i} c_i^{\text{MC}}(\boldsymbol{a}) \qquad (5.25) \\
&= W_i p_i^{\text{cr}} \quad + \sum_{j \in \mathcal{W}_i} c_i^{\text{MC}}(\mathcal{M}_j) + c_i^{\text{MC}}(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}}) \qquad (5.26)
\end{aligned}$$

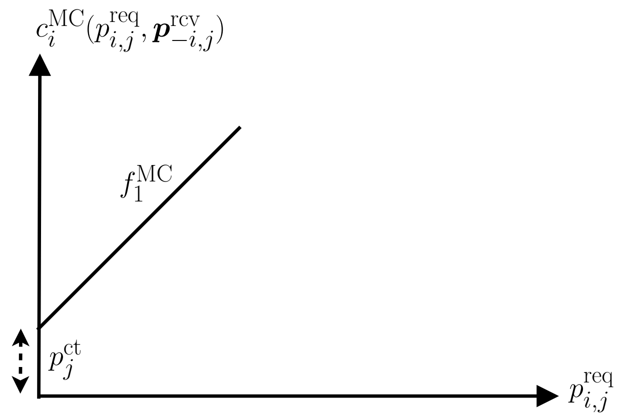
in which $c_i^{\text{MC}}(\mathcal{M}_j)$ and $c_i^{\text{MC}}(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}})$ are the costs of node i due to imposing transmit circuitry power and radio link power on PN j, respectively.

$c_i^{\text{MC}}(\mathcal{M}_j)$ in (5.26) depends merely on the existence of other CNs than node i in $\mathcal{M}_j$ and is given by

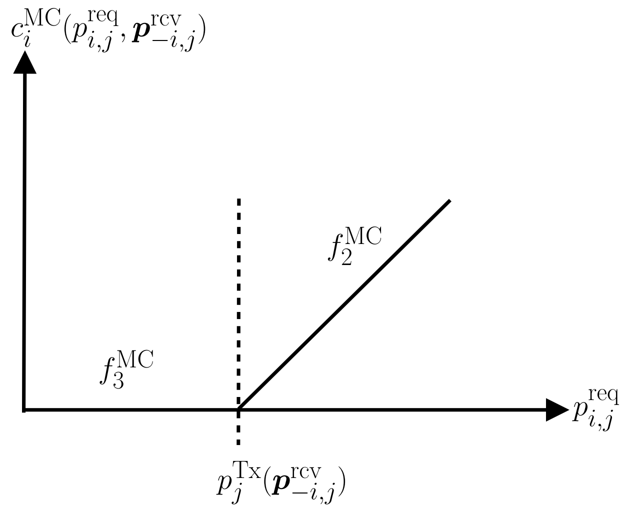
$$c_i^{\text{MC}}(\mathcal{M}_j) = p_j^{\text{ct}} \left(1 - \mathbb{1}_j(\mathcal{M}_j \backslash \{i\})\right) \qquad (5.27)$$

which means that if PN j has another CN than node i, that is, if $\mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 1$, then, node i does not impose any additional circuitry power on node j and hence, $c_i^{\text{MC}}(\mathcal{M}_j) = 0$. Similar to (4.2), $c_i^{\text{MC}}(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}})$ in (5.26) is calculated as

$$c_i^{\text{MC}}(p_{i,j}^{\text{req}}, \boldsymbol{p}_{-i,j}^{\text{rcv}}) = p_j^{\text{Tx}}(\boldsymbol{p}_j^{\text{rcv}}) - p_j^{\text{Tx}}(\boldsymbol{p}_{-i,j}^{\text{rcv}}). \qquad (5.28)$$



(a) The cost function of node i when $\mathbb{1}_j(\mathcal{M}_j) = 0$.



(b) The cost function of node i when $\mathbb{1}_j(\mathcal{M}_j) = 1$.

Figure 5.4. The cost function of player i in (5.30) based on the MC rule in case of choosing PN j under two different cases.

Given (5.27) and (5.28), the cost of node i in (5.25) is given by

$$C_i^{\mathrm{MC}}(\boldsymbol{a}) = W_i p_i^{\mathrm{cr}} + \sum_{j \in \mathcal{W}_i} p_j^{\mathrm{ct}} \left(1 - \mathbb{1}_j(\mathcal{M}_j \backslash \{i\})\right) + p_j^{\mathrm{Tx}}(\boldsymbol{p}_j^{\mathrm{rcv}}) - p_j^{\mathrm{Tx}}(\boldsymbol{p}_{-i,j}^{\mathrm{rcv}}). \qquad (5.29)$$

Note that, Given (5.27) and (5.28), $c_i^{\mathrm{MC}}(\boldsymbol{a})$ in (5.25) can be broken down as follows:

$$c_i^{\mathrm{MC}}(\boldsymbol{a}) = \begin{cases} f_1^{\mathrm{MC}} = p_j^{\mathrm{ct}} + p_{i,j}^{\mathrm{req}}, & \text{if } \mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 0 \\ f_2^{\mathrm{MC}} = p_{i,j}^{\mathrm{req}} - p_j^{\mathrm{Tx}}(\boldsymbol{p}_{-i,j}^{\mathrm{rcv}}), & \text{if } \mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 1, p_{i,j}^{\mathrm{req}} = \max\limits_{h \in \mathcal{M}_j} \{p_{h,j}^{\mathrm{req}}\} \\ f_3^{\mathrm{MC}} = 0 & \text{if } \mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 1, p_{i,j}^{\mathrm{req}} \neq \max\limits_{h \in \mathcal{M}_j} \{p_{h,j}^{\mathrm{req}}\}. \end{cases} \qquad (5.30)$$

Figures 5.4a and 5.4b show the cost function of node i under two different cases of $\mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 0$ and $\mathbb{1}_j(\mathcal{M}_j \backslash \{i\}) = 1$, presented in (5.30), respectively. As can be seen, when $\mathbb{1}_j(\mathcal{M}_j\backslash\{i\}) = 1$, the cost function $c_i^{\mathrm{MC}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}})$ is a piece-wise linear function. Given the piece-wise linearity of the cost function, we propose the MILP problem shown in (5.31) for decision making at every node $i \in \mathcal{P}$. In the MILP, given in (5.31), $\boldsymbol{w}_i$ is a binary vector of length $|\mathcal{A}_i|$ defined as $\boldsymbol{w}_i = [w_{i,j}|j \in \mathcal{A}_i]$ where $w_i(j) := w_{i,j} = 1$ if node i chooses node $j \in \mathcal{A}_j$ as its PN. We assume that the nodes in $\mathcal{A}_i$ are sorted according to their index, starting from S.

$$
\begin{aligned}
&\underset{\boldsymbol{p}_i^{\mathrm{req}},\boldsymbol{t}_i,\boldsymbol{w}_i}{\operatorname{argmin}} && \sum_{j\in\mathcal{A}_i} w_{i,j}p_i^{\mathrm{cr}} + t_{i,j}, && \forall i \in \mathcal{P} && \text{(5.31a)}\\
&\text{subject to} && && && \\
& && w_{i,j}p_j^{\min} \le p_{i,j}^{\mathrm{req}} \le w_{i,j}p_j^{\max}, && \forall j \in \mathcal{A}_i && \text{(5.31b)}\\
& && \sum_{j\in\mathcal{W}_i} \frac{p_{i,j}^{\mathrm{req}} g_{i,j}}{\sigma^2} = \gamma^{\min} && \forall j \in \mathcal{A}_i && \text{(5.31c)}\\
& && p_{i,j}^{\mathrm{req}} - p_j^{\mathrm{Tx}}(\boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) + (1-\mathbb{1}_j(\mathcal{M}_j\backslash\{i\}))w_{i,j}p_j^{\mathrm{ct}} \le t_{i,j} && \forall j \in \mathcal{A}_i && \text{(5.31d)}\\
& && \sum_{j\in\mathcal{A}_i} w_{i,j} \le W^{\max} && \forall j \in \mathcal{A}_i && \text{(5.31e)}\\
& && p_{i,j}^{\mathrm{req}}, t_{i,j} \in \mathbb{R}, s_{i,j}, w_{i,j} \in \{0,1\} && \forall j \in \mathcal{A}_i && \text{(5.31f)}
\end{aligned}
$$

Due to the piece-wise linearity of $c_i^{\mathrm{MC}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}})$ we define $t_{i,j}$ as an auxiliary variable which is used in both (5.31a) and (5.31d). $w_{i,j}p_i^{\mathrm{cr}}$ in (5.31a) represents the power imposed on the network by node i due to its signal reception power. Moreover, $t_{i,j}$ in (5.31a) and (5.31d) captures the cost of node i which is a function of the total transmit power of its chosen PNs. In (5.31b), $p_j^{\min}$ is the minimum transmit power of a transmitter in transmission mode. (5.31c) represents the minimum-SNR condition for signal reception. Finally, (5.31e) can restrict the number of PNs that a CN can choose if the system designer sets such a restriction.

5.3.3 Shapley value cost sharing scheme

Despite the complexity of the SV, we will show that it can be represented by a piece-wise linear function, as well as the MC.

Lemma 5.1. *Given the definition of $P_j^{\mathrm{Tx}}(\boldsymbol{a})$ in (5.8), the SV in (4.13) can be written as*

$$c_i^{\mathrm{SV}}(\boldsymbol{a}) = \frac{p_j^{\mathrm{ct}}}{M_j} + \sum_{n=1}^{i} \frac{p_{n,j}^{\mathrm{req}} - p_{n-1,j}^{\mathrm{req}}}{M_j + 1 - n}. \tag{5.32}$$

Proof. Using (5.8), the transmit power of a PN j is composed of two parts; p_j^{ct} as the fixed circuitry transmit power and the transmit power required for the radio link, i.e., p_j^{Tx}. Since these two parts are independent and since the SV satisfies the additivity axiom [SLB08, Ch. 12], the cost of a node i can be written as

$$c_i^{\mathrm{SV}}(\boldsymbol{a}) = c_i^{\mathrm{SV}}(\mathcal{M}_j) + c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) \tag{5.33}$$

in which $c_i^{\mathrm{SV}}(\mathcal{M}_j) = p_j^{\mathrm{ct}}/M_j$. Moreover, the cost share regarding the requests of the CNs, by assuming that they can be sorted as

$$0 = p_{0,j}^{\mathrm{req}} \leq p_{1,j}^{\mathrm{req}} \leq \cdots \leq p_{n,j}^{\mathrm{req}} \leq p_{i,j}^{\mathrm{req}} \leq p_{n+2,j}^{\mathrm{req}} \leq \cdots \leq p_{M_j,j}^{\mathrm{req}}, \tag{5.34}$$

is given by [LO73] [SA11]

$$c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \sum_{k=1}^{i} \frac{p_{k,j}^{\mathrm{req}} - p_{k-1,j}^{\mathrm{req}}}{M_j + 1 - k}. \tag{5.35}$$

Note that, using Lemma 2.1, the cost share of the nodes for the fixed circuitry power is shared equally among the nodes and the cost that depends on the radio link power is shared according to the SV rule defined in (2.23). □

Note that, the cost of a node with the SV does not consist of its own reception power. In fact, here a node aims at minimizing the *cost* it pays for message reception, which could be for instance by a token. Hence, we assume that the node merely minimizes of the power imposed on its chosen PNs.

Lemma 5.2. *Suppose that the requests received by PN j can be sorted as* (5.34)*. The SV cost function, resulted from the radio link power requests in* (5.35)*, can be modeled by a piecewise-linear, increasing function as*

$$c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \frac{p_{i,j}^{\mathrm{req}}}{M_j - n} + \sum_{k=1}^{n \geq 1} \left(\frac{-p_{k,j}^{\mathrm{req}}}{(M_j - k)(M_j - k + 1)} \right). \tag{5.36}$$

Proof. Assume that $p_{i,j}^{\mathrm{req}}$ is the $(n+1)$th lowest request from PN j as shown in (5.34) such that $p_{i,j}^{\mathrm{req}} = p_{n+1,j}^{\mathrm{req}}$. Based on (5.35) by considering $i = n+1$, $c_{j,i}^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}})$ can be written as a function of n as

$$c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \frac{p_{i,j}^{\mathrm{req}} - p_{n,j}^{\mathrm{req}}}{M_j + 1 - (n+1)} + \sum_{k=1}^{n} \frac{p_{k,j}^{\mathrm{req}} - p_{k-1,j}^{\mathrm{req}}}{M_j + 1 - k}. \tag{5.37}$$

By expanding the right side of (5.37) and some transformations, (5.37) can be written as

$$c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \frac{p_{i,j}^{\mathrm{req}}}{M_j - n} - \frac{p_{n,j}^{\mathrm{req}}}{M_j - n} + \frac{p_{n,j}^{\mathrm{req}}}{M_j - n + 1} + \cdots - \frac{p_{1,j}^{\mathrm{req}}}{M_j - 1} + \frac{p_{1,j}^{\mathrm{req}}}{M_j}. \tag{5.38}$$

Eq. (5.38) is equivalent to

$$c_i^{\mathrm{SV}}(p_{i,j}^{\mathrm{req}}, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \frac{p_{i,j}^{\mathrm{req}}}{M_j - n} + \sum_{k=1}^{n \geq 1} \left(\frac{-p_{k,j}^{\mathrm{req}}}{(M_j - k)(M_j - k + 1)} \right). \tag{5.39}$$

It can be derived from (5.39) that the cost of node i is obtained by a linear function whose slope and y-intercept depend on the interval that $p_{i,j}^{\mathrm{req}}$ falls in. Eq. (5.39) shows that if $p_{i,j}^{\mathrm{req}}$ increases and falls inside an interval with a higher n, the slope of the function $c_{j,i}$ in (5.39) increases accordingly. Besides, the y-intercept of $c_{j,i}$ decreases. Therefore, $c_{j,i}$ in (5.39) forms a piece-wise linearly increasing function in the interval $[0, p_j^{\max}]$. □

Theorem 5.2. *Let $\mathcal{M}_{j\backslash i} := \mathcal{M}_j \backslash \{i\}$ be the set of CNs of PN j without node i with the number $M_{j\backslash i}$ of CNs. Let $p_{i,j}^{\mathrm{req}}$ be the $(n+1)$-th smallest request among the CNs of PN j as* (5.34)*. Then, the cost of a node i if it joins PN j according to the SV is obtained by*

$$c_i^{\mathrm{SV}}(\boldsymbol{a}) = m_i(n) p_{i,j}^{\mathrm{req}} + y_i(n, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) \tag{5.40}$$

in which

$$m_i(n) = \frac{1}{M_{j\backslash i} + 1 - n} \tag{5.41}$$

and

$$y_i(n, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) = \frac{p_j^{\mathrm{ct}}}{M_{j\backslash i} + 1} + \sum_{k=1}^{n \geq 1} \left(\frac{-p_{k,j}^{\mathrm{req}}}{(M_{j\backslash i} - k + 1)(M_{j\backslash i} - k + 2)} \right). \tag{5.42}$$

Proof. It follows from Lemma 5.1 and Lemma 5.2. □

Note that, unlike the MC where the *cost function* of node i changes if the PN has already another CN (cf. (5.30)), here the cost of node i can always be obtained by a single closed-form function.

Illustrative Example 5.1. *Fig. 5.5 shows $c_i^{\mathrm{SV}}(\boldsymbol{a})$ when $\mathcal{M}_j = \{\mathrm{a}, \mathrm{b}\}$ and $p_{\mathrm{a},j}^{\mathrm{req}} \leq p_{\mathrm{b},j}^{\mathrm{req}}$. In this case, the cost of node i, using* (5.40) *can be obtained by*

$$c_i^{\mathrm{SV}}(\boldsymbol{a}) = \begin{cases} f_1^{\mathrm{SV}} = p_{i,j}^{\mathrm{req}}/3 + p_j^{\mathrm{ct}}/3, & \text{if } p_{i,j}^{\mathrm{req}} \leq p_{\mathrm{a},j}^{\mathrm{req}} \quad (n=0) \\ f_2^{\mathrm{SV}} = p_{i,j}^{\mathrm{req}}/2 + p_j^{\mathrm{ct}}/3 - p_{\mathrm{a},j}^{\mathrm{req}}/6, & \text{if } p_{\mathrm{a},j}^{\mathrm{req}} \leq p_{i,j}^{\mathrm{req}} \leq p_{\mathrm{b},j}^{\mathrm{req}} \quad (n=1) \\ f_3^{\mathrm{SV}} = p_{i,j}^{\mathrm{req}} + p_j^{\mathrm{ct}}/3 - p_{\mathrm{a},j}^{\mathrm{req}}/6 - p_{\mathrm{b},j}^{\mathrm{req}}/2, & \text{if } p_{\mathrm{b},j}^{\mathrm{req}} \leq p_{i,j}^{\mathrm{req}} \quad (n=2) \end{cases}$$

Corollary 5.1. *The optimal request vector of node i, i.e., $\boldsymbol{p}_i^{\mathrm{req}}$ can be obtained by solving an MILP.*

The optimal decision of node i can be obtained by the MILP shown in (5.43). Notice that the parameters used in the MILP of (5.43) are similar to the ones used for the

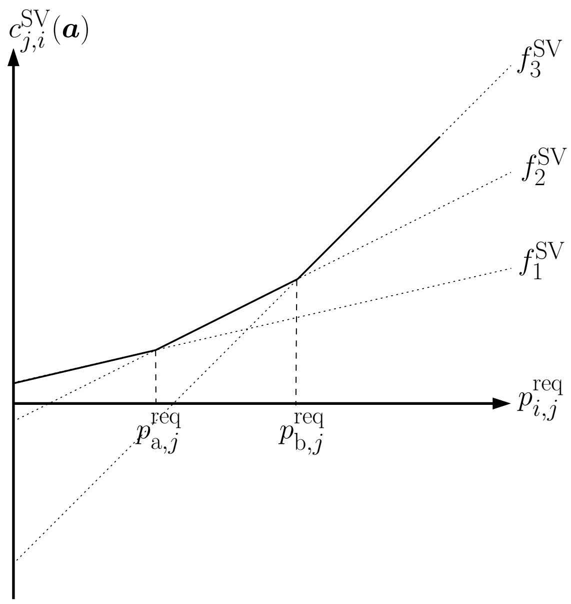


Figure 5.5. The cost function of player i with SV. The cost, depending on the requests of other nodes, can always be found via a linear function.

MC scheme in (5.31). The main difference is the SV-based cost function discussed in Theorem 5.2.

$$\underset{\boldsymbol{p}_i^{\mathrm{req}},\boldsymbol{t}_i,\boldsymbol{s}_i,\boldsymbol{w}_i}{\operatorname{argmin}} \quad \sum_{j\in\mathcal{A}_i} t_{i,j}, \qquad \forall i \in \mathcal{P} \tag{5.43a}$$

subject to

$$w_{i,j}p_j^{\min} \leq p_{i,j}^{\mathrm{req}} \leq w_{i,j}p_j^{\max}, \qquad \forall j \in \mathcal{A}_i \tag{5.43b}$$

$$\sum_{j\in\mathcal{W}_i} \frac{p_{i,j}^{\mathrm{req}} g_{i,j}}{\sigma^2} = \gamma^{\min} \qquad \forall j \in \mathcal{A}_i \tag{5.43c}$$

$$m_i(n)p_{i,j}^{\mathrm{req}} + y_i(n, \boldsymbol{p}_{-i,j}^{\mathrm{rcv}}) \leq t_{i,j} \qquad \forall j \in \mathcal{A}_i, \text{for } n = 0, \ldots, M_j \tag{5.43d}$$

$$\sum_{j\in\mathcal{A}_i} w_{i,j} \leq W^{\max} \qquad \forall j \in \mathcal{A}_i \tag{5.43e}$$

$$p_{i,j}^{\mathrm{req}}, t_{i,j} \in \mathbb{R}, s_{i,j}, w_{i,j} \in \{0,1\} \qquad \forall j \in \mathcal{A}_i \tag{5.43f}$$

5.4 MRC-based centralized approach with MILP

In the previous section, we discussed the decision-making by the nodes with MC and SV cost sharing schemes. In this section, we find the global optimum for both the network energy efficiency and the social cost minimization problems.

