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Decentralized Video Streaming in Multi-Hop Wireless Networks: Incentive Mechanism and Energy Efficiency

MAHDI MOUSAVI AND ANJA KLEIN, (Member, IEEE)

Communications Engineering Lab, Technische Universität Darmstadt, 64283 Darmstadt, Germany

Corresponding author: Mahdi Mousavi (m.mousavi@nt.tu-darmstadt.de)

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ABSTRACT This paper studies video streaming from a source to multiple receivers in wireless networks. The video is streamed with the help of intermediate users who forward the video to others. Two main challenges affect user satisfaction in this network. The users usually have 1) different willingness to contribute (forwarding the video), and; 2) different preferences regarding the video quality. To overcome the challenges, we propose a framework based on an incentive/taxation mechanism in which the forwarding users, depending on their spent energy, are paid by their corresponding receivers. The video is layered such that the more video layers are received, the higher the quality-of-experience (QoE) and the higher the price. Using a decentralized game-theoretic algorithm, we define a user-specific utility function whose maximization determines the number of video layers a user wishes to receive. The utility function captures the user's preferences including the importance of the video quality to her and her willingness to contribute. Our model supports the multicast transmission by which the receivers can use a common forwarder and share the cost. The simulation results show that the proposed model not only provides a higher QoE for the users compared to the preference-agnostic models but also improves the network social-welfare.

INDEX TERMS Game theory, incentive mechanism, multi-hop networks, quality-of-experience, video streaming.

I. INTRODUCTION

Video applications are expected to occupy 75 percent of mobile data traffic by 2022 [1]. It is also well-known that the future generations of communication networks are highly human-centric where the expectations of users regarding the video quality increase over time [2]. In such a video-dominated network, providing high-quality video service for users and meeting their expectations is difficult. Multi-hop communication is envisioned as a technique for tackling this problem by improving the capacity of future wireless networks, for instance by exploiting the caching capabilities of wireless nodes and offloading the traffic from the infrastructure-based networks [3]. Nevertheless, to have an efficient user-centric multi-hop network, a few critical challenges need to be addressed.

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The *first challenge* is regarding the deployment of a multi-hop network. Since the nodes in a wireless network are resource constrained, having an energy-efficient multi-hop communication is of high importance, especially in video streaming scenarios where the data rate that has to be transmitted is relatively high. For the sake of energy efficiency in a multi-hop communication, an overlay network has to be constructed given the available physical links so as to determine the set of nodes that need to forward the video packets to others. In such a case, the success of a technique like multi-hop transmission in a user-centric network depends highly on the users' willingness to contribute to the network [4].

This issue brings us to the *second challenge*: incentive mechanism for user's contribution. Studies show that users are reluctant to contribute to networks without receiving a proper reward [5]. 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 thus, determine the way their device has to act in a network. In a multi-hop transmission, 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.

While the first two challenges are independent of the application, in a video streaming scenario, the user's satisfaction concerning 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 quality-of-service (QoS) for everyone and ignore the preference of *individual* users [6], [7]. 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 overlay network construction and video streaming.

Several questions have to be answered in order to tackle these challenges concerning: i) **Incentive mechanism:** How to provide an incentive for a transmitting user who consumes her energy resource for others? ii) **Contribution impact:** How to reward a user based on the significance of her contribution? For instance, the contribution of a user closer to the source is more crucial than of the one close to the edge. iii) **Overlay network construction:** How to construct an overlay network in a decentralized manner and guarantee its convergence? iv) **Fairness:** When multiple users with different requirements use a common transmitting node, how the receiving users can be treated in a fair manner regarding the reward that the transmitter may ask? v) **User preferences:** How the overlay network has to be constructed based on the individual preference of the users, that is, the user willingness to contribute to the network and the video quality she wishes to perceive? The questions mentioned above interact with each other and, hence, addressing them requires a unified design from a socio-economic perspective.

In this paper, we propose a decentralized game-theoretic algorithm for joint video quality adaptation and overlay network creation in a multi-hop wireless network with one source and multiple receivers. To provide an incentive for the contributing users, the receiving users in this network pay their corresponding transmitting users via virtual currency. Further, to preserve the overlay network energy-efficiency, we design our algorithm based on a cost-sharing game. The cost of transmission in such a game is shared among the receiving users of a transmitter which not only reduces the cost of the receiving users but also helps in network energy-efficiency by exploiting the multicast transmission. Moreover, we propose a mechanism in our model which provides a higher reward for the users whose contribution has a higher impact on the video quality perceived by the others. 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. With our algorithm, the users with higher willingness to contribute, regarding the energy they spend on delivering the video to others, are able to perceive a better video quality. In this work, our objective is to improve the social welfare and the quality-of-experience (QoE) of the users while preserving the network energy efficiency.

A. RELATED WORK AND CONTRIBUTIONS

While prior research on multimedia transmission over wireless networks has mostly focused the QoS constraints [8], [9], there has been a shift in recent years towards the QoE as a more suitable metric for performance evaluation of multimedia contents [10] via measures like the mean opinion score (MOS) [11] or pseudo-subjective quality assessment (PSQA) [9]. 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 [12] or content offloading [4]. The most relevant work to our present work is [4] 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 work present in [4] 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 in a user-centric network depends on the contribution of the users for which a variety of incentive mechanisms have been proposed during the past two decades. These approaches are either based on tit-for-tat [13], reputation [14], taxation [7] or payment via virtual currency [15]. The tit-for-tat is simple but has a limited application [16]. 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 [16]. In [7], 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 [7]. 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 [17], 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. Our proposed mechanism in this work is a combination of payment and taxation. The payment by the receiving users in our model depends on the energy the transmitting users spend. We further propose a taxation mechanism by which every node has to pay a percentage of her reward to her respective parent nodes. By doing so, the nodes closer to the source will automatically end up with a higher reward.

In addition to user satisfaction and providing high QoE for the users, one has to maintain the energy efficiency of the network. Many algorithms have been proposed during the past years for decentralized network construction, e.g., based on the Bellman-Ford algorithm [18] or game-theory [19]. Our present work is built upon our recent work [20] where we proposed a model that streams a video in a network by taking cross-layer parameters into account. In this paper, we extend our work on using a game-theoretic overlay network creation algorithm based on a cost-sharing game with an in-depth analysis. The algorithm is guaranteed to converge to a Nash equilibrium and, unlike the approach proposed in [19], it supports multicast transmission and power control at the nodes. In summary, the main properties of our proposed algorithm are as follows: i) it rewards the users based on the importance of their contribution for the network, ii) it considers the individual user preferences in overlay network construction, iii) it supports multicast transmission and transmit power control and hence, it is suitable for wireless networks, and iv) it is fair in terms of the cost allocation to the users.

The rest of this paper is organized as follows: Section II presents the video and network models. Section III explains our proposed game-theoretic video streaming algorithm. In Section IV the simulation results are presented and finally, Section V concludes the paper.

