

Stability of Longest-Queue-First Scheduling in Linear Wireless Networks with Multihop Traffic and One-Hop Interference

Xiaohan Kang¹, Juan José Jaramillo² and Lei Ying¹

Abstract— We consider the stability of the longest-queue-first (LQF) scheduling policy in wireless networks with multihop traffic under the one-hop interference model. Although it is well known that the back-pressure (BP) algorithm achieves the maximal stability, its computational complexity is very high. In this paper, we consider LQF, a low-complexity scheduling algorithm, which has been shown to have near optimal throughput performance in many networks with single-hop traffic flows. We are interested in the performance of LQF for multihop traffic flows. In this scenario, the analysis of local-pooling factors for LQF does not carry through because of the complicated coupling between queues due to multihop traffic flows. Using fluid limit techniques, we show that LQF achieves the maximal stability for linear networks with multihop traffic and a single destination under the one-hop interference.

I. INTRODUCTION

The scheduling problem in wireless networks with multihop traffic has gained significant attention over the last few decades. One fundamental goal of the design of scheduling policies, among many others, is to decide the set of links to schedule at each time slot in accordance with the underlying interference model, such that the system is stable. The back-pressure algorithm has been proved to be throughput optimal for general multihop traffic settings [1]; i.e., it stabilizes the network as long as the arrivals are within the network throughput region. The algorithm, however, requires the network to solve a maximum-weight independent set problem at each time instance and requires the nodes to exchange queue lengths with their neighbors constantly.

In this paper, we study the stability of longest queue first (LQF) scheduling, which selects links according to queue lengths in a greedy fashion. LQF has been extensively studied as a low complexity approximation of MaxWeight scheduling, and has great throughput and delay performance in many networks. The conditions under which LQF is throughput optimal has been established by Dimakis and Walrand [2] and the performance guarantee of LQF in general networks has been characterized by Joo et al. [3] and estimated under different scenarios [3]–[6]. However, these results all assume single-hop traffic flows in the networks. For networks with multihop traffic, transmitted packets at one link may become the *internal* arrivals to another link. Hence links with small queues may affect the ones with large queues by providing internal arrival, which makes it

difficult to analyze the system using local-pooling factors since the links with larger queues are no longer isolated from those with smaller queues. Although Brzezinski et al. [7] developed conditions for networks with multihop traffic under which a back-pressure-based greedy algorithm achieves the maximal throughput, the performance of LQF for networks with multihop traffic flows is still open. We are interested in tackling this problem.

We focus on the scheduling problem under multihop traffic on a simple network, i.e., a linear network (also known as a tandem network) with single destination and one-hop interference model (also known as primary or node-exclusive interference model). Such networks have been well studied in the literature to provide insights in understanding the fundamental scaling properties of multihop traffic [8]–[11]. In particular, Stolyar [9] and Bui et al. [10] analyzed the asymptotic delay performance of the back-pressure algorithm in large linear networks when no interference is present. To the best of our knowledge, however, neither throughput nor delay performance guarantees of LQF has been obtained under multihop traffic scenario for the linear networks.

This paper proves the throughput optimality of LQF in linear networks. While the result is only for linear networks, it is the first step to understand the following question: to achieve throughput optimality in a wireless network with multihop traffic flows that have fixed routes, is it sufficient to use queue lengths as weights instead of using differential queues? If the answer is positive, then nodes do not need to constantly exchange queue lengths, which eliminates a significant amount of communication overhead.

The novelty in this paper lies in the techniques we adopt to show the stability of the fluid model after the standard construction of fluid limits. Instead of using an explicit Lyapunov function, we follow the observations from the simulation trajectories of an example network and examine the evolution of the states of the deterministic fluid limits. We first show that the system will eventually stay in the state where the fluid at the first queue is zero. Then by combining the first two queues into one using a coupled network argument, we reduce the size of the network by one and conclude that fluids at all queues eventually become zero by induction.

The paper is organized as follows. We introduce the basic model in Section II. In Section III we present our result of throughput optimality of LQF, as well as an intuitive example, formal notations and network equations, construction of fluid limits, and the key proof ideas. Section IV includes some simulation results. Section V concludes the paper.