Theorem 5.3. *Let* $\{\overset{*}{\boldsymbol{a}}_i\}_{i\in\mathcal{P}}^{\mathrm{PTx}}$ *and* $\{\overset{*}{\boldsymbol{a}}_i\}_{i\in\mathcal{P}}^{\mathrm{SC}}$ *be the set of optimum action profiles corresponding to the network's minimum transmit power and the minimum social cost (with a budget-balanced cost sharing scheme), respectively. We always have* $\{\overset{*}{\boldsymbol{a}}_i\}_{i\in\mathcal{P}}^{\mathrm{PTx}} = \{\overset{*}{\boldsymbol{a}}_i\}_{i\in\mathcal{P}}^{\mathrm{SC}}$.

Proof: Theorem 5.3 states that any action profile that minimizes the total *transmit* power in the network minimizes the social cost as well. Using the definition of a budget-balanced cost sharing scheme, for every PN $j \in \mathcal{N}$ we have

$$\sum_{i\in\mathcal{M}_j} c_i^{\mathrm{BB}}(\boldsymbol{a}) = P_j^{\mathrm{Tx}}(\boldsymbol{a}). \tag{5.44}$$

By taking a summation over all the nodes of the network, which can act as PNs, we get

$$\sum_{j\in\mathcal{Q}}\sum_{i\in\mathcal{M}_j} c_i^{\mathrm{BB}}(\boldsymbol{a}) = \sum_{j\in\mathcal{Q}} P_j^{\mathrm{Tx}}(\boldsymbol{a}). \tag{5.45}$$

Note that the cost received by PN is equal to the cost paid by its CNs. Therefore, we can replace the left side of (5.45), which is the total price received by the PNs in the network, with the total cost paid by the CNs. Hence, the left side of (5.45), using (5.15), is equivalent to

$$\begin{aligned}\sum_{j\in\mathcal{Q}}\sum_{i\in\mathcal{M}_j} c_i^{\mathrm{BB}}(\boldsymbol{a}) &= \sum_{i\in\mathcal{P}}\sum_{j\in\mathcal{W}_i} c_i^{\mathrm{BB}}(\boldsymbol{a})\\ &= \sum_{i\in\mathcal{P}} C_i(\boldsymbol{a})\\ &= \mathrm{SC}(\boldsymbol{a})\end{aligned} \tag{5.46}$$

By comparing (5.45) and (5.46), we find that with a budget-balanced cost sharing scheme, the minimum social cost of the network is equal to the minimum transmit power of the network. ■

Before providing the MILP formulation, we define the following.

- $\tilde{S}$: The maximum number of time-slots used for message dissemination in the network. To avoid notational confusion, between the source and the time-slot, we show the source node in this formulation by $\underline{\mathrm{S}}$ and (s) represents the time-slot $1 \leq s \leq \tilde{S}$.
- $\boldsymbol{P}^{\mathrm{Tx}}$ (transmit power matrix): A $(N+1)\times\tilde{S}$ matrix with $\boldsymbol{P} = [\boldsymbol{p}_{(1)}^{\mathrm{Tx}}, \ldots, \boldsymbol{p}_{(\tilde{S})}^{\mathrm{Tx}}]$ in which $\boldsymbol{p}_s = [p_{\underline{\mathrm{S}},(s)}^{\mathrm{Tx}}, p_{1,(s)}^{\mathrm{Tx}}, \ldots, p_{N,(s)}^{\mathrm{Tx}}]^{\intercal}$ is a column vector and $p_{j,(s)}^{\mathrm{Tx}}$ shows the transmit power of node j in time-slot s.

- $\boldsymbol{T}$ (transmission matrix): A $(N+1) \times \tilde{S}$ binary matrix with $\boldsymbol{T} = [\boldsymbol{t}_{\underline{\mathrm{S}}}, \boldsymbol{t}_1, \ldots, \boldsymbol{t}_N]^\intercal$ in which $\boldsymbol{t}_j = [t_{j,(1)}, t_{j,(2)}, \ldots, t_{j,(\tilde{S})}]$ is a row vector of size $1 \times \tilde{S}$ and $t_{j,(s)} = 1$ if node j transmits in time-slot s.

- $\boldsymbol{R}$ (reception matrix): A $N \times \tilde{S}$ binary matrix with $\boldsymbol{R} = [\boldsymbol{r}_1, \ldots, \boldsymbol{r}_N]^\intercal$ in which $\boldsymbol{r}_j = [r_{i,(1)}, r_{i,(2)}, \ldots, r_{i,(\tilde{S})}]$ is a row vector of size $1 \times \tilde{S}$ and $r_{i,s} = 1$ if node i receives the message from a transmitting node that transmits in time-slot s.

- $\boldsymbol{G}$ (channel gain matrix): A $N \times (N+1)$ matrix with $\boldsymbol{G} := [\boldsymbol{g}_1^\intercal, \ldots, \boldsymbol{g}_N^\intercal]^\intercal$ in which $\boldsymbol{g}_i = [g_{i,\underline{\mathrm{S}}}, g_{i,1} \ldots, g_{i,N}]$ is a $1 \times N+1$ row vector and $g_{i,j}$ is the channel gain between transmitter j and receiver i. We set $g_{i,j} = 0$ if $j \notin \mathcal{A}_i$.

- $\boldsymbol{\Gamma}$ (SNR matrix): A $N \times \tilde{S}$ matrix with $\boldsymbol{\Gamma} := [\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_N]^\intercal$ in which $\boldsymbol{\gamma}_i = [\gamma_{i,\underline{\mathrm{S}}}, \gamma_{i,1} \ldots, \gamma_{i,N}]$ is a $1 \times \tilde{S}$ row vector and $\gamma_{i,(s)}$ is the SNR received by node i in time-slot s.

- $\mathbf{1}_N$: A vector of size $N \times 1$ with all its elements equal to 1.

- $\mathbb{I}_{N(i)}$: A vector of size $N \times 1$ with all elements equal to 1 except the i-th element which is equal to 0.

Before presenting the optimization problem, we provide the following lemma.

Lemma 5.3. ***(Big M method)**: Let $v_1, v_2 \in \mathbb{R}_{\geq 0}$ and $b \in \{0,1\}$ all be the variables of an optimization problem. The following non-linear constraint*

$$v_1 = v_2 b \tag{5.47}$$

can be linearized by the following set of constraints

$$v_1 \leq v_2 \tag{5.48}$$

$$v_1 \leq \mathbb{M} b \tag{5.49}$$

$$v_1 \geq v_2 - \mathbb{M}(1-b) \tag{5.50}$$

$$v_1 \geq 0 \tag{5.51}$$

in which $\mathbb{M}$ is a sufficiently large number so that v_2 is upper bounded by $\mathbb{M}$.

Remark 5.3. *According to Lemma 5.3, when $b = 1$, based on the constraints (5.48) and (5.50), v_2 limits v_1 from both upper and lower sides as $v_2 \leq v_1 \leq v_2$. Hence, $v_1 = v_2$ if $b = 1$. Likewise, one can observe that when $b = 0$, according to (5.49) and (5.50) we have $v_2 - \mathbb{M} \leq v_1 \leq 0$. Further, based on the constraint (5.51) together with (5.49) and (5.50) we finally get $0 \leq v_1 \leq 0$ which results in $v_1 = 0$.*

The MILP for the MRC-based multi-hop broadcast is presented in (5.52). Note that, when the network objective is social cost minimization, we set $p_j^{\mathrm{cr}} = 0$ in formulation (5.52a).

$$\min_{\boldsymbol{P},\boldsymbol{T},\boldsymbol{R},\boldsymbol{\Gamma}} \quad \sum_{s=1}^{\tilde{S}} \Big(\sum_{j\in\mathcal{Q}} p_{j,(s)}^{\mathrm{Tx}} + p_j^{\mathrm{ct}} t_{j,(s)} + \sum_{i\in\mathcal{P}} p_j^{\mathrm{cr}} r_{i,(s)} \Big), \tag{5.52a}$$

s. t.:

$$t_{j,(s)} p_j^{\min} \le p_{j,(s)}^{\mathrm{Tx}} \le t_{j,(s)} p_j^{\max}, \qquad \forall j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52b}$$

$$\boldsymbol{t}_j \mathbf{1}_{\tilde{S}} \le 1, \qquad \forall j \in \mathcal{Q} \tag{5.52c}$$

$$\boldsymbol{r}_i \mathbf{1}_{\tilde{S}} \ge 1, \qquad \forall i \in \mathcal{P} \tag{5.52d}$$

$$\sum_{j\in\mathcal{Q}} t_{j,(s)} \le 1, \qquad \forall j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52e}$$

$$r_{i,(s)} \le \sum_{j\in\mathcal{Q}} t_{j,(s)}, \qquad \forall i \in \mathcal{P}, j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52f}$$

$$r_{i,(s)} \le 1 - \sum_{s'=1}^{s} t_{i,(s')}, \qquad \forall j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52g}$$

$$\hat{\gamma}_{i,(s)} = \mathbf{1}_{N+1}^{\intercal} \left[\boldsymbol{p}_{(s)} \odot \mathbb{I}_{N+1(i)} \odot \boldsymbol{g}_i^{\intercal} \right] / \gamma^{\mathrm{th}} \sigma^2, \quad \forall j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52h}$$

$$\gamma_{i,(s)} \le \hat{\gamma}_{i,(s)}, \qquad \forall i \in \mathcal{P}, 1 \le s \le \tilde{S} \tag{5.52i}$$

$$\gamma_{i,(s)} \ge \hat{\gamma}_{i,(s)} - \mathbb{M}(1 - r_{i,(s)}), \qquad \forall i \in \mathcal{P}, 1 \le s \le \tilde{S} \tag{5.52j}$$

$$\gamma_{i,(s)} \le \mathbb{M} r_{i,(s)}, \qquad \forall i \in \mathcal{P}, 1 \le s \le \tilde{S} \tag{5.52k}$$

$$\boldsymbol{\gamma}_i \mathbf{1}_{\tilde{S}} \ge 1, \qquad \forall j \in \mathcal{P} \tag{5.52l}$$

$$t_{j,(s)} \le \sum_{s'=1}^{s-1} \gamma_{j,(s')}, \qquad \forall j \in \mathcal{P}, 2 \le s \le \tilde{S} \tag{5.52m}$$

$$t_{\underline{\mathrm{S}},1} = 1 \tag{5.52n}$$

$$p_{j,(s)}^{\mathrm{Tx}}, \gamma_{i,(s)} \in \mathbb{R}_{\ge 0}, t_{j,(s)}, r_{i,(s)} \in \{0,1\}, \qquad \forall i \in \mathcal{P}, j \in \mathcal{Q}, 1 \le s \le \tilde{S} \tag{5.52o}$$

The constraint in (5.52b) indicates the transmit power constraint. Based on our assumption, every node can transmit in one time-slot. This property has been captured by (5.52c). The condition in (5.52e) indicates that there exists at most one transmission per time-slot. Further, every node receives the message at least in one time slot as shown in (5.52d). The constraint in (5.52f) is due to the fact that a reception occurs in a time-slot if there is at least one transmission. The constraint (5.52g) indicates that a node $i \in \mathcal{P}$ does not receive the message if it has already transmitted it. In fact, $r_{i,s} = 0$ if node i transmits the messages in one of the previous slots $1 \le s' \le s$. The expression in (5.52h), in which $\odot$ shows the element-wise product, calculates the normalized SNR of the signal received at user i in time-slot s. More precisely, given the transmit powers of the users at time-slot s in $\boldsymbol{p}_s$, the expression $\boldsymbol{p}_s \odot \mathbb{I}_{N+1(i)} \odot \boldsymbol{g}_i^\intercal$ gives a vector whose elements are the SNR of the signal received by node i from each of the transmitters $j \in \mathcal{Q}$ in time-slot s. We normalize the SNR to $\gamma^{\text{th}}\sigma^2$, so that $\hat{\gamma}_{i,(s)} \leq 1$. Recall that $\mathbb{I}_{N+1(i)}$ is an all-one column vector of length $N+1$ with the i-th element equal to zero. This helps us to eliminate the SNR received by node i due to its own transmission.

Although (5.52h) determines the SNR available at node i in time-slot s, the actual SNR received by node i depends on whether node i receives the message in this time-slot. Node i uses the signals transmitted in time-slot s if $r_{i,(s)} = 1$. The constraints in (5.52i), (5.52j) and (5.52k) are used based on the big M method, discussed in Lemma 5.3. They have been employed here to find out if node i should receive the message in time-slot s. More precisely, they linearize the following non-linear constraint

$$\gamma_{i,(s)} = r_{i,(s)}\hat{\gamma}_{i,(s)} \tag{5.53}$$

in which $\hat{\gamma}_{i,(s)}$ is a function of the continuous variable $p_{i,(s)}^{\text{Tx}}$ that makes the right side of (5.53) non-linear. We linearize (5.53) via (5.52i), (5.52j) and (5.52k). The constraint in (5.52l) indicates that the aggregated SNR obtained by every node $i \in \mathcal{P}$ must be higher than the minimum SNR. Every node $i \in \mathcal{P}$ can transmit the message in time-slot s if and only if it receives the message with minimum SNR over the previous time-slots. The only exception is the source for which we always have $t_{\underline{\mathrm{S}},1} = 1$.

5.5 Performance analysis

5.5.1 Simulation setup

The channel model and its parameters are the same as in Section 4.4.1. The changes with respect to parameters in Section 4.4.1 are as follows. The total number of nodes varies between 10 and 25. We consider three circuitry powers, $p^{\text{c}} \in \{1\text{ mW}, 10\text{ mW}, 100\text{ mW}\}$. The low circuitry power case is suitable for low-power IoT applications while the high circuitry power can model conventional wireless transmitters [HCB00, WHY06]. We assume that the transmit and receive circuitry powers of the nodes in the network are equal, i.e., $p_j^{\text{cr}} = p_j^{\text{ct}}$ [CGB05]. The results for the network power and the social cost are normalized to the value $v = \tilde{p}^{\text{Tx}} + \tilde{p}^{\text{c}}$ in which $\tilde{p}^{\text{Tx}}$ and $\tilde{p}^{\text{c}}$ represent normalization reference values for the radio link power and the circuitry power, respectively. More precisely, the normalized network power and the normalized social cost are defined as

$$\bar{P}_{\text{net}}^{\text{tot}}(\boldsymbol{a}) = \frac{\sum_{j\in\mathcal{Q}} P_j^{\text{tot}}(\boldsymbol{a})}{v} \tag{5.54}$$

and

$$\overline{\text{SC}}(\boldsymbol{a}) = \frac{\sum_{i\in\mathcal{P}} C_i(\boldsymbol{a})}{v}, \tag{5.55}$$

respectively, where $\bar{P}_{\text{net}}^{\text{tot}}(\boldsymbol{a})$ is defined in (5.12) and $C_i(\boldsymbol{a}) = \sum_{j\in\mathcal{W}_i} c_i^{\text{SV}}(\boldsymbol{a})$ in which $c_i^{\text{SV}}(\boldsymbol{a})$ is defined in (5.32). We set $\tilde{p}^{\text{Tx}} = 200$ mW and $\tilde{p}^{\text{c}} = 10$ mW. Moreover, we do not set any limitation on the number of PNs that a CN is allowed to select.

In order to avoid confusion, we clarify the following terms.

- Total power: The summation of the transmission circuitry power, the reception circuitry power and the power required for transmission over the radio link. The total power of a node and the total power of the network are defined in (5.12) and (5.14), respectively. The total power of the network is also referred to as the network power.
- Total transmit power: The circuitry power required for transmission along with the power required for transmission over the radio link. Total transmit power of a node is defined in (5.8). The total transmit power of the network is the summation of the total transmit power required at the PNs for distributing the message to all the receiving nodes.
- Total radio link power of the network: The summation of the transmit power of the PNs required merely for the radio links.

The algorithms that we consider in this section for evaluation are as follows.

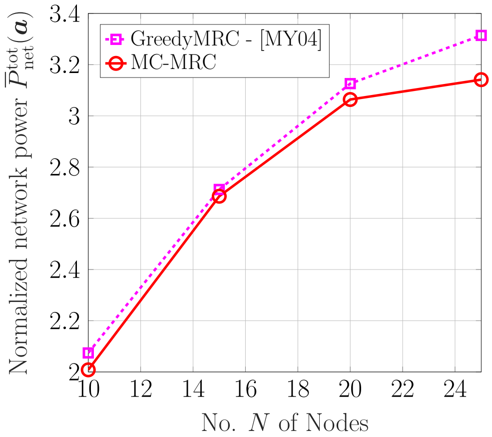
- **GreedyMRC:** The centralized MRC-based greedy algorithm proposed in [MY04]. This algorithm does not consider the circuitry power of the nodes in calculating the network power.
- **MC-MRC, SV-MRC:** Our proposed MRC-based algorithm with MC and SV cost sharing schemes, referred to as MC-MRC and SV-MRC, respectively.
- **MC-OPN, SV-OPN:** The algorithm proposed in the previous chapter in which the nodes can only choose one PN. The MC-based and the SV-based algorithms are in this case referred to as MC-OPN and SV-OPN, respectively.

- **MILP-MRC, MILP-OPN:** the MILP that finds the optimum solution with and without employing the MRC technique, referred to as MILP-MRC and MILP-OPN, respectively. MILP-MRC and MILP-OPN are obtained by solving (5.52) and (4.35), respectively.

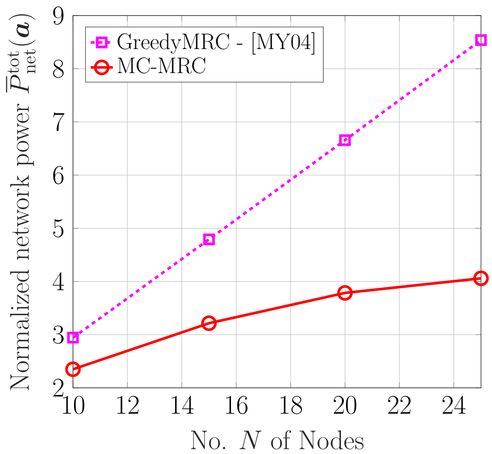
5.5.2 Simulation results

We first show the importance of taking the circuitry power into account for message dissemination. We compare our proposed algorithm with GreedyMRC proposed in [MY04] which is centralized, ignores the circuitry power required at the nodes and merely considers the power required for the radio link in network optimization. Figures 5.6a, 5.6b and 5.6c, correspond to low, medium and high circuitry powers, respectively. First, we observe that by increasing the number of nodes, the network power increases. This is because the circuitry power required at the nodes for message reception imposes additional power on the network which is not negligible. Second, we observe in 5.6a that by increasing the number of nodes, the powers required by both algorithms tend to saturate. When the network becomes denser, the number of PNs required for covering the network and serving all the receiving nodes does not necessarily increase. Hence, by increasing the number of nodes, at some point, the total transmit power of the network required for message dissemination remains unchanged. However, the circuitry power required at the nodes makes the total network power continue to increase. The value of the reception circuitry power in Fig. 5.6c is higher that the other two cases. Thus, in Fig. 5.6c, even if the total transmit power of the network does not change significantly, the high value of the circuitry power for message reception dominates the network's total transmit power. This results in constant increase of the total power of the network in Fig. 5.6c.

