On the Universality of Age-Based Scheduling in Wireless Networks

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***Abstract*—It is well-known that maximum weight scheduling, with link weights which are either functions of queue lengths or the ages of the Head-of-Line (HoL) packets in each queue, maximizes the throughput region of wireless networks with persistent flows. In particular, with only persistent flows, it does not matter for throughput optimality whether one uses queue lengths or HoL ages as weights. In this paper, we show the following interesting result: when some flows in the network are dynamic (i.e., they arrive and depart from the network and are not persistent), then HoL-age-based scheduling algorithms are throughput-optimal while it has previously been shown that queue-length-based algorithms are not. This reveals that, age-based algorithms are *universal* in the sense that their throughput optimality does not depend on whether the arriving traffic is persistent or not. We also present a distributed implementation of the proposed age-based algorithm using CSMA techniques, where each flow only knows its own age and carrier sensing information. Finally, we support our analytical results through simulations. The proof of throughput optimality may be interesting in its own right: it uses a novel Lyapunov function which is the sum of the ages of all the packets in the network.**

I. INTRODUCTION

Maintaining efficient and high-quality communication in wireless networks requires careful management of interference among simultaneous transmissions. A central question in the design of efficient interference management is to determine when and which users are allowed to transmit – an operation commonly referred to as *scheduling*. The seminal works of Tassiulas and Ephremides (e.g., [22], [23], [21]) developed a queue-length-based throughput-optimal strategy, which prioritizes activation of users with the greatest backlog awaiting service, also called *Maximum Weight Scheduling (MWS)*. Here, the throughput-optimal strategy means that it can achieve any throughput subject to network stability that is achievable by any other scheduling strategy. Subsequent works extended throughput to other first-order metrics, such as fairness (e.g., [4], [13], [9], [20]), average energy consumption (e.g., [14], [15], [3]), etc.

Although MWS algorithm exhibits excellent network performance, it implicitly assumes that the system consists of a fixed number of *persistent* flows that continuously inject packets into the network and will never leave the network. This assumption fails to hold in most real-world communication networks, where *dynamic flows* arrive, demand a certain amount of service, and leave the network once the requested service is complete. In such networks, the well-known queue-length-based MWS algorithm fails to achieve maximum throughput. In particular, in [24], the authors presented examples to show that the queue-length-based MWS algorithm is not throughput-optimal in networks with flow-level dynamics over time-varying channels. Subsequent works (e.g., [11], [10], [18], [26]) have developed throughput-optimal scheduling algorithms that do not require any prior knowledge of channels and user demands.

In another interesting work [25], the authors showed that the queue-length-based MWS algorithm also fails to provide maximum throughput in *spatial* wireless networks, even in the absence of time-varying channels, where only certain subsets of the dynamic flows can be activated simultaneously subject to the interference constraints. The intuition is as follows. If a persistent flow does not receive service for a long time, its backlog blows up, which in turn forces the MWS scheduler to serve the flow. This characteristic guarantees the efficiency of the MWS algorithm in the presence of persistent flows. However, in the presence of dynamic flows, where the backlog of a dynamic flow is fixed, the MWS algorithm tends to serve flows with large backlogs and may not provide any service for flows with small backlogs, which results in flows with small backlogs staying in the network forever. Therefore, as the flows with small backlogs continue to arrive, the number of such flows could increase to infinity, leading to network instability.

Even though the authors in [25] developed a region-based version of MWS scheduling, the proposed algorithm requires the careful identification of adequate regions, which not only sacrifices throughput performance but also yields difficulty for distributed implementation. In [2], the authors developed a flow-aware CSMA algorithm for *continuous-time systems*, where each dynamic flow attempts to access the wireless channel after some random time and transmits a packet if the channel is sensed idle. Surprisingly, this simple distributed algorithm achieves the maximum throughput in the presence of dynamic flows. However, it does not achieve the maximum throughput in the presence of persistent flows. This deficiency is pronounced, since it is difficult to differentiate between dynamic and persistent flows in reality.

This motivates us to develop a universal scheduling algorithm that is insensitive to the flow type. That is, we would like to design a throughput-optimal scheduling algorithm in wireless networks serving both persistent and dynamic flows. We find that the flow-level-age, such as the age of dynamic flows and the age of head-of-line files in the persistent flows, is a natural and sufficient information which can be utilized for this purpose. We develop a flow-level-age-based throughput-optimal MWS algorithm, which prioritizes activation of dynamic/persistent flows with the largest age. Even though head-of-line-age-based scheduling (e.g., [12], [1], [19], [5]) has been shown to be throughput-optimal in the presence of persistent flows, it is unclear how it can be generalized to the case with both persistent and dynamic flows. By using a novel Lyapunov function that measures the total waiting time of all files present in the network, we show that age-based scheduling is universal.

We make a remark on the terminology here. By a *dynamic flow*, we refer to a single file which arrives, transfers its packets and departs from the system. Such a file is associated with a node in the network, and thus, when the file departs, the node also departs, which makes the topology of the network itself dynamic. On the other hand, a *persistent flow* is associated with a fixed node in the network which never departs. Such a flow generates files continuously, and each file consists of a collection packets. Notice that, both in the case of persistent and dynamic files, the HoL packet belongs to the HoL file (in the case of dynamic flows, there is only one file at the node), and hence, the age of the HoL packet is the same as the age of the HoL file.

Noting the high-complexity and centralized operation of our proposed algorithm, we also investigate the issue of distributed design of our proposed scheduling algorithm. Recently, distributed Carrier Sense Multiple Access (CSMA)-based scheduling algorithms ([7], [16], [17], [6]) have attracted extensive interest due to their throughput-optimal characteristics in general networks with a fixed number of persistent flows. All such CSMA scheduling algorithms use an appropriate queue-based weights as their CSMA parameters. In this work, we show that CSMA algorithm that is based on age-information achieves maximum throughput when persistent and dynamic flows coexist. Our contributions in this work can be summarized as follows:

- We develop a throughput-optimal age-based scheduling algorithm that is robust to the presence of both persistent and dynamic flows. To the best of our knowledge, this is the first universal wireless scheduler that can optimally support coexisting persistent and dynamic flows. To handle the unique dynamics of flow-level-age, we propose a novel Lyapunov function to show the throughput optimality, which may be interesting in its own right.
- To address the complexity of the proposed algorithm, we present a distributed CSMA implementation of our algorithm, where each flow only needs to know its own age and carrier sensing information.
- We support our analytical results with extensive simulation results, which shows the robustness of the age-based scheduling algorithms.

