Resource Allocation for Video Transcoding and Delivery Based on Mobile Edge Computing and Blockchain

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***Abstract*—By bringing computing capabilities to the network edge, mobile edge computing (MEC) has emerged as a promising technique to enable low-latency video streaming services. However, due to the rapid growth of the number of devices and the heterogeneous formats of the video streams, the traditionally centralized content delivery schemes are insufficient to provide secure, adaptive video services with low complexity. To achieve a decentralized content market among untruthful parties (e.g., users and operators), in this paper, we propose an effective video transcoding and delivery approach based on MEC and blockchain. In the proposed approach, we envision a set of blockchain-based smart contracts to build an autonomous content delivery market, where all the participants are financially enforced by smart contract terms. Then, users, small base stations (SBSs), and content provider (CP) are able to autonomously adjust their strategies according to the content market statistics. Moreover, we formulate the optimization problem, including resource allocation, determining content price and quality levels of contents, as a three-stage Stackelberg game. We analyze the subgame equilibrium for each stage and the interplays of the three-stage game. Lastly, an iterative algorithm is proposed to obtain the solution. Simulation results are presented to show the effectiveness of the proposed approach.**

***Index Terms*—Video transcoding, Blockchain, Smart contracts, Mobile edge computing, Resource allocation, Stackelberg game.**

I. Introduction

With the increasing of video sharing services and applications over various mobile devices, wireless video streaming is fueling an exponential growth of mobile data traffic. Due to the heterogeneous devices and dynamic network conditions, the video streams usually have to be transformed into different bitrate versions to adapt to diverse mobile devices. Nevertheless, video transcoding of large-scale video streams is a computationally intensive operation and requires on-demand provisioning and scalable computational resources.

Mobile edge computing (MEC) has been recognized as a promising solution to process video contents to support adaptive video streaming [1]. Small base stations (SBSs) equipped with MEC servers, which have powerful storage and computation resources, can cache and transcode video streams for users. Then, by obtaining video contents from the proximate SBSs instead of a remote content provider (CP), users can enjoy low-latency services and reliable connection to networks [2]. A MEC-based architecture was proposed in [3] to improve the performance of adaptive video streaming. In this architecture, the MEC server could adjust the bitrate version of the video to match network conditions and devices capacities. In [4], the authors proposed a video bitrate adaptation algorithm in the radio access network. For the resource allocation problems, the authors in [5], [6] studied the dynamic resource allocation for transcoding and delivering adaptive video streaming services. However, the heterogeneous MEC networks in terms of different infrastructures and operators have become less effective for providing wide-range, secure and self-organized video services.

Recently, blockchain is considered as a feasible solution for decentralized data sharing across a large network of participants [7]. The blockchain is a synchronized and distributed public ledger, which is maintained by all the network participants without any centralized controller in a logical Peer-to-Peer (P2P) network [8]. Deepak *et al.* [9] proposed a blockchain-based data provenance framework for the cloud. *JCLedger*, which is a blockchain-based distributed ledger, was proposed in [10] to achieve the cooperation among multiple cloud service providers. To provide a secure and distributed content delivery, the authors in [11] proposed a scalable blockchain-based brokering mechanism allowing several providers to collaborate and to provide the requested service through network service chains. By utilizing edge caching, the authors in [12] designed a decentralized proactive caching system in wireless network based on blockchains.

