

Contribution-Guided Peer Selection for Reliable Peer-to-Peer Video Streaming Over Mesh Networks

Chi-Wen Lo, *Student Member, IEEE*, Chia-Wen Lin, *Senior Member, IEEE*,
Yung-Chang Chen, *Fellow, IEEE*, and Jen-Yu Yu

Abstract—This paper proposes a sender-driven peer selection scheme, including estimation of packet loss propagation, evaluation of peers' contributions, and peer selection based on child-peers' contributions, for mesh-based peer-to-peer (P2P) video streaming systems. The proposed packet loss propagation model takes into account the link packet drop rate, peer dynamics, and forward error correction protection to capture the heterogeneous packet loss behavior of individual substreams transmitted over a mesh network. The evaluation of candidate peers' contributions is modeled through Markov random fields to significantly reduce complexity. Simulation results demonstrate that our peer selection scheme significantly mitigates packet loss in a mesh-based P2P network, compared to other state-of-the-art schemes.

Index Terms—Error protection, forward error correction (FEC), peer selection, peer-to-peer (P2P) video streaming system.

I. INTRODUCTION

DUE TO THE fast growing deployment of advanced network and multimedia technologies, video streaming services are able to provide stable quality. The key of a successful video streaming system lies in the video quality perceived by users. One of the major challenges to video streaming services is packet loss. Since current IP-based networks only support best effort delivery, video packets are not well protected. If a video packet cannot be received before its playback time, the reconstructed video quality may be seriously damaged.

There are two classes of methods to overcome the packet loss problem: retransmission-based and forward error correction (FEC)-based schemes. In retransmission-based schemes [1], [2], a receiver sends a message to a sender to request a lost packet from the sender, and the sender resends the lost packet if her available bandwidth allows. Retransmission-based schemes are particularly useful for noninteractive unicast applications with bursty packet loss. However, since the

retransmission-based schemes introduce additional round-trip time latency, they are not suitable for delay-sensitive video transmissions.

Packet-level FEC has proven to be an efficient means for packet loss recovery in peer-to-peer (P2P) video streaming systems [3], [4], [9]–[13], [18]. In a packet-level FEC-based protection scheme, the channel encoder, such as the Reed–Solomon (RS) code, encodes the video bitstreams into k data packets and additional $n-k$ redundant packets, denoted as $FEC(n, k)$. On one hand, a receiver can completely recover the original data if at least any k out of n packets are received. On the other hand, the $FEC(n, k)$ scheme can only tolerate loss of $n-k$ packets at most. The FEC protection capability can be enhanced by increasing n to ensure an enough number of packets be received, whereas the channel efficiency is reduced as well due to the increased redundancy.

The method proposed in [3] applies FEC to recover packet loss in an overlay streaming system. The FEC codes are decided according to the channel conditions of the segments in a delivery path without taking into account peer dynamics. The performance of FEC codes with different video frame types was analyzed in [4], showing that packet loss in a P2P video streaming system can be mitigated by using unequal error protection, where video frames of higher importance are assigned with more redundancy to mitigate packet loss. The packet loss in P2P streaming systems can also be mitigated by multiple-description coding (MDC) [5].

FEC-based video protection schemes, however, consume more bandwidth resource to transmit the redundant packets. If the available bandwidth of a P2P system cannot afford the enormous amount of redundant packets, packets may be dropped due to traffic congestion. Besides, because the demands for redundant packets may vary largely for heterogeneous peers, an adaptive data protection method for determining an appropriate amount of redundancy for each peer is desirable. Moreover, a peer selection method is required to efficiently allocate the bandwidth resource of a peer to her neighbor peers so as to achieve good streaming performance.

Peer selection mechanisms can be divided into two classes: sender-driven peer selection and receiver-driven peer selection. In sender-driven peer selection, each parent-peer proactively allocates her uplink resource to deliver video data to a selected set of child-peers, who have requested data from the parent-peer, to maximize the overall system performance in terms of throughput, delay, and so on. A few sender-driven

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C.-W. Lo and Y.-C. Chen are with the Department of Electrical Engineering, National Tsing Hua University, Hsinchu 30013, Taiwan.

C.-W. Lin is with the Department of Electrical Engineering and the Institute of Communications Engineering, National Tsing Hua University, Hsinchu 30013, Taiwan (e-mail: cwlin@ee.nthu.edu.tw).

J.-Y. Yu is with Information and Communications Research Laboratories, Industrial Technology Research Institute, Hsinchu 302, Taiwan.

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peer selection methods were proposed in [6]–[11]. In CoDiO [6], parent-peers schedule the delivery of packets to their child-peers according to the impact of the child-peers. Those child-peers who contribute more uplink bandwidth to distribute packets to more succeeding descendants would obtain higher impact values, thereby having higher priority in packet scheduling and resource allocation for requesting packets from their parent-peers. In the method proposed in [7], parent-peers maximize their throughput by executing a child-peer selection process that takes into account the available bandwidth of uplink or downlink links and the playback deadline of parent or child-peers. The rank-based peer selection scheme proposed in [8] transforms the contribution of each peer to a rank. A parent-peer would serve her child-peers whose ranks are higher than the rank of the parent-peer herself. Therefore, the video qualities for high-ranking peers can be guaranteed. In the LayerP2P scheme [9], parent-peers give higher priority in peer selection to those child-peers who have also sent video chunks to the parent-peers. In our previous work in [10], a packet loss accumulation model is proposed to capture the amount of the influence of a loss pack to a peer's descendants. Based on the model, a peer selection scheme based on the contributions of client-peers is proposed, where a peer's contribution is evaluated by the peer's overall packet loss reduction ability on herself and on her descendants when receiving an additional redundant substream. An improved version of the packet loss estimation model in [10] was proposed in [11] to enhance the estimation accuracy.

In contrast, in the receiver-driven selection methods [12]–[16], each child-peer selects a set of parent-peers to request video data from them to maximize the system performance. For example, PROMISE [12] presented a topology-aware peer selection, where child-peers select their parent-peers based on some quality metrics, e.g., delay, loss rate, and available bandwidth, of the parent-peers. In SPANC [13], child-peers select their parent-peers to transmit the video substreams to minimize transmission delay should the network state have a significant change. Network coding is applied in SPANC to generate the redundancy for recovering lost packets, where the amount of redundancy is linearly proportional to the loss rate of a channel. In [14], a layered video data scheduling scheme was proposed to achieve a high delivery ratio of a layered video, where the selection of parent-peers and the scheduling of requested video blocks are based on the importance factors of video blocks and the uplink bandwidths of the parent-peers. In [15], based on the assumption that a child-peer can obtain the available uplink bandwidth information of their parent-peers through gossiping messages, the child-peer executes a parent-peers selection process for maximizing her downlink throughput. In the method proposed in [16], child-peers schedule the multiple senders for multisource transmission over wireless mobile P2P networks so as to maximize the receiving data rate and minimize the power consumption. In NTUStreaming [17], the network protocol, MDC, and packet scheduling are together utilized to achieve better video quality. Both parent-peer and child-peer selections are applied to overcome the problems in heavy peer-churn environments.

In an FEC-based P2P video streaming system, to maximize the efficiency of FEC protection, those peers who can contribute higher packet loss reduction gains should be selected to receive more redundant packets to recover lost packets. Therefore, an accurate model to characterize the error propagation effect due to packet loss is required to evaluate the packet loss reduction gains for individual peers. Packet loss estimation for a P2P network, however, is much more complex than that for traditional client-server structures. Since video packets are sourced from multiple peers rather than a single server, packet loss would propagate through the interpeer transmissions. Moreover, peers will usually unexpectedly join and leave a system, and such peer churns can cause serious packet losses. In [18], the packet loss probability and packet loss accumulation in a multisource tree-based P2P system are analyzed. In a tree-based P2P network, each peer is located in a specific depth in the tree structure. Therefore, the parent-peers of a peer have the same packet loss accumulation if the link packet drop rates between peers are homogeneous. In a mesh-based P2P network, however, the peers are randomly located in an irregular mesh structure. As a result, the packet loss accumulations from the multiple parent-peers are heterogeneous so that the tree-based packet loss model cannot model packet loss well in a mesh-based P2P network. Since many popular P2P streaming systems, such as CoolStreaming [19], PPStreaming [20], and PPLive [21] are mesh-based structures, accurate mesh-based packet loss estimation models are desirable. However, to the best of our knowledge, such a problem has not yet been well addressed in the literature.

Peers in a mesh network usually have complex interactions due to the irregular and complex structures of mesh network, thereby significantly complicating the analysis of mesh network. Probabilistic graphical models offer a systematical tool for describing the spatial interrelations among nodes in a network, making it suitable to characterize the complex interactions among peers in a mesh-based P2P network. Particularly, Markov random fields (MRFs) [22] can model the spatial and stochastic interaction among observable objects. Based on the MRF theory, the optimality criteria of a system can be defined and the optimal solution can be found through the maximum a posteriori (MAP) concept. MRFs have been successfully applied in many applications related to pattern recognition and computer vision. Besides, MRFs have also found applications in modeling the interactions among the autonomous nodes of wireless sensor networks [23], [24], where the nodes possess several constraints, such as limited power and interference, which compose complicated interactions among nodes. By modeling the complex interactions with MRFs, distributed algorithms were proposed in [25] to maximize the posterior to achieve the optimal performance of networks. We will show in Section IV-B that MRFs can be used to simplify the analysis of packet loss propagation in a mesh-based P2P network.

In this paper, by extending our recent works presented in [10] and [11], we propose a sender-driven peer-selection scheme by which a parent-peer can adaptively select child-peers to transmit redundant packets according to the link packet loss rates, peer dynamics, and packet loss propagation among peers. The contribution of the proposed method is

three-fold. First, to the best of our knowledge, the estimation of packet loss propagation in mesh-based P2P networks has not been well addressed because of the mesh networks' irregular and complex structures. We are among the first to propose a model to accurately estimate the loss probabilities of packets to peers at different levels in a mesh-based P2P network. The proposed model takes into account the link packet drop rate, peer dynamics, and amount of FEC protection to characterize the heterogeneous packet loss behavior of individual video substreams transmitted over the irregular transmission paths of a mesh network. Second, we show that probabilistic graphical models such as MRFs can be used to significantly simplify the analysis of packet loss propagation of a peer by considering the interactions and link statistics between the peer and a small set of neighboring descendants, rather than considering all the descendants of the peer. Third, based on the proposed graphical models, we propose a peer selection scheme to effectively mitigate packet loss propagation through an MAP optimization framework.