¹X. Kang and L. Ying are with the School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ 85287, USA {xiaohan.kang, lei.ying.2}@asu.edu

²J. Jaramillo is with the Department of Applied Math and Engineering, Universidad EAFIT, Medellín, Colombia jjaram93@eafit.edu.co

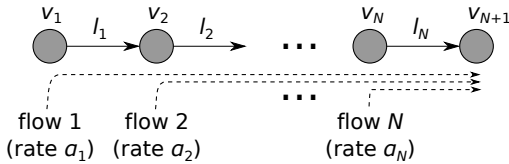


Fig. 1: A linear network with N links. The i^{th} dashed line indicates the flow with source node v_i and destination node v_{N+1} and exogenous packet arrival rate α_i .

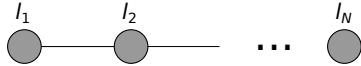


Fig. 2: The one-hop interference graph of Fig. 1

II. MODEL

Consider a linear network represented by a directed graph $G = (V, L)$ with $|V| = N + 1$ nodes and $|L| = N$ links as shown in Fig. 1. Let $V = \{v_1, v_2, \dots, v_{N+1}\}$ and $L = \{l_1, l_2, \dots, l_N\}$, where l_i is the link from node v_i to node v_{i+1} . We assume v_i is the origin node of flow f_i with exogenous (or external) packet arrival rate α_i for $1 \leq i \leq N$, and all flows have the same destination v_{N+1} . In the paper we focus on one-hop interference model, so the interference graph is as shown in Fig. 2.

We assume time is slotted, and in each time slot a subset of the links can be scheduled. Once scheduled, a packet at link l_i is transmitted from node v_i to node v_{i+1} and join the queue at node v_{i+1} if it has not reached the destination v_{N+1} , or leave the network otherwise. As a result, besides external packet arrivals, there can also be *internal* packet arrivals to a node according to the schedule of other links.

The scheduler decides a subset of the links $s \subseteq L$ to be activated in every time slot, called a schedule, such that the schedule is feasible (no interference between scheduled links) and maximal (no other link can be added to the schedule), and then the queue length at each transmitter in the activated subset reduces by 1 if there are any packets to schedule, or remain 0 otherwise. The schedule (also known as activation set) s is represented by an *activation vector* m , which is a binary column vector with N elements. According to the interference model shown in Fig. 2, a schedule s is feasible if no two adjacent links are activated at the same time; i.e., the activation vector m does not contain two consecutive 1's.

In the paper we are interested in LQF with arbitrary tie-breaking rules, and we define it as follows. At each time slot, let Z_i be the queue length at link l_i for $1 \leq i \leq N$. The set of links are sorted with arbitrary tie-breaks such that $Z_{\sigma_1} \geq Z_{\sigma_2} \geq \dots \geq Z_{\sigma_N}$, where $(\sigma_1, \sigma_2, \dots, \sigma_N)$ is the sorted index vector. LQF starts with the schedule $\mathcal{E} = \{\sigma_1\}$, and proceed to consider $i = 2, 3, \dots, N$ inductively and append σ_i to \mathcal{E} if σ_i does not interfere with any link that is already in \mathcal{E} . This procedure ends after the link l_{σ_N} is considered and the resulting schedule \mathcal{E} is the schedule chosen by LQF.

III. STABILITY

In this section we analyze the stability property of LQF in the linear network under the one-hop interference model. We state the main theorem with the proof outline and an illustrative example.

A. Main Result

Theorem 1: LQF is throughput optimal on linear networks with the single-destination multihop traffic under the one-hop interference. \diamond

Theorem 1 states that LQF can stabilize a linear multihop traffic network. Thus using queue lengths instead of queue differences is sufficient. This result may also shed light on the throughput performance of LQF in other networks with multihop traffic, in which the routes are fixed.

The proof consists of the following steps. We first follow the standard construction of the fluid limits. Then we show that eventually the fluids should be such that each fluid is less than or equal to at least one neighbor fluid; i.e., no fluid dominates all its neighbors. After that we prove that the first fluid must decrease with rate at least $\epsilon > 0$. Finally we use a coupled network argument to show that all fluids eventually go to zero under admissible arrival rates, which implies throughput optimality.

We next demonstrate the key ideas of the proof using an example.

B. Three-Link Linear Network

We consider the simple linear network example with four nodes $\{v_1, v_2, v_3, v_4\}$ and three links $\{l_1, l_2, l_3\}$. Suppose flow i has origin v_i and destination v_4 with Bernoulli arrival of rate α_i for $i = 1, 2, 3$. The interference is such that two adjacent links cannot be scheduled at the same time, so either $\{l_1, l_3\}$ or $\{l_2\}$ is scheduled in each time slot. Let $Z_i(n)$ be the queue length on link l_i at time slot n . Then at each time slot, the LQF scheduler first selects the longest queue with arbitrary tie-breaking, then append it to either $\{l_1, l_3\}$ or $\{l_2\}$ according to the first select.

