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Jointly optimized congestion control, forwarding strategy, and link scheduling in a named-data multihop wireless network*

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Abstract: As a promising future network architecture, named data networking (NDN) has been widely considered as a very appropriate network protocol for the multihop wireless network (MWN). In named-data MWNs, congestion control is a critical issue. Independent optimization for congestion control may cause severe performance degradation if it can not cooperate well with protocols in other layers. Cross-layer congestion control is a potential method to enhance performance. There have been many cross-layer congestion control mechanisms for MWN with Internet Protocol (IP). However, these cross-layer mechanisms for MWNs with IP are not applicable to named-data MWNs because the communication characteristics of NDN are different from those of IP. In this paper, we study the joint congestion control, forwarding strategy, and link scheduling problem for named-data MWNs. The problem is modeled as a network utility maximization (NUM) problem. Based on the approximate subgradient algorithm, we propose an algorithm called 'jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS)' to solve the NUM problem distributively and iteratively. To the best of our knowledge, our proposal is the first cross-layer congestion control mechanism for named-data MWNs. By comparison with the existing congestion control mechanism, JOCFS can achieve a better performance in terms of network throughput, fairness, and the pending interest table (PIT) size.

Key words: Information-centric networking; Congestion control; Cross-layer design; Multihop wireless network
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1 Introduction

Named data networking (NDN) (Zhang L *et al.*, 2014), which is funded by the US Future Internet Architecture Program, is a pioneering fully fledged information-centric networking (ICN) (Xylomenos *et al.*, 2014) architecture. NDN changes the meaning of network services from 'delivering packets to a specific destination address' to 'fetching data identified by a specific name'. Based on content-oriented routing and pervasive in-network caching, NDN improves the quality of service (QoS) of users and alleviates congestion.

Due to the characteristics of NDN, using the NDN communication protocol in multihop wireless

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networks (MWNs) (which contain a lot of specific application scenarios, including the ad hoc network, wireless mesh network (WMN), vehicular ad hoc network (VANET), and wireless sensor network (WSN)) has been attracting a lot of attention (Meisel *et al.*, 2010; Amadeo *et al.*, 2012; 2013; 2015; Etefia *et al.*, 2012; Wang *et al.*, 2012; Grassi *et al.*, 2014; 2015) in recent years. These studies have demonstrated the advantages of NDN, compared with Internet Protocol (IP) for building MWN. We call a MWN built with NDN a 'named-data MWN' in this paper.

Named-data MWN has the following advantages (Meisel *et al.*, 2010): First, the demand on link bandwidth resources can be reduced effectively because of NDN's content-oriented routing and in-network caching. Second, routing algorithms of IP cause enormous overheads, which are largely reduced by using NDN. Third, NDN improves the resistance of MWN to the mobility problem because of content-oriented routing, in-network caching, and dynamic multi-path forwarding. Last but not the least, the security of named-data MWNs is based on information objects instead of vulnerable wireless channels.

However, in named-data MWNs, congestion control is still a critical issue. This is because link bandwidth is a scarce resource in the network, leading to small capacities of wireless links according to the Shannon theory. If receivers/providers cannot control the sending rates of Interest/Data to adapt to the congestion status, the network will be stuck in resource exhaust and more serious congestion, leading to a deteriorated QoS.

However, there are few studies about congestion/transport control in named-data MWNs (Amadeo *et al.*, 2013; 2014; Zhang *et al.*, 2013). Amadeo *et al.* (2013) proposed a multi-layer mechanism, called the 'enhanced-content-centric multi-hop wireless network (E-CHANET)', for named-data MWNs. It consists of routing, forwarding, mobility handler, and transport function. The transport function of E-CHANET takes advantage of a sustainable transmission rate of Data packets at the bottleneck node, and the inter Data gap at the content receiver to determine the sending rate of Interest by the receiver. Amadeo *et al.* (2014) proposed a self-regulating interest rate control (SIRC) scheme to address flow control and congestion control. This scheme uses inter-arrival times of Data packets to regulate the sending rate and pace of Interest packets at the receiver side. Zhang *et al.* (2013) used ORBIT, which is an open access platform, to evaluate the chunk-switched hop pull control protocol (CHoPCoP) over wireless networks. CHoPCoP (Zhang F *et al.*, 2014) uses explicit congestion control to cope with the multiple-source, multiple-path situation of NDN.

Although some research has been conducted for congestion control in named-data MWNs, there has not been a cross-layer congestion control to our best knowledge. Independently optimizing congestion control usually degrades the performance of the network.

Existing network protocols operate independently at each layer of the network stack. When these protocols can not cooperate well, layered methodology may cause severe performance degradation. Because interference and multiple access at the physical and medium access control (MAC) layers affect the forwarding strategy and the congestion control performed at forwarding and content layers, this performance degradation is common in named-data MWNs (Laufer *et al.*, 2014).

In the literature about congestion control for MWNs with IP, many studies have verified the advantages of cross-layer optimization, involving congestion control, routing, MAC, and power control (Lin and Shroff, 2004; Ding and Wu, 2013; Ghaderi *et al.*, 2014; Laufer *et al.*, 2014; Qu *et al.*, 2015; Stai *et al.*, 2015).

However, these cross-layer congestion control mechanisms for MWNs with IP cannot be applied to named-data MWNs, because of the following important observations about NDN: (1) There is a 'flow balance' over every bidirectional link—an Interest packet forwarded over a bidirectional link in some direction will trigger a Data packet forwarded by the same bidirectional link in the reverse direction (Li *et al.*, 2015). (2) Bandwidth in named-data MWNs is so scarce that traffic caused by both the Interest and Data should be considered. (3) Different Interest packets of one flow (in this study, we use terminology 'flow' to represent one content retrieval process, different from the 'flow' in MWNs with IP) can be forwarded through dynamic multiple paths.

Enlightened by cross-layer congestion control for MWNs with IP, cross-layer congestion control in named-data MWNs may be a potential solution to enhance the throughput of the network and to improve the efficiency of resource utilization. Therefore, in this study we study the cross-layer design for congestion control, forwarding strategy, and link scheduling for named-data MWNs. We propose an iterative and distributed algorithm named 'jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS)', which jointly optimizes (1) the sending rates of Interest/Data by receivers/providers, (2) selection of Interest/Data to forward over activated links, and (3) the link activation time.

The contributions of this study are listed as follows:

1. First, we study the communication characteristics of named-data MWNs and model the JOCFS problem as a network utility maximization (NUM) problem that aims at enhancing the overall network utility and stabilizing the network.

2. By the Lagrangian relaxation and dual decomposition, we obtain two subproblems to prepare for calculating the approximate subgradient of the dual function. Enlightened by the approximate subgradient algorithm to solve the dual problem (Mijangos, 2006), we propose an iterative algorithm called 'JOCFS' to solve the NUM problem.

3. One of two subproblems, the joint scheduling and forwarding problem (JSFP), is distinct from the link scheduling and routing problem for MWNs with IP. JSFP is additionally constrained by constraints that are related to the 'flow balance' stated above. Because of these additional constraints, the traditional maximum weight matching (MWM) algorithm cannot be applied directly. To overcome this difficulty, we adopt the Lyapunov optimization (Georgiadis *et al.*, 2006) and introduce a class of virtual queues (Neely *et al.*, 2008; Stai and Papavassiliou, 2014) to transform JSFP to multiple MWM problems.

4. After proposing JOCFS, we analyze the convergence of JOCFS and prove that it can converge to the optimal solution of the NUM problem. Moreover, we discuss the distributed implementation of JOCFS.

5. We compare JOCFS with the existing congestion control mechanism by simulation. We find that JOCFS outperforms the existing congestion control mechanism in terms of network throughput, fairness, and the pending interest table (PIT) size.

2 Communication process of the named-data multihop wireless network

There are mainly two types of packets in named-data MWNs: Interest packets and Data packets. The communication process begins from the application of the content receiver sending an Interest packet to retrieve the corresponding Data packet (content chunk). The Interest packet is forwarded by intermediate nodes in the network toward potentially multiple content providers. When the Interest packet arrives at a node that has the solicited Data packet, the Data packet is sent back by the application of this node in response to the Interest packet along the same path in the reverse direction.

The forwarding strategy of a node chooses a neighbor node from the forwarding information base (FIB) entry, and the node forwards a specific Interest packet to this neighbor node. A node forwards a Data packet to the neighbor node from which it receives the corresponding Interest packet (according to the information in PIT). Forwarding a packet to some node is equivalent to forwarding it over a corresponding link. Thus, we use the term 'forward a packet over a link' to represent 'forward a packet to a corresponding node' in this paper.

Due to the communication mechanism of named-data MWNs, over each bidirectional link, there is an interesting and important 'flow balance' between Interest and Data packets. Specifically, if an Interest packet is forwarded over a bidirectional link in the upstream direction (i.e., from the content receiver to the content provider), a corresponding Data packet should be forwarded over the same bidirectional link in the downstream direction (i.e., from the content provider to the content receiver). For instance, as shown in Fig. 1, there is a node h fetching contents from node k with nodes i and j on the path. In this scenario, the number of the Interest packets forwarded over link (i, j) (where i is the transmitting node and j is the receiving node) is approximately equal to that of the Data packets forwarded over link (j, i).

Inspired by the above observation, Yi *et al.* (2013) set a forwarding rate limit of Interest by intermediate nodes to control the traffic caused by Data. Assume that in Fig. 1, the capacity of link (j, i) is $C_{(j,i)}$, and the average size of Data packets over link

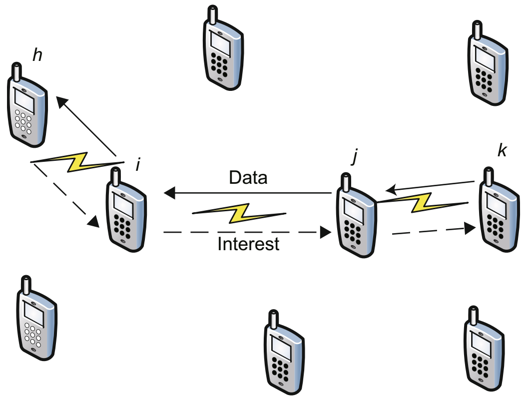

Fig. 1 Flow balance on a bidirectional link between nodes *i* and *j*

(j,i) is S. To avoid congestion over link (j,i), the forwarding rate limit of Interest over link (i,j) should be $L_{(i,j)} = \alpha C_{(j,i)}/S$, where α is a parameter that accounts for the traffic caused by Interest over link (j,i) and the deviation of Data size estimation. We agree with Yi *et al.* (2013) and study the traffic between two nodes in more detail.

