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Quality of service aware traffic scheduling in wireless smart grid communication

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Abstract The next generation electrical power grid, known as smart grid (SG), requires a communication infrastructure to gather generated data by smart sensors and household appliances. Depending on the quality of service (QoS) requirements, this data is classified into event-driven (ED) and fixed-scheduling (FS) traffics and is buffered in separated queues in smart meters. Due to the operational importance of ED traffic, it is time sensitive in which the packets should be transmitted within a given maximum latency. In this paper, considering QoS requirements of ED and FS traffics, we propose a two-stage wireless SG traffic scheduling model, which results in developing a SG traffic scheduling algorithm. In the first stage, delay requirements of ED traffic is satisfied by allocating the SG bandwidth to ED queues in smart meters. Then, in the second stage, the SG rest bandwidth is going to the FS traffic in smart meters considering maximizing a weighted utility measure. Numerical results demonstrate the effectiveness of the proposed model in terms of satisfying latency requirement and efficient bandwidth allocation.

Keywords Communication · Quality of service · Smart grid · Smart meter · Traffic scheduling

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1 Introduction

A smart grid (SG) is an electrical grid with small scale generators and renewable energy sources to supply heterogeneous power demands using information and communication technology [1]. Because of distributed structure, SG is more reliable in terms of maintenance and service as well as is more flexible in using renewable resources. A key requirement to achieve potential advantages of SG is the successful design and implementation of a reliable, secure, and cost-effective communication infrastructure, entitled SG communication system, through which different entities get connected [2].

SG communication system is responsible for maintaining communication among a massive number of heterogeneous devices distributed over a large geographical area. Wide area monitoring and control of a power system along with intelligent decision making can be done through SG communication system [3]. Motivations and challenges behind communication technologies to be adopted by an SG have been reviewed in [4–6]. Security, reliability, scalability, and quality of service (QoS) are some crucial challenges which have been investigated in the literature. In comparison with wireline networks, wireless networks have the advantage of low deployment cost and high flexibility, and are gaining more interest for SG applications. Technical specifications, advantages, disadvantages and possible applications of a number of representative wireless communication in SG has been discussed in [2].

Advanced metering infrastructure (AMI), which is an important functionality to gather a large volume of information from sensors and household appliances, is done through SG communication system [4]. AMI aims at providing consumers with knowledge of their energy usage and the capability of monitoring and control. Smart meters (SMs) installed within consumers houses are basic components of advanced metering infrastructure. They act as gateways to gather information from consumer households and to relay it to the corresponding utilities. In contrast to conventional meters, SMs provide the network utilities with consumers' consumption information and demand profiles. This information is crucial for network operators to provide economic power dispatching and demand side management [7–9].

Basically, two types of information flows exist in AMI. The first is from sensors and electrical appliances to SMs, and the second is between SMs and utilities data centers. While the first data flow can be accommodated through short range technologies such as ZigBee, the second one needs broadband cellular technologies [5]. Moreover, this flow contains heterogeneous traffic such as control commands, multimedia sensing data and meter readings which needs priority-based traffic scheduling schemes due to their QoS requirements [10,11]. As a result, SMs as transmitting nodes in the AMI need to be provided with efficient traffic scheduling schemes.

Communication traffic transmitted by SMs in an SG is classified into two categories: fixed-scheduling (FS) and event-driven (ED) [12,13]. The FS traffic is typically an operational traffic, which occurs on a periodic basis such as SM readings and household appliances monitoring. On the other hand, the ED traffic occurs as a response to electricity supply conditions such as demand response and fault detection. Qualities of service requirements of these traffics are different. ED traffic conveys control and critical information that should be transmitted with a low latency [12]. On the other hand, FS traffic is elastic and tolerates a reasonable delay. One main responsibility of AMI is efficient transmission of traffic by SMs to a relay station called concentrator, as shown in Fig. 1. This node as a gateway is responsible to transmit this traffic to the utility company control center through a wide area network (WAN).

1.1 Related work

Due to a high demand of bandwidth in wireless networks, it is necessary to investigate efficient approaches of bandwidth allocation to SMs in SG communication system. To address this issue, a coexistence scheme has been proposed in [14] in which the required bandwidth of a SG communication system is provided partially by neighboring communication networks via spectrum ordering. Moreover, cognitive radio based SG communication system has been introduced in [15,16]. Cognitive radio refers to the potentiality that wireless systems opportunistically utilize spectrum holes in neighboring networks to mitigate spectrum deficiency. The reliability is low since SG users as secondary users should leave the spectrum upon the arrival of primary users.