The remainder of this paper is organized as follows. The framework of FEC-based error protection is presented in Section II. The proposed packet loss models are described in Section III. In Section IV, the peer selection method is presented. Section V shows the simulation settings and the results. Finally, conclusions are drawn in Section VI.

II. FEC-BASED PACKET PROTECTION SCHEME

In a P2P video streaming system, video packets can get lost due to the following three causes.

- 1) Peer departure: When a parent-peer leaves a system, her child-peers can no longer receive packets from the parent-peer, leading to burst packet loss. The burst packet loss cannot be alleviated until the child-peers find a replacement parent-peer.
- 2) Link packet loss: The requested packets are dropped due to transmission errors or network congestion during transmission.
- 3) Absent packets in the parent-peer: A child-peer cannot obtain packets from her parent-peer because the parent-peer loses the video packets. FEC-based packet protection can fully recover lost packets should a sufficient number of FEC packets be received.

Fig. 1 depicts the scheme of packetization with interleaving used in this paper. Without loss of generality, we assume that k video packets compose an FEC coding unit, denoted as an ensemble. In order to combat against the burst packet loss due to peer churns, our packet interleaver writes source packets to ensembles in the order indicated by the arrows in Fig. 1. Subsequently, the k video source packets of each ensemble are encoded with the packet-level FEC(n, k) code to generate additional $n-k$ redundant packets. The packets in the same corresponding position in a set of ensembles compose a video substream. As illustrated in the example of Fig. 1, video substream #1 contains the first packets from ensembles #1 to # N . During a streaming session, child-peers subscribe to the video substreams (i.e., the pull process) from their parent-peers. Once the parent-peers accept the subscriptions, they

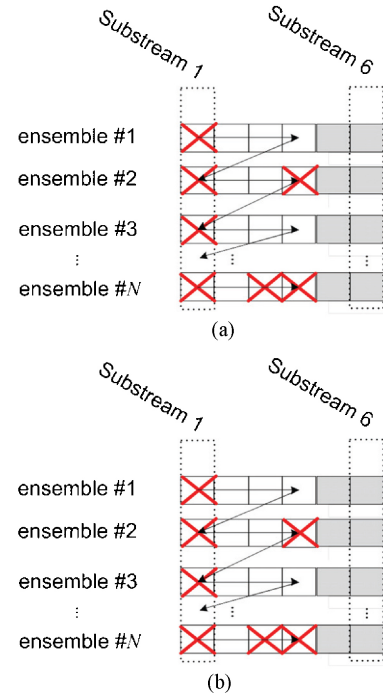


Fig. 1. FEC packetization example with FEC(6, 4) code, where the white blocks indicate the data packets and the grey ones indicate FEC redundant blocks. The red crosses indicate the lost packets. The arrows indicate the packet writing direction in our interleaver. (a) Before FEC recovery. (b) After FEC recovery.

continuously push video packets to their child-peers (i.e., the push process), as known as the push-pull methods [19].

In a heterogeneous environment, the packet drop rates of different links can vary largely. Thus, different peers require different protection capabilities to successfully recover lost packets, i.e., child-peers need FEC codes of different code rates, where the code rate for the FEC(n, k) code is $\frac{k}{n}$. An FEC code with a higher code rate implies lower protection capability. The proposed method applies the punctured RS code [26] to generate the FEC(n, k) code. With the punctured RS code, peer y requires n_y substreams, $n_y \in (k, k+1, \dots, n)$ to decode an ensemble by using a single FEC(n, k) decoder instead of several FEC(n_y, k) decoders. Therefore, a low-complexity decoder can be used to decode the FEC codes with different code rates k/n_y . Then, if the number of received packets in an ensemble is at least k , the source packets can be recovered with the mother code FEC(n, k). In addition, packets encoded with punctured RS mother code can be widely exchanged among peers, whereas the packets encoded with different code rates, for example, FEC(6, 4) and FEC(8, 5) cannot be exchanged. The number of available parent-peers is, therefore, constrained by the exchangeability of FEC codes of different code-rates.

Fig. 1(a) shows an example of packet loss, where the loss of substream #1 causes a burst packet loss in which the first packets of the ensembles are all lost. When the number of received packets in the same ensemble is more than k , the lost packets can be fully recovered, as shown in Fig. 1(b). For ensemble # N , however, the number of received packets is less than k ; therefore, the lost packets cannot be recovered.

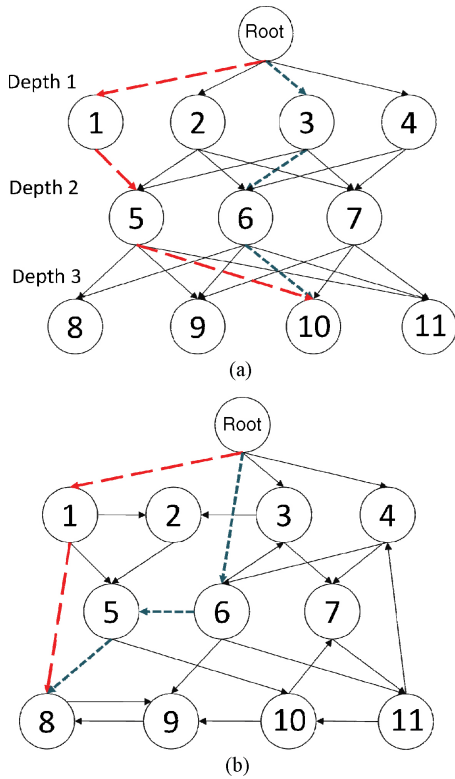


Fig. 2. Two examples of P2P video streaming structures. (a) Tree-based network topology. (b) Mesh-based topology. The red dashed lines and the blue dot-dashed lines indicate two different substreams, whereas the solid lines indicate the other substreams.

In this paper, the number of substreams, which a client-peer can subscribe to from a parent-peer, is constrained to be at most one due to the following reasons: 1) when one parent-peer leaves the system, the child-peer only loses one substreams at the same time [18]; and 2) a client-peer receiving multiple substreams from a parent-peer implies that the video content from the parent-peer can only be distributed to fewer peers with the same uplink bandwidth, limiting the distribution of the content.

III. MODELING PACKET LOSS PROPAGATION IN A MESH NETWORK

As mentioned previously, the error propagation behavior due to packet loss in a mesh-based P2P network is significantly different from that in a tree-based system. Fig. 2(a) shows an example of tree-based topology where each peer is located at a specific depth of a tree. In the tree topology, those peers who are at the same depth will lead to the same degree of loss propagation, assuming that the packet drop rates of links at the same depth are homogeneous. For example, peer #10 who is located at depth 3 receives all video substreams from the server (root) through transmission of three hops. Hence, each substream sent to peer #10 has the same packet loss probability accumulated along the links from the server to peer #10 should the packet drop rates of individual links be homogeneous.

Consider the mesh-based topology shown in Fig. 2(b). Due to peers' self-organized behavior, there is no regular structure that can completely describe the peer interconnections of

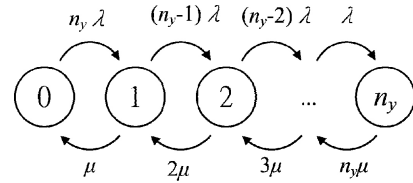


Fig. 3. Transition diagram of $(n_y + 1)$ -state CTMC.

a mesh network. Since peers are randomly located in the mesh network, loss of substreams may cause significantly different degrees of packet loss propagation. As depicted in Fig. 2(b), assuming a substream sent to peer #8 is originated from the root, the substream received via peer #1 traverses two hops from the server, whereas the substream obtained via peer #5 traverses three hops. The accumulated packet loss probabilities of these two substreams are, therefore, not identical. Hence, estimating packet loss propagation in a network with an irregular structure (e.g., a mesh network) is much more complex than that in a regular network structure (e.g., a tree network). Consequently, we need a sophisticated model rather than a simple tree-based model to accurately characterize the error propagation behavior due to packet loss in an irregular mesh-based network.

A. Modeling Arrival Or Departure of Parent-Peers

In what follows, we use the terms “leaving” and “departure” interchangeably to present the leaving of a parent-peer from a network. Assume that parent-peers’ leavings are statistically independent of each other, and that child-peers independently find a replacement parent-peer for each leaving parent-peer. Therefore, the time interval between two consecutive parent-peer departures and the time to find a replacement parent-peer can be modeled by two exponential distributions with means $1/\lambda$ and $1/\mu$, respectively. Consider a sequence of random variables $\{S_i\}_{i=0,\dots,n_y}$ that represent the i leaving parent-peers of peer y who has received n_y substreams from n_y parent-peers. The transitions among states $\{S_i\}_{i=0,\dots,n_y}$ can be modeled by a continuous-time Markov chain (CTMC) [18], [27] of $n_y + 1$ states as depicted in Fig. 3, where parameters μ and λ denote the joining rate and leaving rate of state S_i , respectively. The steady-state probability of state S_i is $P_i^{n_y}$, which indicates that the probability of i parent-peers leaving the system will converge to $P_i^{n_y}$ eventually, where the joining rate of a state equals the state’s leaving rate as formulated by the following recursive balance equations:

$$\left\{ \begin{array}{ll} n_y \lambda P_0^{n_y} = \mu P_1^{n_y} & i = 0 \\ (\mu + (n_y - 1)\lambda) P_1^{n_y} = n_y \lambda P_0^{n_y} + 2\mu P_2^{n_y} & i = 1 \\ (i\mu + (n_y - i)\lambda) P_i^{n_y} = & \\ (n_y - i + 1)\lambda P_{i-1}^{n_y} + (i + 1)\mu P_{i+1}^{n_y} & 0 < i < n_y \\ n_y \mu P_{n_y}^{n_y} = \lambda P_{n_y-1}^{n_y} & i = n_y. \end{array} \right. \quad (1)$$

The balance equations in (1) can be rewritten as

$$\left\{ \begin{array}{l} P_1^{n_y} = \frac{n_y \lambda}{\mu} P_0^{n_y} \\ P_2^{n_y} = \frac{(n_y-1)\lambda}{2\mu} P_1^{n_y} = \frac{n_y(n_y-1)}{2} \left(\frac{\lambda}{\mu}\right)^2 P_0^{n_y} \\ \vdots \\ P_{n_y}^{n_y} = \frac{\lambda}{n_y \mu} P_{n_y-1}^{n_y} = \left(\frac{\lambda}{\mu}\right)^{n_y} P_0^{n_y} \end{array} \right. \quad (2)$$

which can be expressed by the following general form:

$$P_i^{n_y} = \frac{n_y!}{i!(n_y-i)!} \rho^i P_0^{n_y} = \binom{n_y}{i} \rho^i P_0^{n_y} \quad (3)$$

where $\binom{n_y}{i}$ are the binomial coefficients and $\rho = \frac{\lambda}{\mu}$.