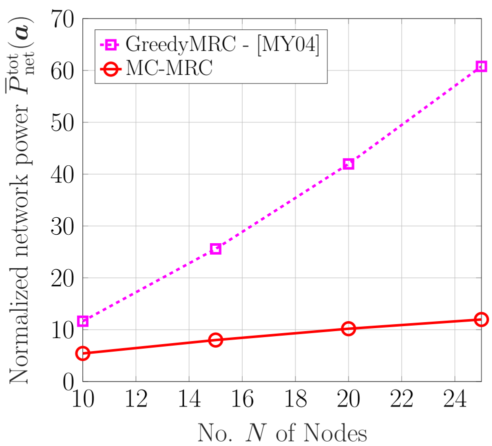
In comparison to the benchmark, our propose algorithm outperforms it in all the three cases shown in 5.6. When the circuitry power of the nodes is high, the performance of our game-theoretic algorithm becomes significantly better than the benchmark algorithm, see Fig. 5.6c. The main reason is that our proposed approach adapts the message dissemination strategy according to the circuitry power of the nodes. In contrast, the nodes in [MY04] transmit over large number of hops in order to minimize the total radio link power of the network. Since each transmission imposes a circuitry power on the total power of the network, the actual power required by [MY04] for message dissemination, after adding the circuitry power of the nodes to the outcome of the algorithm, becomes significantly high. This is more remarkable with high values of the circuitry power.



(a) $p^{\mathrm{c}} = 1$ mW

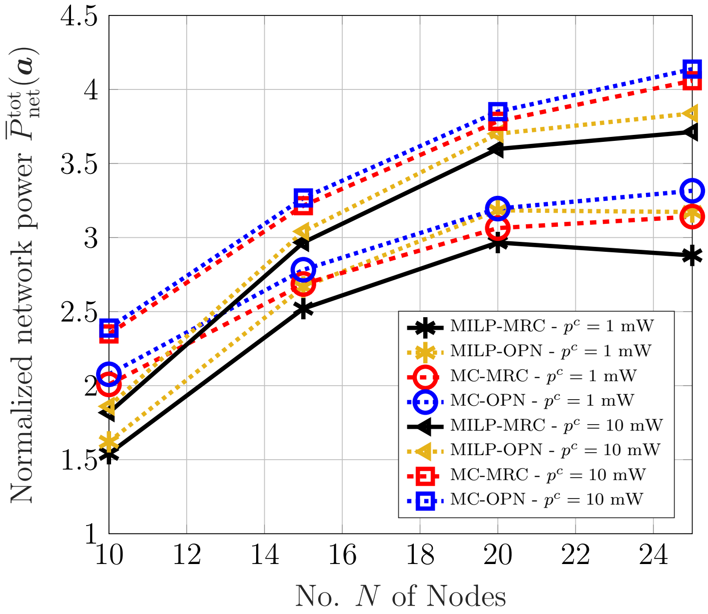


(b) $p^{\mathrm{c}} = 10$ mW

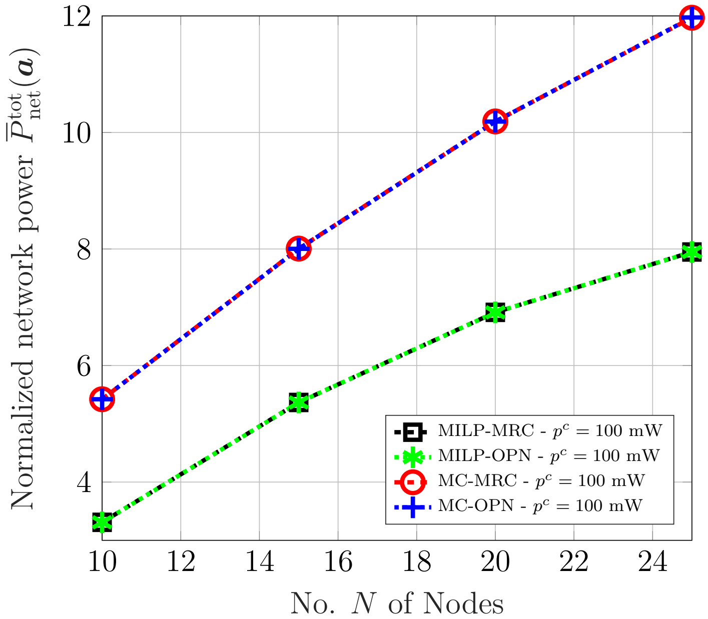


(c) $p^{\mathrm{c}} = 100$ mW

Figure 5.6. Network power for different numbers N of nodes in the network and different values p^{c} of circuitry power.



(a) The network power with $p^{\mathrm{c}} \in \{1 \text{ mW}, 10 \text{ mW}\}$.



(b) The network power with $p^{\mathrm{c}} = 100$ mW.

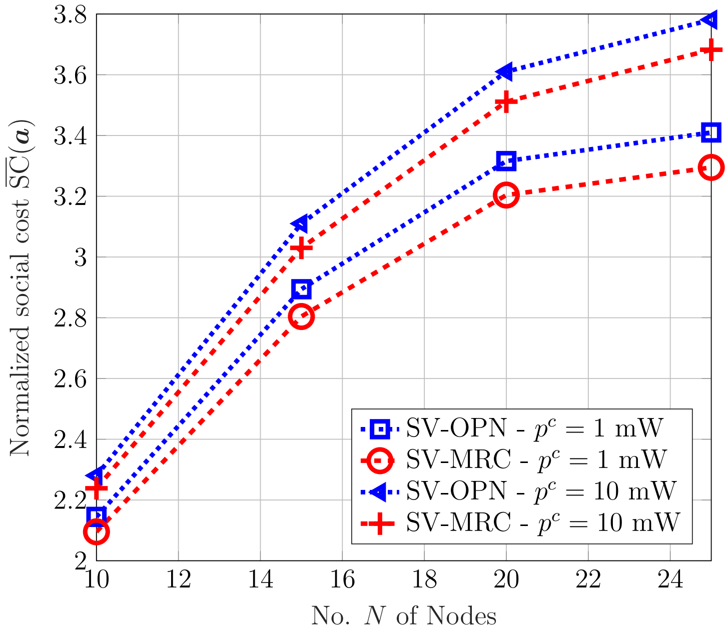
Figure 5.7. The normalized network power for different numbers N of nodes in the network and different values p^{c} of circuitry power.

In Fig. 5.7 we evaluate the effect of employing the MRC in message dissemination. We depict the total power of the network obtained via the MC and the MILP approaches for different numbers of the nodes and different values of the circuitry power. First, we observe that with MRC, the message can be disseminated with a lower power compared to the case of one PN (OPN). Second, we find in Fig. 5.7a that, when the circuitry power is low, employing the MRC technique results in a higher gain compared to the case in which the circuitry power is high. In fact, with low circuitry power (1 mW) where the power required of the radio link dominates the circuitry power, it is beneficial for the nodes to combine the signals from multiple PNs. Conversely in 5.7b, where the circuitry power is high, i.e., 100 mW, the nodes do not exploit the MRC as it requires reception circuitry power over multiple time-slots. In other words, as shown in Fig. 5.7b, even if the nodes are allowed to choose multiple PNs, they only select one PN and hence, the performance of the MPN and OPN approaches are almost the same.

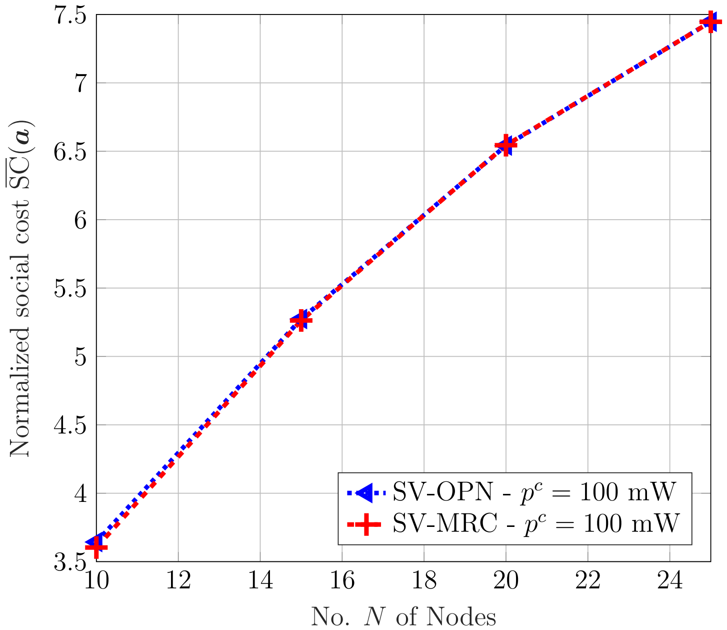
Figure 5.8, evaluates the effect of employing MRC on the social cost. As mentioned earlier, when the objective of the nodes is social cost minimization, the nodes do not consider their own reception circuitry power. In fact, the goal of the nodes in this case is to minimize the power imposed on their chosen PNs and consequently to minimize the cost they pay. Similar to the MC-based game in Fig. 5.7, here, SV-MRC performs better that SV-OPN in terms of the social cost. In other words, the total cost paid by the receiving nodes in order to receive the message reduces when they are allowed to receive the message from more than one PN. By comparing 5.7a and 5.8a, we find that employing the MRC has a slightly higher gain on the SV-based game than the MC-based game. The reason is that in the SV-based game, the reception circuitry power is not considered in the cost function of a CN. Hence, receiving via the MRC over multiple time-slots imposes a lower cost on the receiving nodes compared to the MC-based game in which the cost of reception is also included.

In order to find the effect of the MRC technique on nodes' decision, in Fig. 5.9 we show the average number of PNs per CNwith two values for the circuitry power, 1 mW and 10 mW. Considering the MC-MRC and the SV-MRC for low circuitry power, i.e., $p^{\mathrm{c}} = 1$ mW, we observe that the average number of PNs per CN for the MC-based game is higher than that for the SV-based game. The reason is that, since the objective is network power minimization and since the circuitry power in this case is low, the nodes exploit the MRC technique to a higher extent than the SV-based game in order to reduce their costs as well as the network power.

In addition, we observe that, in general, when the circuitry power increases, the average number of PNs per CN reduces for both the MC-based and the SV-based games. This reduction is more significant for the MC-based game. Recall that, with the MC-based game, the cost of a CN with respect to the transmit circuitry power of its PN is either zero (in multicast) or p^{c} (in unicast), see (5.30). Moreover, according to (5.32), with the SV-based game, the circuitry power of transmission at the PN is equally shared among the CNs. In short, the impact of the transmission circuitry power on the cost function of a node is not as significant as the impact of the reception circuitry power which is



(a) The social cost with $p^{\mathrm{c}} \in \{1 \text{ mW}, 10 \text{ mW}\}$.



(b) The social cost with $p^{\mathrm{c}} = 100$ mW.

Figure 5.8. The normalized social cost for different numbers N of nodes and different values p^{c} of circuitry power.

only captured in the MC-based game. Therefore, as the circuitry power increases from $p^{\mathrm{c}} = 1$ mW to $p^{\mathrm{c}} = 10$ mW, the nodes in the MC-based game react by choosing a lower number of PNs. While in contrast, such an increase of the circuitry power has a lower impact on the decision of the nodes in the SV-based game. For instance, when there are 20 nodes in the network, by increasing the circuitry power from $p^{\mathrm{c}} = 1$ mW

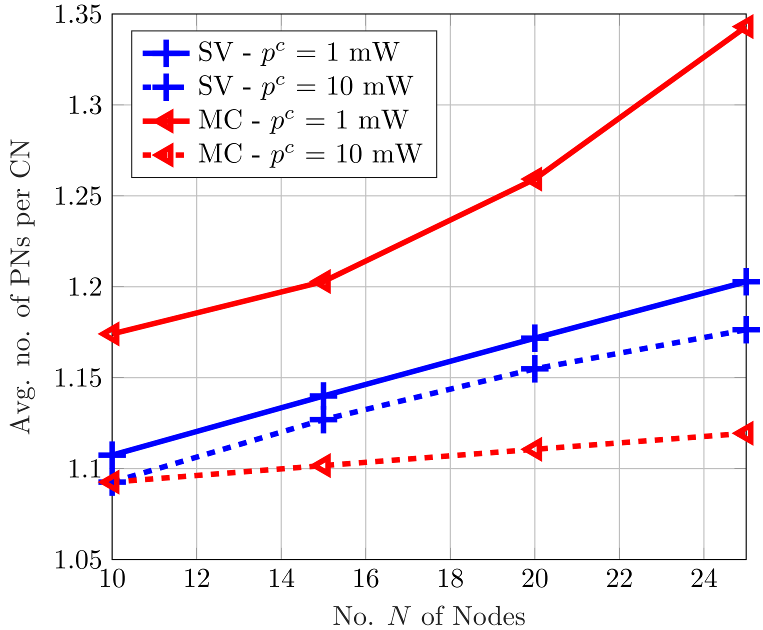


Figure 5.9. The average number of PNs per CN for different numbers N of nodes in the network.

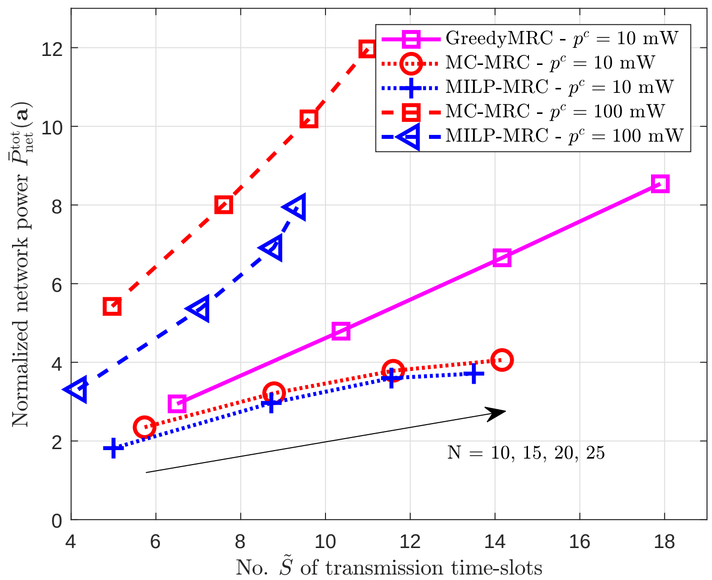


Figure 5.10. Normalized network power $\overline{P}^{\rm tot}_{\rm net}(\boldsymbol{a})$ versus the number $\tilde{S}$ of time-slots used for message dissemination.

to $p^{\rm c} = 10$ mW, the average number of PN per CN with the MC-based game reduces from 1.26 to 1.11 PNs per CN. These numbers for the SV-based game are 1.18 and 1.16 PNs per CN, respectively.

Finally, Fig. 5.10 shows how efficient the resources are used in this network for different algorithms. We plot the network power versus the number of time-slots used in the network for message dissemination. The optimum MILP-based approach and the MC-based game are considered with two different values of circuitry power, that is, $p^c = 10$ mW and $p^c = 100$ mW. Further, the performance of the GreedyMRC is also shown for the case of $p^c = 10$ mW. Since the network power obtained by the GreedyMRC for $p^c = 100$ mW is much higher than the other algorithms, we omit the GreedyMRC for $p^c = 100$ mW. In Fig. 5.10, the closer the points to the origin, the better the resources are used. As can be seen, when the circuitry power increases, the number of time-slots required for message dissemination in the network decreases. In other words, transmissions over a large number of hops impose additional transmission and reception circuitry powers on the nodes. Hence, cost minimization at the nodes results in a message dissemination strategy that requires a lower number of time-slots. Considering both Fig. 5.10 and Fig. 5.9, it can be inferred that by increasing the circuitry power, the nodes tend to receive the message from one PN and the multicast receiving groups are formed by a larger number of CNs so that both the average number of PNs per CN as well as the average number of time-slots required for message dissemination reduce.

5.6 Summary

In this chapter, we extended the game theoretic approach proposed in Chapter 4 in order to exploit the MRC technique at the receiving nodes. By this technique, the nodes are able to combine the signals received from multiple transmitting nodes in order to reduce the network power required for message dissemination. Since the PNs that a receiving node chooses transmit at different time-slots, the circuitry power for receiving the message becomes important. We studied two problems in which the goals are network power minimization, suitable for IoT scenarios, and social cost minimization, suitable for UCNs. MC and SV cost sharing schemes are employed for decision making at the nodes in the former and the latter cases, respectively. We proposed an MILP formulation for decision making by which a node is able to choose its optimum set of PNs along with the transmit power of each of the chosen PNs. We further proposed an MILP to find the globally optimum solution. Simulation results showed that our proposed algorithm outperforms the existing heuristic algorithm concerning the required power for message dissemination. We further showed that since our proposed algorithm captures the effect of circuitry power on the network power, the higher the circuitry power of the nodes, the higher gain is obtained by our proposed algorithm in comparison to the centralized greedy approach. Moreover, we found that when the circuitry power is high, the nodes tend to choose only one PN even though they are allowed to choose multiple PNs. This is due to the fact that receiving the message from multiple PNs, over multiple time-slots, imposes additional reception power on the nodes.

Chapter 6

User-centric application: Multi-hop video streaming

6.1 Introduction

In this chapter, we optimize our game-theoretic network formation algorithm, proposed in Chapter 4, for video streaming algorithm. We propose a decentralized game-theoretic algorithm for joint video quality adaptation and overlay network creation in a multi-hop wireless network. In our model, we capture the preferences of the users concerning the video quality an individual user wishes to obtain and her preferred level of contribution to the network. The algorithm provides higher video quality for the users with higher willingness to contribute, regarding the energy they spend on delivering the video to others. Our objective here is to improve the video quality perceived by the users while preserving the network energy efficiency.

The rest of this chapter is organized as follows: We first overview the scalabe video coding (SVC) and discuss the QoE measurement in Section 6.2. We extend the system model, introduced in Chapter 3, in Section 6.3 for a video streaming scenario. Section 6.4 is the main part of this chapter where we completely discuss our proposed algorithm for the preference-based video streaming. In this section, we first start by modeling the interactions among the users in Section 6.4.1 including a taxation mechanism. These interactions have to be taken into account for incentive mechanism and utility design. In Section 6.4.2 we define the game and its elements. Sections 6.4.2.2 and 6.4.2.3, respectively, discuss how the utility function and the cost function have to be designed for individual users. The decision making of the users in terms of the video quality they prefer to receive and their level of contribution to the network is provided in Section 6.4.2.4. In Section 6.4.2.5 we discuss how the taxation mechanism works and to find its optimum parameter. Simulation results are provided in Section 6.5 and, finally, Section 6.6 summarizes this chapter. Parts of this chapter have been published by the author of this dissertation in [WMA+15, MAHK16, MAK+17, MK19]

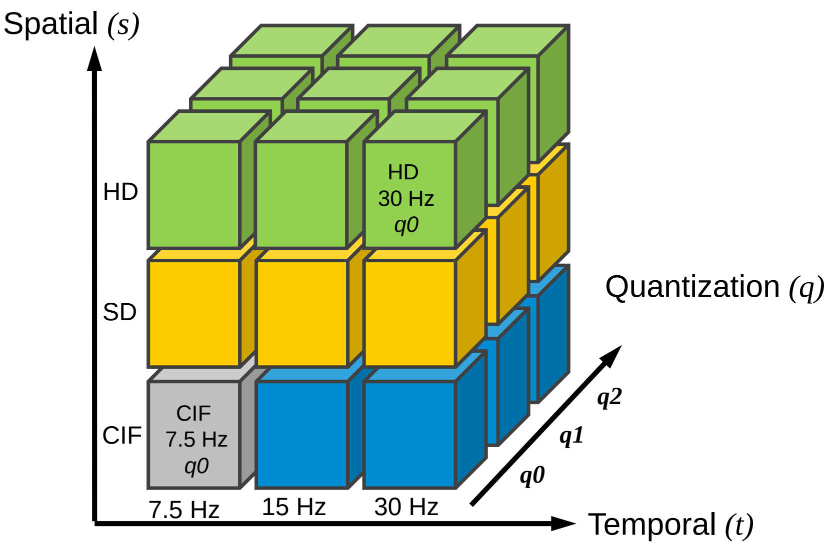


Figure 6.1. The structure of SVC coding [AZP+11]. The base layer is shown in gray.