A typical queue evolution graph for the three-link linear network under LQF is shown in Fig. 3. Here the initial queue lengths are $Z_1(0) = 300$, $Z_2(0) = 120$ and $Z_3(0) = 100$, with arrival rates $\alpha_1 = 0.25$, $\alpha_2 = 0.1$ and $\alpha_3 = 0.05$. We make several interesting observations from the figure:

- 1) The queue lengths look like piecewise linear functions (this is partially due to the law of large numbers over the arrival process).
- 2) The queue dynamics are somewhat complex at the beginning of the time slots (largely due to the internal arrival from other links).
- 3) The first queue eventually drop to close to zero, and the behavior of the rest queues become more predictable.
- 4) Finally all queues seem to be close to zero, so the system is expected to be stable.

In light of the above findings, we first claim that after some time we have either $Z_1(t) = Z_2(t) \geq Z_3(t)$ or $Z_1(t) \leq Z_2(t) = Z_3(t)$, since otherwise one queue will be larger than all its neighbors, resulting a decreasing difference with

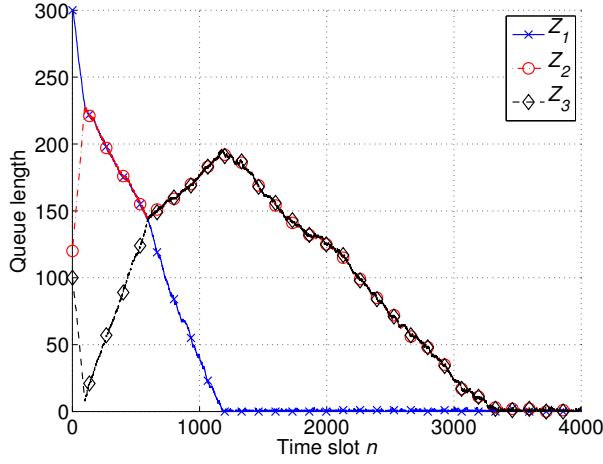


Fig. 3: Queue evolution of the three-link linear network under LQF

its neighbors under LQF. We can then see that if $Z_1(t)$ and $Z_2(t)$ stick together then they must both decrease since $2\alpha_1 + \alpha_2 = 0.6 < 1$, and if $Z_2(t)$ and $Z_3(t)$ stick together then we can compute that $Z_1(t)$ must decrease with rate $\frac{1}{2} - \alpha_1 - \frac{1}{4}\alpha_2 + \frac{1}{4}\alpha_3 = 0.2375 > 0$ since the service rates on links l_1 and l_3 must be equal. We also argue that when the first queue drops to close to zero, it cannot rise again since if it did it would be “forced back” immediately. So at last the three-link linear network is reduced to a 2-link linear network and the remaining two queues go to close to zero as well. The above intuition will lead our way to the rigorous proof for the general linear network case in the rest of this paper.

C. Notations and Network Equations

We use the following notations:

- R : the $(N + 1)$ -by- N routing matrix as is defined by Tassiulas and Ephremides [1], where $R_{ik} = -1$ if link l_k goes from node v_i , $R_{ik} = 1$ if link l_k goes to node v_i with $i \neq N + 1$, and $R_{ik} = 0$ otherwise, for $1 \leq i \leq N + 1$ and $1 \leq k \leq N$. Then in the linear network case the routing matrix is given by

$$R = \begin{pmatrix} -1 & 0 & \cdots & \cdots & 0 \\ 1 & -1 & \ddots & \ddots & \vdots \\ 0 & 1 & \ddots & \ddots & \vdots \\ 0 & 0 & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & 1 & -1 \\ 0 & 0 & \cdots & 0 & 0 \end{pmatrix}, \quad (1)$$

where the last row is all-zero since the node v_{N+1} is the destination for all flows.

- M : the N -by- r binary-entry matrix whose columns are the activation vectors of the possible maximal schedules, where r is the total number of possible maximal schedules. By a little abuse of notation we regard the columns of M as the elements of the set $M = \{m_1, m_2, \dots, m_r\}$.