The size of Data is usually much larger than that of the Interest; thus, the traffic caused by Interest can be ignorable in some scenarios for convenience. However, as for some applications, the content name field of Interest is so long (Jacobson *et al.*, 2009; Wang *et al.*, 2013) that the traffic caused by Interest cannot be ignored. In addition, capacities of the links are usually small in named-data MWNs; thus, it is appropriate to take the capacity consumed by Interest into consideration.

In fact, there are usually Interest and Data packets of different flows forwarded over a link, i.e., link (i,j). To avoid congestion, the sum of all the forwarding rates of Interest and Data over this link should be equal to or smaller than its capacity. In named-data MWNs, the capacity of a link is related to physical factors and link scheduling, i.e., transmitting power, coding, and activation time.

3 System model

3.1 Network model and notations

We consider a named-data MWN with node set N. Let L denote the set of links.

Link scheduling determines which set of noninterfering links is going to transmit at each time slot (Stai *et al.*, 2016). We assume that when activated, the link's transmitting power is fixed. Links that interfere with each other cannot transmit Interest/Data simultaneously. Other interference schemes considering the signal-to-interference-plus-noise ratio (SINR) threshold can also be considered, and JOCFS is easily adapted to these schemes.

In this study, let I_M denote the finite set that has the following elements: maximum sets of links that do not interfere with each other. $I^1, I^2, ..., I^m$ denote the elements (maximum sets of noninterfering links) included in I_M. Link scheduling chooses the set of links $I(t) \in I_M$ to activate at slot t. If link $(i,j) \in I(t)$, then $r_{(i,j)}(t) = r_{(i,j)}^{\max}$, where $r_{(i,j)}^{\max}$ is the transmitting rate of link (i,j) when activated. If $\pi_1, \pi_2, ..., \pi_m$ are the fractions of time for which $I^1, I^2, ..., I^m$ are activated ($\sum\limits_{n=1}^{m} \pi_n = 1$), respectively, then the long-term transmission rate of link (i,j) is (Stai *et al.*, 2016)

$$r_{(i,j)} = \sum_{n:(i,j)\in I^n} r_{(i,j)}^{\max} \pi_n. \quad (1)$$

Let $\boldsymbol{r}^n$ $(n = 1, 2, ..., m)$ denote L-dimensional vectors which represent the transmission rates of all the links when link scheduling chooses $I^n \in I_M$. Let R denote the set consisting of $\boldsymbol{r}^1, \boldsymbol{r}^2, ..., \boldsymbol{r}^m$. Co$(R)$ represents the convex hull of R. It is apparent that any L-dimensional vector which represents the long-term transmission rates of all the links ($\boldsymbol{r} \in \text{Co}(R)$) can be achieved by scheduling links.

The set of all the flows in the network is F, and each flow $f \in F$ has a content receiver set $b(f)$ (with one receiver) and a content providers set $e(f)$ (with potentially many providers). Let x^{fI} (bit/s) be the sending rate of Interest by application of the receiver $i \in b(f)$. x_i^{fD} (bit/s) denotes the sending rate of Data by application of a provider $(i \in e(f))$. a_f denotes the Data-to-Interest packet size ratio of flow f. Each flow has a utility function $U_f(\sum_{i\in e(f)} x_i^{fD})$, which represents the utility of flow f when its whole sending rate of Data is $\sum_{i\in e(f)} x_i^{fD}$. We assume that $U_f(\cdot)$ is strictly concave, non-decreasing, and continuously differentiable, which is a widely adopted assumption for elastic applications (Kelly, 1997; Lin and Shroff, 2004).

In NDN, there are FIB entries in every node which provide possible next-hop nodes for the forwarding strategy (Yi *et al.*, 2014). Specifically, an FIB entry of a flow has all the possible next-hop nodes for Interest of this flow. Recall that we use term 'flow' to denote a content retrieval process. Let $R(f,i)$ denote the set of possible next-hop nodes for Interest of flow f at node i; i.e., node i can forward Interest packets of flow f to a node $j \in R(f,i)$ over link (i,j). At each time slot t, JOCFS's link scheduling module activates an independent set of links, and the forwarding strategy module selects Interest or Data packets from all the flows to forward over these activated links.

We assume that there are queues that contain Interest or Data packets waiting for forwarding, and that each node has two queues of Interest and Data for each flow, which are both reasonable assumptions according to Oueslati *et al.* (2012). Interest packets in the queue of some node i for some flow f contain two parts: packets from application (if node i is the receiver of flow f) and other nodes. Data packets in the queue of some node i and for some flow f contain two parts: packets from the application (if node i is a provider of flow f) and other nodes. Given an Interest sending rates vector $\boldsymbol{x}^I = [x^{fI}, f \in F]$ (from application) and Data sending rates vector $\boldsymbol{x}^D = [x_i^{fD}, f \in F, i \in e(f)]$ (from application), we say that the network is stable under some forwarding strategy and link scheduling policy if lengths of Interest queues and Data queues at each node remain finite. Let $\boldsymbol{x}$ denote the vector whose components are all the components of $\boldsymbol{x}^I$ and $\boldsymbol{x}^D$, i.e., $\boldsymbol{x} = [\boldsymbol{x}^I, \boldsymbol{x}^D]$. We define the capacity region Λ of a named-data MWN as the largest set of sending rate vector $\boldsymbol{x}$, such that if $\boldsymbol{x} \in \Lambda$, there are some possible forwarding strategy and link scheduling policy that can stabilize the network (the network is stable).

For ease of exposition, we list the main notations in Table 1.

Table 1 Notations

Symbol	Definition
R	The set that consists of $\boldsymbol{r}^1, \boldsymbol{r}^2, ..., \boldsymbol{r}^m$
$\mathrm{Co}(R)$	Convex hull of R
x^{fI}	Sending rate of Interest of flow f by application of content receiver $i \in b(f)$
$\boldsymbol{x}^I$	The vector whose components are all the x^{fI}
x_i^{fD}	Sending rate of Data of flow f by application of content provider $i \in e(f)$
$\boldsymbol{x}^D$	The vector whose components are all the x_i^{fD}
$\boldsymbol{x}$	The vector whose components are all the components of $\boldsymbol{x}^I$ and $\boldsymbol{x}^D$
Λ	Capacity region
y_i^{fD}	Auxiliary variable corresponding to x_i^{fD}
$\boldsymbol{y}$	The vector whose components are all the auxiliary variables y_i^{fD}
$\mu_{(i,j)}^{fI}$	Forwarding rate of Interest of flow f over link (i,j)
$\boldsymbol{\mu}^I$	The vector whose components are all the $\mu_{(i,j)}^{fI}$
$\mu_{(i,j)}^{fD}$	Forwarding rate of Data of flow f over link (i,j)
$\boldsymbol{\mu}^D$	The vector whose components are all the $\mu_{(i,j)}^{fD}$
$\lambda_{i,f}^I$	The Lagrangian multiplier associated with inequality (11) corresponding to node i and flow f
$\lambda_{i,f}^D$	The Lagrangian multiplier associated with problem (12) corresponding to node i and flow f
$\boldsymbol{\lambda}$	The vector whose components are all the $\lambda_{i,f}^I$ and $\lambda_{i,f}^D$
$R(f,i)$	The set of possible next-hop nodes for Interest of flow f at node i
$U_f(\cdot)$	Utility function of flow f
E_k	The bound of difference between the objective value of JSFP obtained by Algorithm 1 and the optimal one for iteration k of JOCFS

JOCFS: jointly optimized congestion control, forwarding strategy, and link scheduling; JSFP: joint scheduling and forwarding problem

3.2 Architecture of jointly optimized congestion control, forwarding strategy, and link scheduling

Fig. 2 shows the relationship between JOCFS and NDN protocol stack. JOCFS involves three functional modules of NDN: congestion control function of content receivers and providers, forwarding strategy of nodes, and link scheduling of the network.

Specifically, JOCFS decides the following: (1) sending rates of Interest/Data by applications of

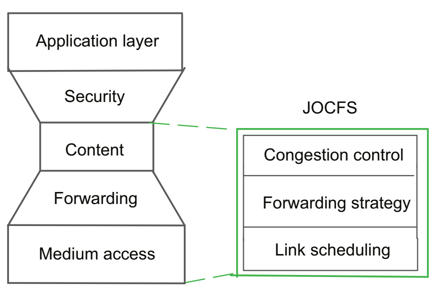

Fig. 2 Mapping jointly optimized congestion control, forwarding strategy, and link scheduling over a generic named-data networking protocol stack

receivers/providers, (2) choosing Interest/Data to forward over activated links, and (3) activation time of the link. These decisions correspond to congestion control, forwarding strategy, and link scheduling, respectively.

4 Problem formulation and decomposition

4.1 Network utility maximization formulation

The idea of various NUM modelings is to maximize the whole network utility as well as to satisfy some constraints. An initial formulation of our NUM problem is

$$\max_{\boldsymbol{x}^D \succeq 0} \quad \sum_{f\in F} U_f \sum_{i\in e(f)} x_i^{fD} \tag{2}$$

$$\text{s.t.} \quad \boldsymbol{x} \in \Lambda, \tag{3}$$

$$\forall f \in F: \sum_{i\in e(f)} x_i^{fD} = a_f x^{fI}, \tag{4}$$

where $\succeq$ denotes the generalized inequality (i.e., every component of one vector is larger than or equal to the respective component of the other vector). Constraint (3) ensures that by finding some appropriate forwarding strategy and link scheduling policy, named-data MWNs can be stabilized. Constraint (4) holds because one Interest packet sent by application of the receiver pulls back one Data packet (maybe from multiple providers) in named-data MWNs, and the Data-to-Interest packet size ratio of flow f is a_f. The receiver of a flow can take advantage of many providers to retrieve Data.