6.2 Notes on video coding and quality of experience

6.2.1 Scalable Video Coding (SVC)

The SVC is an extension of the H.264 codec that can provide multiple video qualities with the same content [SMW07]. Using the SVC technique, a video is scaled into several layers containing a base layer and several enhancement layers. A video encoded by the SVC, in short, SVC video, has three dimensions: spatial (frame resolution), temporal (frame rate) and quantization (encoding precision). Fig. 6.1 represents the SVC with three spatial, temporal and quantization dimensions where each dimension contains two enhancement layers. The enhancement layers on top of the base layer increase the video quality and decoding a certain enhancement layer in a dimension requires receiving all the previous layers in the same scalability dimension. The base layer of the SVC video, that provides a basic video quality, can be decoded independently. The biggest advantages of SVC is its adaptability. In fact, the number of layers that are going to be transmitted from a sender to a receiver can be adapted depending on the channel quality. For example, when the channel quality between a transmitter and receiver is very poor, low layers of SVC video that require low data rate can be transmitted to the receiver. This adaption can reduce the stalling events in video playbacks which have the highest impact on QoE of the users [AZP+11]. Notice that, when the channel quality is poor, the packet loss is relatively high, and providing high video quality at the receiver with smooth playback needs a significantly higher energy-consumption at the transmitter.

6.2.2 QoE vs. QoS

Typically for network optimization, a set of objective parameters, like throughput or energy, are considered as the QoS constraints while the application layer requirements are usually ignored. It is known that fulfilling merely QoS constraints in video streaming scenarios may not necessarily result in user satisfaction. The overall user satisfaction is defined subjectively and is referred to as the QoE. The QoE is measured by the mean opinion score (MOS) [ITU96]. In MoS, the users score the quality of the service they receive based on their level of satisfaction. The score is given by a number between 1 to 5 where 5 and 1 represent the best and worst QoEs, respectively. As the name suggests, the MOS is the mean of the user's satisfaction score.

Assessing the QoE via MoS has to be done offline via surveys and therefore, it is time consuming and may not be applicable for every scenario. To address this problem, several methods have been proposed to objectively measure the QoE, referred to as the objective QoE (OQoE) [CWZ15]. Peak signal power to noise power ratio (PSNR) is one of the most widely-used OQoE measures in the literature for assessing the video quality perceived by the users [CSRK11]. Studies show that measures like the PSNR do not really reflect the user satisfaction as they are content-agnostic [WB09]. In fact, they rely mainly on bit-level accuracy of data transmission and do not consider the human visual system (HVS). To take the properties of HVS into account other measures have been proposed, e.g., structural similarity index metric (SSIM) [WBSS04], video quality metric (VQM) [PW04], and psuedo-subjective quality assessment (PSQA) [MR02]. A more comprehensive review can be found in [CSRK11] [SSBC10] [CWZ15].

In this dissertation, we use the VQM as the OQoE metric[1]. The VQM is a full-reference and user validated metric. It assigns a value between 0 and 1 to the video quality such that a VQM value closer to 1 shows a higher QoE. Measurements show that the VQM values for the QoE are highly correlated with the ones obtained by subjective evaluations [CSRK11].

6.3 System model extension

6.3.1 Video model

The considered video is layered and encoded by scalable video coding (SVC) [SMW07]. The dimensions of the SVC are shown by $\mathbb{S}$ for spatial dimension (frame resolution),

[1] In the rest, we merely use the term QoE.

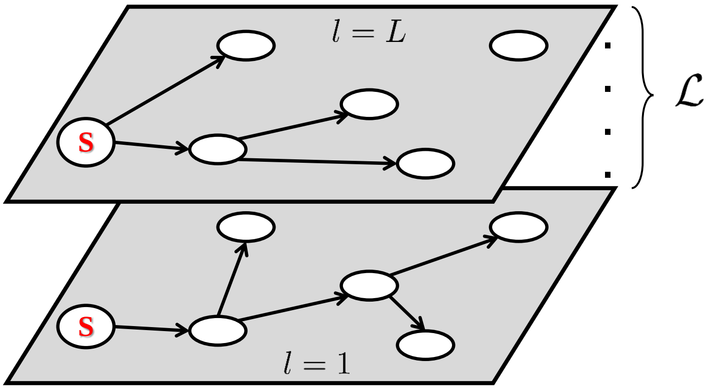


Figure 6.2. The proposed approach for the dissemination of a layered video. Receiving more layers results in higher quality.

$\mathbb{T}$ for temporal dimension (frame rate) and $\mathbb{Q}$ for quantization dimension (encoding precision). We refer to a video layer by a tuple (x, y, z) where $0 \leq x \leq |\mathbb{S}|$, $0 \leq y \leq |\mathbb{T}|$, and $0 \leq z \leq |\mathbb{Q}|$ in which $|\mathbb{S}|$, $|\mathbb{T}|$ and $|\mathbb{Q}|$ are the maximum number of enhancement layers in spatial, temporal and quantization dimensions, respectively. The base layer of the SVC video, denoted by $(0, 0, 0)$, provides a basic video quality and can be decoded independently.

The streamed video in the network is encoded into L layers and the set $\mathcal{L} = \{1, \ldots, L\}$ shows the set of video layers where video layer l requires a transmission rate of $d^{(l)}$ bits per second. $l = 1$ represents the base layer which always has to be transmitted first. Since there are three dimensions in an SVC video, it is essential to determine which of the scalability dimensions (spatial, temporal or quantization), the first enhancement layer ($l = 2$) belongs to. More precisely, the first enhancement video layer can be either $(1, 0, 0)$ or $(0, 1, 0)$ or $(0, 0, 1)$. In Sec. 6.5, we explain how we put different video layers into order. For now, we assume that the layers of the video in $\mathcal{L}$ are ordered and decoding a layer $l \in \mathcal{L}$ implies receiving layer $l-1$ as well. A layer l increases the QoE of a user by $\mathrm{q}^{(l)}$ and $\boldsymbol{q} = [\mathrm{q}^{(1)}, \ldots, \mathrm{q}^{(l)}]^{\mathrm{T}}$ is an $L \times 1$ vector containing the VQM values of all the layers such that $\mathrm{q}^{(l)} > 0$. We assume that the values of $\mathrm{q}^{(l)}$ are available in the metadata of the video.

A node in the network receives a video layer $l \in \mathcal{L}$ either directly from the source or via another node in $\mathcal{P}$. Since the video contains L layers, we propose forming L separate broadcast trees such that each video layer is disseminated by a different broadcast tree, see Fig 6.2. A user determines how many of these broadcast trees she prefers to join. The PN of a CN for the l-th layer of the video is denoted by $a_i^{(l)}$. The set of CNs of PN j for layer l that receive layer l via a multicast transmission from PN j is denoted here by $\mathcal{M}_j^{(l)}$ with cardinality $|\mathcal{M}_j^{(l)}| = M_j^l$. Note that a receiving node may have different

PNs for different video layers. Throughout this chapter, the transmitting nodes on the hops from the source to the PN of a node i are called the upstream nodes of node i. Moreover, the nodes toward the edge of the network which rely on node i on receiving the video are called the downstream nodes of node i.

We define the vector $\boldsymbol{b}_i = [b_i^{(1)}, \ldots, b_i^{(L)}]$ of size $1 \times L$ with $b_i^{(l)} \in \{0, 1\}$ as a binary indicator where $b_i^{(l)} = 1$ shows that layer l is received by node i. More precisely, we have

$$b_i^{(l)} = \begin{cases} 1, & \exists j \in \mathcal{N}_i,\ a_i^{(l)} = j,\ b_i^{l-1} \geq b_i^{(l)} \\ 0, & \text{otherwise} \end{cases} \tag{6.1}$$

in which $\mathcal{N}_i$ represents the neighboring nodes of user i. Condition $b_i^{(l-1)} \geq b_i^{(l)}$ in (6.1) indicates that the layers of the video must be received in consecutive order. We define the QoE of a user i as the aggregated quality of each video layer, i.e.,

$$Q_i = \boldsymbol{b}_i \boldsymbol{q}. \tag{6.2}$$

6.3.2 System model

The total energy required at PN j for unicast transmission of layer l to CN i, denoted by $e_{i,j}^{(l),\mathrm{uni}}$, depends on the data rate $d^{(l)}$ of the layer as

$$e_{i,j}^{(l),\mathrm{uni}} = \frac{d^{(l)}}{n_\mathrm{b}} \left(p_{i,j}^{\mathrm{uni}} + p_j^{\mathrm{ct}}\right) T_s \tag{6.3}$$

in which $p_{i,j}^{\mathrm{uni}}$ is the unicast power required for the link between PN j and CN i defined in (3.4). n_b in (6.3) is the number of bits per symbol transmitted from the PN j with symbol duration T_s. We assume that n_b and T_s are the same at all the nodes and all the video layers. In general, the energy required for transmission of layer l is given by

$$e_j^{(l)} = \max_{i \in \mathcal{M}_j^{(l)}} \left\{ e_{i,j}^{(l),\mathrm{uni}} \right\}. \tag{6.4}$$

The vector $\boldsymbol{e}_j = [e_j^{(1)}, \ldots, e_j^{(L)}]^\mathrm{T}$ is an $L \times 1$ vector with elements representing the consumed energy at node j for transmission of each of the video layers.

We define the vector of video layers *transmitted* by node j as a $1 \times L$ binary vector $\boldsymbol{t}_j = [t_j^{(1)}, \ldots, t_j^{(L)}]$ in which

$$t_j^{(l)} = \begin{cases} 1, & \mathcal{M}_j^{(l)} \neq \varnothing \\ 0, & \text{otherwise,} \end{cases} \tag{6.5}$$

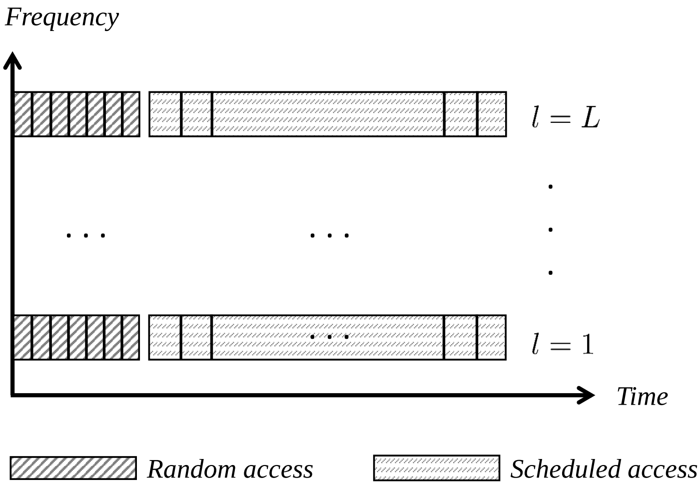


Figure 6.3. Proposed channel access scheme.

so that the total energy consumed at of PN j is given by $E_j = \boldsymbol{t}_j \boldsymbol{e}_j$.

For the channel access scheme, we propose using both time and frequency where each video layer is transmitted on a different orthogonal channel. For instance, in an OFDM-based transmission, each video layer can be transmitted over one or a group of dedicated subcarriers. Besides, we assume that each channel, which is dedicated to a BT, is time-slotted and composed of two sections. The first section as a random-access section used for overhead exchange and BT construction and the second section as a scheduled section for video dissemination, see Fig. 6.3. Such an access for the BT construction of a video layer has been discussed in Section 3.3. Note that our calculations in this chapter, for instance, for energy consumption, cost, etc., are for one second of video. Moreover, we focus on the initial overlay BT construction given the preferences of the users, however, since the proposed algorithm is decentralized it can be updated over the time if required.

6.4 Proposed video dissemination model

6.4.1 Interactions among the users

Before explaining our game-theoretic algorithm, we first introduce different interactions among the users in this network and the parameters involved. In this network, as shown in Fig. 6.4, for any one-hop transmission from a PN to a CN (or a group of CNs in a multicast transmission), a *cost* is paid to the PN by the CN. The payment in this

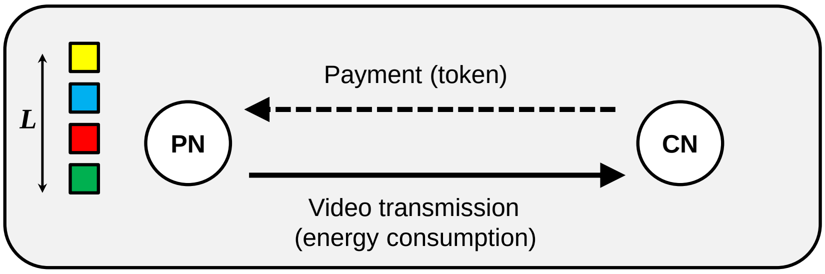


Figure 6.4. A CN receives video layers and pays tokens in exchange.

network is by tokens that the users already possess. From the PN's point of view, the cost paid by the CN is referred to as the *direct reward*.

Definition 6.1. ***(Cost)*** *Let $c_i^{(l)}$ be the cost that node i pays for layer l and $\boldsymbol{c}_i = [c_i^{(1)}, \ldots, c_i^{(L)}]^{\mathrm{T}}$ represent a vector that contains the cost paid by node i to the PNs of each layer, then, the total cost paid by node i to its PNs in order to receive the video is given by*

$$C_i = \boldsymbol{b}_i \boldsymbol{c}_i. \tag{6.6}$$

In the next subsection, we explain how the exact value of the cost, assigned to a receiving user, has to be calculated based on the energy spent by a forwarding user.

Definition 6.2. ***(Direct reward)*** *Let $\beta_i > 0$ be the reward demand coefficient (RDC) of node i. The direct reward of user i for forwarding layer l to her CNs $m \in \mathcal{M}_i^{(l)}$, is defined as*

$$r_i^{(l)} = \beta_i e_i^{(l)}. \tag{6.7}$$

β_i in (6.7), as the RDC of node i, shows the willingness of node i to contribute to the network. Lower values of β_i represent an altruistic user while higher values imply that user i is reluctant for contributing to the network unless she receives a high reward. The RDC for a user who does not want to forward the video to others will be set to $\beta = \infty$ so that it will not be chosen as a PN.

By defining an $L \times 1$ vector $\boldsymbol{r}_i = [r_i^{(1)}, \ldots, r_i^{(L)}]^{\mathrm{T}}$ containing the direct rewards received by node i for each of its transmitted video layers, the *total direct reward* obtained by node i is given by

$$R_i = \boldsymbol{t}_i \boldsymbol{r}_i = \boldsymbol{t}_i \beta_i \boldsymbol{e}_i. \tag{6.8}$$

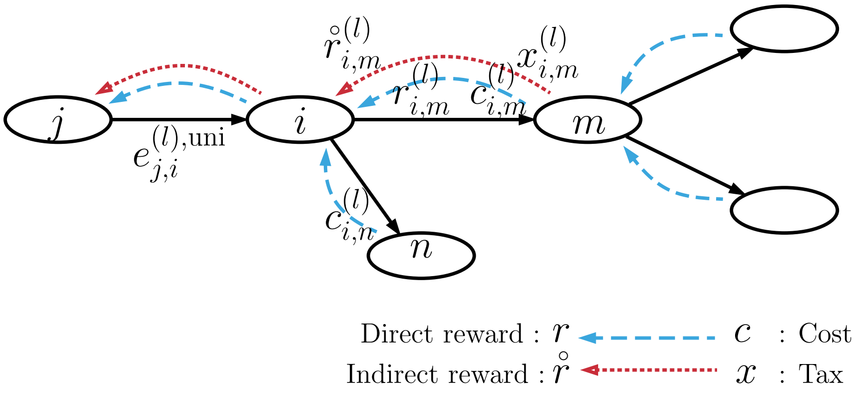


Figure 6.5. The interactions among the nodes for receiving the video and sending the rewards (direct, indirect) back to their PNs.

To capture the impact of a node's contribution to the network, we design a *taxation mechanism*. The taxation mechanism provides a higher reward for the nodes whose contribution plays a crucial role in the network. For instance, in Fig. 6.5, node i plays a more important role in the network than node m. Using this mechanism, a tax is paid from a CN to her corresponding PN in case that the received video layer by the CN is further transmitted to other nodes. Unlike the direct reward that depends on the energy that a PN spends, the taxation mechanism reflects the importance of the role that a node plays in the network.

If node m in Fig. 6.5 forwards the video layer l to her CNs and receives a direct reward from them, node i as the PN of node m receives an indirect reward from her. The indirect reward received by PN i is called tax from node m's point view, see Fig. 6.5. We denote the tax paid by node m to node i for layer l by $x_{i,m}^{(l)}$. Using an $L \times 1$ vector $\boldsymbol{x}_m = [x_m^{(1)}, \ldots, x_m^{(L)}]^{\mathrm{T}}$ containing the tax paid by node m for each of the video layers, the total tax paid by node m is given by

$$X_m = \boldsymbol{t}_m \boldsymbol{x}_m. \tag{6.9}$$

Definition 6.3. ***(Indirect reward)*** *The indirect reward received by PN i for layer l is denoted by $\mathring{r}_i^{(l)}$ and given by*

$$\mathring{r}_i^{(l)} = \sum_{m \in \mathcal{M}_i^{(l)}} x_m^{(l)}. \tag{6.10}$$

Note that in Fig. 6.5, node i has two CNs. While node i receives a direct reward from both of its CNs, the indirect reward is just received from node m as the CN who further forwards the video. By defining $\mathring{\boldsymbol{r}}_i = [\mathring{r}_i^{(1)}, \ldots, \mathring{r}_i^{(L)}]^{\mathrm{T}}$ that contains the indirect rewards a node receives for forwarding each of the layers, the *total indirect reward* received by node i is obtained by

$$\mathring{R}_i = \boldsymbol{t}_i \mathring{\boldsymbol{r}}_i. \tag{6.11}$$

Definition 6.4. ***(Virtual income)****: The virtual income of a node is defined as the sum of its direct and indirect rewards as*

$$V_i = R_i + \mathring{R}_i = \boldsymbol{t}_i \left(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i\right) = \boldsymbol{t}_i \left(\beta_i \boldsymbol{e}_i + \mathring{\boldsymbol{r}}_i\right) \tag{6.12}$$

where $\boldsymbol{v}_i = \boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i$ *is a vector containing the virtual income of node i for the video layers.*

In this network, every user transfers a portion θ of her virtual income as the tax to her PNs. The value of $0 \leq \theta < 1$ as the tax rate is a design parameter and assumed to be fixed for all the nodes in the network independent of the user preference.

Definition 6.5. ***(Tax)*** *The tax paid by node i for layer l is equal to θ times of its virtual income as* $x_i^{(l)} = \theta t_i^{(l)} v_i^{(l)} = \theta \left(r_i^{(l)} + \mathring{r}_i^{(l)}\right)$. *The tax vector paid by node i for all the layers is defined as*

$$\boldsymbol{x}_i = \theta V_i = \theta \boldsymbol{t}_i (\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i). \tag{6.13}$$

Note that a CN pays a tax just to the PNs of the layers which have been forwarded to others by her. For the layers that she does not forward, she pays merely the cost of the video layer.

6.4.2 Game-theoretic model

6.4.2.1 Definition

Here, we extend the game theoretic model we used for a single layer in Chapter 4. Since we have a separate broadcast-tree for each of the layers, the players of the game for each layer are denoted by $\mathcal{P}^{(l)}$ such that $\mathcal{P}^{(l)} \subset \mathcal{P}$. The action of player i for layer l, denoted by $a_i^{(l)}$, is to choose a PN from whom it receives the video layer l. $\mathcal{A}_i^{(l)}$ is the action set of player i for layer l, consisting of the candidate parents of CN i that can transmit layer l to it. Further, $\mathcal{A}_i^{(l)} \in \mathcal{A}^{(l)}$ where $\mathcal{A}^{(l)} := \bigtimes_{i \in \mathcal{P}} \mathcal{A}_i^{(l)}$ is the joint action set of the game for layer l in which $\bigtimes$ denotes the Cartesian product. The action set of user i for all the layers is shown by $\boldsymbol{a}_i = \{a_i^{(l)}\}_{l \in \mathcal{L}}$ and $\boldsymbol{a}_{-i}$ represents the action sets of all the players except player i. The action profile of the game over all the layers is denoted by $\boldsymbol{a} = (\boldsymbol{a}_i, \boldsymbol{a}_{-i}) \in \mathcal{A}$ where $\mathcal{A} := \bigtimes_{l\in\mathcal{L}} \mathcal{A}^{(l)}$ is the joint action set of the whole game over all the layers.