In general, distributed and interference aware resource allocation algorithms for the uplink and downlink of cellular networks has been considered in [17,18]. Moreover, an algorithm for cognitive radio network resource allocation has been proposed by the same authors in [19] considering QoS and spectrum sensing errors. To provide spectrum access diversity, a joint spatial and temporal spectrum sharing technique is proposed in [20] to enhance the spectrum sharing opportunities to increase the communication reliability for demand response management. Finally, a hybrid spectrum access in cognitive-radio-based smart grid communication has been proposed in [21]. The smart grid operators has access to a number of leased spectrum bands, while at the same time, it is allowed to use a portion of cognitive spectrum bands opportunistically. The objective is to minimize the number of leased channels.

1.2 Main contribution

The aforementioned work in the literature does not distinguish between ED and FS traffics in terms of their quality of service requirements. Under the assumption of a given bandwidth, in this paper, we aim to find an efficient and fair resource allocation and traffic scheduling scheme to transmit both ED and FS traffics to the concentrator. To distinguish between these traffics in terms of their QoS requirements, we propose a two-stage traffic scheduling scheme. The ED traffic has the priority to meet the required transmit delay, thus, in the first stage the available bandwidth is scheduled among ED traffics in SMs. On the other hand, in the second stage, we employ a utility based resource allocation, where the rest bandwidth is allocated between FS traffics.

1.3 Paper organization

The paper is organized as follows. System model and traffic scheduling models are presented in Sect. 2. Model solutions and the derived traffic scheduling algorithm are proposed in Sect. 3. Numerical results are given in Sect. 4 and the paper is concluded in Sect. 5.

2 System model

Consider a SG communication system consisting of a concentrator and a set $\mathcal{N} \triangleq \{n : n = 1, \ldots, N\}$ of SMs as shown in Fig. 1. Each SM includes two separate queues of ED and FS packets. Let w_{tot} be the total available bandwidth to be allocated to SMs. The concentrator must be able to allocate this limited spectrum to the traffics in an efficient and fair way. As mentioned in Sect. 1, the priority of ED traffic is more than FS traffic due to its low latency requirement.

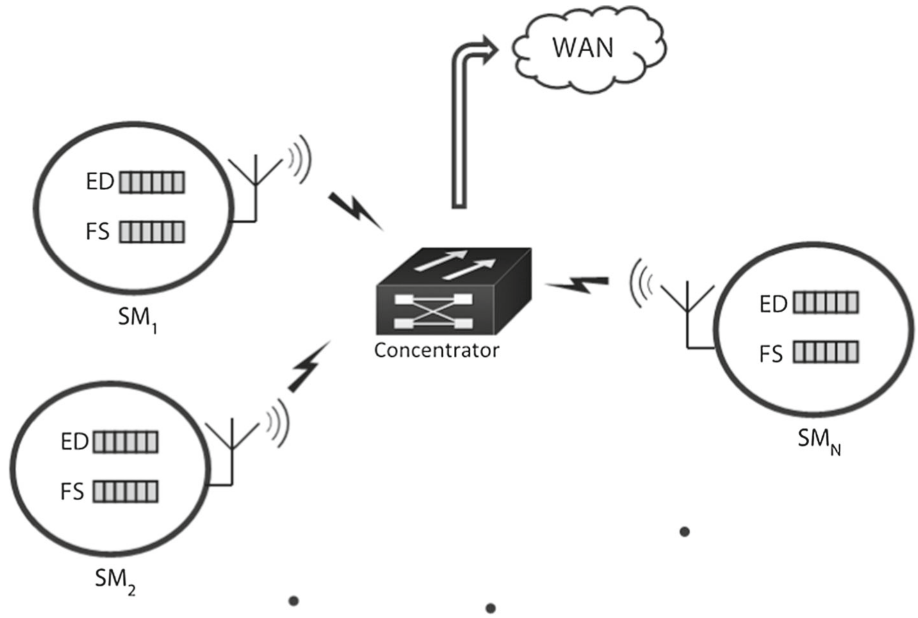

Fig. 1 System model: an AMI consisting of a number of SMs and a concentrator

To distinguish between ED and FS traffics, we propose a two-stage traffic scheduling model in the following.

