Utility-Based Scheduling Disciplines for Adaptive Applications Over the Internet

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Abstract—This letter presents packet scheduling disciplines based on application utility functions and network traffic measurements. The disciplines support different classes of adaptive applications over the Internet, providing differentiation, fairness, and dynamic allocation of network resources. They are composed of a decision procedure, where a fairness criterion based on utility functions is used; and a measurement procedure, which considers the statistics involving packet arrivals and departures. The underlying algorithm is then applied to emulate the *Proportional Differentiation Services*, and is shown—via simulation—that its results outperform the best alternative algorithms published in the literature.

Index Terms—Adaptive applications, fairness criteria, measurement-based procedures, scheduling, utility functions.

I. INTRODUCTION

DESPITE all the evolution the Internet has experienced over the years, the majority of its traffic is still *best-effort*. Even when real-time multimedia applications need to be transported through the network adaptive schemes are suggested where the source itself should adapt to congestion by changing its transmission rate and encoding schemes. Moreover, some popular audio and video applications (e.g., MP3 audio distribution) are based on a *store-and-replay* fashion generating long-lived file transfers, which are essentially *best-effort* and not real-time.

Most of today's diversified applications are attended by a single type of service (same-service-to-all), which usually leads to unfair distribution of resources and lack of differentiation. The work in [1] highlights the need for further research within the *best-effort* service framework and commented about the widespread misconception that *best-effort* service model implies simple mechanisms (e.g., FIFO queue in network nodes).

In this letter *Utility-Based Scheduling (UBS)* disciplines are proposed to support different classes of adaptive applications over the Internet. The disciplines differ from other well-known techniques (e.g., WFQ, WRR) since scheduling decisions are directly controlled by utility function values. In this case the utility functions describe the expected level of performance of each class, and rely on the acquisition of on-line traffic statistics to trigger scheduling decisions. Packets are scheduled ac-

Fig. 1. Measurement window implemented by a circular list.

cording to the *utility maximin fairness criterion*. This criterion allows network resources to be dynamically allocated while providing differentiation, optimality and fairness among classes of traffic. The scheduling discipline is then used to show how utility functions can be applied to emulate the *Proportional Differentiated Services* [2]. Finally simulation results show that the proposed discipline outperform other well-known proposals (e.g., [2], [6]).

II. THE MEASUREMENT PROCEDURE

The main performance parameter considered in this study is the average packet waiting time (delay). This measure is relevant for any type of application, however, for adaptive applications average performance indices are more important than strict bounds [3].

The use of measures has two major advantages: the ability to handle any input traffic distributions and the capacity to capture input traffic variations even at different time scales. For each class in the system we define a measurement window to store information about most recent arrival/departure statistics. The window is implemented by a circular list with two pointers: *head-of-window (hw)* and *head-of-queue (hq)*. Fig. 1 illustrates the mechanism of the windows.

Both pointers move in the counterclockwise direction as packets enter and leave the system, when the system is empty the pointers are aligned. An incoming packet overwrites the *hw* register with its new information while the *hq* packet is the next one to be served. The information stored consists of time-stamps of packets in queue, and waiting times of packets that have already been served. For each window T_j of size $|T_j|$, packet i , $p_j^i \in T_j$, the following notation is used: ts_j^i is the packet i time-stamp, d_j^i is the packet i waiting time, B_j is

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the set of backlogged packets in T_j , and n_j is the size of B_j . The mean delay on window j is given by

$$\begin{aligned} D_j(t) &= \frac{1}{\|T_j\|} \sum_{i \in T_j} d_j^i = \frac{1}{\|T_j\|} \left(\sum_{i \in B_j} d_j^i + \sum_{i \notin B_j} d_j^i \right) \\ &= \frac{1}{\|T_j\|} \left(n_j \cdot t - \sum_{i \in B_j} ts_j^i + \sum_{i \notin B_j} d_j^i \right) \\ &= \frac{1}{\|T_j\|} (n_j \cdot t - S_j + D_j^{\text{dep}}) \end{aligned} \quad (1)$$

where: $j = 1, \dots, C$ classes and $i = 1, \dots, \|T_j\|$. These variables and pointers are updated as indicated below.

At each arrival epoch:	At each service epoch:
$n_j \leftarrow n_j + 1$	$n_j \leftarrow n_j - 1$
$S_j \leftarrow S_j + \text{clock}$	$S_j \leftarrow S_j - ts_j^{hw}$
$D_j^{\text{dep}} \leftarrow D_j^{\text{dep}} - d_j^{hw}$	$d_j^{hw} \leftarrow \text{clock} - ts_j^{hw}$
	$D_j^{\text{dep}} \leftarrow D_j^{\text{dep}} + d_j^{hw}$

Note that the measure procedure does not need to set or modify any packet field, and that the mean delay as a function of time is directly obtained from (1).