Similar to the definition in (3.10), we define $\mathcal{R}_i^{(l)}$ as a set that contains the nodes on the path from the source to node i for video layer l. Thus, node j can be a candidate parent for node i for layer l if node i is not on the path of node j to the source. We set $\mathcal{R}_{\mathrm{S}}^{(l)} = \{\mathrm{S}\}, \forall l \in \mathcal{L}$ and the route of CN i whose PN for layer l is node j is given by $\mathcal{R}_i^{(l)} = \mathcal{R}_j^{(l)} \cup \{i\}$ and $h_i^{(l)} = |\mathcal{R}_i^{(l)}| - 1 = |\mathcal{R}_j^{(l)}|$ shows the number of transmission hops from the source to node i. Second, video transmission over a large number of hops increases the delay for the nodes at the edge of the network. Hence, we assume that the number of hops from the source to a user cannot exceed $h^{\max}$. Considering these two constraints, the action set of node i for layer l is defined as

$$\mathcal{A}_i^{(l)} = \left\{ j \middle| j \in \mathcal{N}_i^{(l)}, i \notin \mathcal{R}_j^{(l)}, |\mathcal{R}_j^{(l)}| \leq h^{\max} \right\}. \tag{6.14}$$

The set of actions of node i is the joint actions of node i for all the layers as

$$\boldsymbol{a}_i = \left\{ a_i^{(l)} \middle| a_i^{(l)} \in \mathcal{A}_i^{(l)}, 1 \leq l \leq L \right\}. \tag{6.15}$$

The proposed game is iterative, and the nodes follow the best response dynamics strategy defined in Section 2.2.1.2. A utility function assigns a value to every node based on the action taken by the nodes such that $u_i(a_i^{(l)}, \boldsymbol{a}_{-i}^{(l)}) : \mathcal{A}^{(l)} \to \mathbb{R}, \forall i \in \mathcal{P}$ in which $u_i(a_i^{(l)}, \boldsymbol{a}_{-i}^{(l)})$ is the utility of node i for layer l and $\mathbb{R}$ represents the real numbers. $U_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}) = \sum_{l\in\mathcal{L}} u_i(a_i^{(l)}, \boldsymbol{a}_{-i}^{(l)})$ is the overall utility of the node in the network. The game G is formally defined by the tuple $G =< \{\mathcal{P}^{(l)}\}_{l\in\mathcal{L}}, \{A_i^{(l)}\}_{i\in\mathcal{P},l\in\mathcal{L}}, \{U_i\}_{i\in\mathcal{P}} >$. The proposed game G is child-driven, that is, a node as a CN chooses her PNs for different layers. In other words, for a certain layer l, a node either refuses to receive that layer, i.e., $b_i^{(l)} = 0$, or if it decides to receive the video layer l, then, i.e., $b_i^{(l)} = 1$, and $a_i^{(l)} = j, j \in \mathcal{A}_i^{(l)}$.

6.4.2.2 Utility design based on user preferences

The utility function of a node must capture three main aspects: the user's utility must (i) increase by receiving higher video quality as it improves user satisfaction, (ii) decrease by the cost the user pays for receiving video layers, (iii) increase when the user receives a reward in exchange of forwarding the video. Thus, We define the utility function of a user $i \in \mathcal{Q}$ as

$$U_i := U_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}) = Q_i - \zeta\left(\alpha_i C_i + X_i\right) + \zeta\left(R_i + \mathring{R}_i\right) \tag{6.16}$$

in which α_i is a user-dependent coefficient that reflects the importance of the video quality for user i. More precisely, a lower value for α_i degrades the impact of the cost paid by the user in the utility function versus the video quality she perceives. Thus, a user who is interested in receiving a high video quality is represented by a low value of α_i. Moreover, in (6.16), ζ matches the physical dimensions of parameters and also determines the value of contribution in the network. For example, in a token-based reward, by choosing a proper ζ, the system designer determines how many tokens per energy unit have to be transferred from a CN to her PN. For the sake of brevity in the rest of this chapter, we assume $\zeta = 1$.

It should also be remarked that a user can interactively and subjectively set her preferences, regarding the video quality she prefers to receive and her level of contribution. The user's inputs then need to be turned to objective parameters, i.e., α_i in (6.16) and β_i (in R_i defined in (6.8)), to be used in the utility function. Such a conversion is out of the focus of our work.

Observation 6.1. *The utility function of node $i \in \mathcal{P}$ can be written as*

$$U_i = \sum_{l \in \mathcal{L}} b_i^{(l)} \Pi_i^{(l),\mathrm{rx}} + t_i^{(l)} \Pi_i^{(l),\mathrm{tx}} \tag{6.17}$$

in which

$$\Pi_i^{(l),\mathrm{rx}} = \mathrm{q}^{(l)} - \alpha_i c_i^{(l)}, \qquad \Pi_i^{(l),\mathrm{tx}} = (1-\theta)\left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \tag{6.18}$$

Proof. Using (6.2), (6.6), (6.9), (6.8), (6.11) in (6.16) gives

$$\begin{aligned} U_i &= \boldsymbol{b}_i \boldsymbol{q} - \alpha_i \boldsymbol{b}_i \boldsymbol{c}_i - \boldsymbol{t}_i \boldsymbol{x}_i + \boldsymbol{t}_i \boldsymbol{r}_i + \boldsymbol{t}_i \mathring{\boldsymbol{r}}_i \\ &= \boldsymbol{b}_i \left(\boldsymbol{q} - \alpha_i \boldsymbol{c}_i\right) + \boldsymbol{t}_i \left(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i - \theta(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i)\right). \end{aligned} \tag{6.19}$$

Expanding (6.19) over the layers and inserting (6.7) in it, we get

$$U_i = \sum_{l \in \mathcal{L}} b_i^{(l)} \left(\mathrm{q}^{(l)} - \alpha_i^{(l)} c_i^{(l)}\right) + t_i^{(l)} (1-\theta) \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \tag{6.20}$$

□

If user i decides to receive layer l, then her action is given by

$$a_i^{(l)} = \underset{j \in \mathcal{A}_i^{(l)}}{\operatorname{argmin}} \quad c_{j,i}^{(l)} \qquad (b_i^{(l)} = 1). \tag{6.21}$$

Recall that $b_i^{(l)}$ is the decision variable of user i for layer l. The NE is then defined by

$$U(\boldsymbol{a}_i^*, \boldsymbol{a}_{-i}^*) \geq U(\boldsymbol{a}_i, \boldsymbol{a}_{-i}), \qquad \forall i \in \mathcal{P}, \boldsymbol{a}^*, \boldsymbol{a} \in \mathcal{A}. \tag{6.22}$$

6.4.2.3 Choice of the cost function

The cost function plays a critical role in our proposed mechanism. Depending on her cost, the decision of a user in the network, and consequently, her QoE may significantly change. In this work, we restrict our attention to the class of budget-balanced cost-sharing schemes which is defined in (4.15).

The cost-sharing scheme to be used in this network must have the following properties: i) It has to be budget-balanced so that the reward obtained by a PN (with RDC $\beta_i = 1$) is equal to the value of energy she consumes. ii) It has to guarantee the convergence of the game to an NE. iii) It must prevent free-riding so that $c_{i,m}^{(l)} > 0, \forall i \in \mathcal{M}_i^{(l)}$. iv) It has to be scaled by the RDC of a transmitter, so that the higher the RDC, the higher the cost allocated to its CNs. v) It must be fair in order to assign a cost to a CN in proportion to the energy she imposes on her chosen PN.

We choose the Shapley value as the cost-sharing scheme that not only satisfies all the conditions above [SLB08], but also it allows the nodes to perform transmit-power control without compromising the convergence of the game [MASK19].

Definition 6.6. ***(Shapley value):*** *Assume that the required direct rewards for every unicast link from the PN j to the multicast receiving nodes in $\mathcal{M}_j^{(l)}$ are sorted as $0 \le \beta_j e_{1,j}^{(l),\text{uni}} \le \cdots \le \beta_j e_{M_j^l,j}^{(l),\text{uni}}$ such that $e_j^{(l)} = e_{M_j^l,j}^{(l),\text{uni}}$. Then, the cost that CN i pays to PN j for layer l, based on the Shapley value, is obtained by [LO73]*

$$c_{j,i}^{(l)} = \beta_j \sum_{k=1}^{i} \frac{e_{k,j}^{(l),\text{uni}} - e_{k-1,j}^{(l),\text{uni}}}{M_j^l + 1 - k}, \qquad a_i^{(l)} = j. \tag{6.23}$$

Lemma 6.1. *A non-cooperative cost-sharing game with the Shapley value as the cost-sharing scheme is a potential game [MW13a].*

Proposition 6.1. *The game G converges to an NE.*

Proof. The game G that we propose is played for each layer $l \in \mathcal{L}$ separately. Although receiving the higher layers implies receiving the lower layers, the main difference in the game of layer l compared to layers $l' > l$ is the difference between the number of players, i.e., $|\mathcal{P}^{(l')}| \le |\mathcal{P}^{(l)}|$. Hence, to evaluate the convergence of the game, we can focus on one layer. The game G, for a given layer l, can be seen as a multicast cost-sharing game in which the nodes choose a resource with minimum cost to maximize their utility function. Based on lemma 6.1, the game G is a potential game that possesses at least one NE which can be reached by employing the best response dynamics [MS96]. □

Remark 6.1. *As stated in Section 2.2.1.3, the performance of a game theoretic algorithm can be measured by analyzing its worst-case performance, called the price of anarchy (PoA). Due to the dependency of the video layers to each other and the complexity of the proposed framework that includes a joint incentive and taxation mechanism, it is not straightforward to find the PoA of the game G. Nevertheless, under a special case where the nodes do not perform power control and use a fixed transmit power instead, the PoA can be obtained. In such a case, according to Lemma 2.1, the SV equally shares the cost of transmission among the CNs of a PN as $1/M_j$. Considering a fixed and equal transmit power for the nodes of the network and by setting $\theta = 0$, $L = 1$ and $p_j^{\mathrm{ct}} = 0$, the PoA of the game with SV rule is bounded by $O(\sqrt{N}\log^2 N)$ [CCLE+07].*

Theorem 6.1. *The social welfare of the game G is given by*

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|}\left(\sum_{i\in\mathcal{P}} \boldsymbol{b}_i(\boldsymbol{q} - \alpha_i \boldsymbol{c}_i) + \sum_{i\in\mathcal{Q}} \boldsymbol{t}_i \beta_i \boldsymbol{e}_i\right). \tag{6.24}$$

Proof. According to (2.6) the SW is defined as

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|}\sum_{i\in\mathcal{Q}} U_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}). \tag{6.25}$$

To find the social welfare of (6.24), without loss of generality, we first focus on one layer $l \in \mathcal{L}$. Further, we omit $b_i^{(l)}$ and $t_i^{(l)}$ for the nodes which receive or transmit the video layer l, respectively, as they are equal to 1, cf. (6.5) and (6.1). Since the source is the owner of the video and does not pay for the video, $\Pi_{\mathrm{S}}^{(l),\mathrm{rx}}$ in (6.18) for the source is equal to zero. Hence, the utility of the source node for layer l is equal to her virtual income, and according to (6.16), is given by

$$u_{\mathrm{S}}^{(l)} = \beta_{\mathrm{S}} e_{\mathrm{S}}^{(l)} + \mathring{r}_{\mathrm{S}}^{(l)}. \tag{6.26}$$

Using (6.11), we can extend $\mathring{r}_{\mathrm{S}}^{(l)}$ in (6.26) as

$$\mathring{r}_{\mathrm{S}}^{(l)} = \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \theta v_m^{(l)} = \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \theta\left(r_i^{(l)} + \mathring{r}_i^{(l)}\right) = \theta \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \tag{6.27}$$

Then, the utility of the source in (6.26) is written as

$$u_{\mathrm{S}}^{(l)} = \beta_{\mathrm{S}} e_{\mathrm{S}}^{(l)} + \theta \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \tag{6.28}$$

Using (6.20), the sum of utilities of the CNs of the source in $\mathcal{M}_{\mathrm{S}}^{(l)}$ is given by

$$\begin{aligned}\sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} u_i^{(l)} &= \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)} + (1-\theta)\left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right)\right)\\ &= \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)} + \beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right) - \theta \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \end{aligned} \tag{6.29}$$

Using (6.28) and (6.29), the sum of the utilities of the source node and its CNs is equal to

$$\sum_{i\in\{\mathrm{S}\}\cup\mathcal{M}_{\mathrm{S}}^{(l)}} u_i^{(l)} = \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)}\right) + \sum_{i\in\{\mathrm{S}\}\cup\mathcal{M}_{\mathrm{S}}^{(l)}} \beta_i e_i^{(l)} + \sum_{i\in\mathcal{M}_{\mathrm{S}}^{(l)}} \mathring{r}_i^{(l)}. \tag{6.30}$$

The very right term in (6.30) is the indirect reward of the CNs of the source in $\mathcal{M}_{\mathrm{S}}^{(l)}$. Similar to (6.27), one can extend (6.30) toward the edge of the network where the nodes do no forward the video and the very right term becomes equal to zero. Hence, by a summation over all the layers, it is straightforward to find the social welfare given in (6.24). □

As it can be observed, the social welfare trades the average QoE of the users and the reward they receive off against the cost they pay.

Definition 6.7. ***(Social Cost)*** *The social cost of the game G is defined as the total payment of the users for receiving the service as*

$$\mathrm{SC} = \sum_{i\in\mathcal{Q}} C_i + X_i. \tag{6.31}$$

Theorem 6.2. *The social cost of the game G with a budget-balanced cost-sharing scheme is equal to the total reward received by the contributing users of the network, i.e.,*

$$\mathrm{SC} = \sum_{i\in\mathcal{Q}} R_i = \sum_{i\in\mathcal{Q}} \boldsymbol{t}_i \beta_i \boldsymbol{e}_i. \tag{6.32}$$

Proof. The proof outline is similar to the proof of Theorem 6.1. By summing up the costs paid by CNs, and since with a budget-balanced cost-sharing scheme, the tax paid by CNs is equal to the indirect reward received by their respective PNs, (6.32) is obtained. □

Observation 6.2. *If $\alpha_i = 1, \forall i \in \mathcal{P}$, then the SW in (6.24) is given by*

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|} \sum_{i\in\mathcal{P}} \boldsymbol{b}_i \boldsymbol{q}. \tag{6.33}$$

Proof. The proof is straightforward using Theorem 6.2 and the proof given for Theorem 6.1. □

Observation 6.3. *No new token is generated and the total number of tokens in the network remains unchanged.*

Based on Theorem 6.2, the total cost paid by the receiving users in the network is equal to the reward obtained by the contributing users as the social cost. In other words, the taxation mechanism that we propose is a way to transfer the tokens from receiving nodes to the to contributing users. Note that we assume the nodes possesses enough tokens for payment.

6.4.2.4 Decision making in two stages

Every node that receives the video, including the source as the first node, distributes a so-called HELLO message in the network. This message contains the number of video layers and the corresponding VQM value of each layer. In addition, it contains the list of CNs of a PN for each layer and the corresponding unicast power required for the link to each of the CNs. The game is child-driven, and after receiving the HELLO message, a node decides about the number of video layers she wants to receive and the corresponding PN for each layer. Before discussing how a node solves its problem, we present the following corollary.

Observation 6.4. *In* (6.18)*, we always have* $\Pi_i^{(l),\mathrm{tx}} \geq 0$*. Then, if a node which possesses a given layer, receives a request from another node to serve it as a PN, accepting the request is a dominant strategy.*

Corollary 6.1. *The decision of node i is just determined by $b_i^{(l)}, \forall l \in \mathcal{L}$.*

More precisely, if a node i already possesses a layer, it forwards if it receives a request. If it does not possess the layer while receiving a request, then, $b_i^{(l)}$ determines whether node i receives this layer (and consequently forwards). We define $\mathcal{W}_i^{(l)}$ as the set of nodes which request video layer l from node i and replace $t_i^{(l)}$ by $\mathbb{1}_i^{(l)} \in \{0,1\}$ as a binary indicator such that $\mathbb{1}_i^{(l)} = 1, \text{if } \{\mathcal{M}_i^{(l)} \cup \mathcal{W}_i^{(l)}\} \neq \varnothing$.

To make a decision, a node solves its utility maximization problem in two stages with different constraints that we explain using Fig. 6.5 in the following.

Stage 1: Receive a number of available video layers

At the first stage, every node $i \in \mathcal{P}$ maximizes her utility function by finding the best PNs $j \in \mathcal{A}_i^{(l)}, \forall l \in \mathcal{L}$ based on the layers that are *currently available* at her neighboring nodes. Then, node i joins the chosen PNs by sending a JOIN message to them. The optimization problem at a node can be formulated as an integer programming problem as:

$$\begin{aligned}
\textbf{OPT 1:} \quad & \max_{\boldsymbol{b}_i} \quad \sum_{l\in\mathcal{L}} b_i^{(l)} \left(\Pi_i^{(l),\mathrm{rx}} + \mathbb{1}_i^{(l)}\Pi_i^{(l),\mathrm{tx}}\right) && \text{(6.34a)}\\
& \text{s.t.:} \\
& \qquad b_i^{(l)} \le b_i^{(l-1)}, \qquad 2 \le l \le L, && \text{(6.34b)}\\
& \qquad b_i^{(l)} \in \{0,1\}. && \text{(6.34c)}
\end{aligned}$$

(6.34b) indicates that to get a specific video layer, receiving the previous layers is necessary. Recall that the binary indicator $\mathbb{1}_i^{(l)} = 1$ if node i has a CN or a request for video layer l.

Stage 2: Request the preferred video layers

Let us assume that node i decides to receive $L_i^{(\mathrm{r})}$ layers as a result of solving **OPT 1**. At the second stage, node i assumes that *all the layers* of the video are available at all of its neighboring nodes, i.e, $b_j^{(l)} = 1, \forall j \in \mathcal{N}_i$ and solves the utility maximization problem for $L_i^{(\mathrm{r})}+1 \le l \le L$ under the new assumption. If receiving higher video layers improves the utility of node i, then, node i is able to increase its utility by receiving additional layers that are currently not available at its neighboring nodes[2]. In this case, node i incentivizes another user, say node j, to get additional video layers that node i wishes to receive. More precisely, node i proposes to pay a tax equal to $x_i^{(l)} = \theta v_i^{(l)}$ to node j indicating its interest in receiving video layer l, see Fig. 6.5. Then, node j, by having such a proposed indirect reward from user i (equal to $\mathring{r}_i^{(l)} = x_i^{(l)}$), can get the video layer l from another user and serve node i (if doing so improves its utility). To ask a node $j \in \mathcal{N}_i$ for additional layers, node i sends a request message (REQ) to node j so that we have $i \in \mathcal{W}_j^{(l)}$. The optimization problem at the second stage is written as:

$$\begin{aligned}
\textbf{OPT 2:} \quad & \max_{\boldsymbol{b}_i} \quad \sum_{l\in\mathcal{L}} b_i^{(l)} \left(\Pi_i^{(l),\mathrm{rx}} + \mathbb{1}_i^{(l)}\Pi_i^{(l),\mathrm{tx}}\right) && \text{(6.35a)}\\
& \text{s.t.:} \\
& \qquad b_i^{(l)} \le b_i^{(l-1)}, \qquad L_i^{(\mathrm{r})} + 2 \le l \le L, && \text{(6.35b)}\\
& \qquad b_i^{(l)} = 1, \qquad 1 \le l \le L_i^{(\mathrm{r})}, && \text{(6.35c)}\\
& \qquad b_j^{(l)} = 1, \qquad \forall j \in \mathcal{A}_i^{(l)}, l \in \mathcal{L}, && \text{(6.35d)}\\
& \qquad b_i^{(l)} \in \{0,1\}, \qquad L_i^{(\mathrm{r})} + 1 \le l \le L, && \text{(6.35e)}
\end{aligned}$$

[2] Note that, if a preferred video layer was available in the neighboring area, the node would receive it as a result of solving **OPT 1**.