II. NETWORK AND SYSTEM MODELS

A. NETWORK AND VIDEO PROPERTIES

A wireless network is considered composed of $N+1$ nodes, with a source S that intends to stream a video to a set $\mathcal{P}$ of N other nodes. The set $\mathcal{Q} = \mathcal{P} \cup \{\mathrm{S}\}$ represents the set of all nodes in the network. The video is layered and encoded by scalable video coding (SVC) [21]. SVC is an extension of the H.264 codec that can provide multiple video qualities with the same content. Using SVC technique, a video is scaled into a base layer and several enhancement layers. A video encoded by SVC, in short, SVC video, has three dimensions: spatial $\mathbb{S}$ (frame resolution), temporal $\mathbb{T}$ (frame rate) and quantization $\mathbb{Q}$ (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 enhancement layers on top of the base layer increase the video quality and decoding a specific enhancement layer in a dimension requires receiving all the previous layers in the same dimension. The base layer of the SVC video, denoted by $(0, 0, 0)$, provides a basic video quality and can be decoded independently. The most significant advantage of SVC is its adaptability. With SVC, the number of layers, 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 poor, only low layers of an SVC video are transmitted to the receiver, requiring low data rate. This adaptation sacrifices the video quality, but it reduces stalling events in video playbacks which have the highest negative impact on the QoE [22].

In order to quantify the QoE of the users, we use video quality metric (VQM) as an objective QoE measure [23]. The VQM is a full-reference, and user validated metric. It assigns a value between 0 and 1 to the video quality such that the 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 [24].

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 a 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. IV, 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 $j \in \mathcal{P}$. The video dissemination flow from the source to all other nodes of the network forms a tree-graph rooted at the source, called the broadcast-tree (BT). In fact, the algorithm that finds the BT finds a route for message dissemination to every node. Since the video contains L layers, we propose forming L separate BTs such that each video layer is disseminated by a different BT, see Fig 1. A user determines how many of these broadcast trees she prefers to join. We call a node $j \in \mathcal{Q}$ that transmits video layer l to the receiving node $i \in \mathcal{P}$ the parent node (PN) of node i for layer l and denote it by $a_i^{(l)}$. Node i is then referred to as the child node (CN) of PN j for layer l. The set of CNs of PN j for layer l that receive layer l via a multicast transmission from PN j is denoted by $\mathcal{M}_j^{(l)}$ with cardinality $|\mathcal{M}_j^{(l)}|$. Note that a receiving node may have different PNs for different video layers. Throughout this paper, the transmitting

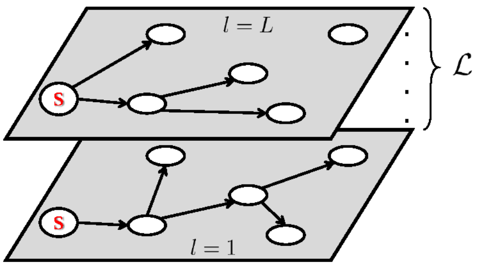


FIGURE 1. The proposed approach for the dissemination of a layered video. Receiving more layers results in higher quality.

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 $\boldsymbol{b}_i = [b_i^{(1)}, \dots, b_i^{(L)}]$ 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

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

in which $\mathcal{N}_i$ represents the neighboring nodes of user i. Condition $b_i^{(l-1)} \geq b_i^{(l)}$ 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.,

$$Q_i = \boldsymbol{b}_i \boldsymbol{q}. \tag{2}$$

B. PHYSICAL LAYER AND CHANNEL ACCESS MODELS

From physical layer point of view, every node $j \in \mathcal{Q}$ in this network has a transmit power constraint $p_j^{\max}$. We consider a threshold model such that a minimum signal to noise ratio (SNR), denoted by γ^{th}, is required at a CN in order to successfully decode the signal transmitted from its PN. In the transmission from PN j to CN i, the received SNR at the CN is calculated by

$$\gamma_{i,j} = \frac{p_j^{\text{Tx}} g_{i,j}}{\sigma^2} \tag{3}$$

in which p_j^{Tx} is the transmit power of PN j, $g_{i,j}$ is the channel gain between them and σ^2 is the noise power at node i. Consequently, the transmit power at PN j in a unicast transmission to CN i considering γ^{th} is obtained by

$$p_{i,j}^{\text{uni}} = \frac{\gamma^{\text{th}} \sigma^2}{g_{i,j}}. \tag{4}$$

It is assumed that γ^{th} and $g_{i,j}$ for the nodes i and j are the same for all the video layers. Thus, the minimum power required at the PN j for transmission to CN i, i.e., $p_{i,j}^{\text{uni}}$, is independent of the video layer. The difference comes from different data rates required by each of the video layers that result in different energy consumption at the PN.

Due to the power constraint at the nodes of the network, node i cannot be served by any arbitrary node in the network. The set of the nodes that can serve node i considering their power constraint, called the neighboring nodes of node i, is denoted by $\mathcal{N}_i$ and defined as

$$\mathcal{N}_i = \left\{ j \middle| j \in \mathcal{Q} \backslash \{i\}, p_j^{\text{uni}} < p_j^{\max} \right\}, \quad \forall i \in \mathcal{P}. \tag{5}$$

The power required at a wireless transmitter j for proper operation is composed of two parts; the power p_j^{Tx} required for amplifying the signal to be transmitted over the radio link and the circuitry power required for running internal electrical modules such as digital to analog converter, digital signal processing module, etc., denote by p_j^{cir}. Unlike the transmission power that depends on the channel quality between a transmitter and its receiver, the circuitry power is usually fixed [25]. We have shown in [26] that beside the transmission power, the circuitry power has a significant impact on the energy-efficiency of the network. Hence, we consider the total power required at a transmitter for layer l as

$$p_j^{(l)} = p_j^{(l),\text{Tx}} + p_j^{\text{cir}} \tag{6}$$

in which $p_j^{(l),\text{Tx}}$ is the transmit power required for layer l. In a multicast transmission, where a PN transmits to multiple CNs, $p_j^{(l),\text{Tx}}$ is given by $p_j^{(l),\text{Tx}} = \max_{i \in \mathcal{M}_j^{(l)}} \{p_{i,j}^{\text{uni}}\}$, that is, the CN in $\mathcal{M}_j^{(l)}$ that requires the highest unicast power determines the transmit power of node j for l.