Next we describe capacity region Λ formally. We adopt a 'node-centric' way similar to Lin and Shroff (2004). Differently, we take into consideration additional constraints because of NDN's communication pattern. The following inequalities describe constraints related to Λ:

$$\begin{aligned}&\forall f \in F,\ i \notin e(f):\\ &x^{fI} I_{\{i\in b(f)\}} + \sum_{j:i\in R(f,j)} \mu_{(j,i)}^{fI} \le \sum_{j\in R(f,i)} \mu_{(i,j)}^{fI},\end{aligned} \tag{5}$$

$$\begin{aligned}&\forall f \in F, i \notin b(f):\\ &x_i^{fD} I_{\{i\in e(f)\}} + \sum_{j\in R(f,i)} \mu_{(j,i)}^{fD} \le \sum_{j:i\in R(f,j)} \mu_{(i,j)}^{fD},\end{aligned} \tag{6}$$

$$\begin{aligned}&\forall f \in F, \forall (i,j): j \in R(f,i):\\ &\qquad a_f \mu_{(i,j)}^{fI} \le \mu_{(j,i)}^{fD},\end{aligned} \tag{7}$$

$$\sum_{f\in F} (\mu_{(i,j)}^{fI} + \mu_{(i,j)}^{fD}) \in \mathrm{Co}(R), \tag{8}$$

where $I_{\{a\in A\}}$ is an indicator function which equals 1 if $a \in A$ and 0 otherwise, and $\mu_{(i,j)}^{fI}$ and $\mu_{(i,j)}^{fD}$ represent the forwarding rate of Interest and Data of flow f over link (i,j), respectively.

Constraint (5) is for stability of queues of Interest packets. Rate of Interest forwarded to node i from other nodes ($\sum_{j:i\in R(f,j)} \mu_{(j,i)}^{fI}$) plus rate of Interest sent by application (x^{fI}) (if node i is the receiver) should be equal to or less than the rate of Interest forwarded out of node i to other nodes ($\sum_{j\in R(f,i)} \mu_{(i,j)}^{fI}$). The exception is content providers because Interest packets are satisfied by these nodes. Constraint (6) is for stability of queues of Data packets. Rate of Data forwarded to node i from other nodes ($\sum_{j\in R(f,i)} \mu_{(j,i)}^{fD}$) plus rate of Data sent by application x_i^{fD} (if i is a provider) should be equal to or less than the rate of Data forwarded out of node i to other nodes $\sum_{j:i\in R(f,j)} \mu_{(i,j)}^{fD}$. The exception is content receivers because Data packets are received by these nodes. Constraint (7) is due to the 'flow balance' between Interest and Data over a bidirectional link, as described in Section 2. The forwarding rate (packets per second) of Interest of flow f over link (i,j) should be controlled under the forwarding rate (packets per second) of Data of the same flow over link (j,i) to avoid excess Interest packets occupying the capacity of link (i,j) and PIT's overgrowth. Constraint (8) ensures that the sum of capacity demanded by Interest and Data of all the flows can be provided by scheduling links.

There are mainly two differences between our described capacity region and that of MWNs with IP. First, the capacity consumption can be divided into two kinds: Interest and Data forwarding. Both Interest and Data contribute to the traffic in named-data MWNs. This is different from MWNs with IP. Second, Interest and Data forwarding has a unique relationship (inequality (7)), which affects link scheduling a lot, as will be shown in Section 5.1.

In the following we present our NUM problem formally. We call this problem 'P1', described as

$$\mathrm{P1}: \max_{\boldsymbol{x}^D \succeq 0} \quad \sum_{f\in F} U_f \sum_{i\in e(f)} x_i^{fD} \tag{9}$$

$$\text{s.t.} \quad \text{constraints (4), (7), and (8),} \tag{10}$$

$$\forall f \in F, i \notin e(f):$$
$$\sum_{j \in R(f,i)} \mu_{(i,j)}^{fI} - x^{fI} I_{\{i \in b(f)\}} - \sum_{j: i \in R(f,j)} \mu_{(j,i)}^{fI} \geq 0, \tag{11}$$

$$\forall f \in F, i \notin b(f):$$
$$\sum_{j: i \in R(f,j)} \mu_{(i,j)}^{fD} - x_i^{fD} I_{\{i \in e(f)\}} - \sum_{j \in R(f,i)} \mu_{(j,i)}^{fD} \geq 0. \tag{12}$$

Let $\boldsymbol{\mu}^I$ and $\boldsymbol{\mu}^D$ denote the vectors whose components are all the $\mu_{(i,j)}^{fI}$ and $\mu_{(i,j)}^{fD}$, respectively.

Next, we analyze convexity and strong duality of P1. Since $U_f(\cdot)$ is strictly concave, objective function (9) is concave (not strictly) with respect to $\boldsymbol{x}^D$ (Lin and Shroff, 2004). Constraints (4), (7), (11), and (12) are linear inequality or equality constraints. Constraint (8) implicitly demands that $\boldsymbol{\mu}^I$ and $\boldsymbol{\mu}^D$ should be in a convex set (Boyd and Vandenberghe, 2009). Thus, P1 is a convex problem. On the other hand, it is easy to see that P1 satisfies Slater's condition. Thus, P1 has a strong duality, and the optimal objective value of P1 is equivalent to that of its dual problem.

4.2 Problem decomposition

To decompose P1 into subproblems of different protocol layers, we associate a Lagrangian multiplier $\lambda_{i,f}^I$ with constraint (11), and $\lambda_{i,f}^D$ with constraint (12). We assume $\lambda_{i,f}^I = 0$ if $i \in e(f)$, and $\lambda_{i,f}^D = 0$ if $i \in b(f)$. We use $\boldsymbol{\lambda}$ to denote the vector whose components are all the $\lambda_{i,f}^I$ and $\lambda_{i,f}^D$. Then the Lagrangian multiplier of P1 is

$$\begin{aligned} L(\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}) &= \sum_{f \in F} U_f\Big(\sum_{i \in e(f)} x_i^{fD}\Big) \\ &+ \sum_{f \in F} \sum_{i \notin e(f)} \Bigg[\sum_{j \in R(f,i)} \mu_{(i,j)}^{fI} - \sum_{j: i \in R(f,j)} \mu_{(j,i)}^{fI} - x^{fI} I_{\{i \in b(f)\}} \Bigg] \lambda_{i,f}^I \\ &+ \sum_{f \in F} \sum_{i \notin b(f)} \Bigg[\sum_{j: i \in R(f,j)} \mu_{(i,j)}^{fD} - \sum_{j \in R(f,i)} \mu_{(j,i)}^{fD} - x_i^{fD} I_{\{i \in e(f)\}} \Bigg] \lambda_{i,f}^D. \end{aligned} \tag{13}$$

By some polynomial calculation such as combining similar terms, the right-hand side of Eq. (13) can be transformed into

$$\sum_{f \in F} \Bigg[U_f \sum_{i \in e(f)} x_i^{fD} - \lambda_{b(f),f}^I x^{fI} - \sum_{i \in e(f)} \lambda_{i,f}^D x_i^{fD} \Bigg] \tag{14}$$

$$+ \sum_{f \in F} \sum_{i \in N} \sum_{j \in R(f,i)} (\lambda_{i,f}^I - \lambda_{j,f}^I) \mu_{(i,j)}^{fI} \tag{15}$$

$$+ \sum_{f \in F} \sum_{i \in N} \sum_{j: i \in R(f,j)} (\lambda_{i,f}^D - \lambda_{j,f}^D) \mu_{(i,j)}^{fD} \tag{16}$$

$$\text{s.t.} \quad \text{constraints (4), (7), and (8).} \tag{17}$$

For ease of exposition, let $\phi(\boldsymbol{x}; \boldsymbol{\lambda})$ represent component (14) and $\psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda})$ the sum of components (15) and (16). Thus, the dual function $D(\boldsymbol{x})$ is as follows:

$$\begin{aligned} &\max_{\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D \succeq 0} \ \phi(\boldsymbol{x}; \boldsymbol{\lambda}) + \psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}) \\ &\text{s.t.} \quad \text{constraints (4), (7), and (8).} \end{aligned} \tag{18}$$

$D(\boldsymbol{x})$ can be decomposed into two parts, flow control problem (FCP) and JSFP:

$$\begin{aligned} &\text{FCP} : \max_{\boldsymbol{x} \succeq 0} \quad \phi(\boldsymbol{x}; \boldsymbol{\mu}) \\ &\text{s.t.} \quad \text{constraint (4).} \end{aligned} \tag{19}$$

$$\begin{aligned} &\text{JSFP} : \max_{\boldsymbol{\mu}^I, \boldsymbol{\mu}^D \succeq 0} \quad \psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}) \\ &\text{s.t. constraints (7)and (8).} \end{aligned} \tag{20}$$

Remark FCP and JSFP are similar to subproblems of MWNs with IP (Lin and Shroff, 2004). There are mainly two differences between our decomposition and that of MWNs with IP. First, FCP is related to sending rate control of both Interest and Data. Moreover, it is subject to constraint (4). Second, JSFP is related to the forwarding strategy and link scheduling, which is additionally subject to links' flow balance constraint (7). These additional constraints make the traditional MWM algorithm (Tassiulas and Ephremides, 1992; Lin and Shroff, 2004) improper for this subproblem.

5 Approximate subgradient of the dual function

We propose JOCFS to solve P1 based on the iterative approximate subgradient method (Mijangos, 2006). We add a superscript (or subscript) k to a variable (or parameter) to represent the value of this variable (or parameter) at iteration k of JOCFS.