Algorithm 2 Decision making by node i

HELLO message is received at node i
for for all $l \in \mathcal{L}$ **do**
    Find $\mathcal{A}_i^{(l)}$
    for for all $j \in \mathcal{A}_j^{(l)}$ **do**
        Calculate the unicast energy using (6.3)
        Calculate $c_{j,i}^{(l)}$ using (6.23)
        Find $a_i^{(l)}$ using (6.21) and corresponding $c_i^{(l)}$
    end for
    Find $\mathring{r}_i^{(l)}$ using (6.10)
    Calculate $\Pi_i^{(l),\text{rx}}$ and $\Pi_i^{(l),\text{tx}}$ using (6.18)
end for
Solve (6.34)
for for all $l \in \mathcal{L}$ **do**
    if $b_i^{(l)} = 1$ and node i has no PN for layer l **then**
        JOIN : $i \xrightarrow{l} j$, $a_i^{(l)} = j$
        $\mathcal{R}_i^{(l)} = \mathcal{R}_j^{(l)} \cup \{i\}$
    else if $b_i^{(l)} = 1$ and node i receives layer l **then**
        LEAVE : $i \xrightarrow{l}$ current parent
        JOIN : $i \xrightarrow{l} j$, $a_i^{(l)} = j$
        $\mathcal{R}_i^{(l)} = \mathcal{R}_j^{(l)} \cup \{i\}$
    end if
end for
Solve (6.35)
for for all $l \geq L_i^{(r)}$ **do**
    if $b_i^{(l)} = 1$ **then**
        REQ : $i \xrightarrow{l} j$, $a_i^{(l)} = j$
        Propose $x_{j,i}^{(l)} = \theta \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right)$
    end if
end for
Broadcast the HELLO message

When it comes to node j to decide, it first finds $r_j^{(l)}$ and $\mathring{r}_j^{(l)}$ based on (6.7) and (6.10) over the set $\mathcal{W}_j^l$ (instead of $\mathcal{M}_j^l$) for all the layers $l \in \mathcal{L}$. Then, it solves the optimization problems **OPT1** and **OPT2** as explained above. The same procedure is performed at every node. Through iterations, when a node that currently receives layer l finds another PN that improves her utility, the node sends LEAVE and JOIN messages to her current PN and new PN, respectively. Table 2 provides a Pseudo-code that describes the whole algorithm. In this table, sending a message from CN i to PN j for layer l of the video, say a JOIN message, is denoted by JOIN : $i \xrightarrow{l} j$.

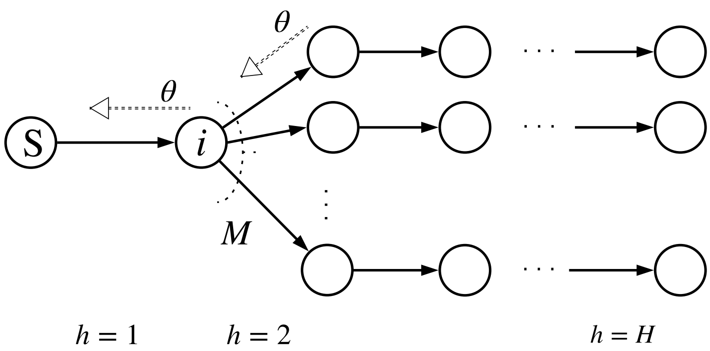


Figure 6.6. A structure in which node i's contribution is vital for the network.

6.4.2.5 Notes on the tax rate

The tax paid by the users influences the decision of the nodes and their collaboration. From a designer's perspective, the optimum value of the tax rate, denoted by θ^*, is defined as the value that maximizes the utility of a user and consequently maximizes the chance for her contribution. For instance, a proper value of θ can incentivize node i in Fig. 6.6 which is located at a critical point of the network so that it provides further video layers to the nodes located at its downstream. The optimum value of θ, i.e., θ^*, depends on the structure of the broadcast-tree and the position of the node in it. Since the nodes in the network are randomly distributed, and the broadcast-tree does not have a fixed structure, there does not exist a unique θ^* for every node and every structure.

In the rest of this subsection, we consider the structure shown in Fig. 6.6 as an instance, and find θ^* for the node i which is located at a critical point. This will give us a sense of how the tax rate has to be set. Let us assume that the nodes are evenly distribute over the network, so that the energy consumption of the PNs for a given video layer is equal. We denote the average reward that a node receives from its CNs by $\bar{r} = \mathbb{E}[\beta_m e_m^{(l)}], \forall m \in \mathcal{Q}$.

In this structure, the broadcast-tree consists of H hops in total, node i has M CNs and the other nodes have one CN. Note that $M = 1$ in Fig. 6.6 corresponds to a line structure.

Lemma 6.2. *In a line structure for a broadcast-tree, the average utility function corresponding to video layer l for a node $i \in \mathcal{P}$ who is $(H-1)$ hops away from the edge of the network, is*

$$\bar{u_i}^{(l)} = q^{(l)} + \left(1 - \alpha_i - \theta^{(H-1)}\right)\bar{r}. \tag{6.36}$$

Proof. By expanding (6.20), the average value of the utility function of node i is given by

$$\begin{aligned}\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(\bar{r} + \theta\left(\bar{r} + \theta\bar{r} + \cdots + \theta^{(H-3)}\bar{r}\right)\right)\\ &= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(1 + \theta(1 + \theta + \cdots + \theta^{(H-3)})\right)\bar{r}. \end{aligned} \tag{6.37}$$

The right side of (6.37) contains a geometric sum. Hence,

$$\begin{aligned}\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(1 + \theta\left(\frac{1-\theta^{(H-2)}}{1-\theta}\right)\right)\bar{r}\\ &= q^{(l)} - \alpha_i\bar{r} + \left(1 - \theta + \theta\left(1 - \theta^{(H-2)}\right)\right)\bar{r} \qquad (6.38)\\ &= q^{(l)} + \left(1 - \alpha_i - \theta^{(H-1)}\right)\bar{r}. \qquad (6.39)\end{aligned}$$

□

Now, the we have the following theorem for θ^*.

Theorem 6.3. *The optimum value of the tax rate, θ^*, that maximizes the utility of node i in Fig. 6.6 is given by*

$$\theta^* = \sqrt[(H-2)]{\frac{M-1}{M(H-1)}}, \qquad M \geq 1, H \geq 2. \tag{6.40}$$

Proof. We assume that node i does not possess video layer $l \in \mathcal{L}$ while the other nodes request this layer from their respective upstream nodes. The optimum value of θ for motivating node i for contributing to the network is the value that maximizes its utility function. Similar to (6.38) in Lemma 6.2, the average utility of node i with M CNs can be written it as

$$\begin{aligned}\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + \left(1 - \theta + M\theta\left(1 - \theta^{(H-2)}\right)\right)\bar{r}\\ &= q^{(l)} - \alpha_i\bar{r} + \left(1 + (M-1)\theta + -M\theta^{(H-1)}\right)\bar{r}.\end{aligned} \tag{6.41}$$

Taking the derivative of (6.37) with respect to θ leads to

$$\frac{d\bar{u}_i}{d\theta} = \left(M - 1 - M(H-1)\theta^{(H-2)}\right)\bar{r}. \tag{6.42}$$

Setting (6.42) to zero results in (6.40). □

Note that the optimum value of θ is independent of the average reward required for the links and the video layer, that is, $\hat{r}$ and l, respectively. We show θ^* in Fig. 6.7 and Fig. 6.8 for different values of M and H, respectively. Interestingly, for a line structure, the optimum value of the tax rate is $\theta = 0$. In fact, the selfish behavior of the node

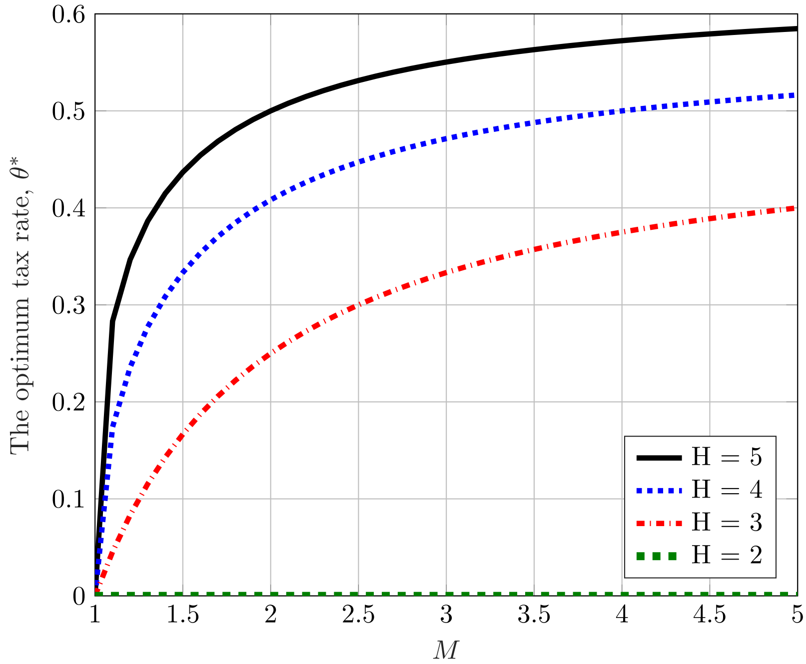


Figure 6.7. The optimum tax rate for node i in the structure given in Fig. 6.6 versus different values of M.

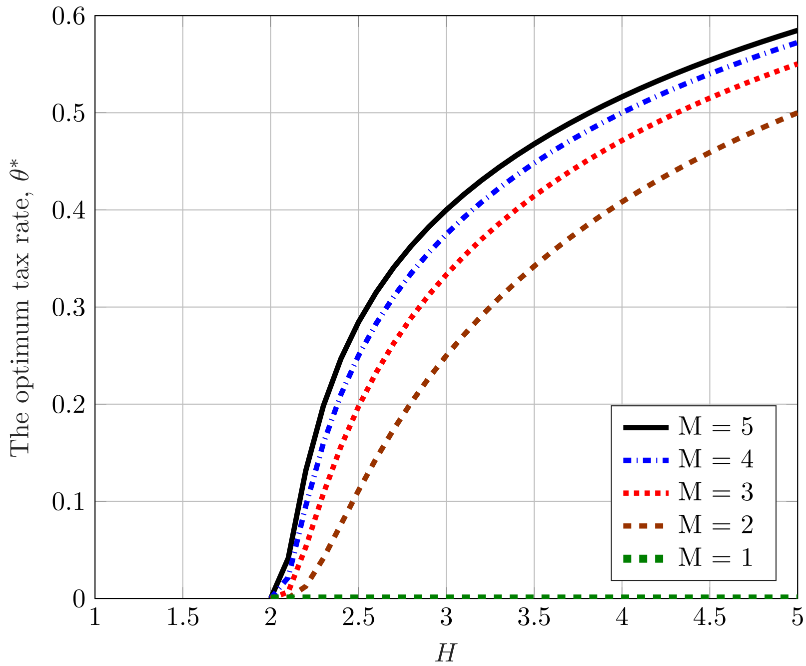


Figure 6.8. The optimum tax rate for node i in the structure given in Fig. 6.6 versus different values of H.

i results in receiving the total reward of its contribution for itself as it plays a critical role for others. When M increases, θ^* increases as well and the best strategy for node

i is to provide the layers for the nodes and benefit from the tax that the downstream nodes pay.

Corollary 6.2. *High values of tax rate θ degrade the network performance.*

Proof. Eq. (6.40) shows that θ^* for a node like i increases by the number M of CNs it serves, see Fig. 6.7 and Fig. 6.8. Such a result is obtained by assuming that all the other downstream nodes of node i have already received a request from its CN and sent it to their upstream nodes until the final requests reach node i. Since node i's downstream nodes have just one CN each, θ^* for them, according to (6.40) and by considering $M = 1$ is equal to 0. Therefore, even if one has to increase θ for a node like i to increase the chance of its contribution, nodes i's contribution depends on receiving a request from its downstream nodes which will be incentivized with lower values of θ. Therefore, with an equal tax rate for the whole network, when θ increases, the overall chance for nodes' contribution is expected to decrease. □

6.5 Performance analysis

6.5.1 Simulation setup

We consider a 1000m $\times$ 1000m network in which the nodes are randomly and uniformly distributed. The number of nodes varies between 20 and 50, and in each realization of the network, one of the nodes is randomly chosen as the source. The channel model and its parameters are the same as in Section 4.4.1. Here, as the video quality is sensitive to packet-loss, we set the minimum required SNR at the receiving nodes is set to $\gamma^{\mathrm{th}} = 15$ dB. Further, we assume that $p_j^{\max} \in [250, 350]$ mW and $p_j^{\mathrm{ct}} \in [150, 250]$ mW, respectively. The number of bits per symbol is set to $n_b = 2$ with symbol duration $T_s = 10^{-6}$s. Similar to the previous chapters, the simulations are carried out in MATLAB and the optimization problems of are solved using CVX along with Gurobi.

6.5.2 Properties of the video layers and the order of the enhancement layers

The videos used through the simulation are three videos encoded by scalable video Coding H.264/SVC provided by xiph.org[3] called *CrowdRun*, *BlueSky* and *ParkJoy*.

[3]https://media.xiph.org/video/derf/

Table 6.1. Video properties used for the simulation [Abb12].

(x, y) $(\in \mathbb{S}, \in \mathbb{T})$	layer l	Data rate: $d^{(l)}$ (Mbps)	VQM: $\mathrm{q}^{(l)}$	agg. Data rate (Mbps)	agg. VQM: Q
(0,0)	1	0.6980	0.2585	0.6980	0.2585
(0,1)	2	0.3508	0.1616	1.0487	0.4200
(0,2)	3	0.3829	0.1513	1.4316	0.5713
(0,3)	4	0.1969	0.1556	1.6285	0.7269
(0,4)	5	0.0784	0.1632	1.7069	0.8901
(1,4)	6	2.4739	0.0789	4.1808	0.9690
(2,4)	7	3.8541	0.0185	8.0349	0.9875
(3,4)	8	5.9385	0.0125	13.9733	1.0000

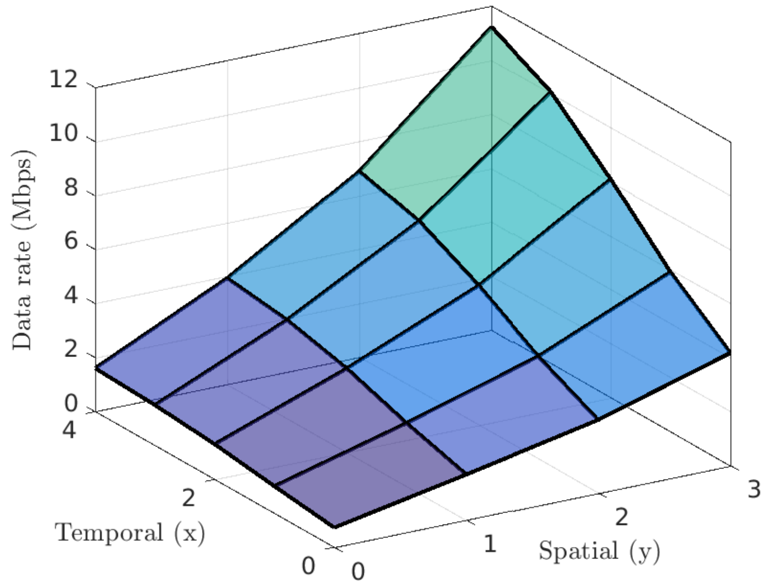
The videos contain three spatial and four temporal layers as enhancement layers on top of the base layer. The average VQM values of different video layers of the mentioned videos, as well as their corresponding data rate required for transmission, are provided in Fig. 6.9 [Abb12]. A complete mapping between the video layers and their corresponding VQM values and data rates are provided in [Abb12].

The sequence of the transmission of the enhancement layers plays a crucial role in the receiving node's utility. By considering Fig 6.9, we can see that receiving one enhancement layer in the *temporal* dimension improves the perceived quality much more than receiving one enhancement layer in the *spatial* dimension. Besides, the enhancement layers of the temporal dimension require a lower data rate than that of the spatial dimension. Low data rate transmission not only reduces the energy consumption at a PN, but also reduces the cost assigned to the CNs, cf. (6.23).

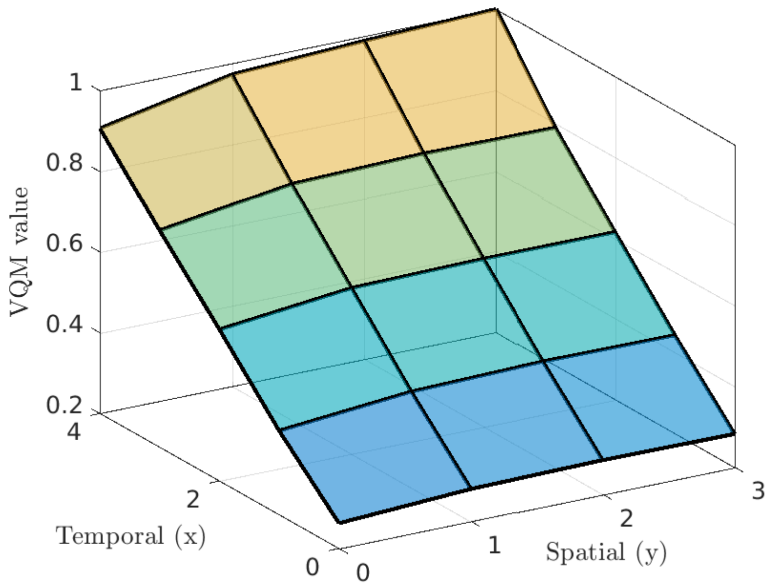
Hence, the best order for transmission of the enhancement layers is to transmit all the temporal layers prior to the spatial layers. With such an order, the VQM values and the corresponding required data rate of each layer used throughout the simulations are shown in Table 6.1.

6.5.3 Utility function setup

The parameters captured by the utility function span from the physical layer (energy) to the application layer (video quality) and user level (preferences). Therefore, they need to be set up carefully in order to work together correctly. Since the VQM values are already normalized between 0 and 1, we first normalize the energy values. The



(a) Data rate



(b) VQM values.

Figure 6.9. Required data rates and corresponding VQM values for different layers of H.264/SVC [Abb12].

energy values required for unicast communication (6.3) between any two nodes are normalized to a reference energy value denoted by E^{ref}. We define E^{ref} as the energy a node needs to spend to transmit *all* the video layers to a node located at a standard distance. Denoting by $d^{\rm std}$ and $g(d^{\rm std})$ the standard distance and the corresponding channel gain at such a distance, respectively, $E^{\rm ref}$ is given by

$$E^{\rm ref} := \sum_{l=1}^{L} \frac{d^{(l)}}{n_{\rm b}} \left(\frac{\gamma^{\rm th}\sigma^2}{g(d^{\rm std})} + p^{\rm ct} \right) T_s. \tag{6.43}$$

In our simulation setup we set $d^{\rm std} = 10$m.

To model the willingness of the users to contribute to the network, we consider the RDC $\beta_i \in \{0.5, 1, 1.5, \infty\}$ which correspond to the most altruistic users (50% of the users), the average users (25% of the users), the reluctant users (15% of the users) and the users who do not want to contribute at all (10% of the users), respectively. Likewise, to model the preferences of the users regarding the video quality they wish to receive, we assume that there are three types of users whose preferences are captured by $\alpha_i \in \{0.1, 0.5, 1\}$. These parameters correspond to the most passionate users in receiving highest video quality (50% of the users), the average users (30% of the users) and the users who are not much interested in paying the price for having high video quality (20% of the users), respectively. It should also be remarked that we define the most passionate user as the user whose utility function is maximized by receiving all the video layers from a transmitter with $\beta = 1$ and the standard distance $d^{\rm std}$ from it. By such a definition we obtain $\alpha_i = 0.1$.