II. System Model

A. Basic Setup

We consider a wireless network with a fixed number of persistent flows coexisting with dynamic flows arriving in a fixed area, where a *persistent flow* means that the flow persistently injects files into the network and will never leave the network. In contrast, a *dynamic flow* means that the flow that will leave the network once it completes its transmission. We assume that the system operates in *slotted time.* Since a dynamic flow is associated with a node, the topology of the network itself changes over time. Thus, it is difficult to characterize the interference in such networks using maximum independent sets, as is done traditionally. Instead, we partition the area over which the network operates into K different regions, such that at most one flow can be scheduled in each region in each time slot and flows in different regions may or may not be scheduled simultaneously depending on the interference constraints. Note that this area partitioning is just for the purpose of conveniently characterizing the interference constraints, and our algorithms (in particular, our distributed algorithm) do not rely on the details of this partition.

We call a set of regions that can provide service to their flows simultaneously a *feasible set of regions*. Let Ω be the collection of feasible sets of regions. For example, Fig. $1(a)$ shows a wireless network with five regions under the one-hop interference model, where the neighboring regions cannot provide service for flows at the same time. Thus, a transmission in region 1 interferes with the transmission in regions 2, 3, 4 but not with region 5. The maximal feasible sets of regions in such a network are $\{3\}$, $\{1,5\}$, $\{2,4\}$ and $\{2,5\}$. Also, Fig. 1 shows the two snapshots of the network, where the network topology changes due to the arrival and departure of the dynamic flows.

Let $\mathcal{N}_i^{(d)}[t]$ be the set of dynamic flows in region i in time slot t, and $\mathcal{N}_i^{(p)}$ be the set of persistent flows in region i. Note that the number of persistent flows $|\mathcal{N}_i^{(p)}|$ is fixed in each region, where $|\mathcal{A}|$ denotes the cardinality of set $\mathcal{A}$. We call a set of flows that can be scheduled simultaneously as a feasible schedule and denote it as

$$\mathbf{S}[t] \triangleq \{S_{i,j}[t], j \in \mathcal{N}_i^{(d)}[t] \cup \mathcal{N}_i^{(p)}, i = 1, 2, ..., K\},$$

where $S_{i,j}[t] = 1$ if the flow j in the region i is scheduled in slot t and $S_{i,j}[t] = 0$, otherwise. Let $\mathcal{S}[t]$ be the set of all feasible schedules in slot t. With a little bit abuse of notation, we also use $S_i[t]$ to denote whether the service is provided in region i in time slot t.

We maintain a queue for each persistent flow. We use $Q_{i,j}^{(p)}[t]$ to denote the queue-length of persistent flow j in region i in time slot t. Let $A_{i,j}^{(p)}[t]$ be the number of files arriving in queue j in region i in slot t that are independently and identically distributed (i.i.d.) over time with mean $\lambda_{i,j}^{(p)} > 0$, and $A_{i,j}^{(p)}[t] \leq A_i^{\max}$ for some $A_i^{\max} < \infty$, $\forall i, t \geq 0$. We

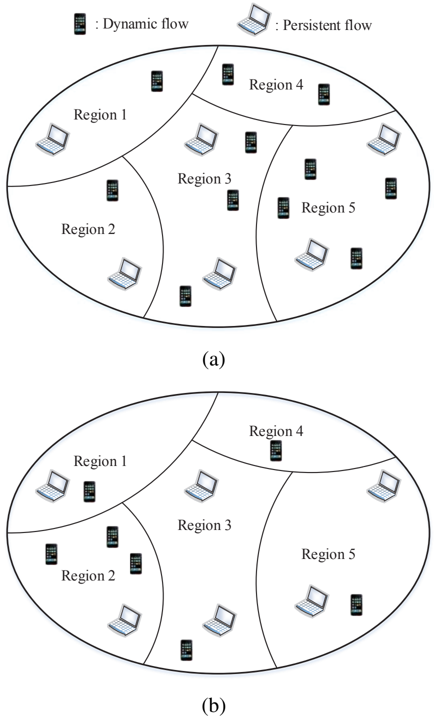

Fig. 1. Two snapshots of a wireless network with five regions: the network topology changes due to the departure and arrival of dynamic flows.

use $F^{(p)}_{i,j,l}[t]$ to denote the number of packets constituting file l arriving at queue j in region i in slot t that follows any random distribution with mean $\eta^{(p)}_{i,j} > 0$ and $F^{(p)}_{i,j,l}[t] < F^{\max}_i$ for some $F^{\max}_i < \infty$. Let $\mathcal{M}^{(p)}_{i,j}[t]$ be the set of files of persistent flow j in region i in time slot t. Files in each queue are served in First-Come-First-Serve (FCFS) order, i.e., the Head-of-Line (HoL) file in each queue is always served first. Let $\rho^{(p)}_{i,j} \triangleq \lambda^{(p)}_{i,j}\eta^{(p)}_{i,j}$ be the traffic intensity of the persistent flow j in region i.

We assume that $A^{(d)}_i[t]$, which denotes the number of dynamic flows arriving in region i in slot t, are i.i.d. over time with mean $\lambda^{(d)}_i > 0$, and $A^{(d)}_i[t] \le A^{\max}_i$ for some $A^{\max}_i < \infty, \forall i, t \ge 0$. We use $F^{(d)}_{i,j}[t]$ to denote the number of packets of flow j arriving at region i that follows any random distribution with mean $\eta^{(d)}_i > 0$, and $F^{(d)}_{i,j}[t] < F^{\max}_i$. Let $\rho^{(d)}_i \triangleq \lambda^{(d)}_i \eta^{(d)}_i$ be the traffic intensity of the dynamic flows in region i.