Since $\sum_{i=0}^{n_y} P_i^{n_y} = 1$, we have

$$P_0^{n_y} = \frac{1}{\sum_{i=0}^{n_y} \binom{n_y}{i} \rho^i}. \quad (4)$$

For a requested substream, the probability of a parent-peer who holds the substream staying in the system can be modeled by a CTMC of two states $\{S_0, S_1\}$. Therefore, the balance equation becomes

$$\lambda P_0^1 = \mu P_1^1. \quad (5)$$

Since $P_0^1 + P_1^1 = 1$, we can obtain the steady-state probability of each state

$$\begin{cases} P_0^1 = \frac{1}{1+\rho} \\ P_1^1 = \frac{\rho}{1+\rho} \end{cases} \quad (6)$$

B. Packet Loss Models

In a P2P streaming session, lost packets can be recovered should an enough number of FEC packets be received. In what follows, we derive the packet loss probability models for peers in a mesh network by modifying the models in [18].

The packet loss probability that peer y receives n_y substreams from n_y parent-peers can be expressed by

$$Q_y(n_y) = \sum_{i=0}^{n_y} P_i^{n_y} \cdot q_{y,i} \quad (7)$$

where $q_{y,i}$ denotes the packet loss probability due to departures of i parent-peers. The calculation of $q_{y,i}$ is described below.

When the number of leaving parent-peers exceeds $n_y - k$ [i.e., $i > n_y - k$ in (7)], the lost packets cannot be recovered. A requested packet may not be received by a peer due to the following three events: 1) the parent-peer unexpectedly leaves the system during the transmission of a requested substream; 2) the live parent-peer of the substream does not have the packet; and 3) the live peer owns the packet, but the packet is dropped during the transmission. The overall packet loss probability caused by the three events can be expressed by

$$q_{y,i>n_y-k} = \underbrace{\frac{i}{n_y}}_{\text{event 1}} + \underbrace{\left(\frac{n_y-i}{n_y} \cdot Q_y^p\right)}_{\text{event 2}} + \underbrace{\left(\frac{n_y-i}{n_y} \cdot (1-Q_y^p) \cdot d_y^p\right)}_{\text{event 3}} \quad (8)$$

where the three terms on the right-hand side of (8) represent the occurrence probabilities of the three events, respectively. Q_y^p denotes the average packet loss rate of substreams in peer y 's parent-peers, and d_y^p is the average packet loss rate of the links between peer y and its parent-peers. Q_y^p can be calculated by

$$Q_y^p = \frac{1}{n_y} \sum_{j=0}^n \{SI_y(j) \cdot Q_x^{s_j}\} \quad (9)$$

where $SI_y(j)$ stands for the substream indicator function, with $SI_y(j) = 1$ indicating the subscription of peer y to substream j , and $SI_y(j) = 0$ indicating no subscription of substream j . Note that $\sum_{j=0}^n SI_y(j) = n_y$. $Q_x^{s_j}$ is the packet loss probability of substream j in parent-peer x . The average packet drop rate d_y^p can be computed by

$$d_y^p = \frac{1}{n_y} \sum_{j=0}^n \{SI_y(j) \cdot d_x^{s_j}\} \quad (10)$$

where $d_x^{s_j}$ denotes the packet loss rate of the link to transmit substream j whose parent-peer is peer x .

As shown in (8), when the number of leaving peers $i \leq n_y - k$, the lost packets can be completely recovered. In contrast, the lost packets caused by parent-peer departures are not recoverable, should the number of received packets from the $n_y - i$ surviving live peers be less than k . This packet loss probability C_1 can be calculated by

$$C_1 = \frac{i}{n_y} \sum_{w=0}^{k-1} \binom{n_y-i}{w} \cdot \{(1-Q_y^p)(1-d_y^p)\}^w \cdot \{1 - (1-Q_y^p)(1-d_y^p)\}^{n_y-i-w}. \quad (11)$$

Besides, in event 2 a lost packet caused by the unavailability of a packet that is requested from a live parent-peer is also not recoverable, if the number of received packets from the surviving live peers is less than k . This packet loss probability C_2 can be calculated by

$$C_2 = \left(\frac{n_y-i}{n_y} \cdot Q_y^p\right) \cdot \sum_{w=0}^{k-1} \left\{ \binom{n_y-i-1}{w} \cdot ((1-Q_y^p)(1-d_y^p))^w \cdot (1 - (1-Q_y^p)(1-d_y^p))^{n_y-i-1-w} \right\}. \quad (12)$$

Finally, a lost packet being dropped during the transmission cannot be recovered until receiving at least k packets from the surviving live peers. The loss probability C_3 becomes

$$C_3 = \left\{ \frac{n_y-i}{n_y} \cdot (1-Q_y^p) \cdot d_y^p \right\} \cdot \sum_{w=0}^{k-1} \left\{ \binom{n_y-i-1}{w} \cdot ((1-Q_y^p)(1-d_y^p))^w \cdot (1 - (1-Q_y^p)(1-d_y^p))^{n_y-i-1-w} \right\}. \quad (13)$$

As a result, $q_{y,i \leq n_y-k}$ is obtained by

$$q_{y,i \leq n_y-k} = C_1 + C_2 + C_3. \quad (14)$$

C. Error Propagation Caused by a Lost Substream

In (9), estimating the packet loss probability for peer y requires the knowledge about the packet loss probabilities of all substreams in the corresponding parent-peers. Meanwhile, peer y has to estimate the packet loss probability for each subscribed substream such that the child-peers of peer y can estimate their packet loss probability accordingly.

Note that when peer y requests substream j from peer x , the packets of substream j may have already been lost by peer x

with probability $Q_x^{s_j}$. Moreover, the probabilities that peer x keeps staying in the system and leaves the system are P_0^1 and P_1^1 , respectively. Therefore, the mean packet loss probability of substream j in peer x is $P_0^1 \cdot Q_x^{s_j} + P_1^1 \cdot 1$. In the case that peer x owns the packets of substream j and the packets are dropped during transmission with probability $d_x^{s_j}$, the packet loss probability that peer y receives substream j from peer x without any FEC protection becomes

$$C_4 = 1 - \{1 - (P_0^1 \cdot Q_x^{s_j} + P_1^1 \cdot 1)\} \cdot (1 - d_x^{s_j}). \quad (15)$$

A lost packet of substream j cannot be recovered, if the number of packets received from the remaining $n_y - 1$ substreams is not enough for FEC recovery. The probability of such an event can be expressed by

$$C_5 = \sum_{i=0}^{n_y-1} P_i^{n_y-1} \sum_{w=0}^{k-1} \left\{ \binom{n_y-i-1}{w} \cdot ((1 - Q_y^{p\#j}) (1 - d_y^{p\#j}))^w \cdot (1 - (1 - Q_y^{p\#j}) (1 - d_y^{p\#j}))^{n_y-i-1-w} \right\} \quad (16)$$

where $Q_y^{p\#j}$ denotes the average packet loss rates of the remaining substreams from parent-peers except peer x , and $d_y^{p\#j}$ denotes the average packet drop rates of the links to the parent-peers except peer x .

As a result, the packet loss probability of substream j after FEC recovery becomes

$$Q_y^{s_j} = C_4 \cdot C_5. \quad (17)$$

IV. PROPOSED CONTRIBUTION-GUIDED PEER SELECTION

In order to recover lost packets, a peer can subscribe to corresponding redundant substreams by sending subscription messages to neighboring peers. Suppose peer y sends a message to peer x to request a redundant substream. Peer x then adds peer y into her candidate set \tilde{C}_x . However, due to the limited uplink capacity of peer x , the uplink capacity has to be efficiently allocated to maximize streaming performance. To this end, we propose a peer selection scheme by which a parent-peer chooses those child-peers who can offer the largest contributions in reducing downstream packet loss with the assigned redundant substreams. Based on the proposed packet loss estimation models, our peer selection method would reject the subscription requests from those “low-contribution” candidate peers whose subscription cannot effectively assist in recovering lost packets. Let $n_y + \sigma_{xy}$ be the total number of substreams expected to be received by peer y , where $\sigma_{xy} \in \{1, 0\}$ indicates the peer selection decision for candidate peer y , i.e., if peer x selects peer y as a child-peer, $\sigma_{xy} = 1$; otherwise, $\sigma_{xy} = 0$. We use the set of random variables $\bar{\sigma}_x = \{\sigma_{xy} | y \in \tilde{C}_x\}$ to represent the set of peer selection decisions.

