Power Minimization with Quality-of-Information Outages

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***Abstract*—In this paper, we consider Quality-of-Information (QoI) aware transmission policies for a dynamic environment. In particular, we focus on the time-varying nature of the observation quality of the environment in practical networks which leads to uncertainty in satisfying QoI requirements specified by end users. The goal of this paper is to meet QoI requests from end users with minimum resources. Specifically, power is allocated dynamically depending on observation accuracies and QoI requirements. We formulate a dynamic scheme for scheduling with the objective of minimizing the energy consumption at the network while satisfying constraints on outage probability for QoI. Lyapunov stability arguments are used to define a policy based on the instantaneous observation qualities and QoI requirement satisfaction levels. Numerical results demonstrate that significant improvements in delivered QoI are realized with identical power expenditure using our QoI-aware resource allocation algorithm compared with traditional maximum-rate schedulers.**

***Index Terms*—Quality of Information, Outage, Scheduling, Resource Allocation, Energy.**

I. Introduction

For many applications, as tactical networks, surveillance, and crowd sourcing, where the main goal is sound decision making, Quality of Service (QoS)-based approaches that are agnostic to the application or content of data may not be sufficient. Consequently, there is growing interest in moving from traditional QoS metrics as throughput, packet delivery ratio, fairness, and delay, towards new notions of quality associated with information. This lead to a set of attributes, including provenance [1], accuracy and precision [2] [1] [3], reliability [2], corroboration [1] [4], age/freshness and timeliness [2] [1] [5] started to emerge as factors impacting the *Quality-of-Information* (QoI) [2] [1].

Recently, we have proposed QoI-aware scheduling policies with random observation arrivals for a single link, trading the attributes of accuracy and freshness [6]. This has been extended to the multiple source scenario in [7]. We have also characterized the set of utility-maximizing QoI vectors and associated rate allocation for multiuser networks [8]. As pointed out in [6], [7] [9], in reality it is not possible to ensure that the same level of quality is ensured for all time/tasks.

The aforementioned work aims to maximize the expected performance measures in a best-effort fashion given fixed system resources. On the other hand, in many real-world scenarios, performance is specified in terms of quality requirements at an end user. For such scenarios, rather than solely focusing on expected performance measures in a best-effort fashion, a more prominent objective is to ensure that the quality requirements at the end user is satisfied by the network as much as possible. In other words, by defining the instances when the end-delivered QoI is below the desired level as *QoI-outage*, the main focus is to ensure that the worst case tolerable QoI-outage requirements are satisfied with minimum system resources.

We consider a network where an end user assigns tasks to be performed sequentially, and users with sensing capabilities respond to each task. We are interested in resource allocation to ensure that the requested QoI is satisfied with minimum network resources. In this paper, we consider a dynamic network where observation qualities are time-varying. As a particular example, we consider a scenario where multiple sources transmit to an end user. If the observations are sufficiently accurate, than the QoI requirement may be satisfied. However, even in such a case, the required resources significantly depend on the observation quality, as well as on channel gains. The dynamic nature of observation qualities leads to a sequential decision-making problem to minimize power expenditure while still ensuring QoI-outage requirements.

Among attributes that can effect QoI, we focus particularly on *accuracy* and *timeliness*. These two attributes are fundamental representatives in the sense that accuracy is an indicator of the quality of the initial information content and generating information at the sources, while timeliness is concerned with the capability and the quality of the network to deliver the information. In this paper, we consider the scenario where factors as illumination and weather conditions lead to time-varying accuracy attributes of observed information at sources.

The sources generating the information are coupled through the achievable rate regions supported by the network. Thus, power allocation and rate scheduling decisions should be made jointly to balance energy and QoI satisfaction performance. We use Lyapunov stability arguments to develop algorithms that attempt to strike such a balance. Numerical results demonstrate that QoI-aware rate allocation significantly outperforms QoI-agnostic traditional schedulers in terms of both QoI-outage and average QoI delivered to the end user. While the notion of outage capacity has been addressed in traditional communications [10], [11], to our knowledge this work is the first attempt to

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develop outage-aware resource allocation algorithms for new information quality attributes.