In every iteration k, JOCFS first uses $\boldsymbol{\lambda}^k$ to calculate the sending rates of Interest and Data (denoted as $\boldsymbol{x}^{Ik}$ and $\boldsymbol{x}^{Dk}$, respectively), and decide the forwarding rates of Interest and Data (denoted as $\boldsymbol{\mu}^{Ik}$ and $\boldsymbol{\mu}^{Dk}$, respectively). Then JOCFS uses all the $\boldsymbol{x}^{Ik}$, $\boldsymbol{x}^{Dk}$, $\boldsymbol{\mu}^{Ik}$, and $\boldsymbol{\mu}^{Dk}$ to obtain the approximate subgradient of the dual function. At the end of every iteration k, JOCFS updates Lagrangian multipliers $\boldsymbol{\lambda}^k$. The details of JOCFS will be presented in Section 6. In every iteration k of JOCFS, we require $\boldsymbol{x}^{Ik}$, $\boldsymbol{x}^{Dk}$, $\boldsymbol{\mu}^{Ik}$, and $\boldsymbol{\mu}^{Dk}$ to calculate the approximate subgradient of $D(\boldsymbol{x})$ at $\boldsymbol{\lambda}^k$. Thus, we need to solve FCP and JSFP in every iteration k of JOCFS to obtain those variables. In Sections 5.1 and 5.2, all the variables (or parameters) have the values of them at iteration k of JOCFS; thus, we omit superscript (or subscript) k for ease of exposition.

5.1 Solution to the joint scheduling and forwarding problem

In the following, based on the Lyapunov optimization approach in Georgiadis *et al.* (2006), we propose Algorithm 1 to solve JSFP. Assume a virtual discrete time queueing system that is related to constraint (7), with vector backlog process $\boldsymbol{P}(t) = \left\{P^f_{(i,j)}(t),\ \forall f \in F, \forall i \in N, \forall j \in R(f,i)\right\}$. We call this class of queues 'V-Queue' in this study. Forwarding rates vector processes of Interest and Data (denoted as $\boldsymbol{\mu}^I(t)$ and $\boldsymbol{\mu}^D(t)$, respectively) influence the V-Queue dynamics as follows:

$$P^f_{(i,j)}(t+1) = \max\left[P^f_{(i,j)}(t) - \mu^{fD}_{(j,i)}(t), 0\right] + a_f \mu^{fI}_{(i,j)}(t), \tag{21}$$

where $\mu^{fI}_{(i,j)}(t)$ (or $\mu^{fD}_{(i,j)}(t)$) is the forwarding rate of Interest (or Data) of flow f over link (i,j) at time slot t, $\mu^{fI}_{(i,j)}(t)$ (or $\mu^{fD}_{(i,j)}(t)$) is a component of $\boldsymbol{\mu}^I(t)$ (or $\boldsymbol{\mu}^D(t)$), and Eq. (21) is constructed to make Algorithm 1 satisfy constraint (7). If V-Queues are stabilized, then constraint (7) is satisfied (Neely, 2010).

Remark (on Algorithm 1) (1) Step 3 of Algorithm 1 is actually a MWM problem, which can be solved by many methods (Bayati *et al.*, 2005; 2008; Sharma *et al.*, 2006). Hence, we do not focus on algorithms of solving MWM in this study. (2) Algorithm 1 is the 'subalgorithm' of JOCFS. Specifically, Algorithm 1 runs during every iteration k of JOCFS.

Algorithm 1 Joint forwarding strategy and link scheduling

Input: Lagrangian multipliers $\boldsymbol{\lambda}$; $V > 0$. Set all the $P^f_{(i,j)}(0) = 0$.
During every time slot $t = 0, 1, ..., M-1$, for every link $(i,j) \in L$, do the following:

1: For all f's that satisfy $j \in R(f,i)$:

$$\omega^{fI}_{(i,j)}(t) = V(\lambda^I_{i,f} - \lambda^I_{j,f}) - a_f P^f_{(i,j)}(t), \tag{22}$$

For all f's that satisfy $i \in R(f,j)$:

$$\omega^{fD}_{(i,j)}(t) = V(\lambda^D_{i,f} - \lambda^D_{j,f}) + P^f_{(j,i)}(t). \tag{23}$$

2: Choose $\omega^{I*}_{(i,j)}(t)$, $\omega^{D*}_{(i,j)}(t)$, $f^I_{(i,j)}(t)$, and $f^D_{(i,j)}(t)$ as follows:

$$\begin{cases} \omega^{I*}_{(i,j)}(t) = \max\limits_{f: j \in R(f,i)} \omega^{fI}_{(i,j)}(t), \\ \omega^{D*}_{(i,j)}(t) = \max\limits_{f: i \in R(f,j)} \omega^{fD}_{(i,j)}(t), \\ f^I_{(i,j)}(t) = \arg\max\limits_{f: j \in R(f,i)} \omega^{fI}_{(i,j)}(t), \\ f^D_{(i,j)}(t) = \arg\max\limits_{f: i \in R(f,j)} \omega^{fD}_{(i,j)}(t). \end{cases} \tag{24}$$

3: Assign weight $\omega_{(i,j)}(t)$ to link (i,j) as follows:

$$\omega_{(i,j)}(t) = \max\left\{\omega^{I*}_{(i,j)}(t), \omega^{D*}_{(i,j)}(t)\right\}, \tag{25}$$

and schedule links by solving

$$\max_{\boldsymbol{c} \in R} \sum_{(i,j) \in L} \omega_{(i,j)}(t) c_{(i,j)}, \tag{26}$$

where $c_{(i,j)}$ is the transmission rate of link (i,j) when transmission rates vector $\boldsymbol{c}$ is chosen.

4: If $c_{(i,j)} > 0$:
if $\omega^{I*}_{(i,j)}(t) \geq \omega^{D*}_{(i,j)}(t)$, then forward Interest of flow $f^I_{(i,j)}(t)$ over link (i,j) at transmission rate $c_{(i,j)}$ and set $\mu^{fI}_{(i,j)}(t) = c_{(i,j)}$ where $f = f^I_{(i,j)}(t)$;
if $\omega^{D*}_{(i,j)}(t) > \omega^{I*}_{(i,j)}(t)$, forward Data of flow $f^D_{(i,j)}(t)$ over link (i,j) at transmission rate $c_{(i,j)}$ and set $\mu^{fD}_{(i,j)}(t) = c_{(i,j)}$ where $f = f^D_{(i,j)}(t)$.

5: Update $P^f_{(i,j)}(t)$ for all f's satisfying $j \in R(f,i)$ by Eq. (21).

Theorem 1 Given λ, JSFP's objective value attained by Algorithm 1 satisfies

$$\psi(\overline{\boldsymbol{\mu}}^I(M), \overline{\boldsymbol{\mu}}^D(M); \boldsymbol{\lambda}) \geq \psi^*(\boldsymbol{x}) - \frac{B}{V}, \tag{27}$$

where $\overline{\boldsymbol{\mu}}^I(M)$ and $\overline{\boldsymbol{\mu}}^D(M)$ are defined as follows:

$$\begin{cases} \overline{\boldsymbol{\mu}}^I(M) \triangleq \dfrac{1}{M}\sum\limits_{t=0}^{M-1}\boldsymbol{\mu}^I(t), \\ \overline{\boldsymbol{\mu}}^D(M) \triangleq \dfrac{1}{M}\sum\limits_{t=0}^{M-1}\boldsymbol{\mu}^I(t). \end{cases} \tag{28}$$

$\psi^*(\boldsymbol{x})$ is JSFP's optimal objective value given $\boldsymbol{\lambda}$. B is a positive constant that satisfies

$$B \geq \frac{1}{2}\sum_{(i,j),f}\left[\mu_{(j,i)}^{fD}(t)^2 + a_f^2\mu_{(i,j)}^{fI}(t)^2\right] \tag{29}$$

for every time slot $t=0,1,...,M-1$, where $\sum_{(i,j),f}$ is the short form of $\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}$. Constraint (7) is satisfied.

Proof The proof procedure is similar to Theorem 5.1 in Georgiadis *et al.* (2006) (see Appendix A).

From Theorem 1, we can see that Algorithm 1 is in fact a suboptimal joint forwarding strategy and link scheduling algorithm. From the viewpoint of JOCFS, Algorithm 1 approximately solves JSFP in every iteration k of JOCFS. For iteration k of JOCFS, we denote $E_k = B/V_k$ as a bound of difference between JSFP's objective value obtained by Algorithm 1 and its optimal objective value. V_k is a parameter at iteration k of JOCFS. Parameter V of Algorithm 1 is set equal to V_k at iteration k of JOCFS.

5.2 Solution to the flow control problem

Substituting Eq. (4) into $\phi(\boldsymbol{x};\boldsymbol{\lambda})$, FCP can be further transformed as follows:

$$\begin{aligned} &\max_{\boldsymbol{x}^D\succeq 0}\sum_{f\in F}\left[U_f\sum_{i\in e(f)}x_i^{fD} - \lambda_{b(f),f}^I\sum_{i\in e(f)}\frac{x_i^{fD}}{a_f}\right. \\ &\qquad\left.-\sum_{i\in e(f)}\lambda_{i,f}^D x_i^{fD}\right] \\ &=\max_{\boldsymbol{x}^D\succeq 0}\sum_{f\in F}\left[U_f\sum_{i\in e(f)}x_i^{fD}\right. \\ &\qquad\left.-\sum_{i\in e(f)}\left(\frac{\lambda_{b(f),f}^I}{a_f}+\lambda_{i,f}^D\right)x_i^{fD}\right]. \end{aligned} \tag{30}$$

We have assumed that $U_f(\cdot)$ is strictly concave. However, the objective function of problem (30) is not strictly concave in $[x_i^{fD}]$ (Lin and Shroff, 2004). We overcome this problem by using the proximal optimization algorithm (Bertsekas and Tsitsiklis, 1989). We can introduce an auxiliary variable y_i^{fD} for each x_i^{fD}, and problem (30) can be modified to be

$$\begin{aligned} &\min_{\boldsymbol{x}^D\succeq 0,\boldsymbol{y}}\sum_{f\in F}\left[\sum_{i\in e(f)}\left(\frac{\lambda_{b(f),f}^I}{a_f}+\lambda_{i,f}^D\right)x_i^{fD}\right. \\ &\left.-U_f\sum_{i\in e(f)}x_i^{fD}+\frac{1}{2c}\sum_{i\in e(f)}(x_i^{fD}-y_i^{fD})^2\right], \end{aligned} \tag{31}$$

where $\boldsymbol{c}>0$ and $\boldsymbol{y}$ is the vector whose components are all the y_i^{fD}. Now for any fixed $\boldsymbol{y}$, problem (31) is strictly convex with respect to $\boldsymbol{x}^D$, and it is equivalent to problem (30) (with respect to the same optimal objective value and optimal primal variables $\boldsymbol{x}^D$) (Lin and Shroff, 2004).