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

$$e_{i,j}^{(l),\text{uni}} = \frac{d^{(l)}}{n_{\text{b}}} \left(p_{i,j}^{\text{uni}} + p_j^{\text{circ}} \right) T_s \tag{7}$$

in which n_{b} 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 nodes and all the video layers. In general, the energy required for transmission of layer l is then given by

$$e_j^{(l)} = \max_{i \in \mathcal{M}_j^{(l)}} \left\{ e_{i,j}^{(l),\text{uni}} \right\} \tag{8}$$

The vector $\boldsymbol{e}_j = [e_j^{(1)}, \dots, e_j^{(L)}]^{\text{T}}$ 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 $\boldsymbol{t}_j = [t_j^{(1)}, \dots, t_j^{(L)}]$ in which

$$t_j^{(l)} = \begin{cases} 1, & \mathcal{M}_j^{(l)} \neq \varnothing \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

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

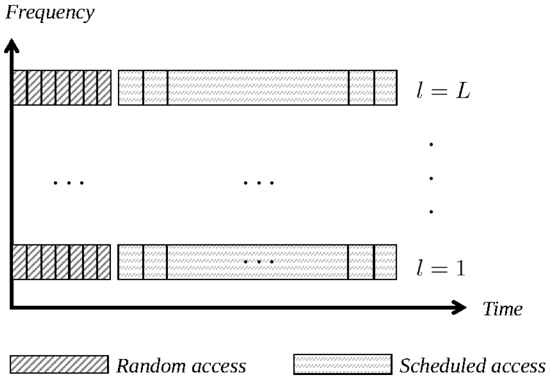


FIGURE 2. Proposed channel access scheme.

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. 2. For example, in the random access section, a node sends a request to her chosen PN to join her and receive a certain video layer. This request is sent in the frequency channel dedicated to the video layer she prefers to receive. When a node receives a request from another node and becomes a PN, she reserves a time slot for herself in the second section, that is, the scheduled section. Further, she broadcasts the index of the slot in her neighborhood so that the other PNs avoid using this slot. Such a channel access enables us to prevent the intra-network interference, as every PN transmits the packets to its CNs via its own dedicated channel resources.

Note that our calculations in this paper, for instance, for energy consumption, 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.

III. PROPOSED VIDEO DISSEMINATION ALGORITHM

A. INTERACTIONS OF THE NODES IN THE NETWORK AND USER PREFERENCES MODEL

In this network, as shown in Fig. 3, 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 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*.

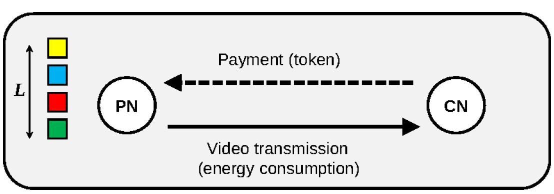


FIGURE 3. A CN receives video layers and pays tokens in exchange.

Definition 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

$$C_i = \boldsymbol{b}_i \boldsymbol{c}_i. \tag{10}$$

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 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

$$r_i^{(l)} = \beta_i e_i^{(l)}. \tag{11}$$

β_i in (11) as the RDC of node i shows the willingness of node i to contribute in the network. Lower values of β_i represent an altruistic user while higher values imply that user i is reluctant for contributing in 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 the transmitted layers, the *total direct reward* obtained by node i is given by

$$R_i = \boldsymbol{t}_i \boldsymbol{r}_i = \boldsymbol{t}_i \beta_i \boldsymbol{e}_i. \tag{12}$$

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. 4, 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.

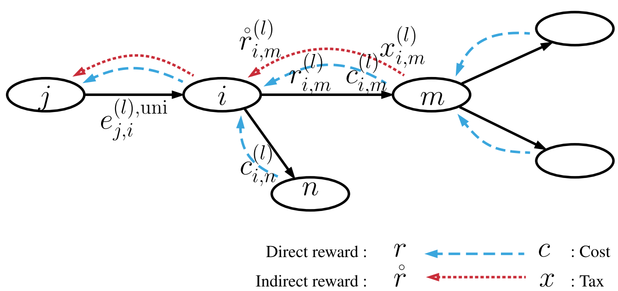


FIGURE 4. The interactions among the nodes for receiving the video and sending the rewards (direct, indirect) back to their PNs.

If node m in Fig. 4 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. 4. 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

$$X_m = \boldsymbol{t}_m \boldsymbol{x}_m. \tag{13}$$

Definition 3 (Indirect Reward): The indirect reward received by PN i for layer l is denoted by $\mathring{r}_i^{(l)}$ and given by

$$\mathring{r}_i^{(l)} = \sum_{m \in \mathcal{M}_i^{(l)}} x_m^{(l)}. \tag{14}$$

Note that in Fig. 4, 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

$$\mathring{R}_i = \boldsymbol{t}_i \mathring{\boldsymbol{r}}_i. \tag{15}$$

Definition 4 (Virtual Income): The virtual income of a node is defined as the sum of its direct and indirect rewards as

$$V_i = R_i + \mathring{R}_i = \boldsymbol{t}_i \left(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i\right) = \boldsymbol{t}_i \left(\beta_i \boldsymbol{e}_i + \mathring{\boldsymbol{r}}_i\right) \tag{16}$$

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 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

$$\boldsymbol{x}_i = \theta V_i = \theta \boldsymbol{t}_i (\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i). \tag{17}$$

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.

The notations used through this paper are summarized in Table 1. Recall that the boldface small letters represent vectors. Further, the capital letters denote the value associated to all the video layers, e.g., R_i, that represents the total direct reward received by user i in exchange for forwarding the video layers. In Table 1, we only define the scalar parameters, e.g., $r_i^{(l)}$, the direct reward received by user i for video layer l.

B. GAME-THEORETIC MODEL

In this section, we propose a game theoretic framework for BT construction. We propose a non-cooperative game model for video dissemination in the network. The players of the game are all the nodes of the network except the source, i.e., the elements of the set $\mathcal{P}$. Since we have a separate BT 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 $\mathcal{A}^{(l)} := \times_{i \in \mathcal{P}} \mathcal{A}_i^{(l)}$ is the joint action set of the game for layer l in which $\times$ 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 $\mathcal{A} := \times_{l \in \mathcal{L}} \mathcal{A}^{(l)}$ is the joint action set of the whole game over all the layers.

There are two constraints that need to be considered in defining the action set of a user. First, from a tree-graph point of view, a node i cannot choose node m which is one of its descendants, as by doing so, a loop occurs in the BT and the connection between node i and the source will be lost. 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

$$\mathcal{A}_i^{(l)} = \left\{ j \middle| j \in \mathcal{N}_i^{(l)}, i \notin \mathcal{R}_j^{(l)}, |\mathcal{R}_j^{(l)}| \leq h^{\max} \right\}. \tag{18}$$

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

$$\boldsymbol{a}_i = \left\{ a_i^{(l)} \middle| a_i^{(l)} \in \mathcal{A}_i^{(l)}, 1 \leq l \leq L \right\}, \tag{19}$$

in which $\varnothing$ represents a null element in case that node i decides not to receive layer l.

The proposed game is iterative, and the nodes follow the best response dynamics strategy, that means, in each iteration of the game, a node updates its action and best-responds to the actions taken by the other nodes in previous iterations. A utility function assigns a value to every node based on the action taken by the nodes such that $u_i(a_i^{(l)}, \boldsymbol{a}_{-i}^{(l)}) : \mathcal{A}^{(l)} \rightarrow \mathbb{R}, \forall i \in \mathcal{P}$ 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

TABLE 1. Definition of notations used through this paper.