- $Z_i(n)$ for $1 \leq i \leq N$: the queue length at link l_i at time slot n (before arrivals and departures happen in time slot n).
- $E_i(n)$ for $1 \leq i \leq N$: the cumulative exogenous arrival to link l_i up to time slot n . We assume the increments of $(E_i(n))$ are temporally i.i.d. and independent across i . The exogenous arrival rate is $\mathbb{E}[E_i(n) - E_i(n-1)] = \alpha_i$ for all n .
- $A_i(n)$ for $1 \leq i \leq N$: the cumulative arrival to link l_i up to time slot n . This includes both exogenous and internal arrivals.
- $D_i(n)$ for $1 \leq i \leq N$: the actual cumulative departure from link l_i up to time slot n .
- $T_j(n)$ for $1 \leq j \leq r$: the cumulative service time (in number of time slots) of schedule m_j up to time slot n .
- $Y_i(n)$ for $1 \leq j \leq r$: the cumulative idle time (in number of time slots) of link l_i up to time slot n (when link l_i is chosen by the scheduler but does not actually send packets). Note that even if the queue at link l_i is empty at the time of scheduling, the scheduler can still choose the schedule $m \in M$ such that $l_i \in m$, in which case $Y_i(n)$ will increase instead of $D_i(n)$. For non-idling (or work-conserving) scheduling policies $Y_i(n)$ can only increase when the queue at link l_i is empty.

Let $Z(n), E(n), A(n), D(n), T(n), Y(n)$ be the corresponding column vectors. Then we refer to $\mathbb{X}(n) = (Z(n), E(n), A(n), D(n), T(n), Y(n))$ as the *queueing network process*. Let $\mathcal{X} = \mathbb{Z}_+^{5N+r}$ be the space where \mathbb{X} lives. Then \mathbb{X} is an \mathcal{X} -valued stochastic process defined for nonnegative integer values of n . Let Ω be the set of sample paths specifying the exogenous arrival processes $(E_i(n))$ and the possible tie-breaks of the scheduler. Note that under the LQF policy $\mathbb{X}(\cdot)$ forms a discrete Markov chain. The dynamics of the network are described by the following *queueing network equations*:

$$A(n) = E(n) + (R_0 + I_N)D(n-1) \quad (2)$$

$$Z(n) = Z(0) + A(n) - D(n) \quad (3)$$

$$\sum_{j=1}^r T_j(n) = n \quad (\text{or } e^T T(n) = n) \quad (4)$$

$$D(n) = MT(n) - Y(n) \quad (5)$$

for any nonnegative integer n , where $(\cdot)^T$ denotes the transpose, e is the all-one column vector, R_0 is the square matrix consisting of the first N rows of the routing matrix R , and I_N is the N -by- N identity matrix. Moreover, if the scheduling is non-idling, then we also have

$$Y_i(n) - Y_i(n-1) = \begin{cases} 1 & \text{if } Z_i(n-1) = 0 \text{ and} \\ & \sum_{j: i \in m_j} (T_j(n) - T_j(n-1)) = 1 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

for $1 \leq i \leq N$ and $n \geq 1$. All of the variables take nonnegative integers in each component, and E, A, D, T, Y are nondecreasing. Also we assume the initial conditions are

$$E(0) = A(0) = D(0) = Y(0) = 0 \text{ and } T(0) = 0. \quad (7)$$

For the LQF policy, we have in addition to (2), (3), (4), (5), (6) and (7):

$$T_j(n) - T_j(n-1) = 1 \Rightarrow m_j \in \text{LQF}(Z(n-1)), \quad (8)$$

where $\text{LQF}(Z)$ is the set of possible LQF maximal schedules given queue length vector Z . We assume that the schedule is always maximal regardless of the queues being empty or not, so $\text{LQF}(Z) \subseteq M = \{m_1, m_2, \dots, m_r\}$.

D. Fluid Limits

We define the scaled systems based on the queueing network process for each sample path, and show that the scaled systems converge along some subsequence to deterministic systems called fluid limits.

We first extend the definition of \mathbb{X} for arbitrary nonnegative time $t \geq 0$ by piecewise linear interpolation

$$\mathbb{X}(t) = (1 + [t] - t)\mathbb{X}([t]) + (t - [t])\mathbb{X}([t] + 1),$$

where $[t]$ is the largest integer less than or equal to t . Then \mathbb{X} is an \mathcal{X} -valued stochastic process with $\bar{\mathcal{X}} = \mathbb{R}_+^{5N+r}$, and is continuous for $t \geq 0$ given any fixed sample path $\omega \in \Omega$.