For every flow f, the aim is to solve

$$\begin{aligned} &\min_{\boldsymbol{x}^{fD}\succeq 0,\boldsymbol{y}^{fD}}\sum_{i\in e(f)}\left(\frac{\lambda_{b(f),f}^I}{a_f}+\lambda_{i,f}^D\right)x_i^{fD}-U_f\sum_{i\in e(f)}x_i^{fD} \\ &\qquad+\frac{1}{2\boldsymbol{c}}\sum_{i\in e(f)}\left(x_i^{fD}-y_i^{fD}\right)^2, \end{aligned} \tag{32}$$

where $\boldsymbol{x}^{fD}$ is the vector whose components are all the x_i^{fD} ($i\in e(f)$) for flow f, and $\boldsymbol{y}^{fD}$ represents the vector whose components are all the y_i^{fD} corresponding to all the components of $\boldsymbol{x}^{fD}$.

Thus, FCP is decomposed into subproblems which are to be solved by every single flow f. To solve problem (32), we adopt an iterative method in Proposition 4.1 of Bertsekas and Tsitsiklis (1989). After x_i^{fD} ($i\in e(f)$) are calculated, x^{fI} is calculated by Eq. (4).

5.3 Calculating the approximate subgradient

We denote the vector form of the left-hand side of inequalities (11) and (12) as $g(\boldsymbol{x},\boldsymbol{\mu}^I,\boldsymbol{\mu}^D)$. $\boldsymbol{x}^k$, $\boldsymbol{\mu}^{Ik}$, and $\boldsymbol{\mu}^{Dk}$ are primal variables and $\boldsymbol{\lambda}^k$ is the Lagrangian multiplier vector at iteration k of JOCFS. We prove that $g(\boldsymbol{x}^k,\boldsymbol{\mu}^{Ik},\boldsymbol{\mu}^{Dk})$ is an E^k-subgradient of $D(\boldsymbol{x})$ at $\boldsymbol{\lambda}^k$ by following a similar procedure in Bertsekas (1999).

Lemma 1 $g(\boldsymbol{x},\boldsymbol{\mu}^I,\boldsymbol{\mu}^D)$ is an E^k-subgradient of $D(\boldsymbol{x})$ at $\boldsymbol{\lambda}^k$.

Proof See Appendix B.

6 Algorithm and implementation

In this section, we describe JOCFS that can solve P1 distributively and iteratively, and then discuss some implementation issues of JOCFS.

6.1 Algorithm for solving P1

We propose Algorithm 2 to solve P1.

Algorithm 2 Jointly optimized congestion control, forwarding strategy, and link scheduling

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Initialize: initial values of Lagrangian multipliers $\boldsymbol{\lambda}^1$, $0.5 < p < 1$, $V_1 = 1$, and $s_1 = s$, where $s > 0$ is a constant.

For every iteration k, do the following:

1: The network runs Algorithm 1 with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^k$ and $V = V_k = k^p$ for M time slots. The network schedules links. The nodes forward Interest/Data according to Algorithm 1.

Assign $\overline{\boldsymbol{\mu}}^I(M)$ and $\overline{\boldsymbol{\mu}}^D(M)$ (attained by Algorithm 1) to $\boldsymbol{\mu}^{Ik}$ and $\boldsymbol{\mu}^{Dk}$, respectively.

2: For every flow f, solve problem (32) with $\boldsymbol{\lambda}^I_{b(f),f} = \boldsymbol{\lambda}^{Ik}_{b(f),f}$ and $\boldsymbol{\lambda}^D_{i,f} = \boldsymbol{\lambda}^{Dk}_{i,f}$ $(i \in e(f))$ by the method described in Section 5.2 and obtain x_i^{fDk} $(i \in e(f))$. Then calculate x^{fIk} by Eq. (4).

3: Update $\boldsymbol{\lambda}^k$ by

$$\boldsymbol{\lambda}^{k+1} = [\boldsymbol{\lambda}^k - s_k g(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk})]^+, \tag{33}$$

where $s_k = s/k^p$, and $[\cdot]^+$ denotes projection on positive orthant.

JOCFS is an iterative algorithm with iterations indexed by k. There are M time slots in every iteration of JOCFS. In other words, JOCFS updates $\boldsymbol{\lambda}^k$ per M slots. From Lemma 1 we see that steps 1 and 2 of every iteration k are to calculate $(\boldsymbol{x})^{Ik}$, $(\boldsymbol{x})^{Dk}$, $\boldsymbol{\mu}^{Ik}$, and $\boldsymbol{\mu}^{Dk}$ that are needed to calculate an E^k-subgradient of dual function $D\boldsymbol{\lambda}$ at $\boldsymbol{\lambda}^k$. Thus, JOCFS is in fact an approximate subgradient method (Mijangos, 2006) to solve P1. Theorem 2 states the convergence of JOCFS to the optimal solution of P1.

Theorem 2 JOCFS converges to the optimal solution of P1, i.e.,

$$\begin{cases} \lim\limits_{k\to\infty} (\boldsymbol{x})^k = (\boldsymbol{x})^*, \\ \lim\limits_{k\to\infty} \boldsymbol{\mu}^{Ik} = \boldsymbol{\mu}^{I*}, \\ \lim\limits_{k\to\infty} \boldsymbol{\mu}^{Dk} = \boldsymbol{\mu}^{D*}, \end{cases} \tag{34}$$

where $(\boldsymbol{x})^*$, $\boldsymbol{\mu}^{I*}$, $\boldsymbol{\mu}^{D*}$ are the optimal solutions of P1.

Proof See Appendix C.

6.2 Implementation issues

First, we describe the iterative process of Algorithm 2. JOCFS is an iterative algorithm with every iteration k consisting of M time slots.

During every iteration k of JOCFS, the network schedules links, and the nodes forward Interest/Data according to Algorithm 1 with $(\boldsymbol{\lambda}) = (\boldsymbol{\lambda})^k$ and $V = V_k$. $(\boldsymbol{\mu})^{Ik}$ and $(\boldsymbol{\mu})^{Dk}$ are attained by Algorithm 1.

At the same time (steps 1 and 2 in Algorithm 2 are parallel, not sequential), for every flow f, the receiver calculates x_i^{fDk} $(i \in e(f))$ by solving problem (32) with $\lambda^I_{b(f),f} = \lambda^{Ik}_{b(f),f}$ and $\lambda^D_{i,f} = \lambda^{Dk}_{i,f}$ (some of the components of $(\boldsymbol{\lambda})^k$), calculates x^{fIk} according to Eq. (4), and then sends Interest at rate x_i^{fDk}/a_f toward every provider $i \in e(f)$. Note that JOCFS decides the sending rate of Data packets by provider $i \in e(f)$ by deciding the sending rate of Interest packets that are to be satisfied only by provider $i \in e(f)$, which can be implemented by a mechanism similar to E-CHANET (Amadeo *et al.*, 2013). Note that x^{fIk} and x_i^{fDk} are components of $\boldsymbol{x}^k$.

At the end of iteration k, JOCFS updates Lagrangian multipliers $(\boldsymbol{\lambda})^k$ by Eq. (33) using $\boldsymbol{x}^k$, $(\boldsymbol{\mu})^{Ik}$, and $(\boldsymbol{\mu})^{Dk}$. We assume that the time duration for solving problem (32) and updating Lagrangian multipliers $(\boldsymbol{\lambda})^k$ is much shorter than M time slots.

Every node i stores and updates $\lambda^I_{i,f}$ for all f's that satisfy $i \notin e(f)$, $\lambda^D_{i,f}$ for all f's that satisfy $i \notin b(f)$, and $P^f_{(i,j)}$ for all f's and j's that satisfy $j \in R(f,i)$.

Algorithm 1 runs in step 1 of every iteration k of JOCFS. First, weight $\omega_{(i,j)}(t)$ of every link (i,j) is decided by $\lambda^I_{i,f}$, $\lambda^I_{j,f}$, $\lambda^D_{i,f}$, $\lambda^D_{j,f}$, $P^f_{(i,j)}$, and $P^f_{(j,i)}$, which are stored and updated by the transmitter and receiver of link (i,j). Second, there have been many distributed algorithms for solving MWM problems. Third, to update $P^f_{(i,j)}$, node i needs only $\mu^{fI}_{(i,j)}$ and $\mu^{fD}_{(j,i)}$, which are locally measurable.

In step 2 of every iteration k of JOCFS, the receiver of flow f needs $\lambda^I_{b(f),f}$ (which is stored and updated locally) and all the $\lambda^D_{i,f}$ $(i \in e(f))$. The value of $\lambda^D_{i,f}$ is stored and updated by provider $i \in e(f)$ and is carried to the receiver by Data packets that are sent by provider $i \in e(f)$. This information-fetching process enables the receiver to obtain $\lambda^D_{i,f},\ i \in e(f)$.

In step 3 of every iteration k of JOCFS, to update $\lambda^I_{i,f}$, node i needs only $\mu^{fI}_{(i,j)}$ (for all $j \in R(f,i)$), $\mu^{fI}_{(j,i)}$ (for all $i \in R(f,j)$), and x^{fI} (if $i \in b(f)$). These variables are all locally measurable. To update $\lambda^D_{i,f}$, node i needs only $\mu^{fD}_{(i,j)}$ (for all $j : i \in R(f,j)$), $\mu^{fD}_{(j,i)}$ (for all $j \in R(f,i)$), and x^{fD}_i (if $i \in e(f)$), which are also locally measurable.

It can be seen from the above discussion that JOCFS is a distributed and iterative algorithm that can jointly optimize congestion control, forwarding strategy, and link scheduling.