2.1 Stage one: ED traffic scheduling model

Let Q_n^{ED} be the queue length of ED traffic in SM n. It is assumed that packets of each ED queue arrive following a Poisson process of mean λ_n packets per time slot. Moreover, let $c_n^{ED} = w_n^{ED} log_2(1+\gamma_n)$ bps/Hz be the part of link capacity between SM n and the concentrator, which is allocated to ED traffic. Note that γ_n is the channel signal to noise ratio of this link and w_n^{ED} is the allocated bandwidth to this ED queue. Moreover, to address the delay requirement of ED queues, in this paper, we take advantage of Little's law. This law expresses the queue average latency or service time T_n^{ED} in terms of average queue length $\bar{Q}_n^{ED}$ and average arrival rate λ_n as $T_n^{ED} = \frac{\bar{Q}_n^{ED}}{\lambda_n}$.

Considering aforementioned discussion, traffic scheduling of ED traffics is formulated as

$$\min_{\{w_n^{ED}\}_{n\in\mathcal{N}}} \sum_{n=1}^{N} \left(w_n^{ED}\right)^2 \tag{1a}$$

$$\text{s.t.} \quad \frac{\bar{Q}_n^{ED}}{\lambda_n} \leq d_n^{ED} \qquad \forall n \in \mathcal{N} \tag{1b}$$

$$\lambda_n \leq c_n^{ED} \qquad \forall n \in \mathcal{N} \tag{1c}$$

$$\sum_{n=1}^{N} w_n^{ED} \leq w_{tot} \tag{1d}$$

$$w_n^{ED} \geq 0 \qquad \forall n \in \mathcal{N}. \tag{1e}$$

where constraint (1b) states that the average latency for ED traffic in SM n should not exceeds d_n^{ED}. Constraint (1c) ensures that the arrival rate to each queue should be equal or less than the rate out of this queue. This constraint results in queue stability with a dynamic control strategy [22]. Constraints (1d) and (1e) are also due to the limit total bandwidth and non-negative portion of bandwidth to be allocated to the queues. Moreover, the objective function is a cost measure of the bandwidth. Without loss of generality, it is assumed to be a squared function in this paper.

2.2 Stage two: FS traffic scheduling model

In the second stage, the concentrator monitors the FS traffics and allocates the rest bandwidth $w_{rest} = w_{tot} - \sum_{i=1}^{N} w_n^{ED*}$ to these traffics, where $\sum_{i=1}^{N} w_n^{ED*}$ is the aggregate allocated bandwidth in problem (1). Let w_n^{FS} be the allocated bandwidth to the FS traffic in SM n. Therefore, the capacity for this traffic is $c_n^{FS} = w_n^{FS} \log_2(1+\gamma_n)$.

In the case of FS traffic that has elastic property, we use a well-known approach of utility-based resource allocation presented in the literature [23]. Associated with each FS queue, there is a utility function $u(c_n^{FS})$ which addresses the effectiveness of the assigned capacity to the FS traffic. Here, we adopt a weighted logarithmic utility function for each queue as $u(c_n^{FS}) \triangleq a_n \log(c_n^{FS})$ which results in a proportional fairness between FS queues. Note that a_n is a weight to address the number of appliances served by SM n.

Maximizing the sum-utility in the SG is done in the second stage of the proposed traffic scheduling model, as in the following:

$$\max_{\{w_n^{FS}\}_{n\in\mathcal{N}}} \sum_{n=1}^{N} \log(c_n^{FS}) \tag{2a}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} w_n^{FS} \leq w_{rest} \tag{2b}$$

$$w_n^{FS} \geq 0 \qquad \forall n \in \mathcal{N}. \tag{2c}$$

3 Proposed traffic scheduling scheme

Having proposed the traffic scheduling models, in this section, these models are analyzed and solved to be used by a proposed traffic scheduling algorithm.

3.1 Stage one: ED traffic scheduling scheme

Due to time-varying channel gains between SMs and the concentrator as well as ED traffic arrival rates, problem (1) is not deterministic. Therefore, we are to employ a stochastic programming approach to capture the randomness of these parameters over the realization time.