Although some excellent works have been done on MEC and blockchain extensively, there are still some challenges to be addressed. First, video transcoding is a time-consuming task and requires scalable computational resources. Since each video is divided into multiple segments, and each segment can be requested at different bitrate versions, the resource allocation problem for video transcoding becomes more challenging. Second, to provide adaptive video services for large-scale of end devices effectively, resource allocation strategies should

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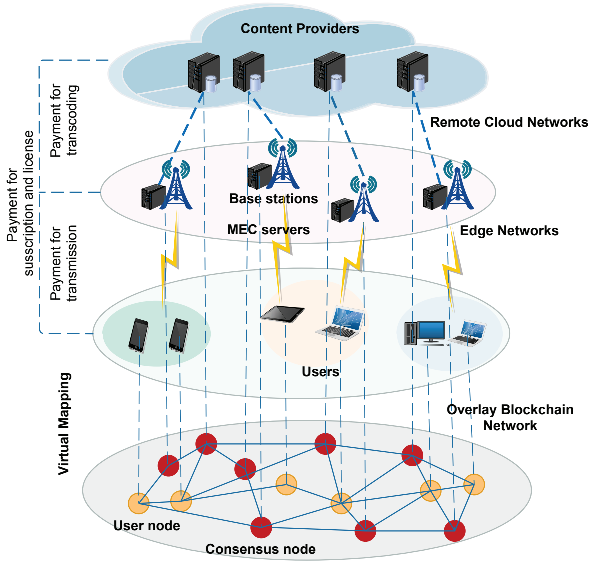

Fig. 1: Blockchain-based MEC Network Architecture

be dynamically adjusted without any centralized controller. Lastly, to enable a secure, feasible and decentralized video streaming services, the content trading processes among the untrusted CPs, SBSs, and users should be well designed.

Thus, in this paper, to address above issues, we propose a video transcoding and delivery approach based on MEC and blockchain, which provides distributed, secure, and on-demand video services at the edge of the networks. In the proposed approach, all participants (i.e. users, SBSs, and CP) are enforced by smart contracts and are able to autonomously adjust their strategies according to the content market statistics. We model the optimization problem, including resource allocation, determining content price and quality levels of contents, as a three-stage Stackelberg game. We analyze the subgame equilibrium for each stage and discuss the interplays between different stages. An iterative algorithm is developed to obtain the feasible solution. Lastly, the simulation results are presented to show the performance gains of the proposed approach compared with other existing schemes.

The remainder of our work is organized as follows. In Section II, we present the network model and the proposed approach. In Section III, we present and analyze the three-stage Stackelberg game and propose an iterative algorithm to obtain feasible solutions. Simulation results and discussions are given in Section IV. Finally, we conclude this paper in Section V.

II. Network Model and Proposed Approach

This section introduces the network model and proposed video transcoding and delivery approach.

A. Network Model

We consider a virtual P2P blockchain network as the backbone of the decentralized content delivery network, which is illustrated as Fig. 1. There are $\mathcal{M}$ SBSs equipped with MEC servers that own limited caching and computing resources but enough to meet the demands of the CP. We assume that $\mathcal{N}$ users served by these SBSs enjoy video contents provided by one CP (e.g. Youtube or Netflix). All content files $f \in \mathcal{F}$ are chunked into l different segments with a fixed length, and each segment has different bitrate versions in different formats. Then, we consider a rate β_n, where $0 < \beta_n \leqslant 1$, to scale down the original videos and represent the different quality levels of video required by user n. One user can only select one quality level of one video at the same time. Lastly, the whole available spectrum bandwidth is $\mathcal{W}$. The channel does not vary during the transmission of a packet and perfect instantaneous Channel Quality Information (CQI) is available.

Assume that SBSs have cached proactively a set of popular contents [13]. For an arbitrary SBS m, it charges the CP for allocating computing resources f_m (Mbps) and charges the user for allocating power p_{mn} (W). We consider a split-spectrum approach where the same spectrum is split among its nearby interfering SBSs and spectrum within one SBS is orthogonally assigned to every user [14]. Then, suppose that SBS m delivers required video contents to user n via wireless access links. The data rate of user n that connects to the m-th SBS can be denoted as

$$\mathcal{R}_{mn} = w_{mn} \log_2 \left(1 + \frac{p_{mn}|h_{mn}|^2}{\delta^2}\right) \tag{1}$$

where $|h_{mn}|^2$ denotes the channel gain between SBS m and user n; w_{mn} denotes the allocated bandwidth of SBS m to user n; δ^2 denotes the power spectrum density of the additive white Gaussian noise (AWGN).