II. System Model

We consider a scenario where tasks are issued from an end user in a tactical network. Tasks arrive sequentially at time instants $\{b_1, b_2, ...\}$ with stochastic interarrival times, which are greater than or equal to T, i.e. $b_{t+1} - b_t \geq T, \forall t > 0$. Information sources S_i respond to the task and generate information related with the task. This can correspond to phenomena related with the environment. The information content available at the source is associated with several attributes, as accuracy, credibility, precision, freshness which can be prioritized depending on the specific task.

The overall importance of the information to the task is characterized by the QoI of the piece of information. Two types of QoI can be defined: *delivered-QoI*, i.e. the QoI associated with a piece of information generated and delivered by the network, and *desired-QoI*, which is the QoI requested from the network. In this paper, contrary to previous approaches [1], [6], [9], we focus on the desired QoI. QoI can be represented by a ***QoI-vector***, which is a vector of attribute-value pairs: e.g., $[type = image,\ timeliness = 15s,\ accuracy = 600\times800,\ FOV = 150\,mm\,per\,meter\ldots]$, where FOV is the ***field of view*** which represents the (angular or linear or areal) extent of the observable world seen at any given moment.

QoI functions allow a requestor of information to define the relationships and trade-offs between information metrics. For example, QoI may degrade as precision of information decreases, or improve with timeliness, i.e., as the delay in retrieving the information decreases. In general, the QoI derived at the end user depends on environment conditions (illumination, humidity/rain, moving obstacles), and on attributes inherent to the information generated at the source, e.g., resolution, completeness, field of view, provenance, and effects of network delivery (e.g. timeliness). For instance, let us consider the application of optical character recognition (OCR), where images are sent to an end user. The accuracy requirement may be that 90 percent of characters must be decoded properly. This maps to a resolution of the page image.

Obviously, the required accuracy and precision will impact how small we can make a file. Additionally, we have timeliness. The latency that is achieved is a function of the size of the file and the rate at which is used for transmission. This creates a tradeoff with accuracy and precision. Let us consider a file of s bits transmitted over a link with rate r bps. This results in an accuracy attribute of a, which is a function of s, as well as timeliness t_d as the timeliness attribute equals $\frac{s}{r}$.

We define the following QoI function as a composite function of both attributes as:

$$QoI(a, t_d) = QoI(a(s), t_d(s, r)). \tag{1}$$

For a given application, and the file type, there exists a specific relation between the file size of the information and its accuracy, i.e. $s(a)$ can take an arbitrary form depending on the application and the file type. We follow the natural assumption that $s(a)$ is a non-decreasing function of a for a specific type of information and application. Note that the file size s affects both a and t_d in (1), which results in a non-trivial effect on QoI.

The effect of timeliness t_d on QoI is described as a timeliness function $g(t_d)$. For this paper, we specifically consider the QoI function in the form of $accuracy \times timeliness$, i.e.,

$$QoI = a \times g(t_d). \tag{2}$$

In the rest of the paper, via (1) and (2), we define an alternative function for QoI $Q(a, r)$ which captures the timeliness property and reflects the effect of rate more explicitly. We will discuss specific quality functions in Section IV.

Once the decision to transmit is made by the sources, the information available is fed into a wireless channel with a certain rate. While we will present precise expressions for a specific network scenario in Section IV, in the general case rates are a function of physical layer properties as channel gains, and scheduling among sources defined by the link layer. We assume that channels are static, but the model could also be readily extended to the *quasi-static* channel model where the channels potentially change after each task.

III. Power-aware QoI-outage Satisfaction

We assume that the structure of the quality functions and behavior according to timeliness parameters are known at the sources. We consider slotted operation where network decisions may be dynamically adapted at the beginning of each task. We also assume that the tasks are all independent of each other, and at most one task is processed by the network at any time.