In the beginning, among the existing variables in problem (1), the average queue lengths are not available. Therefore, for the time being, we continue by ignoring constraint (1b) and write the problem as

$$\min_{\{w_n^{ED}\}_{n\in\mathcal{N}}} \sum_{n=1}^{N} \left(w_n^{ED}\right)^2 \tag{3a}$$

$$\text{s.t.} \quad (1c) - (1e). \tag{3b}$$

Incorporating constraint (1c) into the objective function, the partial Lagrange function is written as

$$L\left(\left\{w_n^{ED}, q_n^{ED}\right\}_{n\in\mathcal{N}}\right) = \sum_{n=1}^{N} \left(w_n^{ED}\right)^2 + \sum_{n=1}^{N} q_n^{ED}\left(\lambda_n - c_n^{ED}\right) \tag{4}$$

where $\left\{q_n^{ED} \geq 0\right\}_{n\in\mathcal{N}}$ is the set of Lagrange multipliers corresponding to constraint (1c). Optimizing with respect to primal variables $\{w_n^{ED}\}_{n\in\mathcal{N}}$ yields the dual function as

$$D\left(\left\{q_n^{ED}\right\}_{n\in\mathcal{N}}\right) = \inf_{\{w_n^{ED}\}_{n\in\mathcal{N}}} \left\{L\left(\left\{w_n^{ED}, q_n^{ED}\right\}_{n\in\mathcal{N}}\right) | (1d), (1e)\right\} \tag{5}$$

which provides a lower bound on the optimal value of the primal problem for every feasible value of the dual variables [24]. Therefore, the tightest lower bound is obtained by the dual problem as

$$\max_{\{q_n^{ED}\}_{n\in\mathcal{N}}} D\left(\{q_n^{ED}\}_{n\in\mathcal{N}}\right) \tag{6a}$$

$$\text{s.t.} \quad q_n^{ED} \geq 0 \qquad \forall n \in \mathcal{N}. \tag{6b}$$

Prior to solve the dual problem, it is needed to evaluate the dual function in (5), which is equivalent to

$$\min_{\{w_n^{ED}\}_{n\in\mathcal{N}}} \sum_{n=1}^{N} \left(w_n^{ED}\right)^2 + \sum_{n=1}^{N} q_n^{ED}\left(\lambda_n - c_n^{ED}\right) \tag{7a}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} w_n^{ED} \leq w_{tot} \tag{7b}$$

$$w_n^{ED} \geq 0 \quad \forall n \in \mathcal{N}. \tag{7c}$$

Under the assumption of given q_n^{ED}'s, this is a quadratic convex problem that can be solved using software packages. In this paper, we use CVX [25] to derive the optimal allocated bandwidths $\{w_n^{ED*}\}_{n\in\mathcal{N}}$.

Having obtained the optimal allocated bandwidths in the primal problem (7), it is turn to derive optimal Lagrange multipliers in the dual problem (6). Considering the concave property of this problem [24], it can be solved efficiently using an iterative subgradient method. In a time horizon indexed by t, given $w_n^{ED}(t)$ and accordingly $c_n^{ED}(t)$ at time slot t, each Lagrange multiplier $q_n^{ED}(t)$ is updated as

$$q_n^{ED}(t+1) = \left[q_n^{ED}(t) + \alpha\left(\lambda_n - c_n^{ED}\right)\right]^+ \quad n \in \mathcal{N} \tag{8}$$

where $\lambda_n(t) - c_n^{ED}(t)$ is the subgradient of the dual function with respect to q_n^{ED}, α is a step size, and $[x]^+ = \max(0, x)$.

The gradient iteration (8) is efficient to find the optimal solution. A key knowledge we need in this equation are values for every λ_n and γ_n. Assumption of known probability density functions for these parameters may be reasonable for theoretic studies. However, the importance of practical spectrum allocation schemes motivates the optimal strategy by *learning* the parameter time variations on-the-fly. Interestingly, a stochastic gradient iteration can be developed to solve (8) without probability density functions of λ_n and γ_n. To this end, we devise online iterations for *dynamic* decisions based on per instant realizations of $\lambda_n(t)$ and $\gamma_n(t)$ as

$$q_n^{ED}(t+1) = \left[q_n^{ED}(t) + \alpha\left(\lambda_n(t) - c_n^{ED}(t)\right)\right]^+ \quad n \in \mathcal{N} \tag{9}$$

This iteration is the stochastic estimates of that in (8). Provided that ED traffic arrival rates and signal-to-noise ratios are stationary and ergodic, the stochastic gradient iteration (8) and the ensemble gradient iteration (9) produce a pair of primary and averaged systems [26]. Convergence of such stochastic gradient iterations can be established statistically, provided that α is small enough. Such a proof for a typical problem is provided in the "Appendix".