B. Proposed Approach with Blockchains and MEC

In this subsection, we propose a video transcoding and delivery approach that involves a series of small smart contracts for ensuring the correct execution of the content trading. Each entity (e.g., a CP, an SBS or a user) maps itself as a node in the blockchain network and is identified by a unique "transaction address", using the hash-code of its public key.

During a process of video transcoding and delivery, users first request a set of contents with specific preferences. Once the request arrives in the blockchain, a content brokering contract (CBC) that specifies required contents is created and published. Then the CP is notified of the new CBC and use it to create a content licensing contract (CLC). The CLC specifies the content price to the user, a reference to the CBC, and the maximum price to SBSs for transcoding and delivery. Once the CLC is visible on the blockchain, SBSs respond by publishing content delivery contracts (CDCs), which specify the resource prices for delivering content and the reference to the CLC. Finally, the original CBC collects all the related CDCs, selects the cheapest one to implement the content delivery and terminates all other contracts. After content trading, a user pays for the content transaction through an address of a CP and pays for the delivery transaction through an address of an SBS, respectively. CP pays to a set of SBSs for the content processing transaction through addresses of SBSs. Then the payees (CPs or SBSs) generate transaction records, and the payers (CPs or users) verify and digitally sign the transaction records and upload them for audit.

We adopt a consensus mechanism based on proof-of-stake (PoS) and consider that the CP and SBSs work as the consensus nodes to participate in the consensus process. The users work as user nodes and only send requests for content delivery. To validate transactions and create blocks, CP and SBSs that work as forger first put their own coins at 'stake' and then participate in the consensus process. We measure the stake of each SBS by its transcoding and delivery reward collected and consider the CP's stakes are proportional to the amount of unconfirmed payment for contents in the last time slot. Since they have staked their own money, they are generally incentivized to validate the correct transactions. If they validate a fraudulent transaction, they lose their holdings and their rights to participate as a forger in the future. This ensures that the CP or SBSs cannot abuse the content transcoding and delivery environment.

III. Proposed Three-stage Stackelberg Game

In this section, we present and analyze the three-stage Stackelberg game for content processing. Then an iterative algorithm is proposed to obtain the feasible solution.

A. Problem Formulation

In three-stage Stackelberg game, the upstage acts as the leader, which makes the decision first. The downstage is the follower and reacts subsequently based on leader's strategy. In stage I, an SBS m acts as the leader and determines the resource price z_m. In stage II, the CP decides how many computing resources and which SBS to purchase based on the resource price. Then, the CP determines the content price and sells the content to users. In stage III, a user n selects which quality level of contents to purchase from CP and how much power resource to purchase from SBSs.

1) Resource Allocation Model for SBSs: Assume that each SBS is selfish and independent of gaining the revenue as much as possible. Each SBS's revenue depends on its own resource cost and resource price, as well as the price offered by the other SBSs. To maximize the revenue, each SBS needs to find an optimal price z_m by solving the following problem

$$\max_{z_m \geqslant \gamma_m} \mathcal{U}_{SBS}^m(z_m) = \max_{z_m \geqslant \gamma_m} (z_m - \gamma_m)(\zeta_f a_m f_m + \zeta_p \sum_{n=1}^{N} p_{mn}) \tag{2}$$

where γ_m denotes the resource cost of the SBS m (e.g., the computing cost and the networking cost); ζ_f and ζ_p are weighted factors to adjust the balance between the computing resource price and the power resource price; $a_m \in \{0,1\}$ denotes whether CP selects SBS m to process its content or not. If CP selects SBS m, $a_m = 1$; otherwise, $a_m = 0$.