Define QoI-outage for task t with desired QoI $Q_{desired}$ as

$$o(t) = \begin{cases} 0, & if \sum_{i=1}^{M} Q_i(a_i(t), r_i(t))\} \geq Q_{desired} \\ 1, & if \sum_{i=1}^{M} Q_i(a_i(t), r_i(t))\} < Q_{desired}, \end{cases}$$

that is an indicator of whether the total QoI delivered to the end user from M sources meets $Q_{desired}$ or not. The outage probability P_{outage} for QoI requirement $Q_{desired}$ is defined as the long term average of the outage realizations over tasks, i.e., the average QoI-outage per task:

$$P_{outage}(Q_{desired}) := \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[o(\tau)]. \tag{3}$$

Ultimately, the aim is, if possible under the observation statistics, to satisfy that $P_{outage}(Q_{desired})$ is less than or equal to the QoI-outage requirement ϵ with minimum network resources, i.e., transmission power expenditure.

In other words, we consider an outage constraint ϵ such that

$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[o(\tau)] \leq \epsilon. \tag{4}$$

We start with the case where a centralized controller makes transmission decisions for all M sources based on complete knowledge of the system parameters and the history of QoI-outages. The objective is to minimize the total energy consumption at the network while ensuring that the outage probability constraint (4) is satisfied. This leads to the following optimization problem:

$$\min_{\vec{p}(t),\vec{\beta}(t)} \quad \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i=1}^{M}\mathbb{E}[p_i(\tau)] \qquad \textbf{(PO)}$$

$$\text{s.t.} \quad \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}[o(\tau)] \leq \epsilon,$$

$$(r_1(t),...,r_M(t)) \in \mathcal{R}(\vec{p}(t),\vec{\beta}(t),\vec{h}) \qquad (5)$$

where $p_i(t)$ are the powers allocated to source i, $h_i(t)$ are channel gains of links from source i to the destination, and $\beta_i(t)$ are the time division parameters which reflect the proportion of time source i is scheduled. $\vec{p}$, $\vec{\beta}$ and $\vec{h}$ denote vectors of power, time-sharing variables and channel states. $\mathcal{R}$ denotes the achievable rate region.

Note that the objective in **(PO)** is equivalent to minimizing the average power per task by normalizing by the total long-term task arrival rate. Let $\mathcal{P}^*(\epsilon)$ denote the solution to **(PO)** as a function of the outage constraint ϵ. This solution represents the energy-outage trade-off. In general, this will be a decreasing function of ϵ.

In principle, for a given QoI-outage constraint, **(PO)** can be solved via dynamic programming. However, such a solution quickly becomes intractable except for very simple observation quality processes and requires *a priori* knowledge of observation statistics. Instead, we will follow the approach in [12], [13] [11], and use Lyapunov stability arguments to yield an approximate solution to **(PO)**. This approach is based on generalizing the classical back-pressure algorithm, which is guaranteed to stabilize packet queues, if this is possible under capacity constraints [14].

A. General Methodology

We propose a QoI-aware Outage-based joint rate scheduling and power allocation Algorithm **(QOA)** which chooses the power values of each source and time sharing variables to approximate the solution to **(PO)**. To track the outage constraint over time, we use the idea of a *virtual outage queue*. Define $x(t)$ as the virtual outage queue with constant service rate ϵ and arrival rate $o(t)$. If this outage queue is stable, then (4) is satisfied. Then, the virtual outage queue dynamics are as:

$$x(t+1) = \max\left(x(t)-\epsilon, 0\right) + o(t). \qquad (6)$$

In this problem, since $x(t)$ corresponds to the state of the system, we define the corresponding Lyapunov function as

$$L(t) = L(x(t)) = \frac{1}{2}x(t)^2. \qquad (7)$$

Since for for any V, W, Y, Z satisfying $V \leq \max(Y - Z, 0) + W$ we have

$$V^2 \leq Y^2 + Z^2 + W^2 - 2Y(Z-W), \qquad (8)$$

the Lyapunov drift is equal to

$$\begin{aligned}\Delta(x(t)) &= \mathbb{E}\{L(x(t+1)) - L(x(t))|x(t)\}\\ &= B - x(t)\mathbb{E}\{\epsilon - o(t)|x(t)\},\end{aligned} \qquad (9)$$