Because $\lambda_n(t)$ and $c_n^{ED}(t)$ are inflow and outflow rates of the queue of ED traffic in SM n, $q_n^{ED}(t)$ can be considered as a measure of the queue length Q_n^{ED} at time slot t. Inspecting (9), we derive

$$Q_n^{ED}(t) = \alpha q_n^{ED}(t) \quad \forall t. \tag{10}$$

Having derived a coupling between queue lengths and Lagrange multipliers in the dual domain, it is time to reconsider constraint (1b) as $Q_n^{ED}(t) \leq \lambda_n(t) d_n^{ED}$. Considering this constraint along with derivations (8) and (10), the queue length dynamic is written as

$$Q_n^{ED}(t+1) = \left[Q_n^{ED}(t) + \left(\lambda_n(t) - c_n^{ED}(t)\right)\right]_0^{\lambda_n(t) d_n^{ED}} \qquad n \in \mathcal{N} \tag{11}$$

where $[x]_a^b$ is the projection of x into interval $[a, b]$. Therefore, we satisfied delay constraint (1b) by a modification in the dual domain.

One main point in the solution of problem (1) is to check its feasibility. For the case of a large number of SMs or high arrival rates, the bandwidth required to satisfy the delay constraint (1b) of ED traffics exceeds the available w_{tot} in the SG. This certainly violates constraint (1d) and results in an unfeasible solution.

In order to check the feasibility of this problem, here, we derive an approximate lower bound on the required w_{tot} for given SG communication system parameters. This derivation is based on the requirement of having stable queues for ED traffics. In order to ensure stability for a queue, the average arrival rate should not exceed the average service rate. Under the assumption of an equal channel gains for all SMS and based on the queue stability statement, in overall, we can write

$$\sum_{n=1}^{N} \lambda_n \leq w_{tot} \log_2(1 + \gamma_n) \tag{12}$$

which results in

$$w_{tot} \geq \frac{\sum_{n=1}^{N} \lambda_n}{\log_2(1 + \gamma_n)}. \tag{13}$$

This is a lower bound on the total bandwidth in order to ensure feasibility for problem (1).

3.2 Stage two: FS traffic scheduling scheme

Problem (2) can be solved using Lagrange decomposition. To do that, the Lagrange function can be written as

$$\begin{aligned} L\left(\{w_n^{FS}\}_{n\in\mathcal{N}}\right) &= \sum_{n=1}^{N} a_n \log(c_n^{FS}) - \mu \left(\sum_{n=1}^{N} w_n^{FS} - w_{rest}\right) \\ &= \sum_{n=1}^{N} \left(a_n \log(c_n^{FS}) - \mu w_n^{FS}\right) + \mu w_{rest} \end{aligned} \tag{14}$$

where $\mu \geq 0$ is the Lagrange multiplier corresponding to constraint (2b). This function can be decomposed into sub-functions corresponding to individual SMs. Maximizing each sub-function with respect to w_n^{FS}, we derive

$$\frac{\partial L\left(\{w_n^{FS}\}_{n\in\mathcal{N}}\right)}{\partial w_n^{FS}} = \frac{a_n}{\ln 10} \frac{\log_2(1+\gamma_n)}{w_n^{FS} \log_2(1+\gamma_n)} - \mu = 0 \tag{15}$$

which results in $w_n^{FS} = \frac{a_n}{\mu \ln 10}$. Following the complementary slackness property in dual optimization [24], written as $\mu(\sum_{n=1}^{N} w_n^{FS} - w_{rest}) = 0$, we substitute w_n^{FS} and derive the optimal Lagrange multiplier as $\mu = \frac{\sum_{n=1}^{N} a_n}{w_{rest} \ln 10}$. This derivation accordingly results in

$$w_n^{FS} = \frac{a_n}{\sum_{n=1}^{N} a_n} w_{rest} \quad \forall n \in \mathcal{N}. \tag{16}$$

3.3 Traffic scheduling algorithm

Following the traffic scheduling problems and solutions provided for ED and FS traffics, in this section, we propose a QoS-aware smart grid traffic scheduling (Q-SGTS) algorithm accordingly. Q-SGTS is summarized in Algorithm 1.