III. DECISION PROCEDURE—SCHEDULING

A. Utility Functions

A formal definition can be given in terms of the set of allocated resources, A (where a_i is the amount of resource i), and the QoS vector, Q (where $q_i(A): \mathbb{R}^M \rightarrow \mathbb{R}$ defines a different QoS measure as a function of those resources)

M different resources:	$A = \{a_1, \dots, a_M\}$
QoS vector:	$Q = \{q_1, \dots, q_N\}$
Utility function:	$u = f(Q): \mathbb{R}^N \rightarrow [0, 1]$.

The key idea is that applications do not value the resource by itself but the performance derived from it, therefore, by working directly with the utility functions the resources can be allocated dynamically and in an optimal way. In the reminder of this letter, we consider single variable and monotonically increasing utility function, $Q = \{q\}$ and $u = f(q)$. For adaptive applications it is convenient to define an upper bound to the mean delay and so the QoS parameter q is expressed as the difference between the maximum allowed delay and the current delay: $q = D^{\text{max}} - D$. For each class j , utility values are evaluated using different types of functions: $u_j = g_j(D_j^{\text{max}} - D_j)$, where D_j is given by (1).

B. Decision Criterion

The goal of the scheduling algorithm is to maximize the performance of the system and at the same time guarantee fairness. We use the fairness definition introduced in [4], [7] in the context of data networks and known as *maximin criteria*. However, instead of using the throughput as the QoS parameter we are working directly with packet delays. In terms of microeconomic theory, this criterion defines a *Social Welfare* function that is

egalitarian [9]. Then, for $\|T_j\| = T$, the scheduler objective can be characterized by the *utility maximin fairness criterion*:

$$z(t) = \max_t \min_j g_j \left(D_j^{\text{max}} - \frac{1}{T} (n_j(t) \cdot t - S_j(t) + D_j^{\text{dep}}(t)) \right). \quad (2)$$

Even though (2) is defined for all time t , scheduler decisions are restricted to departure epochs only, which limits the control actions to those time instants. The optimal solution to (2) can only be obtained if all the events that might happen in the system until the next control epoch are known. Since this is neither possible nor necessary, we propose two different policies for the scheduler: *near-optimal* and *greedy*.

Given two consecutive decision epochs, t and $t + \Delta t$, the near-optimal policy aim is to find out how to make a decision on time t that will lead to a solution which is as close as possible to $z(t + \Delta t)$ for a predetermined value of T (e.g., the *monitoring timescale* [2]). In order to reduce complexity, two basic assumptions are taken: 1) inter-arrival times of packets on each window are i.i.d. and 2) Δt is simplified and represents the next arrival in the system or the next service completion time, whichever comes first. At the i th-arrival on queue j , the T -sized sample mean and variance¹ of the packet inter-arrival times is computed using the information stored in the measurement windows

$$\begin{aligned} \hat{\mu}_j^{(i)} &= (\text{clock} - ts_j^{hw})/T \\ \hat{\sigma}_j^{2, (i)} &= \hat{\sigma}_j^{2, (i-1)} + \frac{(T \cdot \hat{\mu}_j^{(i-1)} - \Delta ts_j^{\text{old}}) \cdot (\Delta ts_j^{\text{old}} - \Delta ts_j^{\text{new}})}{0.5T(T-1)} \\ &\quad - \frac{(\Delta ts_j^{\text{old}})^2 - (\Delta ts_j^{\text{new}})^2}{T} \end{aligned} \quad (3)$$

where $\Delta ts_j^{\text{old}} = ts_j^{(hw+1)} - ts_j^{hw}$, $\Delta ts_j^{\text{new}} = \text{clock} - ts_j^{(hw-1)}$.

If the sample is large enough [8], we can apply the Central Limit Theorem to estimate Δt . In our implementation, we consider the values of $Q(x)$, the complementary cdf of a $N(0, 1)$, stored in a table to speed up calculations. By letting $I_j(k)$ be the sum of k consecutive interarrival times on queue j , we have for the next arrival

$$Q \left(\frac{I_j(T) - T \cdot \hat{\mu}_j}{\hat{\sigma}_j \cdot \sqrt{T}} \right) = \bar{p} \quad (4)$$

$$I_j(T) = T \cdot \hat{\mu}_j + Q^{-1}(\bar{p}) \cdot \sqrt{T} \cdot \hat{\sigma}_j. \quad (5)$$

We approximate packet size by an exponential distribution with mean $1/\beta$. Note that other distributions may also be used without modifying the main algorithm, Δt is given by

$$\Delta t = \min \left[\min_j \{ ts_j^{hw} + I_j(T) - t \}, -\log(\bar{p})/\beta \right]^+. \quad (6)$$

The Near-Optimal Algorithm:

1. **set** $\bar{p} = p_o$.
2. **compute** Δt from (6).
3. **for all** backlogged classes **compute** $u_j = g_j(t + \Delta t)$.
4. **schedule** class of minimum u_j .