A. Evaluating a Peer's Contribution

In our peer selection scheme, when a candidate child-peer requests a redundant substream from a parent-peer, the

parent-peer will evaluate the candidate peer's contribution of distributing the substream to her descendants. To do so, we estimate the packet loss reduction contributed by a candidate child-peer. The more the packet loss reduction contributed by a candidate peer, the lower the packet loss probability of the peer and her descendants, and the higher the candidate peer's contribution. Since peer y is also a parent-peer of her child-peers (e.g., peer z), the packet loss occurring in peer y will propagate to peer z as well. When peer y obtains one additional redundant substream, the packet loss probability of peer y and her descendants will all be mitigated. The influence of packet loss reduction ΔQ_y on the average packet loss probability of the substreams in peer z 's parent-peers can be estimated by

$$Q_z^p = \frac{1}{n_z} \left[\left(\sum_{v \in \text{parent}(z)} Q_v^{s_j} \right) - \Delta Q_y^{s_j} \right] \quad (18)$$

where n_z denotes the number of substreams received by peer z , $\Delta Q_y^{s_j}$ stands for the packet loss reduction on substream j when peer y receives one more redundant substream as follows:

$$\Delta Q_y^{s_j} = Q_y^{s_j}(n_y) - Q_y^{s_j}(n_y + \sigma_{xy}). \quad (19)$$

As a result, the packet loss reduction (contributed by peer y) for peer z can be calculated by

$$\Delta Q_z = Q_z(n_z) - Q_z(n_z, \Delta Q_y^{s_j}) \quad (20)$$

where $Q_z(n_z, \Delta Q_y^{s_j})$ denotes the packet loss probability of peer z that receives n_z substreams, and it is a function of $\Delta Q_y^{s_j}$. Then, ΔQ_z can influence the next-level descendants in the same way. As a result, such packet loss reduction on a peer would benefit the peer's succeeding descendants.

B. Characterizing Packet Loss Reduction Gains

According to the previous models, the packet loss reduction of a peer would also benefit its descendants. An analytic tool is required to characterize the propagation effect of packet loss reduction in an irregular mesh network. To this end, we propose the use of probabilistic graphical models to characterize the overall packet loss reduction gain in a mesh-based P2P network. Suppose a packet loss occurring in a parent-peer will influence her descendants along the delivery paths for up to M levels. In the models, the energy function in terms of the peer selection decision choices $\bar{\sigma}_x$ is defined as follows:

$$H(\bar{\sigma}_x | \bar{\sigma}_{L-x}) = H_1(\bar{\sigma}_x) + H_2(\bar{\sigma}_x | \bar{\sigma}_y) + \dots + H_M(\bar{\sigma}_x | \bar{\sigma}_l) \quad (21)$$

where

$$H_1(\bar{\sigma}_x) = \sum_{y \in \tilde{C}_x} Q_y(n_y + \sigma_{xy}) \quad (22)$$

$$H_2(\bar{\sigma}_x | \bar{\sigma}_y) = \sum_{y \in \tilde{C}_x} \sum_{z \in \text{child}(y)} Q_z(n_z, \Delta Q_y^{s_j}) \quad (23)$$

$$H_M(\bar{\sigma}_x | \bar{\sigma}_l) = \underbrace{\sum_{y \in \tilde{C}_x} \sum_{z \in \text{child}(y)} \dots \sum_{m \in \text{child}(l)} Q_m(n_m, \Delta Q_l^{s_j})}_M \quad (24)$$

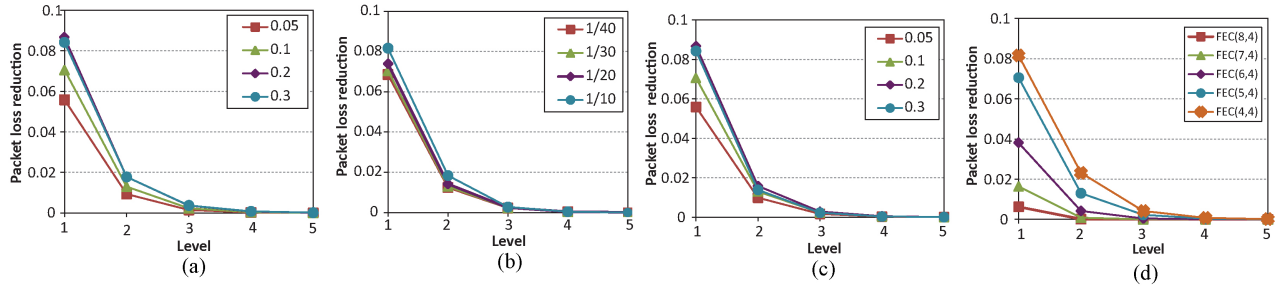


Fig. 4. Average packet loss reduction for peers at different levels with different settings of parameters. (a) Q_k^p . (b) ρ . (c) Link packet drop rate. (d) $FEC(n, k)$.

In (21), the energy function involves the packet loss probabilities for the set of child-peers selected by a parent-peer and their descendants at all M levels. The energy term H_1 for the first-level child-peers of parent-peer x (at the zeroth level) indicates the packet loss probability for the peers in $\bar{\mathbf{C}}_x$, as indicated in (22), and the energy term H_2 indicates the packet loss probability for the second-level child-peers, as shown in (23). Suppose at the M th level, the propagation effect of packet loss reduction in the whole P2P network has all been considered by H_M in (24). The decision of peer selection can be related to a probabilistic graphic model by the Gibbs distribution [22] as follows:

$$P(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x}) = \frac{1}{Z} \exp[-H(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x})] \quad (25)$$

where $Z = \sum_{\bar{\sigma}} \exp[-H(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x})]$ is a normalization factor, and $\bar{\mathbf{L}}$ denotes the set of all live peers.

As a result, the peer selection can be based on MAP or equivalently on minimizing the energy function by finding

$$\bar{\sigma}_x^* = \arg \max_{\bar{\sigma}_x} P(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x}) = \arg \min_{\bar{\sigma}_x} H(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x}). \quad (26)$$

Note that the calculation of energy terms in (21) has to traverse the peer selection decisions of all affected peers, which assumes that the knowledge about the network topology and link conditions is available to peers. Since a mesh-based P2P network is rather dynamic due to peer churns, the energy calculation process is complex and consumes lots of overheads, making it impractical in real applications should no simplification be made. In what follows, we shall show that the energy calculation can be significantly simplified without sacrificing estimation accuracy severely by exploiting the Markovian properties of the model. Besides, we shall also show how to achieve optimal decision of peer selection with the simplified graphical model.

To derive the optimal decision of peer selection based on the Markovian property, we first express the local energy function $H^L(\bar{\sigma}_x | \bar{\sigma}_{N_x})$ by the following Gibbs distribution:

$$P(\bar{\sigma}_x | \bar{\sigma}_{N_x}) = \frac{1}{Z} \exp[-H^L(\bar{\sigma}_x | \bar{\sigma}_{N_x})] \quad (27)$$

where $Z = \sum_{\bar{\sigma}} \exp[-H^L(\bar{\sigma}_x | \bar{\sigma}_{N_x})]$ is a normalization factor, and $\bar{\sigma}_{N_x}$ denotes the peer selection decisions of neighbors instead of the all live peers in $\bar{\mathbf{L}}$ in (25).

The optimal peer selection can be decided by

$$\bar{\sigma}_x^* = \arg \max_{\bar{\sigma}_x} P(\bar{\sigma}_x | \bar{\sigma}_{N_x}) = \arg \min_{\bar{\sigma}_x} H^L(\bar{\sigma}_x | \bar{\sigma}_{N_x}). \quad (28)$$

Note that the Hammersley–Clifford theorem [22] shows that $\bar{\sigma}_x$ is an MRF on $\bar{\mathbf{L}}$ with respect to N_x if and only if $\bar{\sigma}_x$ is a Gibbs random field (GRF) on $\bar{\mathbf{L}}$ with respect to N_x . Accordingly, if the energy function in (21) can be approximated well with a local energy function, the proposed probabilistic graphical models will become a kind of MRFs in which the random variable set $\bar{\sigma}_x$ is conditionally independent of child-peers that are not neighbors of parent-peer x . Hence, the Markovianity condition is satisfied, i.e., $P(\bar{\sigma}_x | \bar{\sigma}_{\bar{\mathbf{L}}-x}) = P(\bar{\sigma}_x | \bar{\sigma}_{N_x})$. We shall show below empirically that the proposed packet loss propagation model is Markovian. Therefore, the energy function in (21) can be significantly simplified with a small number of local energy terms.

Fig. 4 illustrates the average packet loss reduction on the succeeding descendants of a peer by using the proposed models. In Fig. 4(a), we set $\rho = 1/30$ and $FEC(5, 4)$ for each peer and calculate the average packet loss reduction gains for individual peers under different values of Q_k^p . Assuming there is one peer receiving one additional redundant substream, i.e., $FEC(6, 4)$, we evaluate on the amounts of packet loss reduction on the peer herself and on the peer's descendants at succeeding levels. Denoting the child-peer who receives one additional redundant substream as level-1 child-peer, the packet loss gain for the child-peer can be calculated by $\Delta Q_y = Q_y(n_y) - Q_y(n_y + 1)$, whereas the gain for a child-peer at the next level is $\Delta Q_z = Q_z(n_z) - Q_z(n_z, \Delta Q_y^s)$. In Fig. 4(b), we set $Q_k^p = 0.1$, and $d_x^p = 0.1$ for each peer and calculate the average packet loss reduction gains on peers under different values of ρ . In Fig. 4(c), we set $Q_k^p = 0.1$ and $\rho = 1/30$ for each peer and calculate the packet loss reduction gains on peers under different values of d_x^p . In Fig. 4(d), we set $Q_k^p = 0.1$, $d_x^p = 0.1$ and $\rho = 1/30$ and calculate the packet loss reduction gains for different $FEC(n, k)$ settings. Fig. 4 demonstrates that the packet loss reduction gain for level-2 child-peers inherited from the level-1 child-peer who receives an additional substream reduces to 0.013 on average, and, for level-3 child-peers, reduces to 0.002, which is only 3.5% of the gain to level-1 peer. The packet loss reduction gain for descendants at lower succeeding levels decreases rapidly and therefore becomes negligible. As a result, the packet loss reduction gain for a succeeding descendant is

considered negligible if the depth of level is higher than two. Consequently, the energy function in (21) can be approximated reasonably well with only two terms including the candidate child-peer and her next-level child-peers as follows:

$$H^L(\bar{\sigma}_x|\bar{\sigma}_{N_x}) = H_1(\bar{\sigma}_x) + H_2(\bar{\sigma}_x|\bar{\sigma}_y) \quad (29)$$

where $H^L(\bar{\sigma}_x|\bar{\sigma}_{N_x})$ denotes the local energy and $\bar{\sigma}_{N_x} = \{\bar{\sigma}_y|y \in \bar{\mathbf{C}}_x\}$ denotes the peer selection decisions of neighbors.