Notation	Definition
S	The source
$\mathcal{P}$	The set of all receiving nodes
$\mathcal{Q}$	The set of all node in the network including the source, $\mathcal{Q} = \mathcal{P} \cup \{\mathrm{S}\}$
L	Total number of video layers
$\mathcal{L}$	The set of video layers
$L_i^{(r)}$	Number of video layers received by user i
$M_j^{(l)}$	Number of CNs of PN j
$\mathcal{M}_j^{(l)}$	The set of CNs of PN j
$t_i^{(l)}$, $\boldsymbol{t}_i$	Binary variable, $t_i^{(l)} = 1$ if user i transmits the video layer l
$b_i^{(l)}$, $\boldsymbol{b}_i$	Binary variable, $b_i^{(l)} = 1$ if user i receives the video layer l
$\mathrm{q}^{(l)}$, $\boldsymbol{q}$	VQM value of video layer l
Q_i	QoE of user i, $Q_i = \sum_{l \in \mathcal{L}} b_i^{(l)} \mathrm{q}^{(l)}$
$d^{(l)}$	Data rate of the video layer l
$e_i^{(l)}$, $\boldsymbol{e}_i$	Energy spend by user i for forwarding video layer l
$e_{i,j}^{(l),\mathrm{uni}}$	Energy spend by PN j for unicast transmission of video layer l to CN i
$c_i^{(l)}$	Cost of video layer l for user i
$r_i^{(l)}$, $\boldsymbol{r}_i$, R_i	Direct reward received by user i in exchange for transmission of video layer l
$x_i^{(l)}$	Tax paid by user i for video layer l
$x_{j,i}^{(l)}$, $\boldsymbol{x}_i$, X_i	Tax paid by CN i to PN j for video layer l
$\mathring{r}_i^{(l)}$, $\mathring{\boldsymbol{r}}_i$, $\mathring{R}_i$	The indirect reward received by user i in exchange for transmission of video layer l
$v_i^{(l)}$, $\boldsymbol{v}_i$, V_i	Virtual income of user i for forwarding video layer l
$u_i^{(l)}$, $\boldsymbol{u}_i$, U_i	Utility of user i for video layer l
α_i	Interest of user i in receiving high-quality video
β_i	Willingness of user i for contribution to the network
θ	Tax value
λ	Number of tokens to be received per unit of energy spend for forwarding the video
$a_i^{(l)}$	Action of user (player) i for video layer l
$A_i^{(l)}$	Action set of user i for video layer l, $a_i^{(l)} \in A_i^{(l)}$
$\mathbb{1}_i^{(l)}$	Binary indicator, $\mathbb{1}_i^{(l)} = 1$ if user i is asked for forwarding the video layer l

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 $a_i^{(l)} = j, j \in \mathcal{A}_i^{(l)}$.

C. UTILITY FUNCTION DEFINITION

In this section, we define the utility function for the nodes. The utility function plays a critical role in the decision made by the users and network optimization. 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

$$U_i := U_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}) = Q_i - \lambda\,(\alpha_i C_i + X_i) + \lambda \left(R_i + \mathring{R}_i\right) \tag{20}$$

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 (20), λ 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 λ, 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 $\lambda = 1$.

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 (20) and β_i (in R_i defined in (12)), to be used in the utility function. Such a conversion is out of the focus of our work.

Observation 1: The utility function of node $i \in \mathcal{P}$ can be written as

$$U_i = \sum_{l \in \mathcal{L}} b_i^{(l)} \Pi_i^{(l),\mathrm{rx}} + t_i^{(l)} \Pi_i^{(l),\mathrm{tx}} \tag{21}$$

in which

$$\Pi_i^{(l),\mathrm{rx}} = \mathrm{q}^{(l)} - \alpha_i c_i^{(l)}, \quad \Pi_i^{(l),\mathrm{tx}} = (1-\theta)\left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)}\right). \tag{22}$$

Proof: Using (2), (10), (13), (12), (15) in (20) gives

$$\begin{aligned} U_i &= \boldsymbol{b}_i \boldsymbol{q} - \alpha_i \boldsymbol{b}_i \boldsymbol{c}_i - \boldsymbol{t}_i \boldsymbol{x}_i + \boldsymbol{t}_i \boldsymbol{r}_i + \boldsymbol{t}_i \mathring{\boldsymbol{r}}_i \\ &= \boldsymbol{b}_i (\boldsymbol{q} - \alpha_i \boldsymbol{c}_i) + \boldsymbol{t}_i \left(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i - \theta(\boldsymbol{r}_i + \mathring{\boldsymbol{r}}_i)\right). \end{aligned} \tag{23}$$

Expanding (23) over the layers and inserting (11), in it we get

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

■

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

$$a_i^{(l)} = \underset{j \in \mathcal{A}_i^{(l)}}{\mathrm{argmin}} \quad c_{j,i}^{(l)} \ (\text{if } b_i^{(l)} = 1). \tag{24}$$

Recall that $b_i^{(l)}$ is the decision variable of user i for layer l. The Nash equilibrium (NE) point is assumed as the solution concept of the game at which none of the players can increase her utility by changing her decision unilaterally [27]. The action profile $\boldsymbol{a}^*$ is an NE of the game if

$$U(\boldsymbol{a}_i^*, \boldsymbol{a}_{-i}^*) \geq U(\boldsymbol{a}_i, \boldsymbol{a}_{-i}), \quad \forall i \in \mathcal{P}, \boldsymbol{a}^*, \ \boldsymbol{a} \in \mathcal{A}. \tag{25}$$

D. CHOICE OF THE COST FUNCTION AND CONVERGENCE TO THE NE

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 changes. In this work, we restrict our attention to the class of budget-balanced cost-sharing schemes.

Definition 6 (Budget-Balanced Cost-Sharing Scheme): In game theory, a cost-sharing scheme is budget-balanced if the sum of the cost allocated to the users who share a common resource is equal to the value of the resource (here, to the reward that has to be paid) [27], that is,

$$r_j^{(l)} = \sum_{i \in \mathcal{M}_j^{(l)}} c_{j,i}^{(l)}. \tag{26}$$

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 [27] but also it allows the nodes to perform transmit-power control without compromising the convergence of the game [26].

Definition 7 (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 $0 \leq \beta_j e_{j,1}^{(l),\mathrm{uni}} \leq \cdots \leq \beta_j e_{j,M_j^{(l)}}^{(l),\mathrm{uni}}$ such that $e_j^{(l)} = e_{j,M_j^{(l)}}^{(l),\mathrm{uni}}$. Then, the cost that CN i pays to PN j for layer l, based on the Shapley value, is obtained by [28]

$$c_{j,i}^{(l)} = \beta_j \sum_{k=1}^{i} \frac{e_{j,k}^{(l),\mathrm{uni}} - e_{j,k-1}^{(l),\mathrm{uni}}}{M_j^{(l)} + 1 - k}, \quad a_i^{(l)} = j. \tag{27}$$

Lemma 1: A non-cooperative cost-sharing game with the Shapley value as the cost-sharing scheme is a potential game [29].