2) Content Price Model for CP: CP's profit depends on the quality levels of contents required by users and the amount of computing resource consumption. Let $q_{nf} \in \{0,1\}$ denotes whether user n selects the content file f or not. If user n selects content file f, $q_{nf} = 1$; otherwise, $q_{nf} = 0$. To maximize its profit, CP needs to determine its content price y and the required computing resource f_m. The optimization problem for the CP can be formulated as

$$\begin{aligned}\max_{f_m \geqslant 0, y \geqslant \phi} \mathcal{U}_{CP}(f_m, y) = \max_{f_m \geqslant 0, y \geqslant \phi} \alpha_v (y - \phi) \sum_{n=1}^{N} \sum_{f=1}^{F} \sum_{l=1}^{L} \beta_n q_{nf} B_{fl} \\ - \alpha_f \sum_{m=1}^{M} z_m a_m f_m + \sum_{m=1}^{M} a_m \min \left\{ f_m, \sum_{n=1}^{N} \frac{\beta_n \sum\limits_{f=1}^{F} \sum\limits_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}} \right\}\end{aligned} \tag{3}$$

where α_f and α_v denote weighted factors to represent the tradeoff between the resource cost and content revenue. We assume that α_f and α_v are greater than zero. ϕ denotes the content cost of CP, such as caching cost and backhaul cost; $T_{n,thr}$ represents the maximum delay required by user n. The last term means that we should guarantee users enjoy their video streaming service under tolerable delay.

3) Content Demand Model for Users: Considering the transmission rate and quality level of content jointly, the optimization problem for the user n can be formulated as

$$\begin{aligned}\max_{p_{mn} \geqslant 0, \beta_n \geqslant 0} \mathcal{U}_{user}^n(p_{mn}, \beta_n) = \max_{p_{mn} \geqslant 0, \beta_n \geqslant 0} -\mu_p z_m p_{mn} - \\ \mu_v y \beta_n \sum_{f=1}^{F} \sum_{l=1}^{L} q_{nf} B_{fl} + \min \left\{ \mathcal{R}_{mn}, \frac{\beta_n \sum\limits_{f=1}^{F} \sum\limits_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}} \right\}\end{aligned} \tag{4}$$

where μ_p and μ_v denote weighted factors of the power cost and content cost, respectively. Similarly, we assume that μ_p and μ_v are greater than zero. The last term means that we should consider the balance between transmission rate and proper quality levels of video contents.

B. Analysis of the Proposed Three-State Stackelberg Game

In this subsection, we analyze the proposed game and introduce a backward induction method to solve it.

1) User Level Game Analysis: We decompose the optimization problem into two sub-problems. At first, we keep β_n unchanged and optimize p_{mn}^* to obtain the optimal β_n^*. For an arbitrary user n, its utility function is defined in two cases: (1) $\mathcal{R}_{mn} \leqslant \frac{\beta_n \sum_{f=1}^{F} \sum_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}}$; (2) $\mathcal{R}_{mn} > \frac{\beta_n \sum_{f=1}^{F} \sum_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}}$. For the first case, we can obtain the utility function as

$$\begin{aligned}\mathcal{U}_{user}^n(p_{mn}, \beta_n) =& w_{mn} \log_2 \left(1 + \frac{p_{mn} |h_{mn}|^2}{\delta^2}\right) - \\ & \mu_v y \beta_n \sum_{f=1}^{F} \sum_{l=1}^{L} q_{nf} B_{fl} - \mu_p z_m p_{mn}\end{aligned} \tag{5}$$

When $1 - \mu_v y T_{n,thr} > 0$, the n-th user's utility function is a concave function of p_{mn}, since

$$\frac{\partial^2 \mathcal{U}_{user}^n}{\partial p_{mn}^2} = -\frac{w_{mn} |h_{mn}|^4 (1 - \mu_v y T_{n,thr})}{\ln 2 (p_{mn} |h_{mn}|^2 + \delta^2)^2} < 0 \tag{6}$$

The optimal power allocation strategy p_{mn}^* is derived as

$$p_{mn}^* = \left[\frac{w_{mn}(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m} - \frac{\delta^2}{|h_{mn}|^2} \right]^+ \tag{7}$$