We assume that newly arriving files cannot be scheduled until the next time slot. For ease of exposition, we assume that each flow transfers one packet in each time slot if scheduled. Let $\rho_i \triangleq \rho^{(d)}_i + \sum_{j\in\mathcal{N}^{(p)}} \rho^{(p)}_i$ be the traffic intensity in region i. We use $R^{(d)}_{i,j}[t]$ and $R^{(p)}_{i,j,l}[t]$ to denote the number of residual packets of dynamic flow $j \in \mathcal{N}^{(d)}_i[t]$ and file l in queue $j \in \mathcal{N}^{(p)}_i$ in region i in slot t, respectively. Note that the queue-length of queue $j \in \mathcal{N}^{(p)}_i$ is just the total number of residual packets of persistent flow $j \in \mathcal{N}^{(p)}_i$, i.e., $Q^{(p)}_{i,j}[t] = \sum_{l\in\mathcal{M}^{(p)}_{i,j}[t]} R^{(p)}_{i,j,l}[t]$. The dynamic flows or files of persistent flows leave the system once all their packets have been served, i.e., their residual sizes reduce to 0. We use $T^{(d)}_{i,j}[t]$ and $T^{(p)}_{i,j,l}[t]$ to denote the "age" of dynamic flow $j \in \mathcal{N}^{(d)}[t]$ and file l in queue $j \in \mathcal{N}^{(p)}$ in region i in slot t, respectively, i.e., $T^{(d)}_{i,j}[t]$ and $T^{(p)}_{i,j,l}[t]$ always increase by 1 if their corresponding flows and files do not leave the system, and resets to 0 otherwise. More precisely, the evolution of $T^{(d)}_{i,j}[t]$ and $T^{(p)}_{i,j,l}[t]$ can be written as

$$T^{(d)}_{i,j}[t+1] = \left(T^{(d)}_{i,j}[t] + 1\right)\left(1 - \mathbb{1}_{\{R^{(d)}_{i,j}[t+1]=0\}}\right), \quad (1)$$

$$T^{(p)}_{i,j,l}[t+1] = \left(T^{(p)}_{i,j,l}[t] + 1\right)\left(1 - \mathbb{1}_{\{R^{(p)}_{i,j,l}[t+1]=0\}}\right), \quad (2)$$

where $\mathbb{1}_{\{\mathcal{B}\}}$ is an indicator function of event $\mathcal{B}$. Let $T^{(p)}_{i,j}[t] \triangleq \max_{l\in\mathcal{M}^{(p)}_{i,j}[t]} T_{i,j,l}[t]$ be the age of HoL file of queue j in region i in time slot t.

In this paper, we consider the policies under which the system evolves as a Markov Chain. We call the system *stable* if the underlying Markov Chain is positive recurrent. We define the *capacity region* Λ as the convex hull of the collection of feasible sets of regions Ω, which gives the upper bound on the achievable rates in packets per slot that can be supported by the network under stability for the given interference model. We say that a scheduler is *throughput-optimal* if it achieves the network stability for any traffic intensity vector $\boldsymbol{\rho} \triangleq (\rho_i)_{i=1}^K$ that lies strictly inside the capacity region Λ.

B. Deficiency of Traditional MWS under Dynamic Flows

The well-known queue-length-based Maximum Weight Scheduling (MWS) algorithms ([22], [23]) have been shown to achieve maximum throughput in the presence of a fixed number of persistent flows that persistently inject packets into the network. However, they fail to provide the maximum throughput in wireless networks with dynamic flows. Next, we first give the traditional queue-length-based MWS algorithm for completeness.

Algorithm 1: (Residual-Flow-Size-Based MWS (RFS-MWS) Algorithm): In each time slot t, select a feasible schedule $\mathbf{S}^{(\text{RFS})}[t] \in \mathcal{S}[t]$ that maximizes the aggregate residual size

$$\sum_{i=1}^{K}\left(\sum_{j\in\mathcal{N}^{(d)}_i[t]} R^{(d)}_{i,j}[t]S_{i,j}[t] + \sum_{j\in\mathcal{N}^{(p)}_i} Q^{(p)}_{i,j}[t]S_{i,j}[t]\right).$$

To see the throughput inefficiency of the RFS-MWS Algorithm, we consider a star topology with four regions in the presence of only dynamic flows, where the first three regions do not interfere with each other but with the fourth region. The number of arriving dynamic flows in each region i follows Bernoulli distribution with mean λ_i, $\forall i = 1, 2, 3, 4$. Assume $\lambda_1 = \lambda_2 = \lambda_3 = \lambda$. The size of arriving dynamic flows is always 2 in the first three regions and 1 in the last region. Hence, we have $\rho_1 = \rho_2 = \rho_3 = 2\lambda$, and $\rho_4 = \lambda_4$, where we recall that ρ_i denotes the traffic intensity in region i, $\forall i = 1, 2, 3, 4$. It is easy to see that the achievable rate region in the fourth region is $\{\rho_4 > 0 : \rho_4 < 1 - 2\lambda\}$. Yet, under the RFS-MWS Algorithm, the dynamic flows in the fourth region can never be scheduled if there is an arriving dynamic flow in any of the first three regions, which implies that the maximum supportable traffic intensity in the fourth region should be bounded from above by $(1-\lambda)^3$, i.e., $\rho_4 < (1-\lambda)^3$. Thus, if $\lambda < 1-\sqrt{2/3} \approx 0.1835$, then, $(1-\lambda)^3 < 1-2\lambda$, which implies that the RFS-MWS Algorithm fails to achieve maximum throughput. In [25], the authors provide more examples illustrating the throughput deficiency of the RFS-MWS Algorithms in the presence of dynamic flows.

The deficiency of the RFS-MWS Algorithm is due to the fact that it myopically selects a feasible schedule with the maximal residual size of dynamic flows without the knowledge of the aggregate flow size of dynamic flows in each region. If we view each region as a single link, then, the wireless network with dynamic flows can be seen as a classic wireless network with a fixed number of links, where packets belonging to various dynamic flows are continuously injected into their associated link. Hence, it is easy to verify that the traditional MWS strategy that schedules according to the aggregate flow size at each link is throughput-optimal. However, the number of dynamic flows in each region is hard to obtain in each time slot in practice and thus an appropriate and easily measurable metric approximately reflecting the aggregate flow size of dynamic flows in each region is strongly desirable.

C. Deficiency of Flow-Aware CSMA under Persistent Flows

The flow-aware CSMA algorithm proposed in [2] can achieve the maximum throughput in presence of only dynamic flows in *continuous time*. The algorithm works as follows:

Algorithm 2 (Flow-Aware CSMA Algorithm): Each flow independently generates an exponentially distributed random variable with a *constant* rate and starts transmitting after this random duration unless it senses another transmission before. If the flow senses the transmission, it suspends its backoff timer and resumes it after the completion of this transmission. The transmission time of each link is exponentially distributed with mean 1.

Under the flow-aware CSMA algorithm, each region virtually generates an exponentially distributed random variable with the rate proportional to the number of flows in that region, which follows from the fact that the minimum of two independent exponential random variables is exponentially distributed with the rate that is the sum of rates of these two random variables. Thus, the information about the aggregate flow size is implicitly included in the algorithm resulting in the optimal throughput. However, the flow-aware CSMA algorithm is not throughput-optimal for wireless networks with persistent flows (see [2]).