Claim 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., $|\mathcal{P}^{(l')}| \leq |\mathcal{P}^{(l)}|$. 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 1, the game G is a potential game that possesses at least one NE which can be reached by employing the best response dynamics [30]. ■

Remark 1: The performance of a game theoretic algorithm is 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, the SV equally shares the cost of transmission among the CNs of a PN as $1/M_j$ [26]. Considering a fixed and equal transmit power for the nodes of the network and by setting $\theta = 0$, $L = 1$ and $p_j^{\mathrm{circ}} = 0$, the PoA of the game with SV rule is bounded by $O(\sqrt{N} \log^2 N)$ [31].

Remark 2: By a proper design, one can ensure that the probability of collision in a random access channel, shown in Fig. 2, is negligible. Then, the convergence rate of our proposed game by employing the best response dynamics is $O(N)$ [32].

Definition 8 (Social Welfare): The social welfare of the game G is defined as

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|} \sum_{i \in \mathcal{Q}} U_i(\boldsymbol{a}_i, \boldsymbol{a}_{-i}). \tag{28}$$

Theorem 1: The social welfare of the game G is given by

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|}\left(\sum_{i\in\mathcal{P}} \boldsymbol{b}_i(\boldsymbol{q}-\alpha_i\boldsymbol{c}_i) + \sum_{i\in\mathcal{Q}} \boldsymbol{t}_i\beta_i\boldsymbol{e}_i\right). \quad (29)$$

Proof: The proof is provided in Appendix A. ■

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 9 (Social Cost): The social cost of the game G is defined as the total payment of the users for receiving the service as

$$\mathrm{SC} = \sum_{i\in\mathcal{Q}} C_i + X_i. \quad (30)$$

Theorem 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.,

$$\mathrm{SC} = \sum_{i\in\mathcal{Q}} R_i = \sum_{i\in\mathcal{Q}} \boldsymbol{t}_i\beta_i\boldsymbol{e}_i. \quad (31)$$

Proof: The proof outline is similar to the proof of Theorem 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, (31) is obtained. ■

Observation 2: If $\alpha_i = 1, \forall i \in \mathcal{P}$, then the SW in (28) is given by

$$\mathrm{SW} = \frac{1}{|\mathcal{Q}|}\sum_{i\in\mathcal{P}} \boldsymbol{b}_i\boldsymbol{q}. \quad (32)$$

Proof: Using Theorem 2 and the proof of Theorem 1, it is straightforward to verify (32). ■

Observation 3: No new token is generated and the total number of tokens in the network remains unchanged.

Based on Theorem 2, the total cost paid by receiving users in the network is equal to the reward obtained by contributing users and 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.

E. DECISION MAKING BY THE PLAYERS 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 4: In (22), 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 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 $\mathbb{1}_i^{(l)} = 1$, 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. 4 in the following.

1) 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:

$$\textbf{OPT1}: \max_{\boldsymbol{b}_i} \sum_{l\in\mathcal{L}} b_i^{(l)}\left(\Pi_i^{(l),\mathrm{rx}} + \mathbb{1}_i^{(l)}\Pi_i^{(l),\mathrm{tx}}\right) \quad (33a)$$

$$\text{s.t.: } b_i^{(l)} \leq b_i^{(l-1)}, \quad 2 \leq l \leq L, \quad (33b)$$

$$b_i^{(l)} \in \{0, 1\}. \quad (33c)$$

(33b) 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.

2) 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 $L_i^{(\mathrm{r})} + 1 \leq l \leq L$ 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.[1] 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. 4. 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

[1]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**.

we have $i \in \mathcal{W}_j^{(l)}$. The optimization problem at the second stage is written as:

$$\begin{aligned}
\textbf{OPT2}: \quad & \max_{\boldsymbol{b}_i} \sum_{l\in\mathcal{L}} b_i^{(l)}\left(\Pi_i^{(l),\mathrm{rx}} + \mathbb{1}_i^{(l)}\Pi_i^{(l),\mathrm{tx}}\right) && \text{(34a)}\\
& \text{s.t.: } b_i^{(l)} \le b_i^{l-1}, \quad L_i^{(\mathrm{r})}+2 \le l \le L, && \text{(34b)}\\
& \quad b_i^{(l)} = 1, \quad 1 \le l \le L_i^{(\mathrm{r})}, && \text{(34c)}\\
& \quad b_j^{(l)} = 1, \quad \forall j \in \mathcal{A}_i^{(l)}, l \in \mathcal{L}, && \text{(34d)}\\
& \quad b_i^{(l)} \in \{0,1\}, \quad L_i^{(\mathrm{r})}+1 \le l \le L, && \text{(34e)}
\end{aligned}$$

When it comes to node j to decide, it first finds $r_j^{(l)}$ and $\mathring{r}_j^{(l)}$ based on (11) and (14) 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 1 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 : $i \xrightarrow{l} j$.

F. NOTES ON THE TAX VALUE θ

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. 5 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.

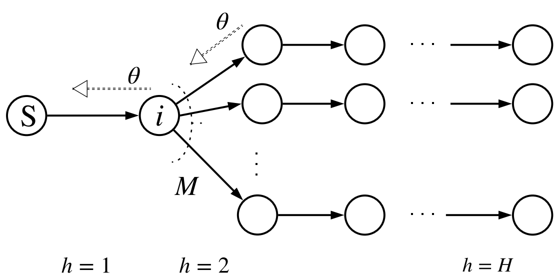


FIGURE 5. A structure in which node i's contribution is vital for the network.

In the rest of this subsection, we consider the structure shown in Fig. 5 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

Algorithm 1 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 (7)
    Calculate $c_{j,i}^{(l)}$ using (27)
    Find $a_i^{(l)}$ using (24) and corresponding $c_i^{(l)}$
  end for
  Find $\mathring{r}_i^{(l)}$ using (14)
  Calculate $\Pi_i^{(l),\mathrm{rx}}$ and $\Pi_i^{(l),\mathrm{tx}}$ using (22)
end for
Solve (33)
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 (34)
for for all $l \ge L_i^{(r)}$ **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

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 BT consists of H hops in total, node i has M CNs and the other nodes have one CN. Note that $M = 1$ in Fig. 5 corresponds to a line structure.