Because the utility function of β_n is monotonic decreasing, the optimal quality level strategy β_n^* is derived as,

$$\beta_n^* = \left[\frac{w_{mn} T_{n,thr}}{\sum\limits_{f=1}^{F}\sum\limits_{l=1}^{L} q_{nf} B_{fl}} \log_2 \left(\frac{w_{mn}|h_{mn}|^2(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m \delta^2} \right) \right]^+ \tag{8}$$

When $1-\mu_v y_f T_{n,thr} < 0$, the utility function of p_{mn} is a convex function, we obtain the minimum of the function as $p_{mn}^* = \left[\frac{w_{mn}(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m} - \frac{\delta^2}{|h_{mn}|^2} \right]^+$. β_n achieves optimal when $p_{mn} = 0$. Then the utility function is a monotonic decreasing function with β_n. So when $\beta_n^* = 0$, the utility function gets the maximum value, but this situation makes no sense in the real networks. Since a user requires service, its data rate and quality level of content should be above zero.

For the second case, the utility function of β_n is derived as

$$\mathcal{U}_{user}^n(p_{mn},\beta_n) = (\frac{1}{T_{n,thr}} - \mu_v y)\beta_n \sum_{f=1}^{F}\sum_{l=1}^{L} q_{fl} B_{fl} - \mu_p z_m p_{mn} \tag{9}$$

When $(1-\mu_v y T_{n,thr}) > 0$, $\mathcal{U}_{user}^n(\beta_n)$ is a monotonic increasing function. We can obtain the optimal quality level as $\beta_n^* = \left[\frac{w_{mn} T_{n,thr}}{\sum_{f=1}^{F}\sum_{l=1}^{L} q_{nf} B_{fl}} \log_2 \left(1 + \frac{p_{mn}^*|h_{mn}|^2}{\delta^2} \right) \right]^+$. Thus, we keep the transmission power p_{mn} unchanged to make β_n^* achieve the optimal value.

When $(1-\mu_v y T_{n,thr}) < 0$, $\mathcal{U}_{user}^n(\beta_n)$ is a monotonic decreasing function. So when $\beta_n^* = 0$, the utility function gets the maximum value, but this situation makes no sense in the real networks as well.

2) CP Level Game Analysis: By using the decomposition method, we first keep the content price y unchanged to get the optimal f_m to maximize $\mathcal{U}_{CP}$, and then we obtain the desired value of y. The CP chooses a set of SBSs with the lowest resource price z_m^* one by one to purchase computing resource. The CP's utility function is also defined in two cases: (1) $f_m \leqslant \sum_{n=1}^{N} \frac{\beta_n \sum_{f=1}^{F}\sum_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}}$; (2) $f_m > \sum_{n=1}^{N} \frac{\beta_n \sum_{f=1}^{F}\sum_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}}$. For the first case, we obtain the utility function as

$$\begin{aligned} \mathcal{U}_{CP}(f_m,y) = \sum_{m=1}^{M} a_m f_m (1-\alpha_f z_m) + \\ \alpha_v (y-\phi) \sum_{n=1}^{N}\sum_{f=1}^{F}\sum_{l=1}^{L} \beta_n q_{nf} B_{fl} \end{aligned} \tag{10}$$

When $1-\alpha_f z_m < 0$, the utility function is monotonic decreasing of f_m and the optimal computing resource allocation $f_m^* = 0$. It only happens when the selected quality level of content is cached exactly at SBS m and delivered to the user directly.

When $1-\alpha_f z_m > 0$, the utility function is monotonic increasing of f_m and the optimal computing resource allocation is $f_m^* = \sum_{n=1}^{N} \left[w_{mn} \log_2 \left(\frac{w_{mn}|h_{mn}|^2(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m \delta^2} \right) \right]^+$.