In practice, it is difficult to distinguish the persistent and dynamic flows. Therefore, it is necessary to design a distributed and universal scheduling algorithm that is throughput-optimal in the presence of both persistent and dynamic flows. Next, we first develop a centralized scheduling algorithm for serving both persistent and dynamic flows, which we later convert to a distributed algorithm.

III. Universal Age-Based Scheduling

In this section, we develop a universal scheduling algorithm that is throughput-optimal for *hybrid* flows, where persistent and dynamic flows coexist.

A. Algorithm Description

A good approximation of the aggregate flow size of dynamic flows in each region is the maximum age of dynamic flows in that region. Indeed, from the Law of Large Numbers [5], the aggregate flow size of dynamic flows is proportional to the maximum age of dynamic flows in each region. In addition, the age of HoL files is a good metric to make transmission decisions in the presence of only persistent flows, since the HoL-age-based scheduling (e.g., [12], [1], [19], [5]) has been shown to be throughput-optimal in such a scenario. Therefore, it may be sufficient to utilize the age of dynamic flows and the age of HoL files of persistent flows to schedule transmissions.

To facilitate the flexibility in the algorithm design, we define a set of functions:
$\mathcal{F} \triangleq$ set of non-negative, non-decreasing, differentiable and concave functions $f(\cdot) : \mathbb{R}_+ \to \mathbb{R}_+$ with $f(0) = 0$ and $\lim_{y\to\infty} f(y) = \infty$.

$$\mathcal{G} \triangleq \{f \in \mathcal{F} : \text{ for } a \geq 1 \text{ there exists a number } c(a) > 0 \text{ depending on } a \text{ such that } f(ax) \leq c(a)f(x), \forall x \geq 1\}.$$

The examples of functions that are in class $\mathcal{G}$ are $f(x) = x$, $f(x) = \sqrt{x}$, $f(x) = \log(1+x)$, $f(x) = \log\log(x+e)$, and $f(x) = \log(1+x)/g(x)$, where $g(x)$ is an arbitrary positive, non-decreasing and differentiable function which makes $f(x)$ an non-decreasing concave function. Next, we propose the following age-based algorithm.

Algorithm 3: (Age-Based MWS (A-MWS) Algorithm): In each time slot t, select a feasible schedule $\mathbf{S}^{(\text{A-MWS})}[t] \in \mathcal{S}[t]$ that maximizes the aggregate age of all flows

$$\sum_{i=1}^{K}\left(\sum_{j\in\mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]\right)S_{i,j}[t] + \sum_{j\in\mathcal{N}_i^{(p)}} f\left(T_{i,j}^{(p)}[t]\right)S_{i,j}[t]\right),$$

where we recall that $T_{i,j}^{(d)}[t]$ is the age of dynamic flow j in region i in time slot t and $T_{i,j}^{(p)}[t]$ is the age of HoL file of persistent flow j in region i in time slot t, and $f \in \mathcal{G}$.

Under the A-MWS Algorithm, only the dynamic flow with the maximum age or the persistent flow with the largest HoL age can be scheduled in each region. Recall that the HoL age of persistent flow is the maximum age of files in its corresponding queue. To make the transmission decisions under the A-MWS Algorithm, it is sufficient to know the age of dynamic flows and the age of the HoL files of persistent flows. Even though we can show the throughput-optimality of the HoL-age-based scheduling (e.g., [12], [1], [19], [5]) in the presence of only persistent flows, it is unclear how the proof can be extended to the case with hybrid flows. Nevertheless, we establish the throughput-optimality of the A-MWS Algorithm by choosing a novel Lyapunov function as the total summation of the function of age of all remaining packets. Unlike the traditional quadratic form counterpart, our Lyapunov function is novel and is of independent interest.

Theorem 1: The A-MWS Algorithm with $f \in \mathcal{G}$ is throughput-optimal, i.e., it stabilizes the system for any arrival intensity vector $\boldsymbol{\rho}$ that is strictly within the capacity region Λ.

This result, whose proof is provided in Section III-B, indicates that it is sufficient to guarantee the throughput-optimality by scheduling transmissions only based on the age of dynamic flows and the age of HoL files of persistent flows. The scheduler need not know the type of flow. This advantage is pronounced in practice, since it is difficult to distinguish the persistent and dynamic flows.

B. Proof of Throughput-Optimality

The proof of Theorem 1 to-be-presented next is of independent interest as it introduces a novel Lyapunov function that can accommodate both persistent and dynamic flows. We start by establishing the following simple inequality.

Lemma 1: For any $f \in \mathcal{F}$, we have

$$\sum_{m=1}^{M-1} f'(m) \leq f(M) + f'(1), \tag{3}$$

holding for any $M \geq 1$.

Proof: By using the Fundamental Theorem of Calculus, we have

$$\begin{aligned} f(M) - f(1) &= \int_1^M f'(\tau) d\tau \\ &= \sum_{m=1}^{M-1} \int_m^{m+1} f'(\tau) d\tau \\ &\overset{(a)}{\geq} \sum_{m=1}^{M-1} \int_m^{m+1} f'(m+1) d\tau \\ &= \sum_{m=1}^{M-1} f'(m+1) \\ &= \sum_{m=1}^{M-1} f'(m) + f'(M) - f'(1), \end{aligned} \tag{4}$$

where the step (a) follows from the fact that $f'(y)$ is non-increasing for any $y \geq 0$ due to the concavity of the function f. Reorganizing the inequality (4) and using the fact that $f(y) \geq 0$ and $f'(y) \geq 0$ for any $y \geq 0$, we have the desired result. ■

We are ready to prove Theorem 1. As the Lyapunov function, we take the total age of all files of both persistent and dynamic flows, which are currently in the system. Mathematically, we choose the Lyapunov function as $V(\mathbf{R}, \mathbf{T}) \triangleq V_1(\mathbf{R}^{(d)}, \mathbf{T}^{(d)}) + V_2(\mathbf{R}^{(p)}, \mathbf{T}^{(p)})$, where

$$V_1(\mathbf{R}^{(d)}, \mathbf{T}^{(d)}) \triangleq \sum_{i=1}^{K} \sum_{j \in \mathcal{N}_i^{(d)}} R_{i,j}^{(d)} f\left(T_{i,j}^{(d)}\right), \tag{5}$$

$$V_2(\mathbf{R}^{(p)}, \mathbf{T}^{(p)}) \triangleq \sum_{i=1}^{K} \sum_{j \in \mathcal{N}_i^{(p)}} \sum_{l \in \mathcal{M}_{i,j}^{(p)}} R_{i,j,l}^{(p)} f\left(T_{i,j,l}^{(p)}\right), \tag{6}$$