7 Simulation results

To verify the functionality of our algorithm, we simulated JOCFS with MATLAB. To show that JOCFS is better than the existing congestion control mechanisms in allocating resources fairly and enhancing the network throughput, we also simulated E-CHANET proposed by Amadeo *et al.* (2013). E-CHANET was adapted in our simulation. It is not a mechanism with the slotted-time assumption; for the purpose of comparison, we implemented a slotted-time version of E-CHANET. Note that the x-axis of simulation result graphs shows the iteration number with every iteration consisting of $M = 8$ time slots, where $M \in \mathbb{N}_+$ is a parameter used in Algorithm 2.

First, we generated a simulation scenario in which a common named-data MWN composed of 10 terminals was simulated. These terminals were located randomly in a grid. The grid represents an area with size of 10×10 units. This is a small-scale simulation scenario which can be used for performance comparison between JOCFS and E-CHANET. A node can communicate directly with another node if the distance between them is under four units. We set the communication range to four units to ensure that any node can communicate with another by potentially several hops. We adopted assumptions for physical layer configuration similar to that in Lin and Shroff (2004): The path loss is d^{-4}, where d is the distance from the transmitter to the receiver. The rate of each link is proportional to SIR; i.e., $r_{(i,j)} = 10 \cdot \mathrm{SIR}_{(i,j)}$. The ambient noise level is $N_0 = 1.0$ unit.

In this scenario, there are four flows each with up to three randomly selected providers. On the other hand, one terminal is selected randomly among other terminals in the grid for every flow to act as the receiver and download content from its corresponding providers (Amadeo *et al.*, 2013). This simulates NDN's multi-source content retrieval scenario.

We compared the performance of JOCFS with E-CHANET in three aspects, i.e., network throughput, fairness, and the size of P-Queue which will be defined later in this section. We ran simulations with the network using JOCFS and E-CHANET, respectively.

The measurement of network throughput is the sum of receiving rates of Data of all the flows. As shown in Fig. 3, the sums of receiving rates of Data of all the flows when the network uses JOCFS are much larger than those when using E-CHANET, except for a few iterations. This is due to the cross-layer design that can achieve more efficient resource utilization and allocation.

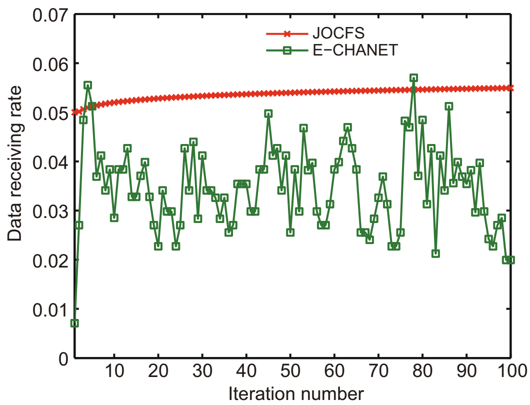

Fig. 3 Sums of receiving rates of Data of all the flows when using jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data multihop wireless network

We use Jain's fairness index (Jain *et al.*, 1998) as the measurement of fairness, which is defined as $J = \frac{\left(\sum_{f\in F}\sum_{i\in e(f)} x^{fD}_i\right)^2}{|F|\sum_{f\in F}\left(\sum_{i\in e(f)} x^{fD}_i\right)^2}$. It can be seen from Fig. 4 that Jain's fairness indices when the network uses JOCFS are larger than those when using E-CHANET, showing that JOCFS outperforms E-CHANET in terms of fairness among different flows. In addition, we note that Jain's indices are near 1 when using JOCFS, because the utility function of every flow is the same (with the same weight value).

Here we define a class of virtual queues $Q(k) =$

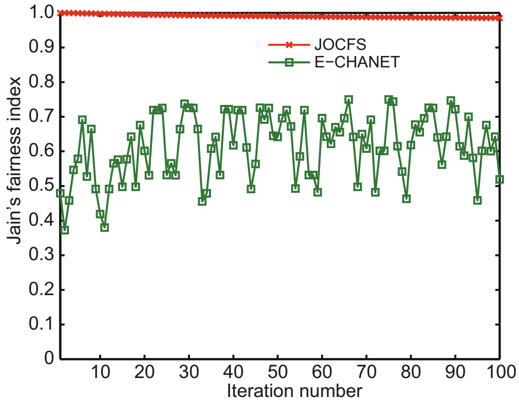

Fig. 4 Jain's fairness indices when using jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data multihop wireless network

$\left\{Q^f_{(i,j)}(k), \forall f \in F, \forall i \in N, \forall j \in R(f,i)\right\}$, which we call 'P-Queue'. Let $\mu^{fI}_{(i,j)}(k)$ denote the forwarding rate of Interest of flow f over link (i,j) during iteration k, and $\mu^{fD}_{(j,i)}(k)$ denote the forwarding rate of Data of flow f over link (j,i) during iteration k. Then the queue dynamics of $Q^f_{(i,j)}$ is $Q^f_{(i,j)}(k) = \max\left[Q^f_{(i,j)}(k-1) - \mu^{fD}_{(j,i)}(k), 0\right] + a_f \mu^{fI}_{(i,j)}(k)$. Recall that a_f is the Data-to-Interest packet size ratio of flow f.

The more 'virtual packets' in one P-Queue (i.e., $Q^f_{(i,j)}(k)$), the larger the difference between the forwarded number of Interest of flow f over link (i,j) and the forwarded number of Data of the same flow over link (j,i). This is an undesirable phenomenon because Interest packets consume excess capacity. Moreover, a larger difference between the forwarded number of Interest and that of Data implies that more pending Interest packets have not been satisfied, implying a larger PIT size. Conversely, a smaller difference between the forwarded number of Interest and that of Data implies that fewer pending Interest packets have not been satisfied, implying a smaller PIT size. To sum up, it is desirable to make P-Queue stable and have fewer backlogs. A queue $Q^f_{(i,j)}$ is called 'strongly stable' if (Georgiadis *et al.*, 2006)

$$\limsup_{K\to\infty} \frac{1}{K} \sum_{k=0}^{K-1} Q^f_{(i,j)}(k) < \infty, \tag{35}$$

Fig. 5 shows the sums of time average backlogs of all the P-Queues in the network in every iteration. From Fig. 5, we can see that both P-Queues of the network when using JOCFS and E-CHANET are strongly stable; however, the sum of time average backlogs of all the P-Queues when the network uses JOCFS is much smaller than that when using E-CHANET. Moreover, we can conjecture that the PIT size when the network uses JOCFS is smaller than that when using E-CHANET.

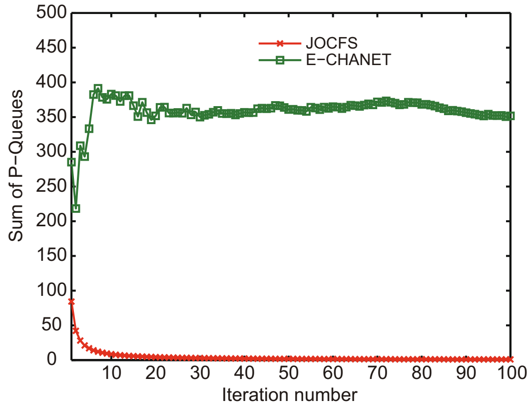

Fig. 5 Sums of time average backlogs of all the P-Queues when the network uses jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data multihop wireless network

In addition to the common named-data MWN scenario, we simulated JOCFS and E-CHANET in the named-data WMN scenario, because specifically this specific scenario needs congestion control and resource allocation. There are some special characteristics of WMN: in the network, there is a gate connected to the Internet. Sometimes there are several gates. We simulated the one-gate scenario because this does not influence JOCFS and E-CHANET's manner. For each flow, this gate node was the provider, and up to two other nodes were selected randomly as providers. In our simulation scenario, the gate node was located at the center of the grid and all other nodes were located randomly in a 10×10 grid. Other configurations were similar to those in the scenario of the common named-data MWN. We compared JOCFS and E-CHANET in three aspects, as in a common named-data MWN scenario.

First, as illustrated in Fig. 6, the throughputs of the network using JOCFS are much larger than those using E-CHANET, except for a few iterations.

Next we compared the fairness among different flows when using JOCFS and E-CHANET. As shown

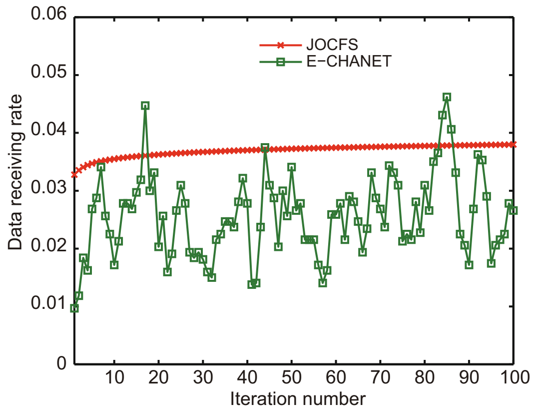

Fig. 6 Sums of receiving rates of Data of all the flows when using jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data wireless mesh network

in Fig. 7, Jain's fairness indices are near one when using JOCFS, and much higher than those when using E-CHANET. Because we set Lagrangian multipliers $\lambda_{i,f}^{D}$ of different flows the same initial value, receiving rates of Data of these flows have the same initial value. Thus, Jain's fairness indices are one at the beginning and go down slightly, because different flows go through different paths and have different available resources.

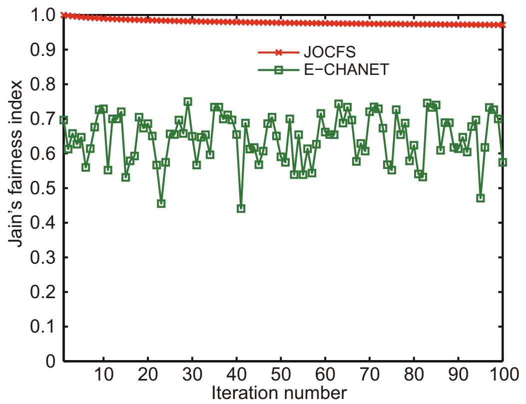

Fig. 7 Jain's fairness indices when using jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data wireless mesh network

Finally, from Fig. 8, the sum of time average backlogs of all the P-Queues when using JOCFS is much lower than that when using E-CHANET, implying a smaller PIT size. Note that the sum of time average backlogs of all the P-Queues when using JOCFS is near zero, but not zero.