For the second case, the utility function is shown below,

$$\begin{aligned} \mathcal{U}_{CP}(f_m,y) = \sum_{m=1}^{M}\sum_{n=1}^{N} a_m \frac{\beta_n \sum_{f=1}^{F}\sum_{l=1}^{L} q_{nf} B_{fl}}{T_{n,thr}} - \\ \alpha_f \sum_{m=1}^{M} z_m a_m f_m + \alpha_v (y-\phi) \sum_{n=1}^{N}\sum_{f=1}^{F}\sum_{l=1}^{L} \beta_n q_{fl} B_{fl} \end{aligned} \tag{11}$$

Because of $-\alpha_f \sum_{m=1}^{M} z_m a_m < 0$, the utility function is monotonic decreasing of f_m and the optimal computing resource allocation is $f_m^* = \sum_{n=1}^{N} \left[w_{mn} \log_2 \left(\frac{w_{mn}|h_{mn}|^2(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m \delta^2} \right) \right]^+$.

Next, we rewrite the utility function $\mathcal{U}_{CP}$ of y as shown in formula (12) and calculate the feasible content price y for CP. Because $\mathcal{U}_{CP}$ is a piecewise function of y, we cannot solve it by derivation directly. We introduce a new variable $D_n = \frac{w_{mn}|h_{mn}|^2 - \ln 2\mu_p z_m \delta^2}{w_{mn}|h_{mn}|^2 \mu_v T_{n,thr}}$ and sort all D_n in ascending order as $D_1 \leqslant D_2 \leqslant \cdots \leqslant D_N$. We get N intervals as $[0,D_1),(D_2,D_3),\cdots,(D_{N-1},D_N)$. By piecewise differentiating of function $\mathcal{U}_{CP}$ in each interval, we obtain it is concave except most D non-differentiable points, since

$$\begin{aligned} \frac{\partial^2 \mathcal{U}_{CP}}{\partial y^2} = -\Bigg\{ \sum_{m=1}^{M}\sum_{n=1}^{N} w_{mn}\mu_v T_{n,thr}^2 \Bigg[\frac{2\alpha_v}{\ln 2(1-\mu_v y T_{n,thr})} \\ + \frac{\mu_v (a_m - \alpha_f z_m a_m + \alpha_v (y-\phi) T_{n,thr})}{\ln 2(1-\mu_v y T_{n,thr})^2} \Bigg] \Bigg\} < 0 \end{aligned} \tag{13}$$

Thus the utility function of CP is a concave function without some non-differentiable points $D_1, D_2, \cdots, D_N$. This non-cooperative competitive game exists at least one Nash

$$\mathcal{U}_{CP} = \sum_{m=1}^{M}\sum_{n=1}^{N} \left\{ w_{mn} \left[a_m - \alpha_f z_m a_m + \alpha_v (y-\phi) T_{n,thr} \right] \log_2 \left(\frac{w_{mn}|h_{mn}|^2(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_m \delta^2} \right) \right\} \tag{12}$$

Algorithm 1 *Resource Allocation Iteration Algorithm*

Initialization: Initialize the maximum number of iterations Γ and set iteration number $\tau = 0$; Initialize a default resource price $\mathbf{z}$ for each SBS.
while $\tau < \Gamma$ **do**
  The CP determines the content price y to their users and the amount of computing resources based on z_m;
  Each user selects the quality level of required contents β_n and decides the amount of power resource p_{mn};
  SBSs update their prices: $z_m(\tau) = \mathcal{G}_m(\mathbf{z}_{-m}(\tau-1))$;
  if $\|\mathbf{z}(\tau) - \mathbf{z}(\tau-1)\| / \|\mathbf{z}(\tau-1)\| \leqslant \epsilon$ **then**
    Output the resource allocation $\mathbf{z}$;
    Break.
  end if
  $\tau = \tau + 1$;
end while

equilibrium (NE). We can obtain this optimal value of y in each interval by multiple methods (e.g., a binary search algorithm and a gradient-based algorithm).