¹Equation (3) provides a faster update on the sample variance than textbook formulas where all the T samples are taken into account.

Fig. 2. Balanced traffic, WMD (continuous) and WTP (dashed), $\langle K \rangle = \langle K_{12} \rangle = \langle K_{23} \rangle$.

The *greedy policy* is quite simple: at each departure time, select the backlogged queue of lowest utility to serve. This policy is equivalent to set $\Delta t = 0$ in the last algorithm.

IV. RESULTS

In order to define quality spacing among different classes of service, the *Proportional Differentiation Services* describe the use of multipliers (δ_j) [2]. Hence, the goal is to perform scheduling in order to maintain the weighted delays of all classes approximately at the same level: $\delta_1 D_1 \simeq \delta_2 D_2 \simeq \dots \simeq \delta_C D_C$. According to [2] one of the most adequate discipline to provide this goal is the *Waiting-Time Priority (WTP)* which is based on the work of [5]. Packets are scheduled in a *high-priority-first* basis and priorities increase with time being weighted by a factor b_j : $p(t) = b_j \cdot (t - t_s)$. The problem with this approach is on finding the optimal weights. The intuitive setting $b_j = \delta_j$ is only precise when $\rho \rightarrow 1$ (input load near 1).

To emulate these services using our framework the class with the lowest multiplier (δ_1) is taken as reference and the following utility functions are used:

$$g_j = \left(\frac{\delta_j}{\delta_1 \cdot D_1^{\max}} \right) (D_j^{\max} - D_j); \quad D_j^{\max} = \frac{\delta_1 \cdot D_1^{\max}}{\delta_j}. \quad (7)$$

Simulation experiments were carried out using Poisson input traffic with loads ranging from 0.7 to 0.99. A direct comparison to the WTP discipline was carried out using the window mechanism of Section II and the *greedy policy*. This discipline is named *Window Mean Delay (WMD)* and constitutes an improvement on our previous work [6].

Three classes of traffic were used: class 1 (lowest priority), class 2 and class 3 (highest priority). The spacing required are defined by the two mean waiting times ratios: $K_{12} = \delta_2/\delta_1$ and $K_{23} = \delta_3/\delta_2$. The ratios were set to “2” ($\delta_1 = 1$, $\delta_2 = 2$ and $\delta_3 = 4$) and sampled from time to time as $\langle K_{12} \rangle = D_1/D_2$ and $\langle K_{23} \rangle = D_2/D_3$. A good performance is then characterized by small variations around “2.” We study two different scenarios: balanced (Fig. 2), where input loads for each class of traffic are identical and, unbalanced (Fig. 3) where the loads differ.

It is clear from the figures that WMD outperformed WTP since it presented the sampled ratio coefficients concentrated closer to the objective value “2” and also has a much higher number of samples meeting exactly the objective. WTP presented a poor

Fig. 3. Unbalanced traffic, WMD (continuous) and WTP (dashed), $\langle K \rangle = \langle K_{12} \rangle = \langle K_{23} \rangle$.

performance for the unbalanced case, since the sampled ratio coefficients were spread out along the $\langle K \rangle$ axis. This undesirable behavior was not observed in the WMD plots and hence confirmed the robustness of our algorithm to handle traffic variations without impacting the performance.

V. CONCLUSIONS

This work proposes a novel scheduling discipline to provide differentiation and fairness to adaptive applications over the Internet. A *Proportional Differentiation Service* was implemented and simulation results have shown that the proposed scheme is more effective than currently known algorithms. Our better results can be explained since the WMD scheme generalizes WTP in terms of the parameter T (for $T = 1$ and using a *greedy policy* WMD is reduced to WTP). The *utility criterion* used—while trying to reach optimality by maximizing the utility functions—also enforces fairness by scheduling the class of minimum utility (2). The effects of that is keeping the utility values approximately at the same level. The freedom to chose other types of utility functions ensures a large degree of flexibility to the proposed algorithm and allows the implementation of other types of services. Finally we note that by controlling the size of the measurement windows it is possible to capture the short-term behavior of the system and provide good performance even for short-lived applications.

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