where B is a term that can be bounded by the sum of second moments of the outage values, since $o(t)$ is bounded by assumption. Here, the expectations are taken over the arrival and control decision statistics. If we add the weighted expected power as a penalty term to (9), we have

$$\begin{aligned}\Delta(S(t)) + V\mathbb{E}\{P_{tot}(t)|x(t)\} =& B - x(t)\mathbb{E}\{\epsilon|x(t)\}\\ &+x(t)\mathbb{E}\{o(t)|x(t)\} + V\mathbb{E}\{P_{tot}(t)|x(t)\},\end{aligned} \qquad (10)$$

where $P_{tot}(t)$ is the total power expended for task t and the weight V is a control parameter to tune the trade-off between average outage performance and the minimum achievable cost. The QoI-aware Outage-based Algorithm (**QOA**) we develop aims at minimizing the sum of Lyapunov drift and penalty by solving the following optimization problem for given $x(t)$:

$$\min_{(\vec{p}(t),\vec{\beta}(t))} x(t)o(t) + V[P_{tot}(\vec{p}(t),\vec{\beta}(t))]. \qquad (11)$$

While we omit a detailed proof due to space constraints, it can be shown that the algorithm solving (11) can stabilize the outage queue whenever feasible in terms of observation arrival statistics, with a trade-off in average power and outage performance tuned through V. We refer readers to [12] for stability of virtual queues.

Note from (11) that (**QOA**) operates only with state value $x(t)$ and parameters for task t, and does not require any a priori observation statistics.

IV. Case Study: Two-Source TDMA System

For clarity of exposition, we concentrate on a fundamental communication model: a two-user multiple access network (Fig. 1) operating under the TDMA protocol. This constitutes a basic and inspiring model for QoI-based resource allocation, which involves scheduling among links and QoI optimization. In this model, the single user capacity for source i is c_i. This capacity depends on the channel conditions $h_i(t)$ and power $p_i(t)$ allocated to source i as $Wlog_2(1+\frac{h_i(t)p_i(t)}{N_oW})$, where N_o is the noise power and W is bandwidth. The TDMA protocol assigns each source i $\beta_i(t) \in [0,1]$ fraction of time, resulting in the following rates for each source (Fig. 2):

$$r_i(t) \leq \beta_i(t)Wlog_2(1+\frac{h_i(t)p_i(t)}{N_oW}), i = 1,2. \qquad (12)$$

We note that the rates allocated to the sources are functions of both the powers allocated and time sharing factors. We assume that channel gains h_1 and h_2 are available at both sources.

We consider a model where the QoI received from each source is assumed to be 0 if information is delivered to the end user with latency greater than the D_i, which corresponds to the timeliness requirement for the application from source i [3]. If latency is less than D_i, the QoI is equal to the accuracy of the information at the source, a_i. Thus, the QoI function can be written as:

$$Q_i(a_i, r_i) = \begin{cases} a_i, & if\,\frac{s_i(a_i)}{r_i} \leq D_i \\ 0, & if\,\frac{s_i(a_i)}{r_i} > D_i. \end{cases}$$

Here, as mentioned earlier, $s_i(a_i)$ is the file size in bits required to represent information of accuracy a_i. $s_i(a_i)$ is typically a concave in a_i, implying diminishing returns.

The source qualities vary throughout time because of environmental conditions (e.g. illumination, weather), resulting in

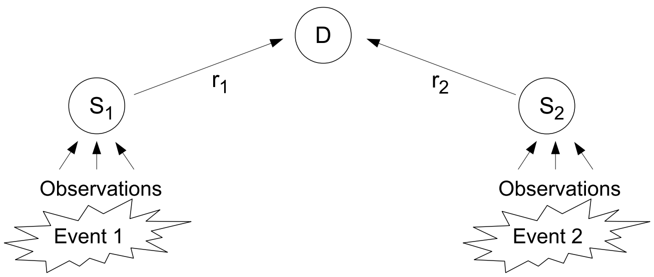

Fig. 1. Two-user MAC channel for QoI-based network.