Let $|\cdot|$ be the L^1 -norm of \mathcal{X} . Fix $\omega \in \Omega$, and let $\mathbb{X}^x(t)$ be the queueing network process with initial state $\mathbb{X}(0) = x$ for $x \in \mathcal{X}^0 = \{y \in \mathcal{X} \mid |y| > 0\}$ and define the *scaled system*

$$\bar{\mathbb{X}}^x(t) = \frac{1}{|x|} \mathbb{X}^x(|x|t).$$

We then have the following proposition giving the existence of the fluid limits, which is similar to Theorem 4.1 in the paper by Dai [12]. We denote by \mathbb{Z}_+ the set of positive integers, and use subscripts to indicate the indices of sequences.

Proposition 1: For a work-conserving scheduling policy, for almost any sample path $\omega \in \Omega$ and any sequence of initial states $(x_k)_k$ with $\{x_k \mid k \in \mathbb{Z}_+\} \subseteq \mathcal{X}^0$ and $|x_k| \rightarrow \infty$ as $k \rightarrow \infty$, there exists a subsequence $(k_p)_p$ with $|x_{k_p}| \rightarrow \infty$ as $p \rightarrow \infty$ such that

$$\bar{\mathbb{X}}^{x_{k_p}}(0) \rightarrow \bar{\mathbb{X}}(0) \quad \text{as } p \rightarrow \infty$$

and

$$\bar{\mathbb{X}}^{x_{k_p}}(t) \rightarrow \bar{\mathbb{X}}(t) \quad \text{u.o.c. as } p \rightarrow \infty$$

for some $\bar{\mathbb{X}}: \mathbb{R}_+ \rightarrow \bar{\mathcal{X}}$, where ‘‘u.o.c.’’ stands for uniform convergence over compact sets [13]. Furthermore,

$$\bar{A}(0) = \bar{D}(0) = \bar{Y}(0) = 0 \text{ and } \bar{T}(0) = 0 \quad (9)$$

$$\bar{A}(t) = \alpha t + (R_0 + I_N)\bar{D}(t) \quad (10)$$

$$\bar{Z}(t) = \bar{Z}(0) + \bar{A}(t) - \bar{D}(t) \quad (11)$$

$$e^{\mathbf{T}\bar{T}(t)} = t \quad (12)$$

$$\bar{D}(t) = M\bar{T}(t) - \bar{Y}(t) \quad (13)$$

and

$$\int_0^\infty \bar{Z}_i(t) d\bar{Y}_i = 0 \quad i = 1, 2, \dots, N. \quad (14)$$

Moreover, all components of $\bar{\mathbb{X}}$ are absolutely continuous [13] because they are Lipschitz continuous, and $\bar{A}, \bar{D}, \bar{T}, \bar{Y}$ are nondecreasing.

Particularly, the fluid limits under LQF satisfy

$$\frac{d\bar{T}_j}{dt}(t) > 0 \Rightarrow m_j \in \text{LQF}(\bar{Z}(t)) \quad j = 1, 2, \dots, r, \quad (15)$$

where $\text{LQF}(\bar{Z})$ is the set of LQF schedules for links $\{i \mid \bar{Z}_i > 0\}$, and t is assumed regular so the derivatives exist. \diamond

Remark. Basically, (9) is the initial condition assumption. (10) says the arrival rates consist of exogenous part and internal part. (11) is the queue evolution equation. (12) comes from the fact that in each time slot there is exactly one maximal schedule chosen by the scheduler. (13) gives the relation among departures, serving time of schedules and idling time. (14) means a link can be idle (when it is chosen by the scheduler) only if the queue length at the link is 0. (15) states that only maximal schedules satisfying the LQF property given the queue fluids $\bar{Z}(t)$ can be chosen at time t , but it does not specify the fractions of the schedules that LQF could choose. The proof of Proposition 1 can be found in the technical report [14].

E. Transient States with Dominating Fluids

We first identify a set of transient states of the space of the queue fluid vectors. Let

$$B_1 = \{Z \in \mathbb{R}_+^N \mid Z_1 > Z_2\}$$

$$B_2 = \{Z \in \mathbb{R}_+^N \mid Z_2 > Z_1, Z_2 > Z_3\}$$

\vdots

$$B_{N-1} = \{Z \in \mathbb{R}_+^N \mid Z_{N-1} > Z_{N-2}, Z_{N-1} > Z_N\}$$

$$B_N = \{Z \in \mathbb{R}_+^N \mid Z_N > Z_{N-1}\}$$

and let

$$B = \bigcup_{i=1}^N B_i.$$

So B is the set of queue fluid vectors such that some queue strictly dominates all of its neighbors (one link has at most two neighbors in linear networks), while $\mathbb{R}_+^N \setminus B$ is the set of queue length vectors without any queue strictly dominating all of its neighbors. We then have the following lemma. (For convenience we ignore all the bars over the fluid limit processes in the rest of the paper.)