and $\mathbf{R}^{(d)} = \left(R_{i,j}^{(d)}, j \in \mathcal{N}_i^{(d)}, i = 1, 2, ..., K\right)$,

$$\begin{aligned} \mathbf{R}^{(p)} &= \left(R_{i,j,l}^{(p)}, l \in \mathcal{M}_{i,j}^{(p)}, j \in \mathcal{N}_i^{(p)}, i = 1, 2, ..., K\right), \\ \mathbf{T}^{(d)} &= \left(T_{i,j}^{(d)}, j \in \mathcal{N}_i^{(d)}, i = 1, 2, ..., K\right), \\ \mathbf{T}^{(p)} &= \left(T_{i,j,l}^{(p)}, l \in \mathcal{M}_{i,j}^{(p)}, j \in \mathcal{N}_i^{(p)}, i = 1, 2, ..., K\right), \\ \mathbf{R} &= (\mathbf{R}^{(d)}, \mathbf{R}^{(p)}), \mathbf{T} = (\mathbf{T}^{(d)}, \mathbf{T}^{(p)}). \end{aligned}$$

Next, we will consider the drift of $V_1(\mathbf{R}^{(d)}, \mathbf{T}^{(d)})$ and $V_2(\mathbf{R}^{(p)}, \mathbf{T}^{(p)})$, respectively. We first focus on the drift $\Delta V_1[t] \triangleq V_1(\mathbf{R}^{(d)}[t+1], \mathbf{T}^{(d)}[t+1]) - V_1(\mathbf{R}^{(d)}[t], \mathbf{T}^{(d)}[t])$. In each region $i = 1, 2, ..., K$, we have

$$\begin{aligned} &\sum_{j \in \mathcal{N}_i^{(d)}[t+1]} R_{i,j}^{(d)}[t+1] f\left(T_{i,j}^{(d)}[t+1]\right) \\ &= \sum_{j \in \mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t+1] f\left(T_{i,j}^{(d)}[t+1]\right) + f(1) \sum_{j=1}^{A_i^{(d)}[t]} F_{i,j}^{(d)}[t], \end{aligned} \tag{7}$$

where the last step follows from the fact that the newly arriving dynamic flows are not served in the current slot. Next, we focus on $\sum_{j \in \mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t+1] f\left(T_{i,j}^{(d)}[t+1]\right)$ in equation (7).

$$\begin{aligned} &\sum_{j \in \mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t+1] f\left(T_{i,j}^{(d)}[t+1]\right) \\ \overset{(a)}{=} &\sum_{j \in \mathcal{N}_i^{(d)}[t]} f\left(\left(T_{i,j}^{(d)}[t]+1\right)\left(1 - \mathbb{1}_{\{R_{i,j}^{(d)}[t+1]=0\}}\right)\right) R_{i,j}^{(d)}[t+1] \\ \overset{(b)}{=} &\sum_{j \in \mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]+1\right) R_{i,j}^{(d)}[t+1] \\ \overset{(c)}{=} &\sum_{j \in \mathcal{N}_i^{(d)}[t]} \left(f\left(T_{i,j}^{(d)}[t]\right) + f'\left(x_{i,j}\right)\right)\left(R_{i,j}^{(d)}[t] - S_{i,j}^{(\text{A-MWS})}[t]\right) \\ \overset{(d)}{\leq} &\sum_{j \in \mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t] f\left(T_{i,j}^{(d)}[t]\right) - \sum_{j \in \mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t] \\ &+ \sum_{j \in \mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t] f'\left(T_{i,j}^{(d)}[t]\right), \end{aligned} \tag{8}$$

where the step (a) uses the dynamics of $T_{i,j}^{(d)}[t]$, i.e., equation (1); step (b) follows from the assumption that $f(0) = 0$; step (c) uses the Mean Value Theorem for some $x_{i,j}$ between $T_{i,j}^{(d)}[t]$ and $T_{i,j}^{(d)}[t]+1$, and the fact that $S_{i,j}^{(\text{A-MWS})}[t] \leq 1$ and

$R_{i,j}^{(d)}[t] \geq 1$, for any $j \in \mathcal{N}_i^{(d)}[t]$; step (d) follows from the fact that $f'(y)$ is non-decreasing and non-negative due to $f(y)$ being non-decreasing and concave for any $y \geq 0$.

By combining the definition of $\Delta V_1[t]$, (7) and (8), we have

$$\mathbb{E}\left[\Delta V_1[t]\right] \leq \sum_{i=1}^{K} \mathbb{E}\left[\sum_{j\in\mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t] f'\left(T_{i,j}^{(d)}[t]\right)\right] - \sum_{i=1}^{K} \mathbb{E}\left[\sum_{j\in\mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t]\right] + f(1)\sum_{i=1}^{K}\rho_i^{(d)}. \tag{9}$$

In order to provide an upper bound on the first term of right-hand side of inequality (9), we consider its expectation conditioned on $T_{i,\max}^{(d)}[t] \triangleq \max_{j\in\mathcal{N}_i^{(d)}[t]} T_{i,j}^{(d)}[t]$, i.e.,

$$\begin{aligned}
&\mathbb{E}\left[\sum_{j\in\mathcal{N}_i^{(d)}[t]} R_{i,j}^{(d)}[t] f'\left(T_{i,j}^{(d)}[t]\right)\middle| T_{i,\max}^{(d)}[t]\right] \\
\overset{(a)}{\leq}&\mathbb{E}\left[\sum_{\tau=t-T_{i,\max}^{(d)}[t]+1}^{t-1} f'(t-\tau)\sum_{j=1}^{A_i^{(d)}[\tau]} F_{i,j}^{(d)}[\tau]\middle| T_{i,\max}^{(d)}[t]\right] \\
&+ A_i^{\max}F_i^{\max} f'(T_{i,\max}^{(d)}[t]) \\
\overset{(b)}{=}&\rho_i^{(d)}\sum_{\tau=t-T_{i,\max}^{(d)}[t]+1}^{t-1} f'(t-\tau) + A_i^{\max}F_i^{\max} f'(T_{i,\max}^{(d)}[t]) \\
\leq&\rho_i^{(d)}\sum_{m=1}^{T_{i,\max}[t]-1} f'(m) + A_i^{\max}F_i^{\max} f'(1) \\
\overset{(c)}{\leq}&\rho_i^{(d)} f(T_{i,\max}^{(d)}[t]) + (\rho_i^{(d)} + A_i^{\max}F_i^{\max}) f'(1).
\end{aligned} \tag{10}$$

where the step (a) follows from the fact that flows in time slot t at most include all flows that came between $\tau = t - T_{i,\max}^{(d)}[t]$ and $t-1$, and the fact that the number of incoming packets of each dynamic flow in each region i in each time slot is not greater than $A_i^{\max}F_i^{\max}$; step (b) follows from the fact the dynamic flows arriving between $t - T_{i,\max}^{(d)}[t] + 1$ and $t-1$ do not served under the A-MWS Algorithm, since the A-MWS always serves the dynamic flows with the maximum age in each region; step (c) uses Lemma 1.