6.5.4 Benchmarks

To evaluate different aspects of our design, we compare our proposed algorithm in terms of energy efficiency and QoE with the following benchmarks.

Without incentive: When the incentive is not enabled in the network, the nodes do not request the video layers which are not available at their neighboring node. In such a case, the nodes merely maximize their utility based on the available layers at their neighboring nodes by solving **OPT1** in (6.34). Note that, with our proposed algorithm, the nodes further solve **OPT2** in (6.35) as discussed in Section 6.4.2.4.

Equal-share (overlay): Equal-share is a well-studied cost-sharing scheme for network creation in which the cost of multicast transmission is equally shared among the receivers. Using the equal-share, the cost of node i in (6.23) is given by $c_{j,i}^{(l)} = e_{M_j^{(l)},j}^{(l),\rm uni}/M_j^{(l)}$. Note that, in order to guarantee the convergence of an equal-share-based cost-sharing game to an NE, the transmit power of the nodes must be fixed (cf. Theorem 4.5) which we set to $p_j = 300$mW in our simulation.

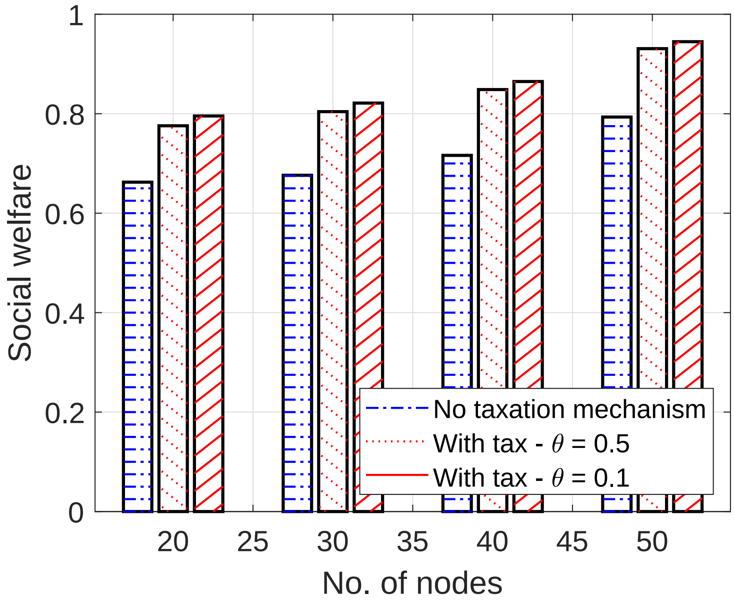


Figure 6.10. The social welfare for different numbers of users.

Flooding (overlay): Flooding is one of the simplest schemes for data dissemination. With flooding, every receiver re-transmits the packets it receives, regardless of whether another node in its neighboring area needs it.

6.5.5 Results and Discussion

6.5.5.1 General performance

Fig. 6.10 and Fig. 6.11 show the social welfare of the network and the average number of received layers for different numbers of nodes. We evaluate our proposed algorithm for two different values of tax rate, $\theta = 0.1$ and $\theta = 0.5$. We further compare our proposed algorithm with the case in which there is no incentive and taxation mechanism. We see in this figure that the social welfare increases when the network becomes denser. Since in a denser network the distances between the nodes are shorter on average, the energy required for transmission and, consequently, the cost that every node has to pay for receiving the video decreases. Therefore, the service is cheaper and the nodes request higher layers of video, as shown in Fig. 6.11. Furthermore, the social welfare is higher when the tax rate is low. This is in accordance with Observation 6.2 where we expected to have a better performance with low tax rates.

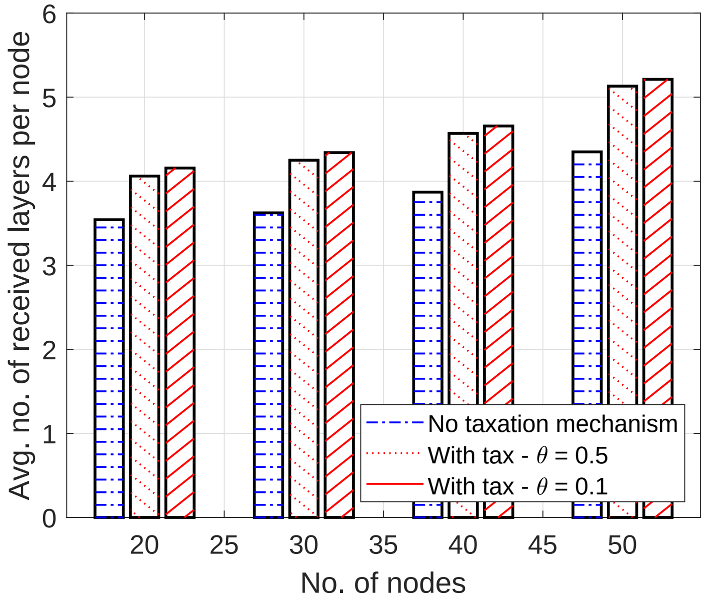


Figure 6.11. The average number of received layers by the users for different numbers of users.

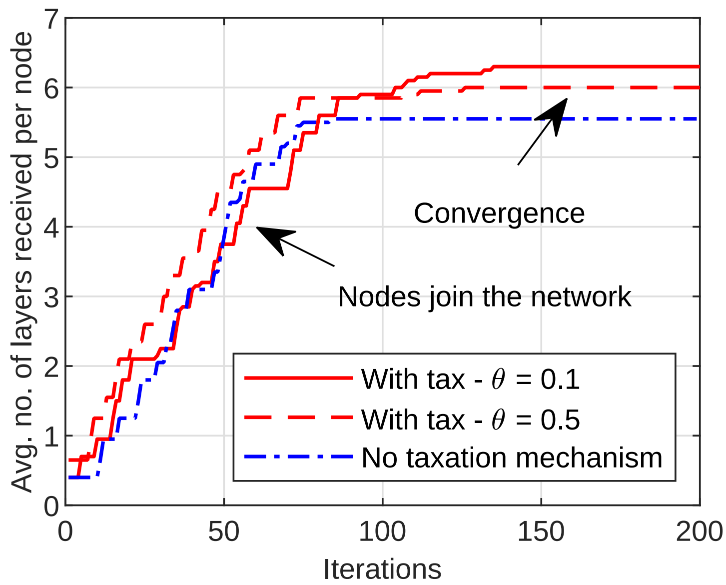


Figure 6.12. The convergence of the game to an NE and the change in the number of received layers.

In Fig. 6.12 and Fig. 6.13, the convergence of the algorithm to an NE is depicted when there are 20 nodes in the network. In all three cases, the algorithm converges to an NE where none of the nodes updates its decision. By enabling our proposed mechanism, higher social welfare and a higher number of video layers can be obtained through more

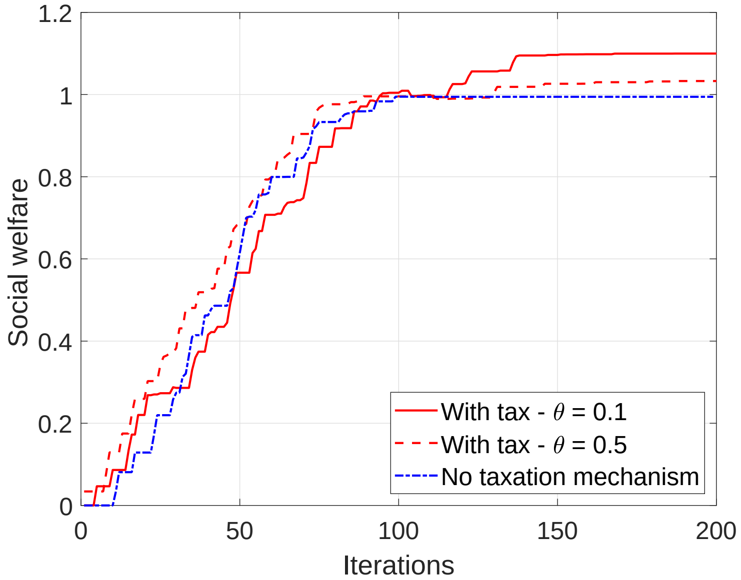


Figure 6.13. The convergence of the game to an NE and the change in the social welfare.

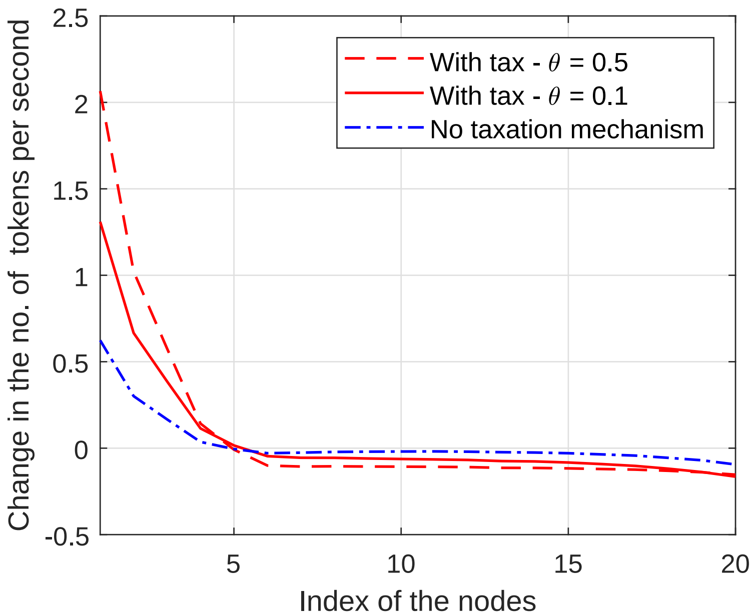


Figure 6.14. The change in the number of tokens of the users. The nodes are indexed based on their distance to the source.

iterations.

Fig. 6.14 shows the change in the number of tokens of each user after constructing the network. The number of tokens is calculated based on the difference in the users' payment and income using (6.16), that is, $\zeta\left(R + \mathring{R} - C - X\right)$ assuming $\zeta = 1$. It is assumed that one token per unit of normalized energy is paid by a receiving user to her transmitting user in a unicast transmission. Recall that, in a multicast transmission the number of tokens that need to be paid are shared among the receivers. There are 20 nodes in the network and the abscissa shows the index of the nodes depending on their proximity to the source. In other words, node 2 is the nearest user to the source and node 20 has the largest distance.

As we can see, the number of tokens of the nodes which are located closer to the source, and typically have a higher contribution, increases. In contrast, the nodes which are located far from the source end up paying their tokens for receiving the video and cannot receive tokens from others. With our proposed mechanism, the curves have a higher slope, and the number of tokens received by the contributing nodes reaches a higher value than for the case without incentive. One can conclude that by using the proposed incentive/taxation mechanism in our algorithm, the available tokens in the network are moved toward the nodes closer to the source whose contribution is vital. This actually results in higher social welfare, already shown in Fig. 6.13. It should be remarked that in all the cases shown in Fig. 6.14, the total number of tokens in the network are equal, and no new token will be generated according to Observation 6.3. The main benefit of our proposed algorithm compared to the case without incentive is the transfer of the tokens from the ones who want to have a better quality to the ones who can contribute.

6.5.5.2 Network creation algorithm

The impact of overlay BT construction algorithm is studied in Fig. 6.15 in which we show the energy consumption in the network versus the QoE of the users. We compare our proposed algorithm with the equal-share-based and flooding-based algorithms explained in Sections 6.5.4. Our proposed algorithm that uses the Shapley value performs better than the other two schemes for data dissemination. E.g., when there are 20 nodes in the network, our algorithm requires 68% and 288% less energy compared to the equal-share and flooding for transmitting four layers of the video. The gain achieved by our algorithm in comparison to the equal-share-based algorithm is a result of transmit-power control at the PNs, cf. Section 6.5.4.

Further, when there are ten nodes in the network, the performance of the equal-share algorithm is close to the performance of our proposed algorithm. The reason is that when the network is sparse, the transmissions are mostly in unicast for which the

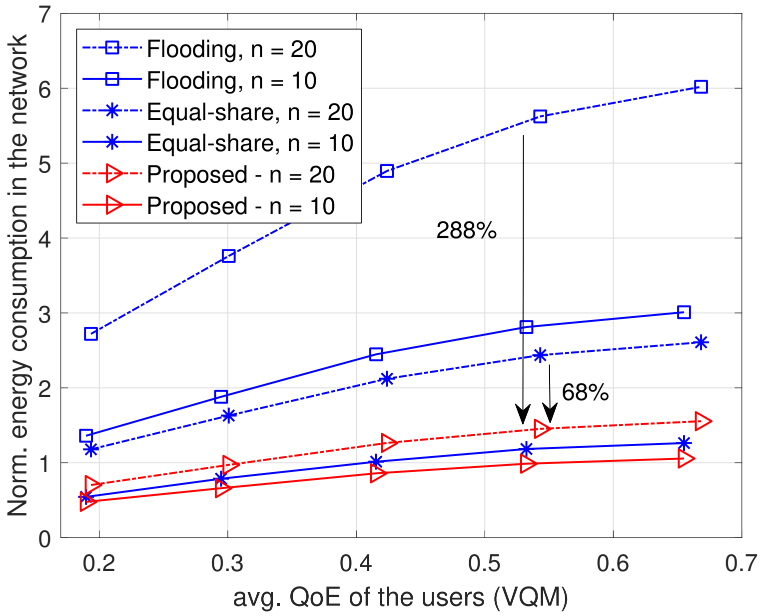


Figure 6.15. The energy required for achieving different levels of QoE for different network creation approaches.

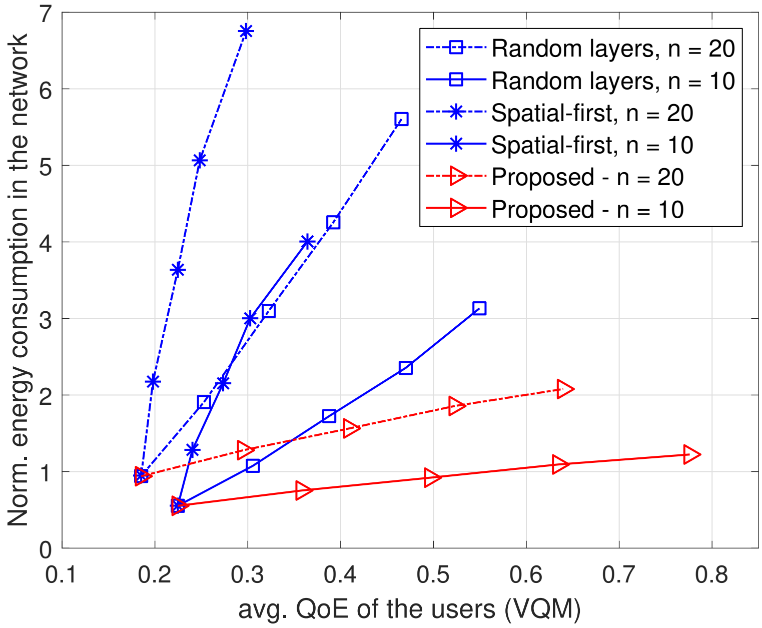


Figure 6.16. The energy efficiency of the network versus average QoE of the users for different orders of video layers transmission.

Equal-share and the Shapley value schemes share the cost of a transmission similarly. In such a case, the single CN pays the whole cost of transmission [MASK19].

6.5.5.3 Impact of the order of layers

In Fig. 6.16, we compare our proposed order of the video layers, cf. Table 6.1, with two other orders; random order and spatial-first order. As the name suggests, in the latter case, we first disseminate the spatial layers after the base layer and then the temporal layers. There are 20 nodes in the network and as Fig. 6.16 shows, our proposed scheme for transmission of the layers has the best performance and spatial-then-temporal performs the worst among the three orders. For instance, when the normalized energy consumed in the network is 2, the average VQM value obtained by our proposed algorithm is 0.65 while the random approach and spatial-first achieve 0.20 and 0.28, respectively. As can be seen in Fig. 6.9, the path taken by the spatial-then-temporal scheme, is very expensive. It requires a high data rate while it improves the QoE marginally. Therefore, the users do not join the broadcast-trees for quality enhancement, and consequently, the average QoE is lower. Hence, the order based on which the enhancement layers are transmitted can significantly impact the QoE of the users.

6.5.5.4 Preference-awareness

Finally, to have a better insight into how our proposed game-theoretic algorithm works, Fig. 6.17 and Fig. 6.18 show the stream of different video layers in the network from PNs to their CNs with and without taking the individual user preferences into account. Different colors in the heat maps shown in Fig. 6.17 and Fig. 6.18 represent different video layers. There are eight layers in total available at the source and the color of a user shows the number of video layers received by the user. In this network, there exist six users including the source. We assume that users 3, 4, and 5 who are located far from the source are interested in receiving a high video quality ($\alpha_i = 0.1, i = 3, 4, 5$) while the source node is not accessible for them. Further, node 2 has low RDC (high willingness for contribution) with $\beta_2 = 0.5$ while for node 1 we have $\beta_1 = 1$ that represents an average user.

In Fig. 6.17, the individual user preferences are ignored and α_i and β_i are set to 1 for all the users. Since nodes 1 and 2 are considered homogeneous concerning the reward that they ask from their respective CNs, node 4 is indifferent in choosing its PN and sends its requests randomly to one of the nodes 1 or 2 for each of the layers.

In Fig. 6.18, we take the individual user preferences into account. As Fig. 6.18 shows, node 2, with low RDC (high willingness for contribution), is chosen by the nodes 3,

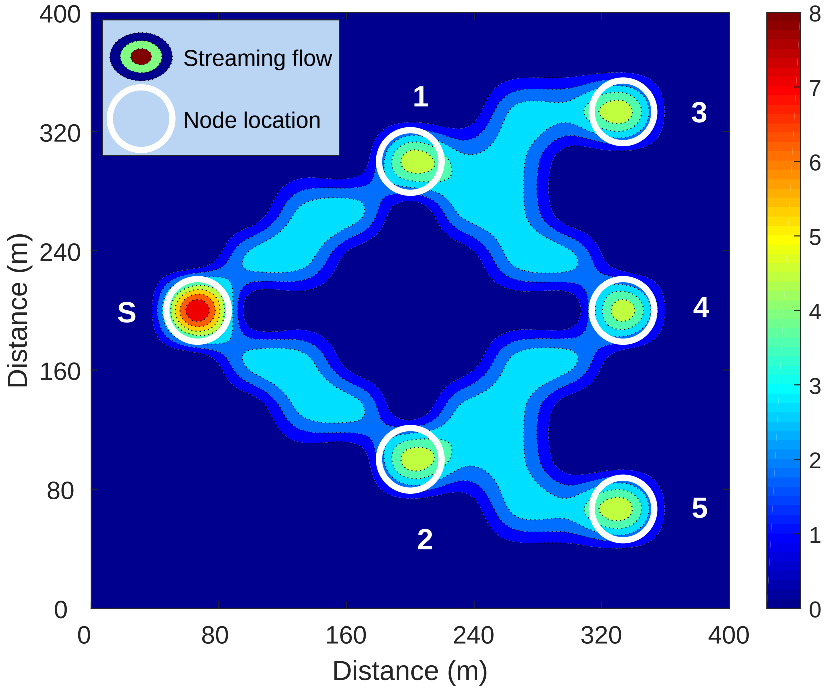


Figure 6.17. The stream of the video and the number of video layers received by the users: User preferences are ignored.

4, and, 5 for providing them the higher layers of the video. This figure clearly shows the impact of taking the individual user preferences into account. Using our proposed algorithm, in contrast to Fig. 6.17, the stream of the video is through the user with high willingness to contribute, i.e., user 2. Further, the users who require a high-quality video, that is, the users 3, 4, and 5, receive six video layers at the end. In fact, thanks to the high willingness of user 2 for contribution, the perceived QoE of the users in Fig. 6.18 is higher in comparison to Fig. 6.17.