Algorithm 1 Q-SGTS algorithm

1: Initialization: $q_n(0) = 0 \quad \forall n \in \mathcal{N}, t = 0$.
2: **while** $\{1\}$ **do**
3: **stage 1:** *ED traffic scheduling*
4: Using the solution of problem (7), obtain $\{w_n^{ED}(t)\}_{n\in\mathcal{N}}$.
5: Using (8) and (11), update Lagrange multipliers and queue lengths.
6: **stage 2:** *FS traffic scheduling*
7: Using the solution of problem (3) in (16), obtain $\{w_n^{FS}(t)\}_{n\in\mathcal{N}}$.
8: $t = t + 1$.
9: **end while**

The algorithm is run over a time horizon index by t. It is assumed that ED traffic arrival rates λ_n's and channel gains γ_n's vary following given probability density functions. Considering the realized values for these parameters, at each time slot t, two stages are done sequentially. Due to the priority of ED traffics, in the first stage, the allocated bandwidth is derived for this traffic using the proposed solution in Sect. 3.1 and queue lengths are updated accordingly. In the second

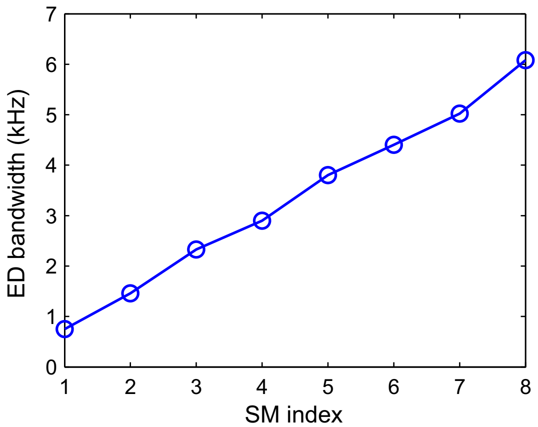

Fig. 2 ED traffic average bandwidth

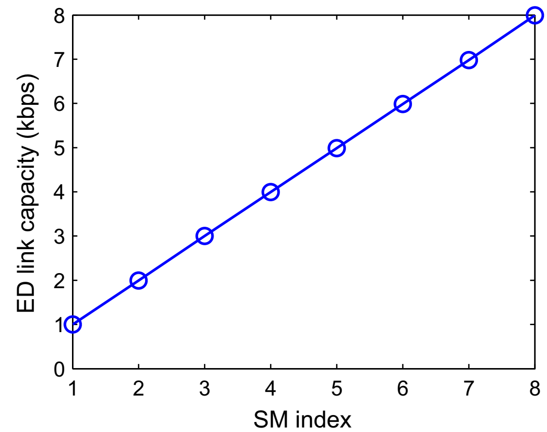

Fig. 3 ED traffic average transmit rate

stage, the rest bandwidth is allocated to FS traffics using the solution in Sect. 3.2. The algorithm continues until the end of the time horizon.

4 Numerical results

Consider a SG communication system with $N = 8$ SMs indexed from $n = 1$ to $n = 8$. We assume that the channel gains from SMs to the concentrator have the same exponential SNR of mean 3 dB. However, SMs are assumed to have different ED traffic arrival rates from mean 1 to 8 kbps, respectively. It is noteworthy that different ED traffic arrival rates represent different number of appliances in each household, which is represented by a corresponding SM. Moreover, the total bandwidth available for all SMs is set to $w_{tot} = 50$ kHz and the minimum required latency for ED traffics is set to be 100 ms. The numerical results of the proposed Q-SGTS algorithm in a time horizon of length 100 time slots are given in the following.

The average allocated bandwidth and link capacity for ED traffics are shown in Figs. 2 and 3, respectively. As shown, the average allocated bandwidth and the corresponding outgoing rate from every ED queue matches its own arrival rate. This is due to constraint (1c), which results in queue stability for ED traffics.

To demonstrate the stability of ED queues, we illustrate the average ED queue lengths in Fig. 4. This figure reveals the stability of these queues in terms of their finite lengths. However, the queue lengths are different; the higher is the arrival rate, the higher is the queue length. This relationship between queue lengths and arrival rates results in approximately the same ED latency, as illustrated in Fig. 5. This figure clearly indicates that latency requirement, (i.e., 100 ms), of ED traffic has been mostly satisfied by the proposed algorithm.