By taking expectation of inequality (10) over $T_{i,\max}^{(d)}[t]$ and substituting it into (9), we have

$$\mathbb{E}[\Delta V_1[t]] \leq \sum_{i=1}^{K}\rho_i^{(d)}\mathbb{E}\left[f(T_{i,\max}^{(d)}[t])\right] + B_1 - \sum_{i=1}^{K}\mathbb{E}\left[\sum_{j\in\mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t]\right], \tag{11}$$

where $B_1 \triangleq f(1)\sum_{i=1}^{K}\rho_i^{(d)} + f'(1)\sum_{i=1}^{K}(\rho_i^{(d)} + A_i^{\max}F_i^{\max})$.

Similarly, we can show

$$\mathbb{E}[\Delta V_2[t]] \leq \sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(p)}}\rho_{i,j}^{(p)}\mathbb{E}\left[f(T_{i,j}^{(p)}[t])\right] + B_2 - \sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(p)}}\mathbb{E}\left[f\left(T_{i,j}^{(p)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t]\right], \tag{12}$$

where $\Delta V_2[t] \triangleq V_2(\mathbf{R}^{(p)}[t+1], \mathbf{T}^{(p)}[t+1]) - V_2(\mathbf{R}^{(p)}[t], \mathbf{T}^{(p)}[t])$, and $B_2 \triangleq f'(1)\sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(p)}}(\rho_{i,j}^{(p)} + A_i^{\max}F_i^{\max}) + f(1)\sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(p)}}\rho_{i,j}^{(p)}$.

Thus, we have

$$\begin{aligned}
&\mathbb{E}\left[\Delta V[t]\right] = \mathbb{E}\left[V(\mathbf{R}[t+1], \mathbf{T}[t+1]) - V(\mathbf{R}[t], \mathbf{T}[t])\right] \\
=&\mathbb{E}\left[\Delta V_1[t]\right] + \mathbb{E}\left[\Delta V_2[t]\right] \\
\overset{(a)}{\leq}&\sum_{i=1}^{K}\mathbb{E}\left[\rho_i^{(d)} f(T_{i,\max}^{(d)}[t]) + \sum_{j\in\mathcal{N}_i^{(p)}}\rho_{i,j}^{(p)} f(T_{i,j}^{(p)}[t])\right] + B \\
&-\sum_{i=1}^{K}\mathbb{E}\left[\sum_{j\in\mathcal{N}_i^{(d)}[t]} f\left(T_{i,j}^{(d)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t]\right] \\
&-\sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(p)}}\mathbb{E}\left[f\left(T_{i,j}^{(p)}[t]\right) S_{i,j}^{(\text{A-MWS})}[t]\right] \\
\overset{(b)}{\leq}&\sum_{i=1}^{K}\rho_i\mathbb{E}\left[f(T_i^{\max}[t])\right] - \sum_{i=1}^{K}\mathbb{E}\left[S_i^{(\text{A-MWS})}[t] f(T_i^{\max}[t])\right] + B,
\end{aligned} \tag{13}$$

where the step (a) follows from inequalities (11) and (12) and is true for $B \triangleq B_1 + B_2$; step (b) is true for $T_i^{\max}[t] \triangleq \max\left\{T_{i,\max}^{(d)}[t], \max_{j\in\mathcal{N}_i^{(p)}} f(T_{i,j}^{(p)}[t])\right\}$ and follows from the fact that the A-MWS Algorithm always selects a dynamic flow with the maximum age or the persistent flow with the maximum HoL age and the fact that at most one flow can be scheduled in each region in each time slot.

For any traffic intensity vector $\boldsymbol{\rho}$ strictly within the capacity region Λ (see [21]), there exists an $\epsilon > 0$ such that

$$\rho_i \leq \sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s})s_i - \epsilon, \qquad \forall i = 1, 2, .., K, \tag{14}$$

where $\mathbf{s} = (s_i)_{i=1}^{K}$ and $\sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s}) = 1$.

By substituting (14) into (13), we have

$$\begin{aligned}
\mathbb{E}\left[\Delta V[t]\right] \leq& -\epsilon\sum_{i=1}^{K}\mathbb{E}\left[f\left(T_i^{\max}[t]\right)\right] + B \\
&+\sum_{i=1}^{K}\sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s})s_i\mathbb{E}\left[f(T_i^{\max}[t])\right] \\
&-\sum_{i=1}^{K}\mathbb{E}\left[f\left(T_i^{\max}[t]\right) S_i^{(\text{A-MWS})}[t]\right].
\end{aligned} \tag{15}$$

Given $\mathbf{T}[t] = (\mathbf{T}^{(d)}[t], \mathbf{T}^{(p)}[t])$, according to the A-MWS Algorithm, we have

$$\begin{aligned}
&\sum_{i=1}^{K}\sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s})s_i f\left(T_i^{\max}[t]\right)\\
=&\sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s})\sum_{i=1}^{K}s_i f\left(T_i^{\max}[t]\right)\\
\leq&\sum_{\mathbf{s}\in\Omega}\alpha(\mathbf{s})\sum_{i=1}^{K}f\left(T_i^{\max}[t]\right)S_i^{(\text{A-MWS})}[t]\\
=&\sum_{i=1}^{K}f\left(T_i^{\max}[t]\right)S_i^{(\text{A-MWS})}[t],
\end{aligned}\tag{16}$$

By substituting (16) into (15), we have

$$\mathbb{E}\left[\Delta V[t]\right] \leq -\epsilon\sum_{i=1}^{K}\mathbb{E}\left[f\left(T_i^{\max}[t]\right)\right] + B. \tag{17}$$

By summing the above inequality over $t = 0, 1, ..., M-1$, we have

$$\limsup_{M\to\infty}\frac{1}{M}\sum_{t=0}^{M-1}\sum_{i=1}^{K}\mathbb{E}\left[f\left(T_i^{\max}[t]\right)\right] \leq \frac{B}{\epsilon}. \tag{18}$$