Lemma 1: B is transient. Formally, given $\alpha_i < 1$ for any $i \in \{1, 2, \dots, N\}$, for any initial conditions $Z(t_0) \in \mathbb{R}_+^N$ at time t_0 with $Z_{\max} = \max_i Z_i(t_0)$, there exists $c_1 > 0$ such that $Z(t) \notin B$ for any $t \geq t_0 + Z_{\max}c_1$ under LQF. \diamond

Remark. The outline of the proof is as follows, and the detailed proof can be found in the technical report [14].

- 1) If $Z \in B$, then there are no adjacent dominating nodes.
- 2) Each dominating node loses its domination in time $Z_{\max}/(1 - \max_i \alpha_i)$.
- 3) Once a node loses domination, it cannot regain it.

F. Stability of the First Fluid Z_1

We now further divide $\mathbb{R}_+^N \setminus B$ into several partitions:

$$C_0 = \{Z \in \mathbb{R}_+^N \setminus B \mid Z_1 = 0\}$$

$$C_1 = \{Z \in \mathbb{R}_+^N \setminus B \mid 0 < Z_1 = Z_2\}$$

$$C_2 = \{Z \in \mathbb{R}_+^N \setminus B \mid 0 < Z_1 < Z_2 = Z_3\}$$

⋮

$$C_{N-1} = \{Z \in \mathbb{R}_+^N \setminus B \mid 0 < Z_1 < \dots < Z_{N-1} = Z_N\}.$$

Then $\{C_0, C_1, \dots, C_{N-1}, B\}$ forms a partition of \mathbb{R}_+^N . We then use the following two lemmas to show C_1, C_2, \dots, C_{N-1} are all transient under admissible arrival rates, so the system has to eventually go to state C_0 where Z_1 stays at 0.

Lemma 2: If the arrival rate vector α is admissible, then there exists $\epsilon > 0$ such that for any regular time $t_1 \geq Z_{\max} c_1$ and $Z(t_1) \notin C_0$ we have

$$\frac{dZ_1}{dt}(t_1) \leq -\epsilon,$$

where Z_{\max} and c_1 are given in Lemma 1. \diamond

Remark. The idea of the proof is that for any sufficiently large regular time t_1 we show that if the fluid of the first queue is positive, then it must decrease with lower-bounded rate. Hence the first fluid reaches zero eventually. The proof can be found in the technical report [14].

Corollary 1: Given the initial conditions and arrival rates in Lemma 2, there exists $c_2 > 0$ such that $Z_1(t) = 0$ for any $t \geq Z_{\max} c_2$. \diamond

Remark. This comes directly from Lemmas 1 and 2. Basically, $Z_1(t)$ has to drop to 0, after which it cannot rise since otherwise the negative derivative forces it to go back to 0.

G. Coupled Network Argument

Based on Corollary 1, we use induction and a coupled network argument to show the following lemma stating the stability of the fluid system, which leads to the stability of the original queueing system by the result of Dai [12].

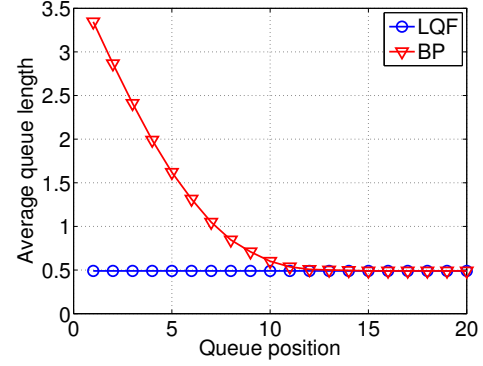
Lemma 3: Given the initial conditions and arrival rates in Lemma 2, there exists $c_3 > 0$ such that $Z_i(t) = 0$ for any $t \geq Z_{\max} c_3$ and any $i = 1, 2, \dots, N$. \diamond

The proof can be found in the technical report [14].