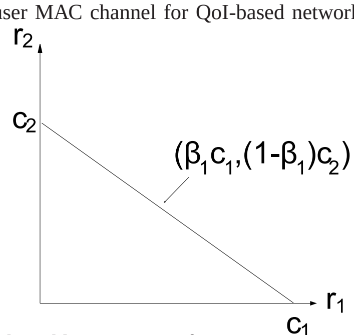

Fig. 2. The achievable rate region for two-source TDMA.

observation accuracies $(a_1(t), a_2(t))$ for task t. The accuracy is constant within a task but potentially varies for the next task with some joint distribution of the sources.

Next, we discuss the joint rate scheduling-power allocation algorithm **QOA** for a specific QoI function and energy cost.

The power-aware QoI-outage satisfaction algorithm consists of mainly two steps:

- Determine which sources should be activated, and determine the proper rate allocation among the sources with candidate power allocation solutions (Scheduling among sources).
- Determine whether to allocate the candidate power allocation solutions, or declare outage.

Next, we discuss these two steps in more detail.

A. Scheduling Among Sources

If the observation accuracies $(a_1(t), a_2(t))$ are such that:

- $Q_{desired} \leq \min(a_1(t), a_2(t))$, then only one source requiring the lower power is a candidate for being scheduled and allocated power. The rate for the scheduled source i is equal to $r_i = \frac{s(a_i(t))}{D_i}$, where
$$i = \arg\min_i \frac{1}{h_i(t)}(2^{(\frac{s(a_i(t))}{D_i})} - 1). \quad (13)$$
- $\min(a_1(t), a_2(t)) < Q_{desired} \leq \max(a_1(t), a_2(t))$, then only one source with the higher observation accuracy is a candidate for being scheduled and allocated power. The rate for the scheduled source i is equal to $r_i = \frac{s(a_i(t)}{D_i}$, where $i = \arg\max_i a_i(t)$.
- $\max(a_1(t), a_2(t)) < Q_{desired} \leq a_1(t) + a_2(t)$, then the scheduler proposes to schedule both sources, with proper power allocation and time sharing optimization. An example solution given below.
- $a_1(t) + a_2(t) < Q_{desired}$, then regardless of the scheduling method, the system declares a QoI-outage for the current task and hence does not expend power.

Next, we discuss the third case, which requires the most involved scheduling decisions. If precisely both sources are required to satisfy $Q_{desired}$ for the current task, we need to set the minimum rates for the sources to meet the timeliness constraints, i.e., $r_i = \frac{s(a_i(t))}{D_i}$, $i = 1, 2$. Note that while the required source rates are specified, the specific power allocation and time division parameters leading to these rates are not unique. Nevertheless, we have the following relation:

$$\beta_i(t) W log_2(1 + \frac{h_i(t)p_i(t)}{N_o W}) = \frac{s(a_i(t))}{D_i}, i = 1, 2 \quad (14)$$

which defines the first step of the power allocation as

$$p_i^{'}(t) = \frac{N_o W}{h_i(t)}(2^{(\frac{s(a_i(t))}{\beta_i(t) W D_i})} - 1). \quad (15)$$

This results in the following optimization problem for the source scheduling step for the time sharing variables:

$$\min_{\beta_1(t), \beta_2(t)} \sum_{i=1}^{2} \frac{N_o W}{h_i(t)}(2^{(\frac{s(a_i(t))}{\beta_i(t) W D_i})} - 1), \quad (16)$$

$$\text{s.t. } \beta_1(t) + \beta_2(t) \leq 1 \quad (17)$$

It can be readily shown that this is a convex optimization problem in $(\beta_1(t), \beta_2(t))$. Let us introduce the Lagrangian multiplier λ for the constraint (17). Than, the Lagrangian function can be expressed as:

$$L(\beta_1, \beta_2, \lambda) = \sum_{i=1}^{2} \frac{N_o W}{h_i(t)}(2^{(\frac{s(a_i)}{\beta_i W D_i})} - 1) + \lambda(\beta_1 + \beta_2 - 1). \quad (18)$$