Since the A-MWS Algorithm only severs the dynamic flows with the oldest age and the dynamic flows in region i in time t at most include the flows that arrived between $t - T_{i,\max}^{(d)}[t]$ and $t-1$, we have

$$\begin{aligned}
\sum_{j\in\mathcal{N}_i^{(d)}[t]}R_{i,j}^{(d)}[t] \leq &\sum_{\tau=t-T_{i,\max}^{(d)}[t]+1}^{t-1}\ \sum_{j=1}^{A_i^{(d)}[t]}F_{i,j}^{(d)}[t] + A_i^{\max}F_i^{\max}\\
\leq &A_i^{\max}F_i^{\max}T_{i,\max}^{(d)}[t], \quad \forall i.
\end{aligned}\tag{19}$$

Similarly, we have

$$Q_{i,j}^{(p)}[t] = \sum_{l\in\mathcal{M}_{i,j}^{(p)}[t]}R_{i,j,l}^{(p)}[t] \leq A_i^{\max}F_i^{\max}T_{i,j}^{(p)}[t], \forall j, \forall i. \tag{20}$$

By combining (19) and (20), we have

$$\begin{aligned}
&f\left(\sum_{j\in\mathcal{N}_i^{(d)}[t]}R_{i,j}^{(d)}[t],\ \max_{j\in\mathcal{N}_i^{(p)}}Q_{i,j}^{(p)}[t]\right)\\
\leq&f\left(A_i^{\max}F_i^{\max}T_i^{\max}[t]\right)\\
\overset{(a)}{\leq}&G_i f\left(T_i^{\max}[t]\right) \overset{(b)}{\leq} G^{\max}f\left(T_i^{\max}[t]\right),
\end{aligned}\tag{21}$$

where the step (a) is true for some constant $G_i > 0$ depending on $A_i^{\max}$ and $F_i^{\max}$, and follows from the property of the function f; step (b) is true for $G^{\max} \triangleq \max_{i=1,2,...,K} G_i$. By combining (21) and (18), we have

$$\begin{aligned}
&\limsup_{M\to\infty}\frac{1}{M}\sum_{t=0}^{M-1}\sum_{i=1}^{K}\mathbb{E}\left[f\left(\sum_{j\in\mathcal{N}_i^{(d)}[t]}R_{i,j}^{(d)}[t],\ \max_{j\in\mathcal{N}_i^{(p)}}Q_{i,j}^{(p)}[t]\right)\right]\\
&\leq\frac{BG^{\max}}{\epsilon},
\end{aligned}\tag{22}$$

which implies stability-in-the-mean property and thus the underlying Markov Chain is positive recurrent [8]. ■

IV. Distributed Implementation

The proposed A-MWS algorithm requires the maximum weight schedule to be determined repeatedly as the the age of dynamic flows and files of persistent flows change. This calls for heavy computation and centralized operations, which is a formidable task in practice. This motivates us, in this section, to design a distributed version of the A-MWS algorithm based on *Glauber Dynamics*, similar spirit to that in [16], [6].

Let $\mathcal{C}_{i,j}[t]$ be the set of flows that are conflict with the (persistent or dynamic) flow j in region i in time slot t. Also, let $w_{i,j}[t]$ be the weight of flow j in region i in time slot t. $w_{i,j}[t] = f(T_{i,j}^{(d)}[t])$ if the flow is dynamic, and $w_{i,j}[t] = f(T_{i,j}^{(p)}[t])$ otherwise, where $f \in \mathcal{G}$. We divide each time slot t into a *control* slot and a *data* slot.

Algorithm 4: (Distributed A-MWS Algorithm in time slot t):

• In the control slot, a decision schedule $\mathbf{m}[t] \in \mathcal{S}[t]$ is selected at random with positive probability $\alpha(\mathbf{m}[t])$. Then, for all flows j in region i that are within $\mathbf{m}[t]$,

(i) If all flows $k \in \mathcal{C}_{i,j}[t]$ are not scheduled in time slot $t-1$, then $S_{i,j}[t] = 1$ with probability $\frac{\exp(w_{i,j}[t])}{1+\exp(w_{i,j}[t])}$, and $S_{i,j}[t] = 0$ with probability $\frac{1}{1+\exp(w_{i,j}[t])}$. Otherwise, $S_{i,j}[t] = 0$.

(ii) $S_{i',j'}[t] = S_{i',j'}[t-1]$ for all $j' \neq j$ or $i' \neq i$.

• In the data slot, use $\mathbf{S}[t]$ (defined in Section II-A) as the transmission schedule.

In the control slot of each time slot, each flow sends an INTENT message with a constant probability p (e.g., we set $p = 0.01$ in the simulation). If flow j in region i does not hear any INTENT messages from its conflicting links $\mathcal{C}_{i,j}[t]$, it will be included in $\mathbf{m}[t]$, otherwise, it will not be included in $\mathbf{m}[t]$. Then, $\mathbf{m}[t]$ is a feasible schedule, since those flows transmitting INTENT messages and do not hear any INTENT messages constitute a feasible schedule.

Under our distributed algorithm, the dynamic flow with the largest age will be served with highest probability while newly arriving flows have a small probability of transmission, especially for large values of the age of the oldest flow in a region. Therefore, it is reasonable to make the *time-scale separation assumption*, i.e., the underlying Glauber dynamics Markov chain converges to the steady-state distribution at a rate much faster than the rate at which the age of the oldest file in a region changes. Under the time-scale separation assumption, the stationary distribution of the distributed A-MWS algorithm in time slot t is given by

$$\pi_{\mathbf{S}}[t] = \frac{1}{Z[t]}\exp\left(\sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(d)}[t]\cup\mathcal{N}_i^{(p)}}w_{i,j}[t]S_{i,j}[t]\right), \mathbf{S}\in\mathcal{S}[t], \tag{23}$$

where $Z[t]$ is the normalized constant such that $\sum_{\mathbf{S}\in\mathcal{S}[t]} \pi_{\mathbf{S}}[t] = 1$. Then, it is easy to establish the following throughput optimality of our distributed algorithm.

Theorem 2: The distributed A-MWS Algorithm with $f \in \mathcal{G}$ is throughput-optimal, i.e., it stabilizes the system for any arrival intensity vector ρ that is strictly within the capacity region Λ.