6.6 Summary

In this chapter, we proposed a novel decentralized game-theoretic algorithm for video streaming in wireless networks with one source and multiple receivers. We propose a joint incentive and taxation mechanism by which the nodes are motivated to contribute to the network and in return get paid by their respective receivers. Our design streams the video into the network by taking the preferences of individual users into account regarding their interest in high video quality and contribution to the network. Further, with our algorithm, the contributing nodes are not only paid based on the energy they

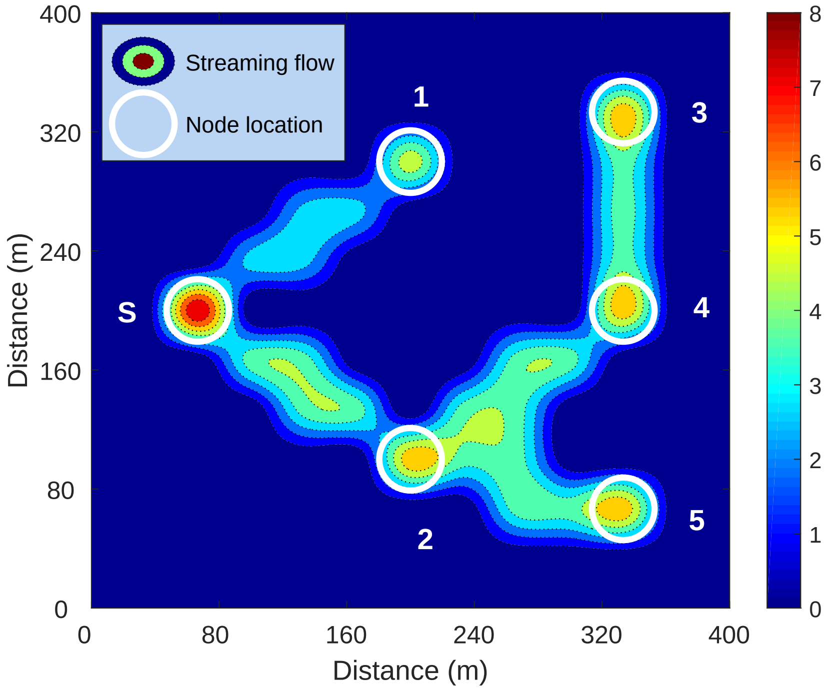


Figure 6.18. The stream of the video and the number of video layers received by the users: User preferences are considered.

spend in the network for transmission of video layers to others, but also based on the importance of their contribution for the rest of the network. Finally, we showed by simulation that our proposed algorithm converges to an NE, the social welfare improves, and the users perceive higher QoE on average.

Chapter 7

Conclusions and outlook

7.1 Conclusions

This chapter provides a summary of the dissertation and discusses the related problem that can be further investigated. In this dissertation, multi-hop broadcast in wireless networks is studied.

It is shown in Chapter 1 that with the current trend in users' interests and the communications industry, multi-hop broadcast is vital for data dissemination in the future generations of communication networks. Since the energy-efficiency is a major challenge in multi-hop networks and since the transmission flow in multi-hop broadcast forms a tree-graph, the MPBT problem is introduced and the need for a decentralized yet efficient algorithm for this problem is discussed. The existing open issues are explained and finally, the main contributions of this dissertation are summarized.

Since game theory is a suitable mathematical tool for modeling the MPBT problem in a decentralized way, in Chapter 2, an overview of game theory is provided. The categories of the game, the solution concepts, and the relevant theorems are introduced. Further, CSG as the main class of game used in this dissertation for the MPBT problem, is discussed.

In Chapter 3, the considered system and network models are described and the MPBT problem is formally defined. Moreover, a MAC scheme is proposed for the decentralized construction of the MPBT problem.

Chapter 4 presents in detail the proposed decentralized approach for the MPBT problem, which is designed based on a non-cooperative cost sharing game. The proposed cost sharing game is shown to be a potential game. Several cost sharing schemes for the MPBT problem are studied in this chapter including MC, SV and ES. First, it is shown that the MC is the best scheme for the MPBT problem. With MC, the potential function of the game is equal to the network power, meaning that, the local objective of the nodes is exactly aligned with the global objective of the network and hence, the optimum BT is always an NE of the game. It is proved that this property does not necessarily hold for budget-balanced cost sharing schemes. Second, concerning the budget-balanced cost sharing schemes, it is shown that, despite its simplicity, the ES does not guarantee the convergence of the game to an NE for the MPBT problem. It is further shown that, to guarantee the convergence when the ES is employed, the PNs in the network have to transmit with a fixed transmit power, regardless of the unicast power needed for the links to their corresponding CNs. This results in a significant increase in the network power. The budget-balanced cost sharing scheme which is fair and also always leads to an NE for the MPBT problem is shown to be the SV. Third, the necessity of having a model that jointly considers the radio link power and circuitry power is emphasized in this chapter. Simulation results show that taking the circuitry power into account jointly with the radio link power, impacts the structure of the BT and remarkably reduces the power required for message dissemination.

In addition, Chapter 4 analyzes the MAC scheme proposed in Chapter 3 . The probability of collision in accessing the shared channel is studied and the average number of nodes which may experience a collision in accessing the channel is calculated. It is shown that by a proper design, the nodes can access the channel and find their initial PNs within a few time-slots with negligible number of collisions. In fact, this can be achieved by allocating an enough number of time-slots for accessing the channel during the first few rounds of the RACH phase.

In Chapter 5, the message dissemination approach introduced in the previous chapter is further extended. More precisely, in this chapter, the receiving nodes employ the MRC technique in order to further reduce the network power by combining the signals transmitted by multiple transmitting nodes. MC and SV cost sharing schemes are considered for decision making at the nodes for network power and social cost minimization, respectively. It is shown that the MRC-based SV and MC cost functions can be formulated as piece-wise linear functions. Hence, an MILP formulation for decision making at the nodes is proposed by which each node chooses its optimum set of PNs along with the transmit power of each of the chosen PNs. Further, an MILP is also presented to find the globally optimum solution of the MRC-based message dissemination. Since the proposed algorithm takes the circuitry power into account and finds the re-transmitting nodes accordingly, it outperforms the existing heuristic algorithm, especially when the the circuitry power or the number of nodes in the network is high. Besides, it shown that exploiting MRC for the MPBT is beneficial, compared to the simple non-MRC approach, when the circuity power of the nodes is low. When the circuitry power is high, the nodes tend to choose only one PN even though they are allowed to choose multiple PNs. This is due to the fact that reception of the message from multiple PNs over multiple time-slots, imposes additional reception power on the nodes. We have also demonstrated that exploiting MRC can reduce the social cost while preserving the fairness in cost allocation and providing incentives for contributing nodes.

Our proposed decentralized data dissemination algorithm is further customized for an SVC-based video streaming in Chapter 6. The focus of this chapter is on UCNs in which having a proper incentive mechanism is critical. To answer the fairness issue, SV is employed as the cost sharing scheme in this chapter. Via a utility function, the proposed model in this chapter captures the interest of the individual users, in terms of the video quality a user wishes to receive and her preferred level of contribution to the network, and constructs the BT accordingly. It is shown that by such a model, the users with a higher willingness for contribution obtain a higher reward and are able to receive a higher video quality as well. Further, a taxation mechanism is proposed in this chapter that rewards the contributing users according to the impact of their contribution. Such a taxation mechanism is shown to be effective as it provides incentives for the nodes closer to the source which results in their contribution to the network. This improves the QoE of the users located far from the source. It is shown by simulation that with the proposed mechanism, the users are able to perceive high QoE while the energy-efficiency of the network is preserved. Further, the social cost, which is the total cost that the users pay in order to perceive a certain QoE, is shown to be reduced by the proposed algorithm.

7.2 Outlook

In this dissertation, the focus is on the energy efficiency of data dissemination in a single-source multi-hop wireless network. The results in this dissertation are based on several assumptions which can be relaxed or generalized. In the following, several possible extensions are presented.

In this dissertation, we assume that there exists one source in the network and based on such an assumption, we find an energy efficient BT for data dissemination. The problem can be extended to the case with multiple sources. For instance, in an IoT scenario where every node may have data for all other nodes, minimum-power data dissemination is challenging. One approach is to have a dedicated BT for every single node and use the corresponding BT for data dissemination when a node has a message for others. This approach results in a high amount of overhead. Another approach is to have only one BT shared by all the nodes. In fact, a single tree-graph is used by all the nodes in which each of the nodes could be a source. By the latter approach, construction of the BT and its maintenance may be easier than the former one, however, finding a proper cost function and designing a game that leads to a low-power BT is not straightforward. More precisely, the flow of the message dissemination depends on the node that acts as the source. Hence, even if the broadcast-tree is fixed, a transmitting node may need to transmit in unicast or multicast depending on the flow of the message. Further, designing a MAC scheme in such a multi-source network, especially in case of concurrent transmissions from multiple sources, is challenging and needs further investigations.

In our work, we assume that the nodes use a fixed MCS. Based on the employed MCS, the minimum SNR required at the receiving users, for decoding the data successfully, is found. Although using a lower order of MCS increases the reliability of transmission, it increases the delay in the network. An interesting problem here is to evaluate the trade-off between the end-to-end delay and the power of the BT, which is specifically important in delay sensitive applications.

Uncertainty is an inherent property of dynamic wireless networks. In a dynamic network, a node can join a network, download the content it wants to receive and then leave the network at a random point in time. So far, we assumed that the nodes in the network are static, however, since the algorithm that we propose is decentralized, the nodes can adapt themselves to the changes in the network. In fact, when required, the nodes can change their PN. In a dynamic network, frequently changing the PN imposes additional power on the network. Moreover, in applications in which the nodes download a file, the incomplete downloaded file may be lost if the receiving node loses its connection to the transmitting node and thus, it may need to start downloading the content again. This increases the energy consumption imposed on the network and hence, the algorithm needs to be generalized in order to cope with network dynamics. In other words, when the network is static, using multi-hop communication may be in favor of the network power, while in a dynamic network, in which the transmitting nodes may leave at some point in time, transmitting over a large number of hops increases the chance of failure. Hence, in a highly dynamic network, having a single-hop broadcast might be a better policy for the network energy efficiency in the long run. *Reinforcement learning* is a suitable approach by which the nodes can learn their optimal policy in choosing the node that they prefer to download the content from. The receiving nodes, depending on network status, decide to either receive their content from a centralized server or from a relay so as their decision will be in favor of the network power. The network status here includes environmental information such as the number of nodes, their velocity, and the buffer status of the other nodes.

Millimeter-wave (mmWave) communication is a promising technique for the future generation of communication networks for data dissemination. One of the main benefits of mmWave is the capability of precise beamforming by which the signal transmitted by a transmitter can be steered into a certain direction. Since by such a technique the signal can be precisely transmitted toward the intended receiver, the interference is avoided on the other nodes. Hence, unlike the traditional omnidirectional transmission, multiple transmitters can use the same shared time and frequency resources while the interference on unintended receivers is avoided. Although beamforming can reduces the network power, designing a decentralized algorithm for beamforming-based data dissemination and ensuring its convergence are challenging and need further investigations.

In the proposed MAC scheme in Chapter 3, every PN reserves a time-slot in the scheduled section for its transmission. Since the number of nodes in the network and consequently the number of PNs are not known in advance, having a fixed number of time-slots in the scheduled section may lead to either over-provisioning or under-provisioning. Designing an efficient MAC scheme in such networks is essential, especially in the case of a multi-source network. Reinforcement learning can also be employed for tackling this problem by which the number of slots required in the scheduled section can be learned over time.

In the proposed video streaming framework in Chapter 6, if the video layer that a given user, say user i, wishes to receive is available at her neighboring users, she obtains it from them directly. Otherwise, she asks one of its neighboring users, say user j, to receive the video layer from another user and forward it to her (user i). User j accepts such a request from user i if doing so improves her own utility. In fact, the decision of user j depends on her local information which is not available at user i. Hence, requesting a video layer from user j may not be the best decision by user i, as user i only considers her own local information. A more sophisticated mechanism here can be employed for further improvement. For instance, a mechanism can be designed in a way to provide the information from multiple-hops at a user. By doing so, user i can make a better decision in the first place and increase the chance of receiving the intended video quality.

List of Acronyms

BDP	Broadcast decremental power
BIP	Broadcast incremental power
BIPSW	Broadcast incremental power with sweeping
BT	Broadcast-tree
CN	Child node
CSG	Cost sharing game
ES	Equal share
HC	Highest cost allocation
IoT	Internet of things
NE	Nash equilibrium
MC	Marginal contribution
MCS	Modulation and coding scheme
MFPBT	Minimum fixed-power broadcast-tree
MPBT	Minimum-power broadcast-tree
MRC	Maximal-ratio combining
MTBT	Minimum-transmission broadcast-tree
M2M	Machine to machine
PN	Parent node
QoE	Quality of Experience
QoS	Quality of Service
RACH	Random access channel
SNR	Signal-to-Noise Ratio
SC	Social cost
SV	Shapley value

SW Social welfare

SVC Scalable video coding

UCN User-centric network

VQM Video quality metric

List of Symbols

a_i	Action of node i
$\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$	Update in the action of player i from a_i to a_i'
$a_i^{(l)}$	Action of user (player) i for video layer l
$\mathcal{A}_i$	Action set of node i
$\mathcal{A}_i^{(l)}$	Action set of user i for video layer l, $a_i^{(l)} \in A_i^{(l)}$
$\mathcal{A}$	Joint action set of a game
$b_i^{(l)}$	Binary variable, $b_i^{(l)} = 1$ if user i receives video layer l
$\boldsymbol{b}_i$	Vector of size $1 \times L$ containing the values of $b_i^{(l)}$
$c_i^{(l)}$	Cost of video layer l for user i
$\boldsymbol{c}_i$	Vector of size $L \times 1$ containing the values of $c_i^{(l)}$
$d^{(l)}$	Data rate of the video layer l
$e_i^{(l)}$	Energy spend by user i for forwarding video layer l
$\boldsymbol{e}_i$	Vector of size $L \times 1$ containing the values of $e_i^{(l)}$
$e_{i,j}^{(l),\text{uni}}$	Energy spend by PN j for unicast transmission of video layer l to CN i
$\underset{\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'}{\Delta} f(.)$	Change in the function $f(.)$ when $\boldsymbol{a} \xrightarrow{i} \boldsymbol{a}'$
h_i	Number of hops from source to node i
L	Total number of video layers
$L_i^{(r)}$	Number of video layers received by user i
$\mathcal{L}$	The set of video layers
M_j	Number of CNs of PN j
$M_j^{(l)}$	Number of CNs of PN j for layer l of the video
$\mathcal{M}_j$	Set of CNs of PN j
$\mathcal{M}_j^{(l)}$	The set of CNs of PN j
$p_j^{\max}$	Maximum transmit power of node j
p_j^{c}	Circuitry power of node j
p_j^{cr}	Reception circuitry power of node j
p_j^{ct}	Transmission circuitry power of node j
$p_{i,j}^{\text{req}}$	Transmit power requested from PN j by node i
$\boldsymbol{p}_i^{\text{req}}$	Set of transmit powers *requested* by node i from its PNs
$\boldsymbol{p}_j^{\text{rcv}}$	Set of power requests *received* by node j from its CNs
$\boldsymbol{p}_{-i,j}^{\text{rcv}}$	Set of power requests *received* by node j from its CNs except the CN i
P_j^{Tx}	Total transmission power of node j including the transmit circuitry power
P_j^{Rx}	Total reception power with MRC technique

$P_{\text{net}}^{\text{tot}}$	Network total power including the radio link power and the circuitry power for transmission and reception
$P_{\text{net}}^{\text{Tx}}$	Network transmit power including the radio link power and the circuitry power for transmission
$\mathcal{P}$	Set of players or receiving nodes
$\mathcal{Q}$	Set of all the nodes in the network, $\mathcal{Q} = \mathcal{P} \cup \{\text{S}\}$
$\text{q}^{(l)}$	VQM value of video layer l
$\boldsymbol{q}$	Vector of size $1 \times L$ containing the values of $\text{q}^{(l)}$
Q_i	QoE of user i, $Q_i = \sum_{l \in \mathcal{L}} b_i^{(l)} \text{q}^{(l)}$
$r_i^{(l)}$	Direct reward received by user i in exchange for re-transmission of video layer l
$\boldsymbol{r}_i$	Vector of size $L \times 1$ containing the values of $r_i^{(l)}$
R_i	Total reward received by user i in exchange for re-transmission of video
$\mathcal{R}_i$	The set of the nodes on the path from the source to node i
$\mathcal{R}_i^l$	The set of the nodes on the path from the source to node i for video layer l
$\mathring{r}_i^{(l)}$	The indirect reward received by user i in exchange for transmission of video layer l
$\mathring{\boldsymbol{r}}_i$	Vector of size $L \times 1$ containing the values of $\mathring{r}_i^{(l)}$
$\mathring{R}_i$	The indirect reward received by user i in exchange for transmission of video
S	Source node
$t_i^{(l)}$	Binary variable, $t_i^{(l)} = 1$ if user i transmits video layer l
$\boldsymbol{t}_i$	Vector of size $1 \times L$ containing the values of $t_i^{(l)}$
T_i	The time-slot in which node i transmits
$u_i^{(l)}$	Utility of user i for video layer l
$\boldsymbol{u}_i$	Vector of size $L \times 1$ containing the values of $u_i^{(l)}$
U_i	Total utility of user i in network
$v_i^{(l)}$	Virtual income of user i for forwarding video layer l
$\boldsymbol{v}_i$	Vector of size $L \times 1$ containing the values of $v_i^{(l)}$
V_i	Total virtual income of user i in exchange for re-transmission of video
W_i	Number of PNs chosen by CN i in case of using MRC technique
$\mathcal{W}_i$	Set of PNs of CN $i, i \in \mathcal{P}$
$x_i^{(l)}$	Tax paid by user i for video layer l
$x_{j,i}^{(l)}$	Tax paid by CN i to PN j for video layer l
$\boldsymbol{x}_i$	Vector of size $L \times 1$ containing the values of $x_i^{(l)}$
X_i	Total tax paid by user i
α_i	Interest of user i in receiving high-quality video

β_i	Willingness of user i for contribution to the network
θ	Tax rate
$\gamma_{i,j}$	SNR of the signal received at node i transmitted by node j via unicast
$\gamma_{i,j}^{\text{req}}(p_{i,j}^{\text{req}})$	SNR of the signal received by node i from transmitter j with $p_{i,j}^{\text{req}}$
$\gamma_{i\|_{\text{MRC}}}^{\text{req}}(\boldsymbol{p}_i^{\text{req}})$	SNR received at node i using MRC technique given its requested power $\boldsymbol{p}_i^{\text{req}}$
γ^{th}	Minimum SNR required at a receiver for decoding the message successfully
ζ	Number of tokens to be received per unit of energy spend for forwarding the video
$(.)^{\intercal}$	Transpose operator

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Supervised Student Theses

Name	Title of the thesis	Thesis type	Date
Domínguez Moreno, Sergio	Practical Broadcast Tree Construction with Potential Game for Energy-Efficient Data Dissemination in Ad-Hoc Network	Bachelor Thesis	01/2018
Engel, Jens	Social-Aware Proactive Caching in Wireless Networks	Bachelor Thesis	10/2017
Conte, Giovanni	Data Transmission in Multi-hop Wireless Networks under Uncertainty: A Prospect-theoretic Approach	Master Thesis	09/2017
Babri, Ali Haroon	Minimum-Power Multi-Hop Broadcast in Wireless Networks: A Learning Approach with Game Theory	Master Thesis	03/2017
Arnaudova, Tatyana	Finding Cluster-Heads by K-means Algorithm for Message Distribution in Ad-Hoc Networks	Bachelor thesis	06/2016

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