The Karush-Kuhn-Tucker (KKT) conditions imply:

$$\frac{\partial L(\beta_1, \beta_2, \lambda)}{\partial \beta_1} = \frac{N_o W \ln 2}{h_1(t)}(2^{(\frac{s(a_1(t))}{\beta_1(t) D_1 W})}(\frac{-s(a_1(t))}{\beta_1^2 W D_1})) + \lambda = 0, \quad (19)$$

$$\frac{\partial L(\beta_1, \beta_2, \lambda)}{\partial \beta_2} = \frac{N_o W \ln 2}{h_2(t)}(2^{(\frac{s(a_2(t))}{\beta_2(t) W D_2})}(\frac{-s(a_2(t))}{\beta_2(t)^2 W D_2})) + \lambda = 0, \quad (20)$$

with complementary slackness condition (CSC)

$$\lambda(\beta_1(t) + \beta_2(t) - 1) = 0. \quad (21)$$

For $\lambda > 0$, we have the following expression for the time sharing parameters $(\beta_1(t), \beta_2(t))$ from (19)-(20):

$$\frac{\ln 2 s(a_1(t)) N_o}{h_1(t)\beta_1(t)^2 D_1} 2^{(\frac{s(a_1(t))}{\beta_1(t) W D_1})} = \frac{\ln 2 s(a_2(t)) N_o}{h_2(t)\beta_2(t)^2 D_2} 2^{(\frac{s(a_2(t))}{\beta_2(t) W D_2})}, \quad (22)$$

equivalently with $\beta_2(t) = 1 - \beta_1(t)$

$$\frac{2^{(\frac{s(a_1(t))}{\beta_1(t) W D_1})}}{2^{(\frac{s(a_2(t))}{(1-\beta_1(t)) W D_2})}} = \frac{s(a_2(t)) h_1(t) \beta_1(t)^2 D_1}{s(a_1(t)) h_2(t)(1 - \beta_1(t))^2 D_2}. \quad (23)$$

After obtaining the optimal time schedule from (23), the first step of the optimal power allocation is completed by inserting it into (15). This input of $(p_1^{'}(t), p_2^{'}(t))$ is passed into the Lyapunov optimization step which compares the power allocation solution with the outage satisfaction queue $x(t)$.

Note that for the special case when Signal-to-Noise Ratio, SNR, (which is equal to $\frac{hp}{N_o W}$) is very low, the relationship between rate and power can be assumed as linear $(log_2(1 +$

$SNR)) \approx SNR$. This assumption notably simplifies the analysis to obtain the solution for $\beta(t)$ as follows. Now,

$$\frac{\beta_i(t)Wh_i(t)p_i(t)}{N_oW} = \frac{s(a_i(t))}{D_i}, \tag{24}$$

which defines the first step of the power allocation as

$$p_i^{'}(t) = \frac{N_o s(a_i)}{\beta_i(t)h_i(t)D_i}, \tag{25}$$

resulting in the following optimization problem for the rate scheduling step for the time sharing variables:

$$\min_{\beta_1(t),\beta_2(t)} \sum_{i=1}^{2} \frac{N_o s(a_i)}{\beta_i(t)h_i(t)D_i}, \tag{26}$$

$$\text{s.t. } \beta_1(t) + \beta_2(t) \leq 1 \tag{27}$$

which is again a convex optimization problem in (β_1, β_2). With Lagrangian analysis, KKT conditions imply the solution:

$$\frac{s(a_1(t))}{h_1(t)\beta_1(t)^2 D_1} = \frac{s(a_2(t))}{h_2(t)\beta_2(t)^2 D_2}, \tag{28}$$

where with $\beta_2(t) = 1 - \beta_1(t)$ we get the closed form solution:

$$\beta_1^*(t) = \frac{1}{1 + \sqrt{\frac{h_1 D_1 s(a_2(t))}{h_2 D_2 s(a_1(t))}}}. \tag{29}$$