In a mesh-based network, peers may constitute a loop in which a peer traverses back to herself through one or multiple hops along different substream delivery paths. Such a loop structure makes the analysis of packet loss reduction very complicated since one peer may belong to different levels in the energy calculation path. However, the property observed in Fig. 4 can be utilized to drastically simplify the analysis of packet loss reduction propagation with loops. In Fig. 2(b), peer #8 and peer #9 compose a 2-loop where peer #8 can traverse back to herself through two hops. Assume that peer #9 is not connected to peer #8 initially, and then peer #8 sends an additional redundant substream to peer #9, thereby constructing a 2-loop, where peer #9 is at levels 1, 3, ..., 2r+1 simultaneously. Such complication in packet loss reduction analysis can also be avoided using the simplified energy calculation in (29).

With the proposed MRF model, each parent-peer can select an optimal set of child-peers in an efficient manner. Suppose parent-peer x selects her child-peers once every peer selection period. During a peer selection period, the child-peers who requested video substreams from peer x are added into the candidate set of peer x . Besides, those child-peers who have supplied the substreams of a video session and have connected to peer x for more than T seconds are added into the candidate set as well. Note that the connection time to a substream source is set to be at least T seconds to avoid frequent switching (i.e., the oscillation effect) among different substream sources. Consequently, the optimal $\bar{\sigma}_x$ is determined by (28) to minimize the overall packet loss probability of the child-peers at only level-1 and level-2, rather than at all levels, under the uplink bandwidth constraint as follows:

$$\begin{aligned} \arg \min_{\bar{\sigma}_x} H^L(\bar{\sigma}_x) = & \sum_{y \in \bar{\mathbf{C}}_x} Q_y(n_y + \sigma_{xy}) \\ & + \sum_{y \in \bar{\mathbf{C}}_x} \sum_{z \in \text{child}(y)} Q_z(n_z, \Delta Q_y^z) \end{aligned} \quad (30)$$

$$\text{subject to } \sum_{y \in \bar{\mathbf{C}}_x} \sigma_{xy} \cdot R_s \leq U_x \text{ and } \sigma_{xy} \in \{1, 0\}$$

where R_s is the bit-rate of a substream and U_x is the uplink bandwidth of peer x .

Equation (30) is equivalent to

$$\arg \max_{\bar{\sigma}_x} \sum_{y \in \bar{\mathbf{C}}_x} \left\{ \sigma_{xy} \cdot \left[\Delta Q_y + \sum_{z \in \text{child}(y)} \Delta Q_z \right] \right\} \sum_{y \in \bar{\mathbf{C}}_x} \quad (31)$$

$$\text{subject to } \sum_{y \in \bar{\mathbf{C}}_x} \sigma_{xy} \cdot R_s \leq U_x \text{ and } \sigma_{xy} \in \{1, 0\}$$

where $\Delta Q_y = Q_y(n_y) - Q_y(n_y + \sigma_{xy})$ and $\Delta Q_z = Q_z(n_z) - Q_z(n_z, \Delta Q_y^z)$ denote the packet loss reduction gains of the child-peers at level-1 and level-2, respectively. This optimization problem is a 0/1 knapsack problem that can be solved by dynamic programming [28].

It should be noted that, in designing a P2P streaming mechanism, the incentive issue should be considered to encourage peers to contribute their resource, such as uplink bandwidth, storage, and computing power. In our method, a parent-peer select a child-peer according to the child-peer's contribution on packet loss reduction to the peer's descendants. Suppose most peers in a network apply the proposed peer selection scheme in which each parent-peer knows her candidate child-peers' contributions. If a peer does not select child-peers who contribute the largest packet loss reduction gains, then the packet loss performances of the peer's child-peers cannot be maximized, thereby also reducing the peer's own contribution. As a result, when the peer requests redundant substreams from the peer's parent-peers, the possibility that the peer be chosen will be reduced due to her low contribution. Therefore, if most peers apply the proposed method, it will provide the incentive to encourage peers to maximize the packet loss reduction gain for their candidate child-peers while selecting child-peers.

V. SIMULATION RESULTS

We used P2Pstrsim [29] to evaluate the accuracies of packet loss estimation models and the performances of peer selection schemes. We used GT-ITM [30] to generate a topology with 2500 peers as the configuration of simulations with P2Pstrsim. The end-to-end delay between two peers is set to be uniformly distributed in the range of 10–500 ms. The simulation time is set to 30 min, where peers uniformly join the network within 30 min, and then leave the system independently after mean user viewing time T_v , which is assumed to be uniformly distributed in the range of $T_v/2 \sim 3T_v/2$. We set $T_v = 30$ min in our simulations, making the viewing time of peers distribute in the range of 15–45 min uniformly. We also assume that each user records the number of parent-peer departures in a time period and the average time to find a new replacement parent-peer so as to calculate parameter ρ for the CTMC model. We encoded a 300-frame CIF (352×288) video at 30 f/s with a bit-rate of 300 kb/s using the JM14.2 H.264 coder [31]. The encoded video bitstream is divided into k substreams, each being further divided into fixed-length packets of 1250 bytes. Each ensemble is encoded with FEC(n, k) code, therefore containing n packets, including k packets from the k substreams, respectively, and $n-k$ additional redundant packets, where $n = 5-8$ and $k = 4$ in our experiments. The peers send out subscription messages to request their unavailable substreams once every data scheduling period that is set to 3 s.

Our simulations are mainly designed to simulate wireline networks with different levels of congestion, which lead to different link packet drop rates (1%–25%). Nevertheless, to address the burst loss problem due to peer churns, our method uses packet-level FEC with interleaving, which, to some extent, can also combat against burst packet loss in wireless links, though the FEC parameters may need to be adjusted.

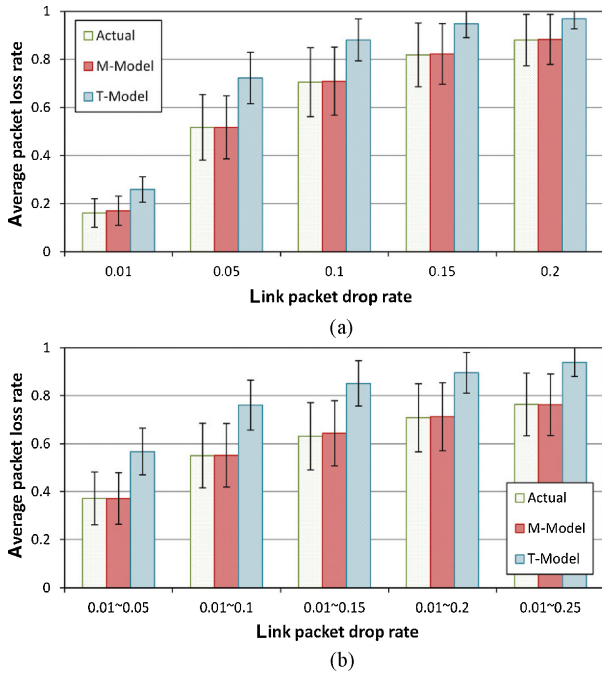


Fig. 5. Packet loss estimation for P2P networks. (a) Homogeneous network of 1000 peers. (b) Heterogeneous network of 1000 peers.

A. Evaluation of Packet Loss Estimation Models

We first evaluate the accuracy of packet loss estimation models. Here, we use the average packet loss rate as the quality metric that indicates the number of lost packets in an ensemble over the number of requested substreams measured by the live peers. The term “lost packets” means those dropped packets that cannot be recovered by ensemble-based packet-level FEC recovery. Each live peer measures the number of lost packets in an ensemble to calculate the packet loss rate every second. The average packet loss rate of all live peers within a 1 min window is then calculated as the average packet loss rate. To be meaningful in performance evaluation, in the calculation, we only take into account the steady-state packet loss rates of peers and drop the data measured in the early transient stage. In Fig. 5, we compare three results: 1) the actual average packet loss rate measured from the received substreams at the live peers, denoted as “actual;” 2) the average packet loss rate estimated by the proposed model, denoted as “M-model;” and 3) the average packet loss rate estimated by the tree-based model, denoted as “T-model.” In this comparison, peer selection is not considered, i.e., parent-peers accept all requests from their child-peers. Note that since the tree-based model cannot be directly applied in a mesh-based P2P network, we modify the tree-based model based on the concept that the packet loss accumulation of each substream in a peer is identical. Therefore, the $Q_x^{s_j}$ in (9) is replaced with Q_x , the estimated packet loss probability of peer x .