Lemma 2: In a line structure for a BT, 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

$$\bar{u_i}^{(l)} = q^{(l)} + \left(1 - \alpha_i - \theta^{(H-1)}\right)\bar{r}. \tag{35}$$

Proof: By expanding (24), the average value of the utility function of node i is given by

$$\begin{aligned}
\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(\bar{r} + \theta\left(\bar{r} + \theta\bar{r} + \ldots + \theta^{(H-3)}\bar{r}\right)\right)\\
&= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(1 + \theta(1 + \theta + \ldots + \theta^{(H-3)})\right)\bar{r}.
\end{aligned} \tag{36}$$

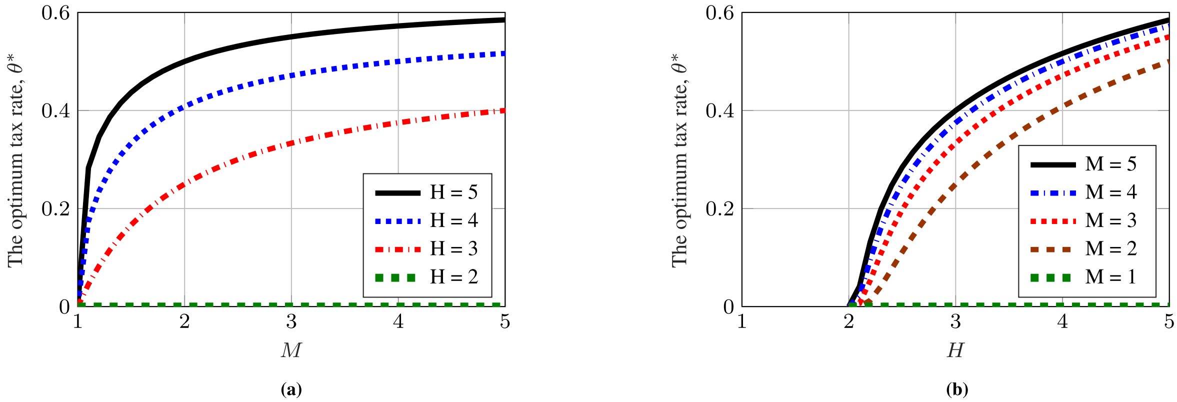


FIGURE 6. The optimum tax rate for node *i* in the structure given in Fig. 5 versus different values of *M* and *H*. (a) The optimum tax rate vs *M* for Fig. 5. (b) The optimum tax rate vs *H* for Fig. 5.

The right side of (36) contains a geometric sum. Hence,

$$\begin{aligned}\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + (1-\theta)\left(1+\theta\left(\frac{1-\theta^{(H-2)}}{1-\theta}\right)\right)\bar{r}\\ &= q^{(l)} - \alpha_i\bar{r} + \left(1-\theta+\theta\left(1-\theta^{(H-2)}\right)\right)\bar{r}\\ &= q^{(l)} + \left(1-\alpha_i-\theta^{(H-1)}\right)\bar{r}.\end{aligned} \quad (37)$$

■

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

Theorem 3: θ^* that maximizes the utility of node i in Fig. 5 is given by

$$\theta^* = \sqrt[(H-2)]{\frac{M-1}{M(H-1)}}, \quad M \geq 1,\ H \geq 2. \quad (38)$$

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 (37) in Lemma 2, the average utility of node i can be written it as

$$\begin{aligned}\bar{u_i}^{(l)} &= q^{(l)} - \alpha_i\bar{r} + \left(1-\theta+M\theta\left(1-\theta^{(H-2)}\right)\right)\bar{r}\\ &= q^{(l)} - \alpha_i\bar{r} + \left(1+(M-1)\theta + -M\theta^{(H-1)}\right)\bar{r}.\end{aligned} \quad (39)$$

Taking the derivative of (36) with respect to θ leads to

$$\frac{d\bar{u}_i}{d\theta} = \left(M-1-M(H-1)\theta^{(H-2)}\right)\bar{r}. \quad (40)$$

Setting (40) to zero results in (38). ■

Note that, the optimum value of θ is independent of the RDC of the node as well as the video layer, i.e., $\hat{r}$ and l, respectively. We show θ^* in Fig. 6 for different values of M and H. Interestingly, for a line structure, the optimum value of the tax rate is $\theta = 0$. In fact, the selfish behavior of the node 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.

Observation 5: High values of tax rate θ degrade the network performance.

Proof: Eq. (38) shows that θ^* for a node like i increases by the number M of CNs it serves, see Fig. 6. 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 (38) 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. ■

IV. SIMULATION RESULTS

A. NETWORK PARAMETERS SETUP

We consider a 1000m × 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 path-loss channel model is considered for the channel gain between any two nodes of the network. Let $d_{i,j}$ and d_0 be the distance between nodes i and j and a reference distance for the channel gain, respectively. Further, by η and ζ we denote the path loss exponent and the signal wavelength, respectively. Then, the channel gain between nodes i and j is obtained by

$$g_{i,j} = \left(\frac{\zeta}{4\pi d_0}\right)^2\left(\frac{d_0}{d_{i,j}}\right)^\eta. \quad (41)$$

For the simulation, we set $\eta = 3$, $\zeta = 0.125$m and $d_0 = 1$m. The maximum transmit power and the circuitry power at the nodes are uniformly distributed over $p_j^{\max} \in [250, 350]$ mW and $p_j^{\mathrm{cir}} \in [150, 250]$ mW, respectively [33]. The minimum required SNR at the receiving nodes is set to $\gamma^{\mathrm{th}} = 15$ dB and the noise power to −90 dBm. The number of bits per symbol

TABLE 2. Video properties used for the simulation [34].

(x, y) $(\in \mathbb{S}, \in \mathbb{T})$	layer l	Data rate: $d^{(l)}$ (Mbps)	VQM: $q^{(l)}$	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

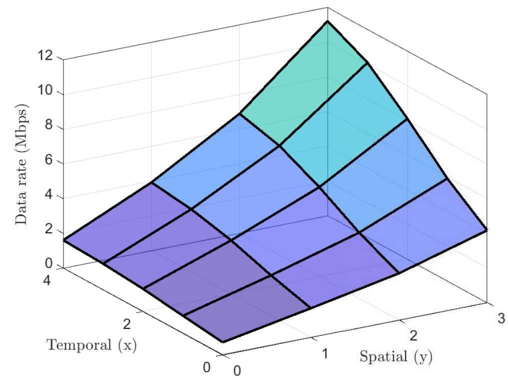
is set to $n_b = 2$ with symbol duration $T_s = 10^{-6}$s. The simulations are carried out in MATLAB[2] and the optimization problems of (33) and (34) are solved using CVX[3] along with Gurobi.[4]

B. PROPERTIES OF THE VIDEO LAYERS AND THE ORDER OF THE ENHANCEMENT LAYERS

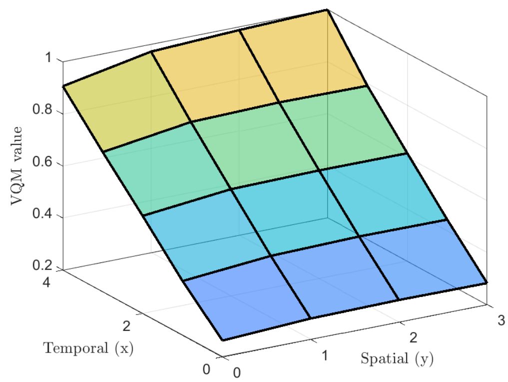
The videos used through the simulation are three videos encoded by scalable video Coding H.264/SVC provided by xiph.org[5] called *CrowdRun*, *BlueSky* and *ParkJoy*. The videos contain three spatial and four temporal layers as enhancement layers on top of the base layer. The average VQM values of different video layers of the mentioned videos, as well as their corresponding data rate required for transmission, are provided in Fig. 7 [34].

The sequence of the transmission of the enhancement layers plays a crucial role in the receiving node's utility. By considering Fig 7, 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. (27).