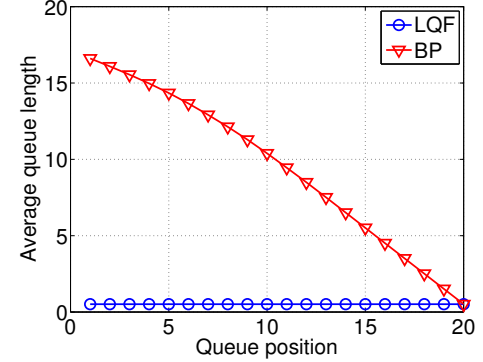
IV. SIMULATIONS

Now we proved that LQF is throughput optimal in a linear network with one-hop interference model. In this section, we simulate the LQF policy and the back-pressure policy over a linear network with multihop traffic under different interference models. The goal of the simulations is twofold: 1) to examine the throughput performance of LQF on linear networks under other interference model; 2) to evaluate the delay performance of both LQF and BP.

Throughout the simulations we fix the network size to be $N = 20$. We assume that there is a single flow with source node v_1 , destination node v_{N+1} , and Bernoulli arrivals with mean α_1 . We consider three interference models: no interference (all links can be transmitting simultaneously), one-hop



(a) Undercritical scenario when $\alpha_1 = 0.49$.



(b) Supercritical scenario when $\alpha_1 = 0.51$.

Fig. 4: Stationary queue lengths for different link positions under no interference.

interference (each link interferes with its direct neighbors) and two-hop interference (each link interferes with its two-hop neighbors). We simulate 1,000,000 time slots for each setting.

A. No Interference

When no interference is present, we can easily see that the stability region of the network is $[0, 1)$. LQF is throughput optimal in this case since all links will always try to transmit and the queue length is at most 1 for any link due to the Bernoulli arrival and the zero initial state. It has however been noticed that there exists a critical point of the arrival rate for linear multihop networks, above which the average total queue lengths (and hence the average delay) will increase quadratically as the network size becomes larger [9], [10]. In Figure 4 we demonstrate that the critical arrival rate is $1/2$ in our discrete-time constant service setting, as opposed to $1/4$ obtained in the continuous-time exponential-service setting by Stolyar [9].

Figure 4a shows the stationary queue lengths of both policies in the undercritical scenario when $\alpha_1 = 0.49 < 1/2$. We note that the stationary queue length of BP decreases quickly as the position increases, and stays at α_1 for the tail link positions. Hence the average total backlog only increases linearly with the network size. By Little's law the delay is also linearly dependent on the network size.

On the other hand, Figure 4b shows the stationary queue

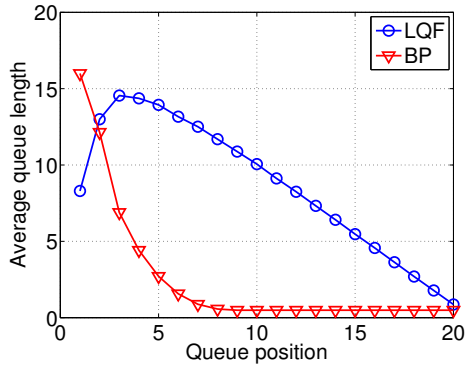


Fig. 5: Stationary queue lengths for different link positions under one-hop interference when $\alpha_1 = 0.49$.

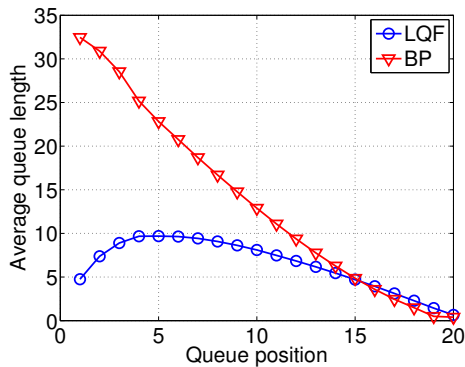


Fig. 6: Stationary queue lengths for different link positions under two-hop interference when $\alpha_1 = 0.32$.

lengths in the supercritical scenario when $\alpha_1 = 0.51 > 1/2$. We see that the stationary queue length of BP decreases linearly as the position increases. Then as the network size increases the average total backlog will increase quadratically, resulting in bad delay performance.

B. One-Hop Interference

Under one-hop interference the stability region becomes $[0, 1/2)$. The stationary queue lengths for both policies when $\alpha_1 = 0.49$ are shown in Figure 5. We notice that in this scenario the average total queue length of LQF is about three times that of BP, yielding comparable delay performances. We conjecture that the delay performance of BP under one-hop interference is good since the restriction of interference forces BP to choose good schedules.