Fig. 5(a) shows the average packet loss rate with the 95% confidence interval in a network of 1000 peers without any FEC protection and peer dynamics. The peer packet loss rate increases with the link packet drop rates. Under a low link packet drop rate (e.g., 1%), both the T-model and M-model can do a good job in packet loss estimation. Nevertheless,

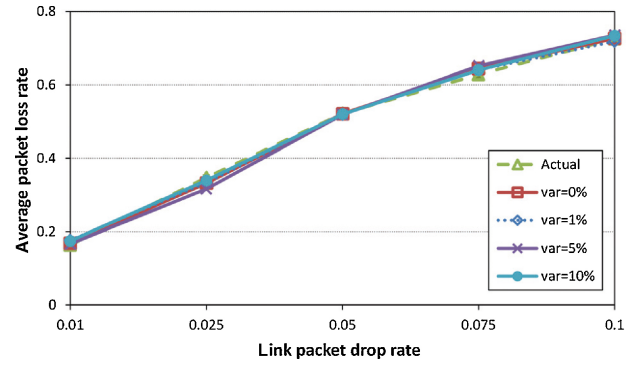


Fig. 6. Impact of nonbiased estimation noise of link packet drop rate on packet loss estimation accuracy. The noise is assumed to be normally distributed with zero mean and different levels of variance.

when the link packet drop rate increases to 5%, 10%, 15%, and 20%, compared with the actual loss rates, the T-model significantly overestimates the packet loss rate by 21%, 18%, 13%, and 8%. In contrast, the proposed M-model still achieves fairly good estimation accuracy for various test cases under different network sizes and link conditions. To further evaluate the performance of our method in a heterogeneous network, five different ranges of link packet drop rates are simulated: [1%, 5%], [1%, 10%], [1%, 15%], [1%, 20%], and [1%, 25%]. The packet loss rate of each link class is set to be uniformly distributed in the setting range, e.g., for the peers of the first class, the link packet drop rate is uniformly distributed in the range of 1%–5%. Fig. 5(b) shows the packet loss estimation results for a heterogeneous network, where the simulation conditions are the same as those in Fig. 5(a) except that the packet drop rates for peers are heterogeneous. The results are consistent with those in Fig. 5(a) in which a higher link packet drop rate leads to a higher packet loss rate. The results show that the M-model still achieves good estimation accuracy under heterogeneous link conditions.

Note that the M-model is based on the assumption that a peer can obtain the accurate link packet drop rates of the peer’s descendants through feedback channels. However, there may exist inaccuracy in estimating the link packet drop rates. Assuming the estimation error of link packet drop rates is normally distributed with zero mean (i.e., no bias), Fig. 6 shows the packet loss estimation results under the estimated link packet drop rate with different variances, ranging from 0% to 10%. The results show that the M-model is still accurate because the noise caused by inaccurate estimation of link packet drop rates is effectively filtered out by the summation operation in (10). However, if the estimates of link packet drop rates are biased (i.e., the mean of estimation error is nonzero), the accuracy of M-model will be affected. Our results show that when the estimation bias becomes 1%, 5%, and 10%, the corresponding average estimation errors of the M-model are 3.4%, 13.5%, and 21.9%, respectively. The reason is that the biased link packet drop rate would lead to the propagation of packet loss estimation error to succeeding child-peers.

Fig. 7 shows the packet loss estimation results for a mesh-based network with peer dynamics ($T_v = 30$ min), where the

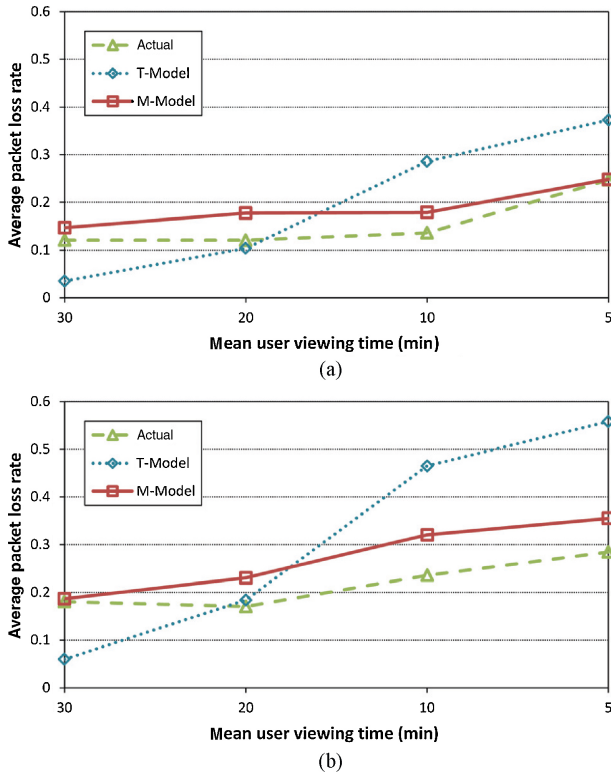


Fig. 7. Packet loss estimation with different data scheduling periods. (a) 3 s. (b) 6 s.

data scheduling periods are set to 3 s and 6 s in Fig. 7(a) and (b), respectively. When a parent-peer leaves the system, the peer's child-peers will send substream subscription messages to discovered replacement parent-peer candidates in the next data scheduling period. A longer period implies that the child-peers require longer time to find the new replacement parent-peers. The results show that the packet loss rate increases as the mean user viewing time decreases. As shown in Fig. 7(a), the absolute estimation errors with the M-model are 0.026, 0.057, 0.042, and 0.001 for the mean user viewing time 30, 20, 10, and 5 min, respectively. In contrast, the absolute estimation errors with the T-model are 0.085, 0.017, 0.15, and 0.126, which are more significant. In Fig. 7(b), the child-peers require longer time to retrieve the unavailable substreams. The result on estimation errors is consistent with Fig. 7(a).

Next, we take into account together the peer dynamics ($T_v = 30$ min), link packet drop rate, and FEC protection to evaluate the accuracies of loss estimation models for a network. The above simulation results demonstrate that the M-model achieves fairly good performance of packet loss estimation for mesh-based P2P networks. In contrast, the T-model leads to significant estimation errors for various link conditions. This is because the M-model takes into account the packet loss of each substream in each transmission hop, whereas the T-model does not consider the heterogeneous packet loss among the substreams in a mesh-based P2P network of 1000 peers. Fig. 8(a) shows the packet loss estimation results with FEC(5, 4) protection, where the peers experience serious packet loss with a loss rate of 75% or above when the link packet drop exceeds 10%, due to the insufficient protection

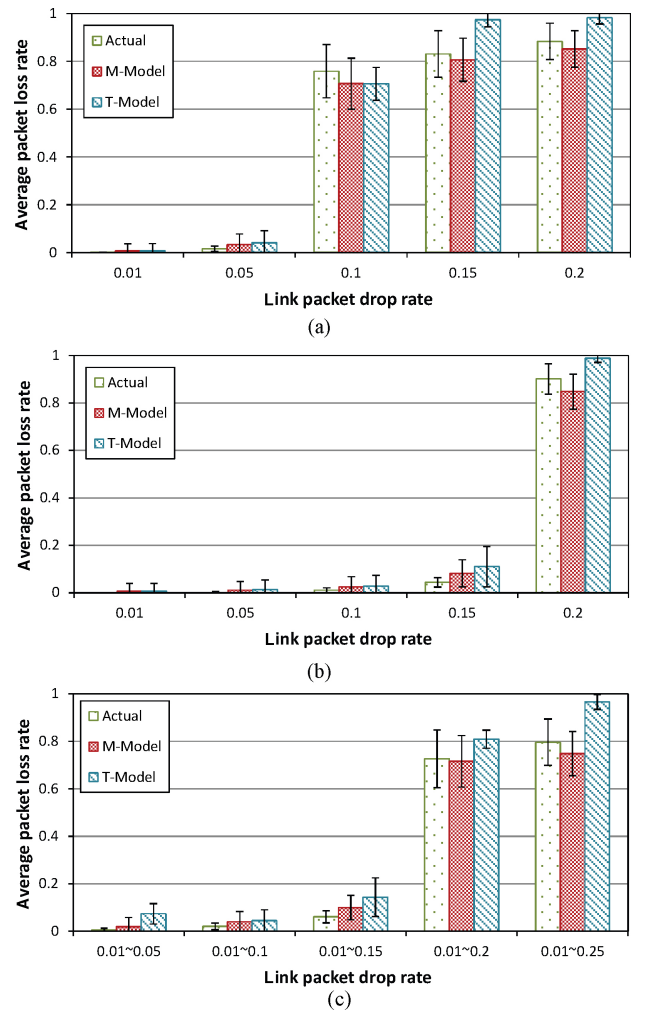


Fig. 8. Packet loss estimation with different FEC codes. (a) FEC(5, 4). (b) FEC(6, 4). (c) FEC(5, 4) under five classes of link conditions.

capability of FEC(5, 4) in coping with high link loss rates and peer dynamics. The sharp transition occurs at the borderline of packet drop rate that FEC(5, 4) can protect against. In such a case, the proposed M-model still does a good job in packet loss estimation. Fig. 8(a) shows that the M-model achieves better estimation accuracy compared to the T-model at various packet drop rates. Fig. 8(b) depicts the packet loss estimation results with FEC(6, 4), where packet loss can be well protected under the link packet drop rates lower than 15%. When the packet drop rate reaches 20%, the M-model still estimates the packet loss accurately, whereas the T-model significantly overestimates the packet loss rate by about 8%. The simulation conditions in Fig. 8(c) are similar to Fig. 8(a) except that the link packet drop rates are heterogeneous. The results show that the M-model still can do a good job under heterogeneous link conditions.

B. Evaluation of Peer Selection Methods

Our proposed peer selection method is a kind of sender-driven peer selection in which parent-peers proactively select their child-peers after receiving the requests from the child-peers. We implemented four peer selection schemes and

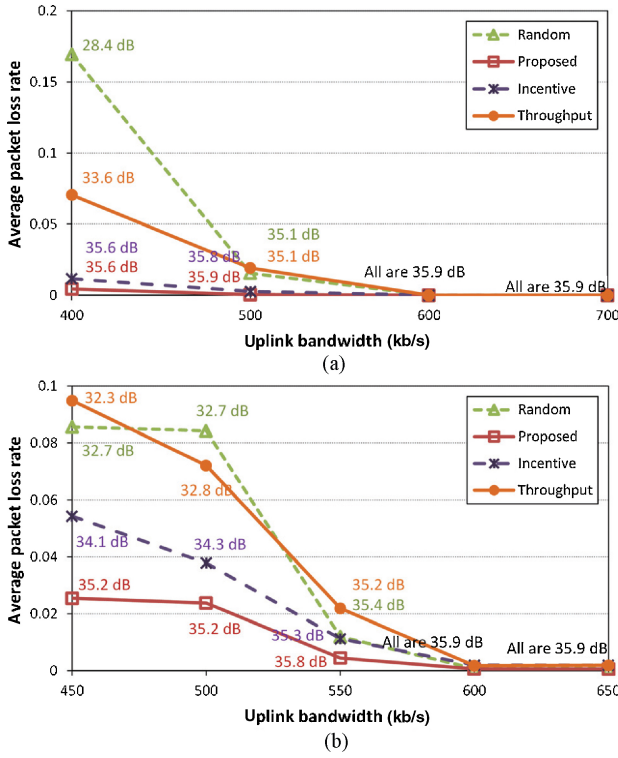


Fig. 9. Packet loss performance comparison of four peer selection schemes at different uplink capacity under (a) 1% link packet drop rate and (b) 10% link packet drop rate. The numbers show the PSNR performances of different methods (indicated in different colors) at different uplink rates.

evaluated their packet loss performances.