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 2.



(a)



(b)

FIGURE 7. Required data rates and corresponding VQM values for different layers of H.264/SVC [34]. (a) Data rate. (b) VQM values.

C. 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 energy required for unicast communication (7) 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, set to $d^{\text{std}} = 10$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),

[2]http://mathworks.com/
[3]http://cvxr.com/cvx/
[4]http://www.gurobi.com/
[5]https://media.xiph.org/video/derf/

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^{std} from it. By such a definition we obtain $\alpha_i = 0.1$.

D. BENCHMARKS

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

1) 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 (33). Note that, with our proposed algorithm, the nodes further solve **OPT2** in (34) as discussed in Section III-E.2.

2) 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 (27) is given by $c_{j,i}^{(l)} = e_{j,M_j^{(l)}}^{(l),\mathrm{uni}}/M_j^{(l)}$. 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 which we set to $p_j = 300\mathrm{mW}$ in our simulation.

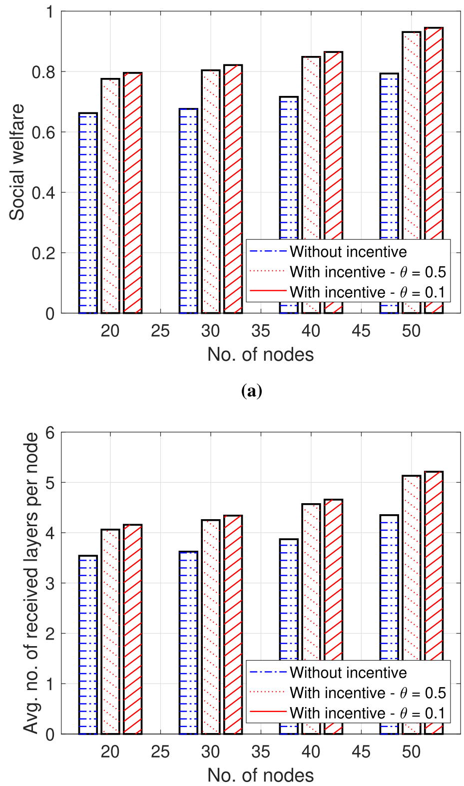
3) FLOODING (OVERLAY)

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.

E. RESULTS AND DISCUSSION

1) GENERAL PERFORMANCE

Fig. 8a shows the social welfare of the network for different number 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 without incentive. 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



(a)

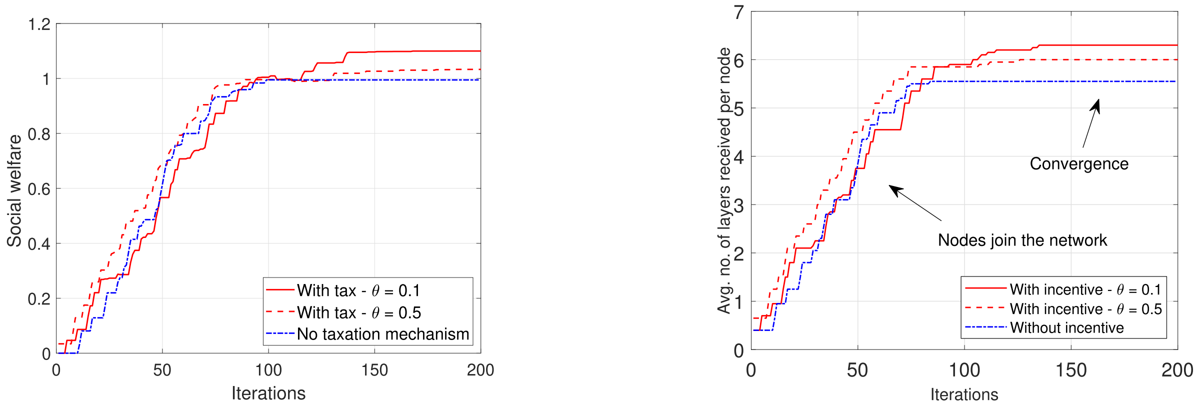
(b)

FIGURE 8. The social welfare and the average number of received layers by the users for different numbers of users. (a) The social welfare. (b) The average number of received video layers.

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 the video. Furthermore, the social welfare is higher when the tax rate is low. This is in accordance with Observation 5 where we expected to have a better performance with low tax rates.

In Fig. 9, 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 incentive mechanism, higher social welfare and a higher number of video layers can be obtained through more iterations.

Fig. 10 shows the change in the number of tokens of each user after constructing the network. The number of tokens is calculated based the difference in the users' payment and income using (20), that is, $\lambda\left(R+\mathring{R}-C-X\right)$ assuming $\lambda = 1$. It is assumed that one token per unit of normalized energy per second 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.



(a) (b)

FIGURE 9. The convergence to an NE for the social welfare and the average number of received video layers by the users. (a) Social welfare. (b) Average number of received layers.

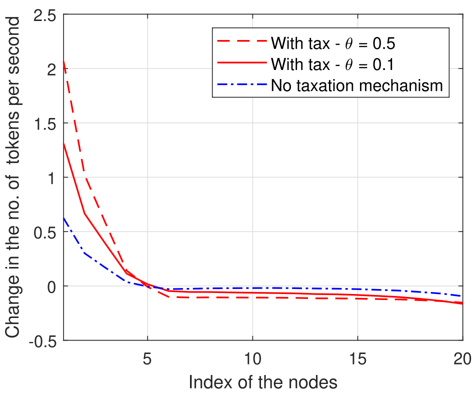


FIGURE 10. Change in the number of tokens of the users. The nodes are indexed based on their distance to the source.

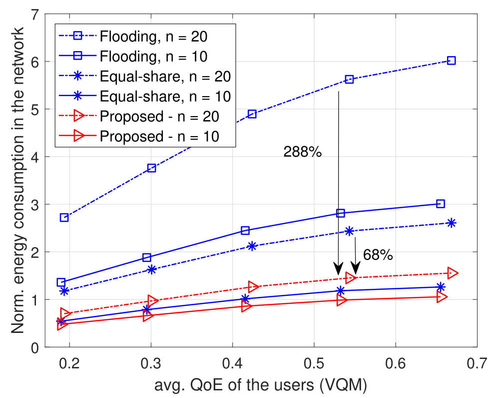


FIGURE 11. The energy required for achieving different levels of QoE for different network creation approaches.

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. 8. It should be remarked that in all the cases shown in Fig. 10, the total number of tokens in the network are equal, and no new token will be generated according to Observation 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.

2) NETWORK CREATION ALGORITHM

The impact of underlay design is studied in Fig. 11 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 IV-D. 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 IV-D.

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 Equal-share and the Shapley value schemes share the cost of a transmission similarly. In such a case, the only CN pays the whole cost of transmission [26].