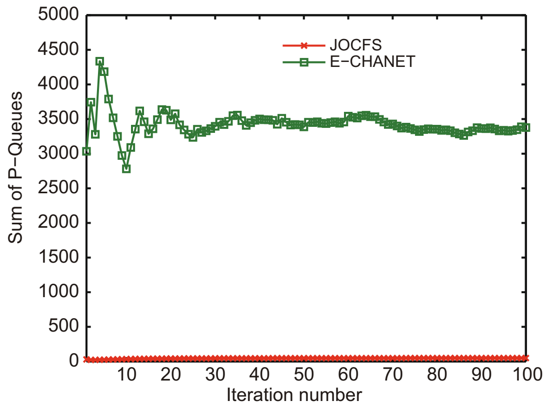

Fig. 8 Sums of time average backlog of P-Queues when using jointly optimized congestion control, forwarding strategy, and link scheduling (JOCFS) and enhanced-content-centric multihop wireless network (E-CHANET) in a named-data wireless mesh network

In summary, JOCFS can achieve a higher network throughput, allocate resources more fairly, and reduce the PIT size.

8 Conclusions and future work

In this paper, we have studied the cross-layer congestion control problem in named-data MWNs. First, we studied the communication characteristics of named-data MWNs and analyzed these characteristics' influences on our NUM modeling. Cross-layer congestion control mechanism for MWNs with IP cannot be applied to named-data MWNs, because of the difference between the communication characteristics of IP and NDN. We then formulated a NUM problem for the joint design of congestion control, forwarding strategy, and link scheduling in named-data MWNs, and proposed an iterative and distributed algorithm (called 'JOCFS') based on the approximate subgradient method to solve our NUM problem. JOCFS not only is distributed spatially, but also jointly optimizes three protocol layers, which are congestion control, forwarding strategy, and link scheduling. Simulation results showed that JOCFS outperforms existing congestion control mechanisms in some aspects, such as network throughput, fairness, and the PIT size.

From both analysis and simulation, we find that cross-layer congestion control outperforms independent optimization of congestion control for named-data MWNs.

For further research, first, we will extend our algorithm to accommodate named-data MWNs with more general interference models and node mobility. Second, the MWM problem has always been a challenging one for link scheduling; therefore, we will continue studying better MWM algorithms. Third, a more extensive performance evaluation is planned.

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Appendix A: Proof of Theorem 1

Proof (Performance bound of Algorithm 1) To prove Theorem 1, we first present a necessary lemma.

Recall that $\mu^{fI}_{(i,j)}(t)$ (or $\mu^{fD}_{(i,j)}(t)$) is the forwarding rate of Interest (or Data) of flow f over link (i,j) at time slot t, and $\mu^{fI}_{(i,j)}(t)$ (or $\mu^{fD}_{(i,j)}(t)$) is the component of $\boldsymbol{\mu}^I(t)$ (or $\boldsymbol{\mu}^D(t)$).

Let $L(\boldsymbol{P}(t))$ represent a Lyapunov function of $\boldsymbol{P}(t)$, $L(\boldsymbol{P}(t)) = \dfrac{1}{2}\sum_{(i,j),f}(P^f_{(i,j)}(t))^2$, where $\sum_{(i,j),f}$ is the short-hand notation of $\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}$. The one-step Lyapunov drift $\Delta(\boldsymbol{P}(t))$ is defined as follows:

$$\Delta(\boldsymbol{P}(t)) \triangleq L(\boldsymbol{P}(t+1)) - L(\boldsymbol{P}(t)). \tag{A1}$$

Note that JSFP's objective function $\psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda})$ is a scalar-valued, linear function (thus concave) with respect to $\boldsymbol{\mu}^I$ and $\boldsymbol{\mu}^D$. Let $\psi^{\rm tar}$ denote a desired 'target' objective function value.

Now we can present Lemma A1, a core lemma used for proof of Theorem 1. It is similar to Theorem 5.4 of Georgiadis *et al.* (2006) except that we consider finite time horizon $t \in \{0, 1, ..., M\}$ but not expectation.

Lemma A1 (Lyapunov optimization) If there are positive constants v, ε, b such that for all time-slots $t \in \{0, 1, ..., M-1\}$ and all queues $\boldsymbol{P}(t)$, the Lyapunov drift satisfies

$$\begin{aligned}&\Delta(\boldsymbol{P}(t)) - v\psi(\boldsymbol{\mu}^I(t), \boldsymbol{\mu}^D(t); \boldsymbol{\lambda})\\ &\le b - \varepsilon\sum_{(i,j),f}P^f_{(i,j)}(t) - v\psi^{\rm tar},\end{aligned} \tag{A2}$$

then the time average queues and utility satisfy

$$\begin{aligned}&\frac{1}{M}\sum_{t=0}^{M-1}\sum_{(i,j),f}P^f_{(i,j)}(t)\\ &\le \frac{b + v(\overline{\psi}(\boldsymbol{x}) - \psi^{\rm tar})}{\varepsilon} + \frac{L(\boldsymbol{P}(0))}{\varepsilon M},\end{aligned} \tag{A3}$$

$$\psi(\overline{\boldsymbol{\mu}}^I(M), \overline{\boldsymbol{\mu}}^D(M); \boldsymbol{\lambda}) \ge \psi^{\rm tar} - \frac{b}{v} - \frac{L(\boldsymbol{P}(0))}{Mv}, \tag{A4}$$

where $\overline{\boldsymbol{\mu}}^I(M)$ and $\overline{\boldsymbol{\mu}}^D(M)$ are defined in Eq. (28), and $\overline{\psi}(\boldsymbol{x})$ is defined as

$$\overline{\psi}(\boldsymbol{x}) = \frac{1}{M}\sum_{t=0}^{M-1}\psi(\boldsymbol{\mu}^I(t), \boldsymbol{\mu}^D(t); \boldsymbol{\lambda}). \tag{A5}$$

To solve JSFP, the goals include: (a) maximizing $\psi(\cdot; \boldsymbol{\lambda})$ with respect to $\boldsymbol{\lambda}^I$ and $\boldsymbol{\lambda}^D$, (b) stabilizing process $\boldsymbol{P}(t)$, and (c) satisfying constraint (8). Goal (c) can be achieved by solving problem (26) and conducting step 4 of Algorithm 1.

An intuitive interpretation of goal (b) is as follows: If the queues of $\boldsymbol{P}(t)$ are stabilized, the time average of the 'server process' $\mu_{(j,i)}^{fD}(t)$ should be greater than or equal to that of the 'arrival process' $a_f\mu_{(i,j)}^{fI}(t)$ (Georgiadis *et al.*, 2006; Neely *et al.*, 2008; Stai and Papavassiliou, 2014). Hence, the stability of $\boldsymbol{P}$ queues ensures constraint (7).

To achieve goals (a) and (b), Algorithm 1 should minimize

$$\Delta(\boldsymbol{P}(t)) - V\psi(\boldsymbol{\mu}^I(t), \boldsymbol{\mu}^D(t); \boldsymbol{\lambda}) \tag{A6}$$

at every time slot t (recall that the minimization expression (A6) is the condition of Lemma A1). As an alternative approach, Algorithm 1 is actually minimizing inequality (A11), which is the upper bound of expression (A6).

The following lemma is important for calculating the upper bound of expression (A6):

Lemma A2 (Georgiadis *et al.*, 2006) If v, u, μ, and A are nonnegative real numbers and

$$v \le \max[u-\mu, 0] + A, \tag{A7}$$

then

$$v^2 \le u^2 + \mu^2 + A^2 - 2u(\mu - A). \tag{A8}$$

The upper bound of expression (A6) is calculated as follows:

$$\begin{aligned}
&\Delta(\boldsymbol{P}(t)) - V\psi(\boldsymbol{\mu}^I(t), \boldsymbol{\mu}^D(t); \boldsymbol{\lambda})\\
=&\frac{1}{2}\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}[P_{(i,j)}^f(t+1)^2 - P_{(i,j)}^f(t)^2]\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}(\lambda_{i,f}^I - \lambda_{j,f}^I)\mu_{(i,j)}^{fI}(t)\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}(\lambda_{i,f}^D - \lambda_{j,f}^D)\mu_{(i,j)}^{fD}(t)
\end{aligned} \tag{A9}$$

$$\begin{aligned}
\le&\frac{1}{2}\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}\left[\mu_{(j,i)}^{fD}(t)^2 + a_f^2\mu_{(i,j)}^{fI}(t)^2\right]\\
&-\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}P_{(i,j)}^f(t)[\mu_{(j,i)}^{fD}(t) - a_f\mu_{(i,j)}^{fI}(t)]\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}(\lambda_{i,f}^I - \lambda_{j,f}^I)\mu_{(i,j)}^{fI}(t)\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}(\lambda_{i,f}^D - \lambda_{j,f}^D)\mu_{(i,j)}^{fD}(t)
\end{aligned} \tag{A10}$$

$$\begin{aligned}
\le&B\\
&-\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}[V(\lambda_{i,f}^I - \lambda_{j,f}^I) - a_f P_{(i,j)}^f(t)]\mu_{(i,j)}^{fI}(t)\\
&-\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}[V(\lambda_{i,f}^D - \lambda_{j,f}^D) + P_{(j,i)}^f(t)]\mu_{(i,j)}^{fD}(t),
\end{aligned} \tag{A11}$$

where B is defined as inequality (29). Eq. (A9) is due to the definition of $\Delta(\boldsymbol{P}(t))$, $L(\boldsymbol{P}(t))$, and $\psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda})$. Inequality (A10) holds by Lemma A2. Inequality (A11) holds because of the definition of B and unit like terms. For convenience, to prove Therorem 1, we construct an assistive problem (A12) as follows:

$$\begin{aligned}
&\max_{\boldsymbol{\mu}^I, \boldsymbol{\mu}^D}\left[\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}(\lambda_{i,f}^I - \lambda_{j,f}^I)\mu_{(i,j)}^{fI}\right.\\
&\qquad\left.+\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}(\lambda_{j,f}^D - \lambda_{i,f}^D)\mu_{(j,i)}^{fD}\right]\\
&\text{s.t.}\quad a_f\mu_{(i,j)}^{fI} + \epsilon \le \mu_{(j,i)}^{fD}\\
&\qquad \forall f\in F,\ \forall(i,j): j\in R(f,i):\\
&\qquad \left[\sum_{f\in F}\mu_{(i,j)}^{fI} + \mu_{(i,j)}^{fD}\right] \in \mathrm{Co}(R),
\end{aligned} \tag{A12}$$

where $\epsilon > 0$ is any positive constant, and define $\boldsymbol{\mu}^I(\epsilon), \boldsymbol{\mu}^D(\epsilon)$ as a solution to problem (A12) and $\psi^\epsilon(\boldsymbol{x})$ as the optimal objective value.