3) SBSs Level Game Analysis: We introduce the Bertrand game to model the competition among SBSs [15]. The set of the game players is $\mathcal{M} = \{1, \cdots, m, \cdots, M\}$, the strategy set is z_m, and the pay off function of the SBS is $\mathcal{U}_{SBS}^m$. The profit of the SBS m depends not only on the resource price z_m and the cost γ_m, but also on the resource prices $\mathbf{z}_{-m}$ offered by the other SBSs. The SBS with the lowest price will occupy the entire content delivery market. Hence, every SBS tries to reduce its resource price until hitting the bottom with zero profit. Without loss of generality, let the cost set in an ascending order $\gamma_1 < \gamma_2 < \cdots < \gamma_M$.

Definition 1 (Nash-equilibrium): A resource price $\mathbf{z}^* = (z_1^*, \cdots, z_m^*, \cdots, z_M^*,)$ is in an NE if neither SBS can increase its profit $\mathcal{U}_{SBS}^m$ by unilaterally changing the price.

The NE of the Bertrand game with multiple SBSs is shown as $\mathbf{z}^* = \{z_1^*, \gamma_2, \gamma_3, \cdots, \gamma_M\}$, where z_1^* denotes the price strategy of the first SBS at the NE. The z_1^* can be derived as $z_1^* = \arg \max\limits_{\gamma_1 \leqslant z_1 < \gamma_2} \mathcal{U}_{SBS}^1(z_1)$ where $\mathcal{U}_{SBS}^1(z_1)$ is the utility function of SBS 1 when it occupies the whole market, shown as formula (14) at the bottom of the page.

C. Analysis of Convergence and Feasibility

In the duopoly case, the convexity of the follower's reaction function is essential for the uniqueness of the Stackelberg equilibrium [16]. Since we have proved that each stage exists an equilibrium in an NE, the NE of the proposed three-stage Stackelberg game model exists. Moreover, since each stage exists a unique equilibrium, the existence and uniqueness of the equilibrium of the proposed three-stage game are guaranteed. Based on the above analysis, a resource allocation iteration algorithm is proposed as shown in algorithm 1. The algorithm will stop when the resource prices $\mathbf{z}$ converge.

Since the resource allocation in the whole network is realized in a distributed manner, the CP, SBSs and users only need to optimize their utility based on the response of other entities. Comparing to the centralized schemes, which optimize a unified objective in a centralized manner, the computational complexity and the signaling overheads of the proposed approach can be reduced significantly.

TABLE I: The simulation parameters

Simulation parameters	Value
The bandwidth	20MHz
The SBSs density	700 SBSs/Km^2
The users density	1000 Users/Km^2
Power spectral density of noise	-174dBm/Hz
Cache capacity of each SBS	[200-400]
Computing capability of each SBS	[100-200]Mbps
The backhaul capacity of the m-th SBS $R_{m,b}$	$[40-100]$Mbps
The maximum transmission power of each SBS	$[1-2]$W

IV. Simulation Results and Discussions

In this section, we evaluate the performance of the proposed approach in wireless networks with MEC and blockchains via Monte Carlo simulation. We consider a $120m \times 120m$ square area in an urban environment. The number of available videos is 1000, with popularity following a Zipf distribution with exponent 0.8. We assume the videos are distributed between 200 kbps and 2 Mbps. The channel gain models presented in 3GPP standardization are adopted here. The key simulation parameters are summarized in Table I.

For comparison, we choose three typical schemes as follows: 1) the no-caching scheme that delivers video file without caching, as labeled as “No caching”; 2) the no-transcoding scheme that delivers video file without transcoding, as labeled as “No transcoding”; 3) the centralized resource allocation scheme is attained by method of exhaustion to minimize the network cost for video transcoding and delivery, as labeled as “Centralized scheme”.