The proof is similar to that in [16] by first establishing the following fact: given $\epsilon > 0$ and $\zeta > 0$, $\exists \overline{W} > 0$ such that if $W^*[t] > \overline{W}$, then the distributed A-MWS picks a schedule $\mathbf{S} \in \mathcal{S}[t]$ satisfying

$$\Pr\{W_{\mathbf{S}}[t] \geq (1-\epsilon)W^*[t]\} \geq 1-\zeta, \tag{24}$$

where $W_{\mathbf{S}}[t] \triangleq \sum_{i=1}^{K}\sum_{j\in\mathcal{N}_i^{(d)}[t]\cup\mathcal{N}_i^{(p)}} w_{i,j}[t]S_{i,j}$ and $W^*[t] \triangleq \max_{\mathbf{S}\in\mathcal{S}[t]} W_{\mathbf{S}}[t]$. The rest of proof is similar to that in Theorem 1, and thus is omitted here for brevity.

V. Simulation Results

In this section, we perform numerical studies to validate the throughput performance of the proposed A-MWS Algorithm and its CSMA implementation. We consider an area (see Fig. 2) partitioned into four regions, where each region contains a persistent flow and continuously arriving dynamic flows. Due to the interference constraints, at most one flow in each region can be active in each time slot. The maximal feasible sets of regions are $\{1,4\}$ and $\{2,3\}$. Therefore, the capacity region of such a network is $\Lambda = \{\boldsymbol{\rho} = (\rho_i)_{i=1}^4 : \rho_1+\rho_2 < 1, \rho_1+\rho_3 < 1, \rho_4+\rho_2 < 1, \rho_4+\rho_3 < 1\}$.

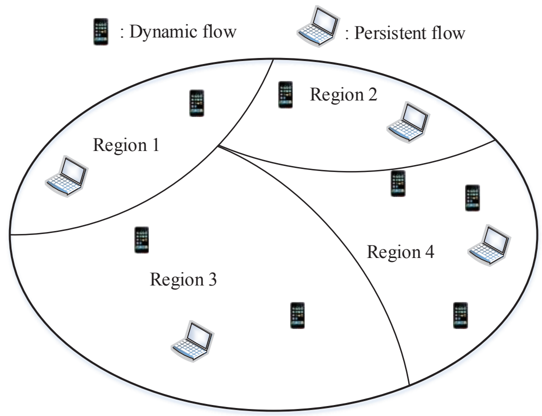

Fig. 2. Wireless network with four regions

We assume that the arrivals of both persistent and dynamic flows follow Bernoulli distribution. The arrival intensity vectors of persistent and dynamic flows are $\boldsymbol{\rho}^{(p)} = [1/4, 1/12, 1/6, 1/2]\times\theta$ and $\boldsymbol{\rho}^{(d)} = [1/2, 1/6, 1/12, 1/4]\times\theta$, respectively, where $\theta \in (0,1)$ characterizes the traffic loaded condition: the larger the θ, the more heavily loaded the system is. In the simulations, we assume that the number of packets of dynamic flows in each region follows the same distribution of random variable X, where X equals to 2 and 8 with equal probability. Also, the file size of persistent flows is always equal to one packet.

A. Throughput Performance of the A-MWS Algorithm

In this subsection, we compare the throughput performance between the A-MWS Algorithm and the RFS-MWS Algorithm. Fig. 3 illustrates the average number of dynamic flows and the average number of files of persistent flows under different load factor θ. It can be observed that the A-MWS Algorithm can stabilize the system for any load factor θ between 0 and 1. In contrast, the average number of files at persistent flows blow up under the queue-length-based RFS-MWS Algorithm. This illustrates the robustness of age-based scheduling to hybrid flows.

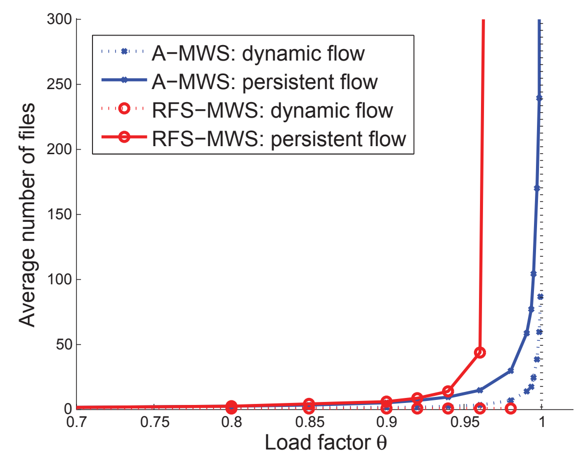

Fig. 3. Comparison of queue-length-based and age-based algorithms

B. Throughput Performance of the Distributed Algorithm

In this subsection, we investigate the throughput performance of the CSMA implementation of our proposed A-MWS Algorithm using linear and logarithmic functions, and compare them with the slightly modified flow-aware CSMA algorithm, whose transmission time is always 1 rather than exponentially distributed with mean 1 in continuous time. From Fig. 4, we can observe that the average number of files of persistent flows increases very fast under the distributed A-MWS Algorithm with linear function and the flow-aware CSMA Algorithm, while it grows much slowly under that with logarithmic function. This indicates that we need to choose a slowly increasing function as the weight function of the CSMA algorithm such that the underlying inhomogeneous Markov chain can converge to the steady-state distribution (see [6]). Also, the flow-aware CSMA fails to provide the maximum throughput in the presence of persistent flows. In contrast, the distributed A-MWS Algorithm with logarithmic function can keep the average number of files of both dynamic and persistent flows low, though at a higher level than its centralized counterpart, for any load factor within 0 and 1.

VI. Conclusions

In this paper, we considered the universal scheduling design in wireless networks with both persistent and dynamic flows. We developed an age-based scheduling algorithm that is

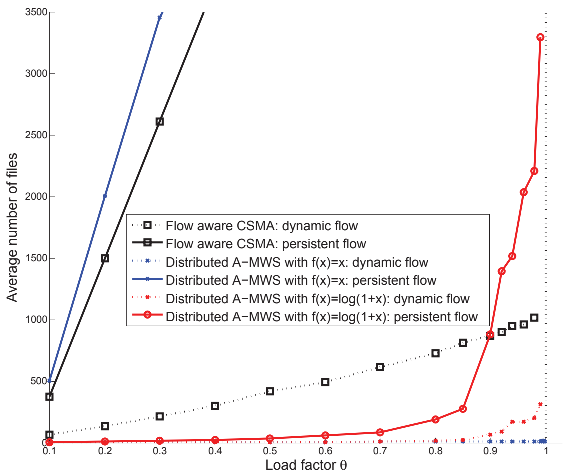

Fig. 4. Throughput performance of the CSMA implementation

throughput-optimal in wireless networks with hybrid flows. Then, we designed a distributed version of the proposed algorithm by using CSMA techniques, where each flow only knows its own age and carrier sensing information. Finally, we validated our results through simulations.

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