- 1) Random peer selection (denoted as “random”): In this scheme, child-peers first randomly send substream request messages to those in the candidate parent-peers list who own the requested substreams. The parent-peers then randomly accept substream requests until their available uplink bandwidth is exhausted [19].
- 2) Incentive-based peer selection (denoted as “incentive”): Child-peers randomly send requests to their parent-peers. The child-peers who send the video substreams to their parent-peers are accepted by the parent-peers with higher priority [9].
- 3) Throughput optimized peer selection (denoted as Throughput): Based on the available bandwidth information of their neighbors obtained through the gossiping messages, child-peers select their parent-peers to maximize their downlink throughput [15].
- 4) Our proposed contribution-guided peer selection in (31) (denoted as “proposed”): Child-peers first send request to their candidate parent-peers randomly as the random scheme does. The parent-peers then choose their child-peers according to the child-peers’ contributions in packet loss reduction to their descendants for up to two levels.

In the following experiments, we choose FEC(8, 4) as the FEC mother code. Therefore, peer y can choose to receive five code-rate FECs of different protection capabilities, i.e., FEC(n_y , 4), $n_y = 4, 5, \dots, 8$, according to the codes’ packet loss gains.

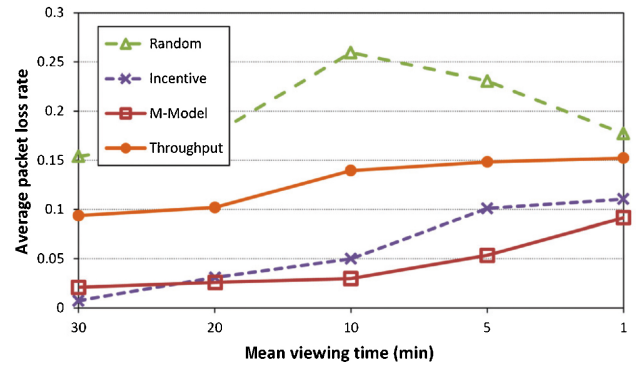


Fig. 10. Packet loss performance comparison of four peer selection mechanisms with various mean user viewing times under 1% link packet drop rate.

Fig. 9 shows the packet loss performances of four peer selection mechanisms with various uplink capacities. Fig. 9(a) shows the packet loss performance under a low packet link drop rate of 1%. The result shows that the random and throughput methods achieve a packet loss rate of lower than 3% when the uplink bandwidth is larger than 500 kb/s, whereas the incentive and proposed methods can achieve the same level of packet loss performance at lower uplink capacity (e.g., less than 400 kb/s). When the available uplink capacity reduces to only 400 kb/s, our method outperforms the others significantly. As shown in Fig. 9(b), when the link packet drop rate increases to 10%, all peer selection methods would consume more uplink bandwidth (say, at least, 450 kb/s) to keep a low packet loss rate. Nevertheless, the proposed method still stably outperforms the others in terms of packet loss rate and peak signal-to-noise ratio (PSNR) performance.

Fig. 10 compares the packet loss performances of four peer selection schemes under different mean user viewing time settings. When a parent-peer unexpectedly leaves a P2P streaming system, her descendants would suffer from burst packet loss. Since the throughput scheme does not take into account the peer departure behavior, its performance is worse than the proposed and incentive methods. In the incentive scheme, those child-peers who contribute more uplink bandwidth resource would receive more redundant substreams to recover the lost substreams. The high-contribution peers, however, would probably receive excessive packets that cannot further improve the packet loss recovery ability, leading to the waste on their parent-peers’ uplink bandwidth and thereby degrading the overall system performance. In contrast, the waste on protection resource can be avoided with the proposed method since, instead of the child-peers’ contributions on uplink bandwidth, our method selects child-peers based on their contributions on packet loss reduction, where CTMC is applied to model the arrival or departure behavior of peers so as to accurately estimate the packet loss gain of a child-peer who can contribute when receiving a requested substream. As a result, the protection resource will be allocated in such a way that low-contribution child-peers can gain reasonable protection without sacrificing the protection capability of high-contribution peers. Hence, the proposed method outperforms the contribution method in terms of the overall packet loss performance of the system.

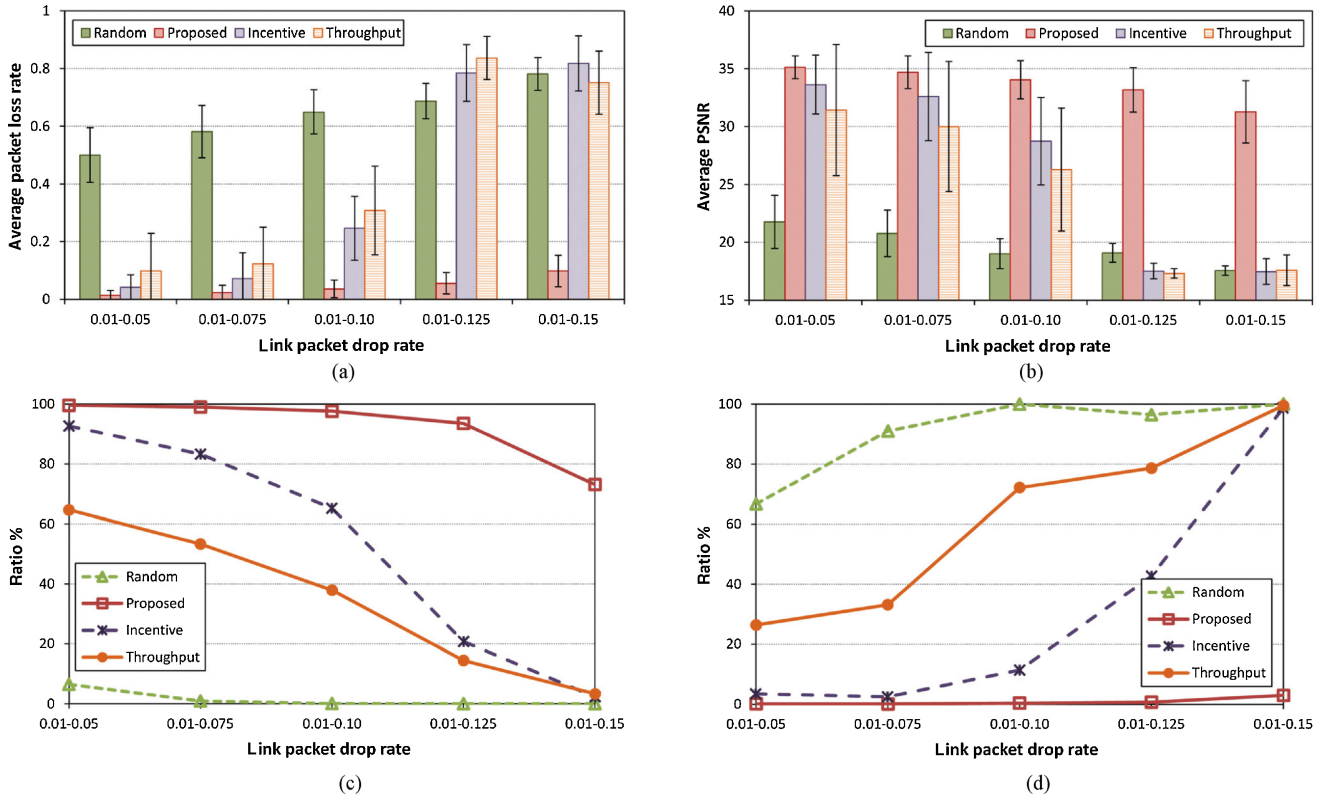


Fig. 11. Visual quality comparison of four peer selection schemes with the uplink bandwidth of 400 kb/s and under heterogeneous link conditions. (a) Packet loss performance. (b) PSNR performance with the best and worst bounds. (c) Ratios of peers who receive good-quality video (higher than 30 dB). (d) Ratios of peers who receive poor-quality video (lower than 25 dB).

Fig. 11(a) compares the packet loss performances of four peer selection schemes with the uplink bandwidth of 400 kb/s and under heterogeneous link conditions. The corresponding average PSNR performances are also compared in Fig. 11(b). The random scheme does not perform well. The other three schemes all achieve good performance under the heterogeneity range [1%, 5%] of link packet drop rate, but the packet loss rates of the incentive and throughput schemes increase sharply when the heterogeneity range of link conditions becomes [1%, 7.5%] and [1%, 10%]. In contrast, the proposed method still maintains significantly better packet loss performance. Fig. 11(b) shows that the proposed method achieves the best objective visual quality compared to the other three peer selection schemes. In order to illustrate the video quality distribution, we also compare two quality metrics: 1) the ratio of peers who receive good-quality video with PSNR higher than a threshold (say 30 dB), as shown in Fig. 11(c); and 2) the ratio of peers who receive poor-quality video with PSNR lower than a threshold (say 25 dB), as shown in Fig. 11(d). Fig. 10(c) shows that, with the proposed method, almost all peers receive good-quality (PSNR is larger than 30 dB) video under the heterogeneity range [1%, 5%], and 73% peers still can receive good-quality video under heavy packet loss range [1%, 15%]. With the incentive and throughput schemes, 92% and 64% peers receive good-quality video under the heterogeneity range [1%, 5%], respectively. However, the percentages drop very quickly in heavier heterogeneity range. On the other hand, Fig. 11(d) shows that, with the proposed method, less than 3% peers receives poor-quality video under

all link loss settings. The percentages of poor-quality video for the random, incentive, and throughput schemes, however, increase sharply to 100%, 98%, and 99%, respectively, under the heterogeneity range of [1%, 15%]. The reason is that, in the proposed peer selection method with the M-model estimator, each parent-peer selects a set of child-peers that contribute the most packet loss reduction gains, thereby recovering more lost packets compared to the other schemes, especially under high link packet drop rates. On the contrary, in the receiver-driven throughput scheme, child-peers would maximize their own input throughput by requesting substreams from their candidate parent-peers. However, the child-peers who can contribute more packet loss gain may not obtain sufficient resource due to the limited uplink bandwidths of the parent-peers. As a result, part of the child-peers will fail to recover lost packets because the uplink bandwidth resources of their neighbors have been exhausted. Such packet loss subsequently propagates to the descendants of those peers who fail to recover the lost packets. Hence, the throughput scheme cannot provide reliable streaming service in an error-prone network with constrained uplink bandwidth capacities.