C. Two-Hop Interference

Under two-hop interference the stability region further shrinks to $[0, 1/3)$. We show the stationary queue lengths for both policies when $\alpha_1 = 0.32$ in Figure 6. Note that in this particular case the average total queue length of LQF is less than half of that of BP, so LQF achieves better delay performance than BP. Whether LQF is throughput optimal for general linear networks under two-hop interference is unknown.

V. CONCLUSIONS

We studied the stability of the longest-queue-first scheduling policy in wireless networks with multihop traffic flows and the one-hop interference model. Using fluid techniques, we proved that LQF is throughput optimal in this scenario. The proof itself is an interesting contribution and can be useful when considering similar fluid systems since we focused on state transition instead of an explicit Lyapunov function. The result may also be a first step to understand the stability performance of LQF in general networks with multihop traffic flows.

VI. ACKNOWLEDGMENTS

We thank Sanjay Shakkottai, R. Srikant and Alexander L. Stolyar for many useful comments. This work was supported in part by the National Science Foundation (NSF) under Grants CNS-1264012 and CNS-1262329, and in part by the Defense Threat Reduction Agency (DTRA) under Grant HDTRA1-13-1-0030.

REFERENCES

- [1] L. Tassiulas and A. Ephremides, "Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks," *IEEE Trans. Autom. Control*, vol. 37, pp. 1936–1948, Dec. 1992.
- [2] A. Dimakis and J. Walrand, "Sufficient conditions for stability of longest queue first scheduling: Second-order properties using fluid limits," *Adv. in Appl. Probab.*, vol. 38, no. 2, pp. 505–521, Jun. 2006.
- [3] C. Joo, X. Lin, and N. B. Shroff, "Understanding the capacity region of the greedy maximal scheduling algorithm in multihop wireless networks," *IEEE/ACM Trans. Netw.*, vol. 17, pp. 1132–1145, Aug. 2009.
- [4] —, "Greedy maximal matching: Performance limits for arbitrary network graphs under the node-exclusive interference model," *IEEE Trans. Autom. Control*, vol. 54, pp. 2734–2744, Dec. 2009.
- [5] B. Birand, M. Chudnovsky, B. Ries, P. Seymour, G. Zussman, and Y. Zwols, "Analyzing the performance of greedy maximal scheduling via local pooling and graph theory," *IEEE/ACM Trans. Netw.*, vol. 20, pp. 163–176, Feb. 2012.
- [6] M. Leconte, J. Ni, and R. Srikant, "Improved bounds on the throughput efficiency of greedy maximal scheduling in wireless networks," *IEEE/ACM Trans. Netw.*, vol. 19, pp. 709–720, Jun. 2011.
- [7] A. Brzezinski, G. Zussman, and E. Modiano, "Local pooling conditions for joint routing and scheduling," in *Proc. Information Theory and Applications Workshop (ITA)*, San Deigo, CA, 2008, pp. 499–506.
- [8] L. Tassiulas and A. Ephremides, "Dynamic scheduling for minimum delay in tandem and parallel constrained queueing models," *Ann. Oper. Res.*, vol. 48, no. 4, pp. 333–355, 1994.
- [9] A. L. Stolyar, "Large number of queues in tandem: Scaling properties under back-pressure algorithm," *Queueing Syst.*, vol. 67, no. 2, pp. 111–126, 2011.
- [10] L. Bui, R. Srikant, and A. Stolyar, "A novel architecture for reduction of delay and queueing structure complexity in the back-pressure algorithm," *IEEE/ACM Trans. Netw.*, vol. 19, no. 6, pp. 1597–1609, December 2011.
- [11] T. Hellings, S. C. Borst, and J. S. van Leeuwen, "Tandem queueing networks with neighbor blocking and back-offs," *Queueing Syst.*, vol. 68, no. 3–4, pp. 321–331, 2011.
- [12] J. G. Dai, "On positive Harris recurrence of multiclass queueing networks: a unified approach via fluid limit models," *Ann. Appl. Probab.*, vol. 5, no. 1, pp. 49–77, 1995.
- [13] H. L. Royden and P. M. Fitzpatrick, *Real Analysis*, 4th ed. Prentice Hall, 2010.
- [14] X. Kang, J. J. Jaramillo, and L. Ying, "Stability of longest-queue-first scheduling in linear wireless networks with multihop traffic and one-hop interference," Arizona State University, Tech. Rep., 2013.