3) IMPACT OF THE ORDER OF LAYERS

In Fig. 12, we compare our proposed order of the video layers, cf. Table 2, with two other orders; random order

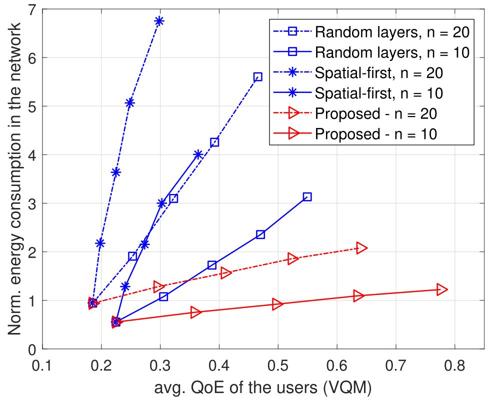


FIGURE 12. The energy efficiency of the network versus average QoE of the users for different orders of video layers transmission.

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. 12 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. 7, 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 higher layer BTs 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.

4) PREFERENCE-AWARENESS

Finally, to have a better insight into how our proposed game-theoretic algorithm works, Fig. 13 shows 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 Fig. 13 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. 13a, 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.

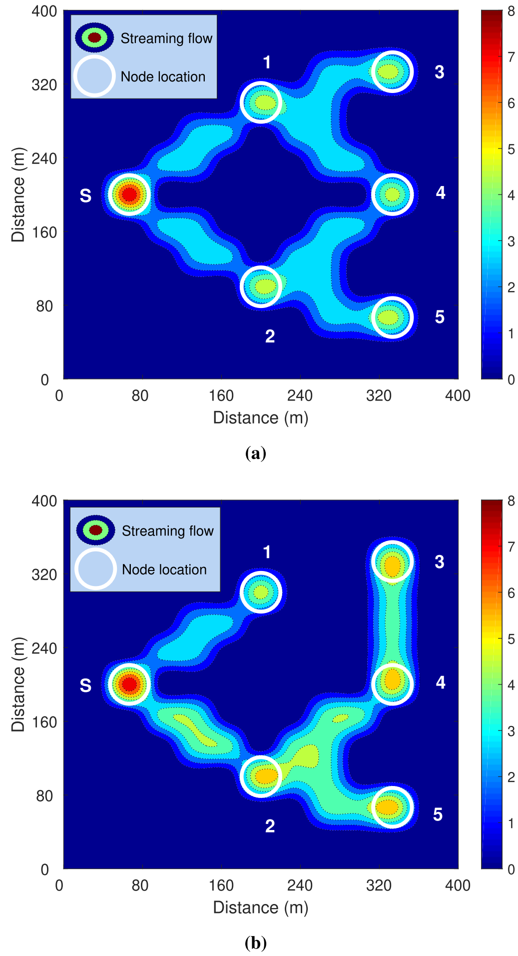


FIGURE 13. The stream of the video and the number of video layers received by the users. (a) User preferences are ignored. (b) User preferences are considered.

In Fig. 13b, we take the individual user preferences into account. As Fig. 13b shows, node 2, with low RDC (high willingness for contribution), is chosen by the nodes 3, 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. 13a, 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. 13b is higher in comparison to Fig. 13a.

V. CONCLUSION

In this paper, 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 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 video QoE on average.

APPENDIX A

To find the social welfare of (29), without loss of generality, we first focus on one layer $l \in \mathcal{L}$. Further, for brevity, 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. Since the source is the owner of the video and does not pay for the video, $\Pi_{\mathrm{S}}^{(l),\mathrm{rx}}$ in (22) for the source is equal to zero. Hence, the utility of the source node is equal to her virtual income, and by using (20) for layer l is given by

$$u_{\mathrm{S}}^{(l)} = \beta_{\mathrm{S}} e_{\mathrm{S}}^{(l)} + \mathring{r}_{\mathrm{S}}^{(l)}. \tag{42}$$

Using (15), we can extend $\mathring{r}_{\mathrm{S}}^{(l)}$ in (42) as

$$\begin{aligned}\mathring{r}_{\mathrm{S}}^{(l)} &= \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \theta v_m^{(l)} = \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \theta \left(r_i^{(l)} + \mathring{r}_i^{(l)} \right) \\ &= \theta \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right).\end{aligned} \tag{43}$$

Then, the utility of the source in (42) is written as

$$u_{\mathrm{S}}^{(l)} = \beta_{\mathrm{S}} e_{\mathrm{S}}^{(l)} + \theta \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right). \tag{44}$$

Using (24), the sum of utilities of the CNs of the source in $\mathcal{M}_{\mathrm{S}}^{(l)}$ is given by

$$\begin{aligned}\sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} u_i^{(l)} &= \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)} + (1-\theta) \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right) \right) \\ &= \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)} + \beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right) \\ &\quad - \theta \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(\beta_i e_i^{(l)} + \mathring{r}_i^{(l)} \right).\end{aligned} \tag{45}$$

Using (44) and (45), the sum of the utilities of the source node and its CNs is equal to

$$\begin{aligned}\sum_{i \in \{\mathrm{S}\} \cup \mathcal{M}_{\mathrm{S}}^{(l)}} u_i^{(l)} &= \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \left(q_i^{(l)} - \alpha_i c_{\mathrm{S},i}^{(l)} \right) \\ &\quad + \sum_{i \in \{\mathrm{S}\} \cup \mathcal{M}_{\mathrm{S}}^{(l)}} \beta_i e_i^{(l)} + \sum_{i \in \mathcal{M}_{\mathrm{S}}^{(l)}} \mathring{r}_i^{(l)}.\end{aligned} \tag{46}$$

The very right term in (46) is the indirect reward of the CNs of the source in $\mathcal{M}_{\mathrm{S}}^{(l)}$. Similar to (43), one can extend (46) 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 (29).

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MAHDI MOUSAVI received the B.Sc. degree from Shahed University, Tehran, Iran, and the M.Sc. degree from Shahid Beheshti University Tehran, Iran. He is currently pursuing the Ph.D. degree with the Technische Universität Darmstadt, Germany.

Since 2014, he has been a Research Associate at the Collaborative Research Center (CRC) 1053 MAKI. His research interests include resource allocation, distributed optimization, and energy-efficiency in wireless networks.

ANJA KLEIN (M'96) received the Diploma and Dr.Ing. (Ph.D.) degrees in electrical engineering from the University of Kaiserslautern, Germany, in 1991 and 1996, respectively.

In 1996, she joined Siemens AG, Mobile Networks Division, Munich and Berlin. She was active in the standardization of third generation mobile radio in ETSI and in 3GPP, for instance leading the 3GPP RAN1 TDD Group. She was the Director of the Development Department and the Systems Engineering Department. In 2004, she joined the Technische Universität Darmstadt, Germany, as a Full Professor and heading the Communications Engineering Laboratory. She has authored more than 280 peer-reviewed papers and has contributed to 12 books. Her current research interests include mobile radio, including interference management, cross-layer design, relaying and multi-hop, computation offloading, smart caching, and energy harvesting. She is an inventor and a co-inventor of more than 45 patents in mobile communications. In 1999, she was named the Inventor of the Year by Siemens AG. She is a member of Verband Deutscher Elektrotechniker—Informationstechnische Gesellschaft.