B. Outage-Aware Power Allocation

Once the candidate power allocation solutions are obtained from the source scheduling step, which also defines β_1, β_2, from (11), the final power allocation step aims to optimize:

$$\min_{p_1(t),p_2(t)} x(t)o(t) + V(p_1(t) + p_2(t)). \tag{30}$$

Note that $o(t)$ is equal to 0 if $p_1(t)+p_2(t) > 0$ and 1 if $p_1(t) = p_2(t) = 0$. Hence, the objective is equal to $V(p_1(t) + p_2(t))$ for no outage and $x(t)$ for outage. Let $P_{req}(t) := p_1^{'}(t)+p_2^{'}(t)$ from the scheduling step. As a result, we have the following power allocation algorithm:

- $p_1(t) = 0, p_2(t) = 0$, if $x(t) < VP_{req}(t)$.
- $p_1(t) = p_1^{'}(t), p_2(t) = p_2^{'}(t)$, if $x(t) > VP_{req}(t)$.

Note that for the fourth case of the scheduling step, outage is declared regardless of this comparison. We note that the algorithm results in power allocation in line with intuition: A large value of $x(t)$ implies that there has been excessive QoI-outages, i.e., QoI-outage performance has not been very satisfactory, which calls for more power allocation to improve QoI-outage performance. On the contrary, a low $x(t)$ implies that QoI-outage violations have been less and the network can afford to turn off power to save from energy while still satisfying QoI-outage requirements. Note also that the algorithm tends to turn off power with a large P_{req}, which might be required due to lower observation accuracies (low accuracies might necessitate more sources to be scheduled). If both $x(t)$ is low and P_{req} is high, the network opportunistically avoids to spend excessive energy since it can sustain the QoI-outage violation introduced. On the other hand, if P_{req} is small, which might imply less sources activated, the power allocator tends to activate the sources. This enables to improve QoI-outage performance without spending too much power.

V. Numerical Results

We demonstrate the performance of the resource allocation algorithms via simulation results. The timeliness parameters are $D_1 = 300ms$, $D_2 = 200ms$ for expiration times. The observation accuracy a_1 varies uniformly in $[0.6, 1]$ and the observation accuracy a_2 varies uniformly in $[0.3, 1]$ and independently from a_1. We assume the relationship $s_i(a_i) = 10^5 a_i^3$ for file sizes in terms of bits, meaning that there is diminishing returns in terms of improved accuracy as file sizes increase. The requested quality of information $Q_{desired}$ is specified as 0.95. We set $V = 1$ for the trade-off parameter, and channel gains $h_1 = 2h_2$.

We compare the QoI-outage and average QoI performance of the "QoI-aware Outage-based Algorithm" **(QOA)** with three different algorithms "Throughput-based" **(TA)**, "Fair" **(FA)** and "Accuracy-based"**(AA)** algorithms for scenarios with different outage requirements. As described in more detail next, the first two algorithms are QoI-agnostic: **(TA)** is a greedy scheduler which focuses on bit-rate and **(FA)** is a fair scheduler. On the other hand, **(AA)** is QoI-aware but does not consider all QoI attributes. For a fair comparison among these four algorithms, given the observation arrival process and QoI requirements ($Q_{desired}$, ϵ), we first evaluate the average power requirement P_r for **(QOA)**. Next, for each of the algorithms we set the power to be equal to the minimum power P_r for each ϵ from **(QOA)**, with the same observation accuracy realizations. That is, given P_r, **(TA)** performs power allocation and time division optimization among sources to maximize total throughput, i.e., sum rate. **(FA)** is a fair scheduler which allocates equal power and time share to each source. On the other hand, **(AA)** is an algorithm which prioritizes the source with higher accuracy. Specifically, given the power budget and regardless of the timeliness constraints and channel conditions, it first schedules the source with more accurate observations.

From Figure 3, we observe that **QOA** is the only scheduler which is able to meet the desired outage requirements. We observe that QoI-agnostic algorithms perform remarkably bad, and in particular the "state-agnostic" *fair* allocator cannot meet the desired QoI for any task (full outage). Moreover, from Figure 4, we observe that **QOA** also delivers much higher average QoI per task by efficiently allocating power depending on observation accuracy states and proper time sharing among sources. We also observe that focusing on only one QoI attribute (accuracy) is not sufficient for satisfactory QoI delivery. The benefits of the virtual outage queues and timeliness-aware source scheduling are substantial.