Fig. 2 shows that, with the increase of the resource price z_m, users and CP have to decrease their required power and computing resources, respectively. The reason is that when the resource price is too high to afford for the users and CP, both of them will reduce their required power and computing resources step by step until stop transcoding and delivering any content. The total network cost plays an important role in optimizing network performance and improving resource

$$\mathcal{U}_{SBS}^1(z_1) = (z_1 - \gamma_1)\left(\zeta_f a_1 \sum_{n=1}^{N}\left[w_{1n}\log_2\left(\frac{w_{1n}|h_{1n}|^2(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_1 \delta^2}\right)\right]^+ + \zeta_p \sum_{n=1}^{N}\left[\frac{w_{1n}(1-\mu_v y T_{n,thr})}{\ln 2\mu_p z_1} - \frac{\delta^2}{|h_{1n}|^2}\right]^+\right) \tag{14}$$

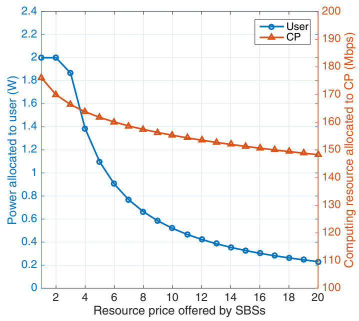

Fig. 2: Resource allocation for CP and users with various resource prices.

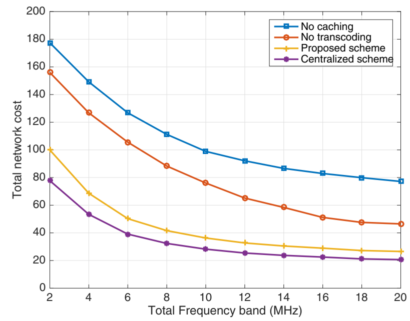

Fig. 3: Total network cost versus the total frequency band.

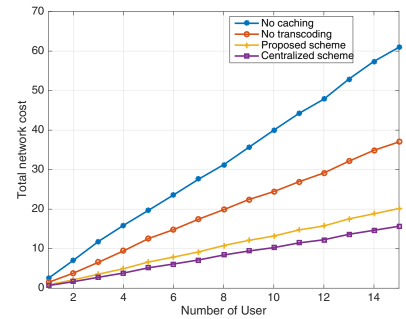

Fig. 4: Total network cost versus the number of user.

utilization. We adopt network cost modeling in [17], which considers energy consumption for transmission, processing, as well as backhaul consumption. Figs. 3 and 4 illustrate the total network cost versus the total frequency band and the number of users, respectively. From Fig. 3, we can also see that all the curves decrease gradually with the increase of the frequency band. This is mainly because of the fact that spectrum allocation usually plays an important role in improving the transmission rate between users and SBSs. Then, it can reduce the network cost for transmission greatly. In Fig. 4, the total network cost of the "No caching" scheme is the highest compared with other schemes. The reason is that, without caching proactively, the SBSs have to transmit contents by fetching from remote CP via backhaul links. Hence, duplicate content transmissions exist and huge backhaul resources are needed to provide. Moreover, when transcoding technology is used, the SBSs can process different quality level of contents at the network edge. In this way, the duplicated content transmission is further reduced and less backhaul resource consumption is needed.

V. Conclusion and Future Work

In this paper, we proposed a video transcoding and delivery approach in blockchain-based MEC networks. In the proposed approach, SBSs equipped with MEC servers provide their resources for supporting adaptive video streaming in a distributed, incentivized and secure manner. Furthermore, we formulated the optimization problem, including resource allocation, determining content price and quality levels of contents, as a three-stage Stackelberg game. We analyzed the subgame equilibrium for each stage and the interplays of the three-stage game. An iterative algorithm was proposed to obtain the solution. Simulation results show that the proposed approach achieves better performance over other existing schemes. For future work, we will jointly consider the efficient content cache placement and transcoding strategies to optimize the users' experience and improve the resource utilization based on the blockchain, edge caching, and computing.

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