In the following, we denote $\mu_{(i,j)}^{fI}(t)$ (or $\mu_{(i,j)}^{fD}(t)$) as the forwarding rate of Interest (or Data) of flow f over link (i,j) at time slot t decided by Algorithm 1. $\mu_{(i,j)}^{fI}(t)$ (or $\mu_{(i,j)}^{fD}(t)$) is the component of $\boldsymbol{\mu}^I(t)$ (or $\boldsymbol{\mu}^D(t)$). We have

$$\begin{aligned}
&\Delta(\boldsymbol{P}(t)) - V\psi(\boldsymbol{\mu}^I(t), \boldsymbol{\mu}^D(t); \boldsymbol{\lambda})\\
\le&B - \sum_{(i,j),f}P_{(i,j)}^f(t)[\mu_{(j,i)}^{fD}(t) - a_f\mu_{(i,j)}^{fI}(t)]\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}(\lambda_{i,f}^I - \lambda_{j,f}^I)\mu_{(i,j)}^{fI}(t)\\
&-V\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}(\lambda_{j,f}^D - \lambda_{i,f}^D)\mu_{(j,i)}^{fD}(t)
\end{aligned} \tag{A13}$$

$$\leq B - \sum_{(i,j),f} P^f_{(i,j)}(t)[\mu^{fD}_{(j,i)}(\epsilon) - a_f \mu^{fI}_{(i,j)}(\epsilon)] - V\sum_{f\in F}\sum_{i\in N}\sum_{j\in R(f,i)}(\lambda^I_{i,f} - \lambda^I_{j,f})\mu^{fI}_{(i,j)}(\epsilon) - V\sum_{f\in F}\sum_{i\in N}\sum_{j:i\in R(f,j)}(\lambda^D_{j,f} - \lambda^D_{i,f})\mu^{fD}_{(j,i)}(\epsilon) \quad \text{(A14)}$$

$$\leq B - \epsilon\sum_{(i,j),f} P^f_{(i,j)}(t) - V\psi^\epsilon(\boldsymbol{x}). \quad \text{(A15)}$$

Inequality (A13) holds according to inequality (A10) and the definition of B. Inequality (A14) holds because Algorithm 1 is actually minimizing the right-hand side of inequality (A11) (which is the same as inequality (A13)). Inequality (A15) holds because $\mu^{fI}_{(i,j)}(\epsilon)$ and $\mu^{fD}_{(j,i)}(\epsilon)$ satisfy the constraints in problem (A12) and $\psi^\epsilon(\lambda)$ is the optimal (maximum) objective value of problem (A12). Inequality (A15) is exactly of the same form as inequality (A2) in Lemma A1. Thus, backlog of $\boldsymbol{P}$ satisfies

$$\frac{1}{M}\sum_{t=0}^{M-1}\sum_{(i,j),f} P^f_{(i,j)}(t) \leq \frac{B + V(\bar{\psi}(\boldsymbol{x}) - \psi^\epsilon(\boldsymbol{\lambda}))}{\epsilon} + \frac{L(\boldsymbol{P}(0))}{\epsilon M}, \quad \text{(A16)}$$

and the objective value of JSFP attained by Algorithm 1 satisfies

$$\psi(\overline{\boldsymbol{\mu}}^I(M), \overline{\boldsymbol{\mu}}^D(M); \boldsymbol{\lambda}) \geq \psi^\epsilon(\boldsymbol{x}) - \frac{B}{V} - \frac{L(\boldsymbol{P}(0))}{MV}. \quad \text{(A17)}$$

The bounds in inequalities (A16) and (A17) hold for any ϵ that satisfies $r^{\min} \geq \epsilon > 0$, where $r^{\min}$ is the minimum positive element of $\mathrm{Co}(R)$. However, the specific value of ϵ influences only the bound calculation, but not Algorithm 1. Thus, we can optimize the bounds in inequalities (A16) and (A17) separately over all possible ϵ's (Georgiadis *et al.*, 2006). Inequality (A16) implies that V-Queues are stabilized; thus, constraint (7) is satisfied. The bound in inequality (A17) is maximized by taking $\epsilon = 0$, yielding inequality (27) in Theorem 1.

Appendix B: Proof of Lemma 1

Proof (Approximate subgradient) First note that the dual function $D(\boldsymbol{x})$ is convex because it is the pointwise maximum of a family of affine functions of $\boldsymbol{\lambda}$ (Boyd and Vandenberghe, 2009). For ease of notation, we assume $\boldsymbol{\lambda} \in \mathbb{R}^n$.

Given $D(\cdot)$, a vector $\boldsymbol{d} \in \mathbb{R}^n$ is an ε-subgradient ($\varepsilon > 0$) of $D(\cdot)$ at a point $\boldsymbol{\lambda}$ if (Bertsekas *et al.*, 2003)

$$\forall \widetilde{\boldsymbol{\lambda}} \in \mathbb{R}^n : D(\widetilde{\boldsymbol{\lambda}}) \geq D(\boldsymbol{x}) + (\widetilde{\boldsymbol{\lambda}} - \boldsymbol{\lambda})^{\mathrm{T}}\boldsymbol{d} - \varepsilon. \quad \text{(B1)}$$

From inequality (27), we can see that in every iteration k, JOCFS maximizes approximately $\psi(\boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}^k)$ with respect to $\boldsymbol{\mu}^I$ and $\boldsymbol{\mu}^D$. On the other hand, JOCFS maximizes $\phi(\boldsymbol{x}; \boldsymbol{\lambda}^k)$ with respect to $\boldsymbol{x}$; thus, JOCFS maximizes approximately $L(\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}^k)$ over $\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D \succeq 0$ in every iteration k of JOCFS. Specifically,

$$L(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk}; \boldsymbol{\lambda}^k) \geq \max_{\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D \succeq 0} L(\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D; \boldsymbol{\lambda}^k) - E^k. \quad \text{(B2)}$$

Similar to Bertsekas (1999) we have

$$\forall \boldsymbol{\lambda} \in \mathbb{R}^n :$$

$$\begin{aligned} D(\boldsymbol{x}) &= \max_{\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D}\left[\sum_{f\in F} U_f \sum_{i\in e(f)} x_i^{fD} + \boldsymbol{\lambda}^{\mathrm{T}} g(\boldsymbol{x}, \boldsymbol{\mu}^I, \boldsymbol{\mu}^D)\right] \\ &\quad + g(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk})^{\mathrm{T}}(\boldsymbol{\lambda} - \boldsymbol{\lambda}^k) \\ &\geq D(\boldsymbol{\lambda}^k) - E^k + g(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk})^{\mathrm{T}}(\boldsymbol{\lambda} - \boldsymbol{\lambda}^k), \end{aligned} \quad \text{(B3)}$$

which proves that $g(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk})$ is an E^k-subgradient of $D(\boldsymbol{x})$ at $\boldsymbol{\lambda}^k$ from the definition of ε-subgradient in inequality (B1).

Appendix C: Proof of Theorem 2

Proof (Optimality of JOCFS) We aim to prove the optimality of solution of JOCFS using the results in Mijangos (2006). First, we analyze the boundness of E^k-subgradient of $D(\boldsymbol{x})$, which is a condition of the results in Mijangos (2006). As for the solution of JSFP, all the $\mu^{fIk}_{(i,j)}$ and $\mu^{fDk}_{(i,j)}$ satisfy $0 \leq \mu^{fIk}_{(i,j)} \leq r^{\max}_{(i,j)}$ and $0 \leq \mu^{fDk}_{(i,j)} \leq r^{\max}_{(i,j)}$, where $r^{\max}_{(i,j)}$ is the transmission rate of link (i,j) when activated. As for FCP, JOCFS actually solves problem (30) that maximizes a concave objective; thus, all the x_i^{fDk} are bounded, so are all the x^{fIk}. Thus, the left-hand side of inequalities (11) and (12) are all bounded, so is E^k-subgradient. Next, because $s_k = s/k^p$ $(0.5 < p < 1, s > 0)$, the following holds:

$$\begin{cases} \sum\limits_{k=0}^{\infty} s_k = \infty, \\ \sum\limits_{k=0}^{\infty} s_k^2 < \infty. \end{cases} \tag{C1}$$

On the other hand, $V_k = k^p$ implies that $E^k = s_k B/s$. Thus, the following holds:

$$\sum_{k=0}^{\infty} s_k E^k = \sum_{k=0}^{\infty} \frac{Bs_k^2}{s} < \infty. \tag{C2}$$

Note that $g(\boldsymbol{x}^k, \boldsymbol{\mu}^{Ik}, \boldsymbol{\mu}^{Dk})$ is the E^k-subgradient of $D(\boldsymbol{x})$ at $\boldsymbol{\lambda}^k$. Using the results in Mijangos (2006), we can conclude that $\boldsymbol{\lambda}^k$ converges to some optimal solution $\boldsymbol{\lambda}^*$. Note that P1 is convex and has a strong duality (Boyd and Vandenberghe, 2009), then through a procedure similar to Proposition 1(b) in Lin and Shroff (2004), we can prove that $\boldsymbol{x}^k$, $\boldsymbol{\mu}^{Ik}$, and $\boldsymbol{\mu}^{Dk}$ converge to some optimal solution.