Next, we compare the packet loss performances of peer selection mechanisms with heterogeneous uplink bandwidths of peers, where the uplink bandwidth distribution is shown in Table I. In the experiment, the bitrate of coded video bitstream ranges from 250 to 400 kb/s and the link packet drop rates from 1% to 10%. At the encoding rate points of 250 kb/s and 300 kb/s, all the peer selection schemes can recover the packet loss well, as shown in Fig. 12. However, the packet loss rates

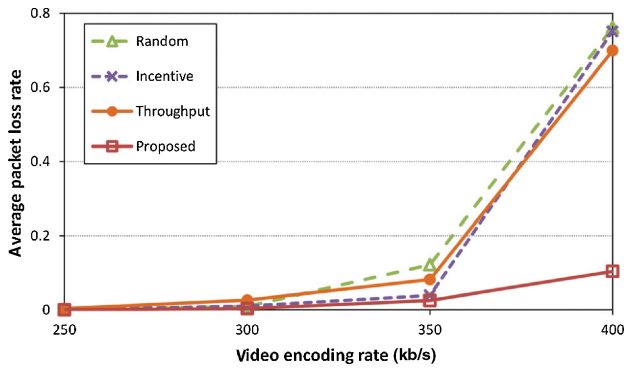


Fig. 12. Packet loss performance comparison of four peer selection schemes for various video bitstream bit-rates.

TABLE I

UPLINK BANDWIDTH DISTRIBUTION IN A P2P NETWORK

Class No.	Type	Uplink Bandwidth (b/s)	Fraction
1	DSL/Cable	128k	20
2	DSL/Cable	384k	50
3	DSL/Cable	1000k	30

of the random and throughput schemes quickly increase at the coding rate points 350 kb/s and higher. At the bit-rate of 400 kb/s, the random, throughput, and incentive schemes all fail in the packet loss recovery, whereas the proposed scheme still can do a good job. The proposed scheme outperforms the other three schemes due to its ability of efficiently allocating the limited uplink capacity to the high-contribution peers. Note that in the incentive-based scheme, the parent-peers who contribute more uplink bandwidth, such as those in class #3 in Table I, will more likely receive more substreams so as to recover more lost packets. Besides, since those peers who contribute larger uplink bandwidth tend to have lower packet loss rate, the packet loss of their child-peers will likely be mitigated as well by inheriting packets from more reliable sources. As a result, the incentive scheme achieves as good performance as that of the proposed scheme under low link packet drop rates or sufficient uplink bandwidth capacity. However, as shown in Figs. 9–12, when the link packet drop rate becomes high or the uplink bandwidth capacity is not sufficient, the performance of the incentive-based scheme will degrade significantly. The main reason is that the peers who can offer high link bandwidth but have low contribution in packet loss gain may consume excessive bandwidth to receive redundant substreams, thereby reducing the number of redundant substreams sent to the peers who can really contribute good packet loss gain but cannot offer high uplink bandwidth. As a result, the video stream protection efficiency will deteriorate when the effective link bandwidth is not sufficient. In contrast, the proposed contribution-guided peer selection scheme addresses the problem by incorporating the incentive perspective into the energy (contribution) calculation, since the peers who contribute more bandwidth resource (i.e., accept the request from more child-peers) usually have higher level-2 packet loss gain when receiving redundant substreams.

Under the same conditions used in Fig. 12, Fig. 13 compares the performances of our method that considers one to four

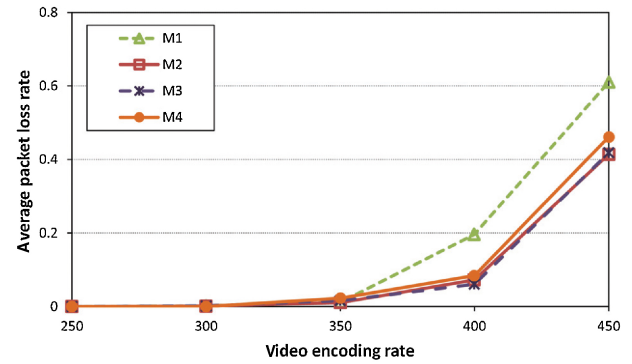


Fig. 13. Packet loss performance comparison of the proposed method considering one to four levels of descendant peers in evaluating the contribution on one peer's error propagation reduction.

levels of descendant peers in evaluating a peer's contribution on error propagation reduction, denoted as M1, M2, M3, and M4, respectively. We can see that all the schemes achieve low average packet loss rate when the video bit-rate is lower than 350 kb/s. But when the video bit-rate is higher than 350 kb/s, M1 leads to significantly higher packet loss compared to the other three methods because considering only the first-level packet loss reduction gain cannot approximate the total amount of contribution well. In contrast, M2 achieves very close packet loss performance to that of M3 and M4, since most of packet loss reduction gains to the third-level and fourth-level peers are negligible. Moreover, the overhead cost for sending information to a parent-peer grows exponentially with the number of levels. Therefore, M2 is a promising choice.

VI. CONCLUSION

To address the packet loss problem for mesh-based P2P streaming systems, we proposed a peer selection scheme involving estimation of packet loss propagation, evaluation of peers' contributions, and sender-driven peer selection based on child-peers' contributions. The proposed packet loss propagation model took into account the link conditions, peer dynamics, and FEC protection capacity so as to achieve accurate estimation. We also showed that the packet loss propagation in a mesh-based P2P network can be modeled by MRFs. As a result, in the peer selection process, the packet loss reduction gain of a candidate child-peer can be well approximated with that estimated by taking into account a small number of neighboring descendants of the peer, rather than considering all affected descendants, thereby reducing estimation complexity significantly. Our experimental results showed that the proposed error propagation model achieved good estimation accuracy and our peer selection scheme significantly outperformed other state-of-the-art schemes.

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Chi-Wen Lo (S'09) received the B.S. and M.S. degrees in electrical engineering from National Taiwan University of Science and Technology, Taipei, Taiwan, in 2004 and 2006, respectively. He has been pursuing the Ph.D. degree with the Department of Electrical Engineering, National Tsing Hua University, Hsinchu, Taiwan, since 2006.

His current research interests include video coding and video streaming.



Chia-Wen Lin (S'94–M'00–SM'04) received the Ph.D. degree in electrical engineering from National Tsing Hua University (NTHU), Hsinchu, Taiwan, in 2000.

He is currently an Associate Professor with the Department of Electrical Engineering and the Institute of Communications Engineering, NTHU. He was with the Department of Computer Science and Information Engineering, National Chung Cheng University, Chiayi, Taiwan, from 2000 to 2007.

Prior to joining academia, he was with Information and Communications Research Laboratories, Industrial Technology Research Institute, Hsinchu, from 1992 to 2000. His current research interests include video content analysis and video networking.

Dr. Lin is an Associate Editor of the *IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY*, the *IEEE TRANSACTIONS ON MULTIMEDIA*, and the *Journal of Visual Communication and Image Representation*. He is also an Area Editor of *EURASIP Signal Processing: Image Communication*. He served as the Technical Program Co-Chair of the IEEE International Conference on Multimedia and Expo (ICME) in 2010, and as the Special Session Co-Chair of the IEEE ICME in 2009. He was a recipient of the 2001 Ph.D. Thesis Award presented by the Ministry of Education, Taiwan. His paper won the Young Investigator Award presented by SPIE VCIP in 2005. He received the Young Faculty Award presented by CCU in 2005 and the Young Investigator Award presented by the National Science Council, Taiwan, in 2006.



Yung-Chang Chen (F'05) received the B.S.E.E. and M.S.E.E. degrees from National Taiwan University, Taipei, Taiwan, in 1968 and 1970, respectively, and the Dr.Eng. degree from Technische Universität Berlin, Berlin, Germany, in 1978.

He has been with the Department of Electrical Engineering, National Tsing Hua University (NTHU), Hsinchu, Taiwan, since 1978, where he is currently a Professor. He has served as the founding Chairman of the Department of Electrical Engineering, National Central University, Chungli, Taiwan, from

1980 to 1983. He served as the Chairman of the Department of Electrical Engineering, NTHU, from 1992 to 1994. He also served as the Dean of the College of Engineering, National Chung Cheng University, Chiayi, Taiwan, from February 2002 to July 2003.

Dr. Chen received the Outstanding Research Award from the National Science Council from 1991 to 1994, the Outstanding Electrical Engineering Professor Award from the Chinese Institute of Electrical Engineers in 2000, and the Industrial Collaboration Award from the Ministry of Education in 2001. He was the General Chair of the 2002 IEEE Pacific-Rim Conference on Multimedia and the IEEE Pacific-Rim Symposium on Image and Video Technology in December 2006.



Jen-Yu Yu received the B.S. and M.S. degrees in computer science from National Chiao Tung University, Hsinchu, Taiwan, in 2000 and 2002, respectively.

He joined Information and Communications Research Laboratories, Industrial Technology Research Institute, Hsinchu, in 2003, where he is currently the Deputy Division Director of the Network-Based Services Technology Division. His current research interests include mobile video streaming, distributed multimedia systems, video surveillance, and video

compression.