Next, in Figure 5 we demonstrate the required total power in order to support different outage requirements. As expected, we observe that average required power increases with more stringent outage requirements.

Last, the average sum rates of the different algorithms are shown in Figure 6. We observe that **QOA** is able to outperform other algorithms in terms of QoI with notably less bits transmitted. This illustrates the significance of QoI-aware resource allocation, as well as the utility of our QOA algorithm when desired-QoI is specified in terms of outage requirements.

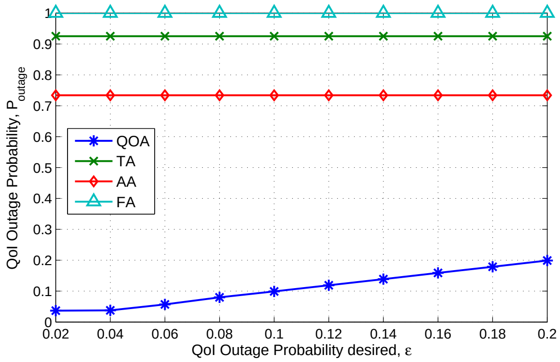

Fig. 3. QoI-outage performance of various schedulers.

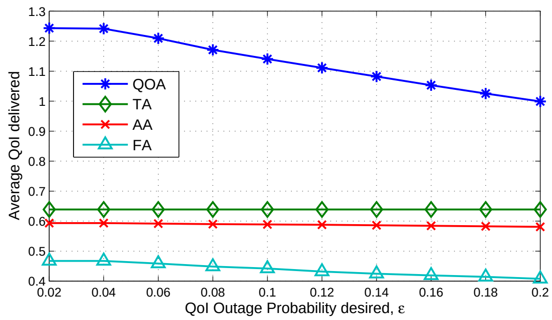

Fig. 4. Average QoI performance of various schedulers.

VI. Conclusion

In this paper, we have focused on the problem of delivering information of requested quality when the underlying observation qualities of are time varying. We have particularly addressed the problem of minimizing an energy cost subject to QoI-outage probability constraints in a network. The sources deliver timeliness sensitive information observed from the environment with stochastically varying observation quality. First, we have presented a general control scheme to jointly optimize the power cost and satisfy QoI-outage constraints. Next, we have provided joint link scheduling-power allocation algorithms for a two-source network operating under the TDMA protocol. We have demonstrated that by efficiently allocating power, with the aid of a QoI-outage queue, significant improvement is obtained in terms of QoI-outage as well as average QoI compared with QoI-agnostic schedulers.

Future work includes treatment of the problem with alternative QoI functions and attributes, as well as extending the detailed resource allocation solutions for more general network scenarios.

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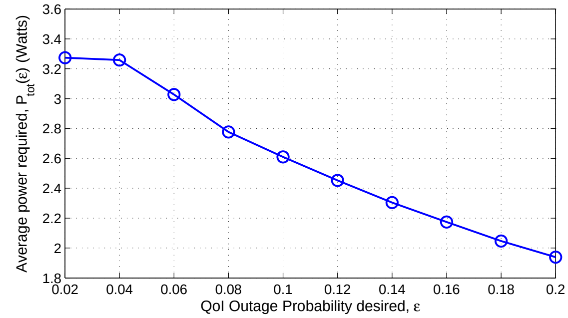

Fig. 5. Average Power to support outage ϵ.

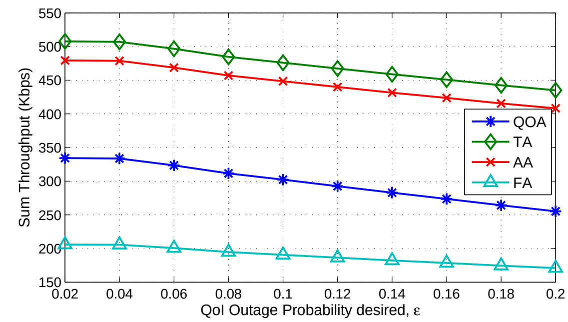

Fig. 6. Sum throughput of various schedulers.

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