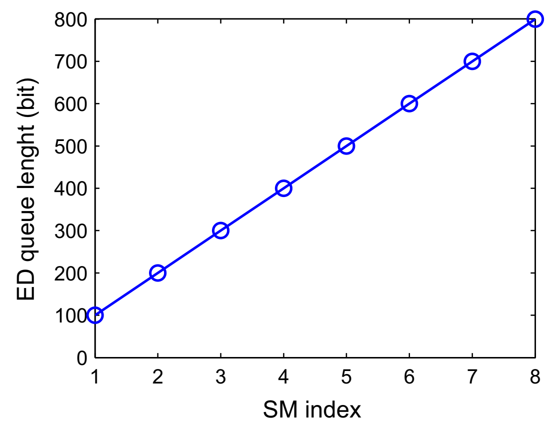

Fig. 4 ED traffic average queue length

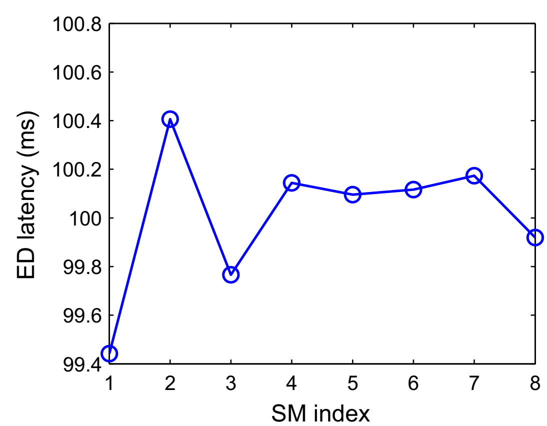

Fig. 5 ED traffic average latency

Having allocated the bandwidth to ED traffic, the rest bandwidth w_{rest} is allocated to FS traffic in the second stage. To get a detailed insight into w_{rest}, it is typically shown over the time horizon in Fig. 6. As observed, depending on the realized ED traffic arrival rates and channel gains, the rest bandwidth varies over the time. Applying the FS traffic

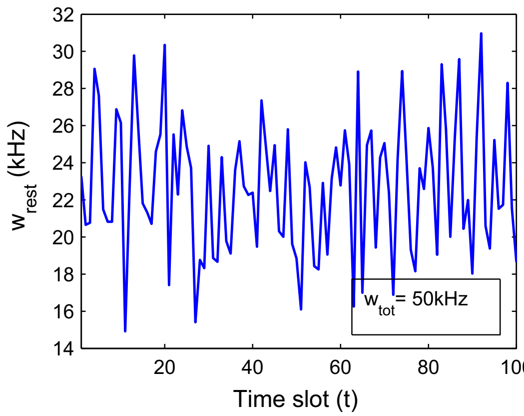

Fig. 6 The rest bandwidth to be allocated to FS traffic

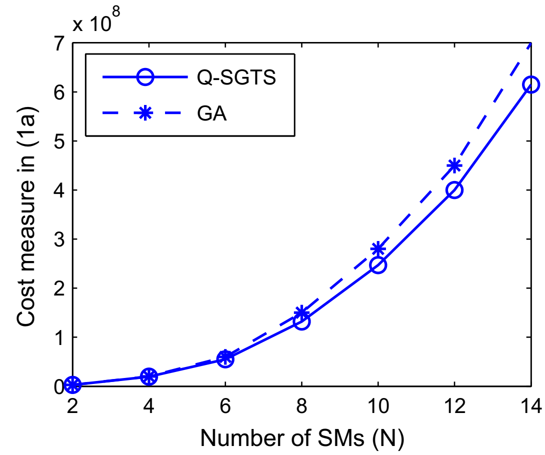

Fig. 8 The cost measure of ED traffic scheduling in stage one

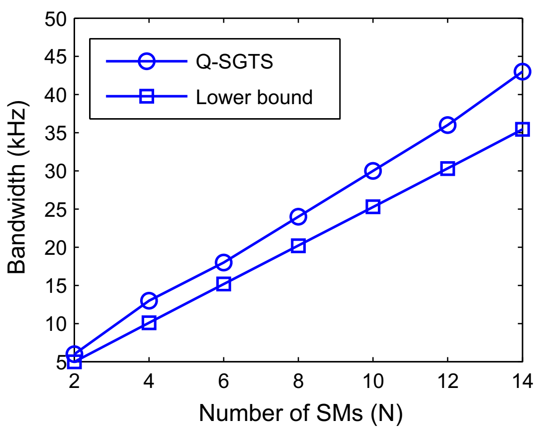

Fig. 7 Required bandwidth to satisfy delay constraint of ED traffic

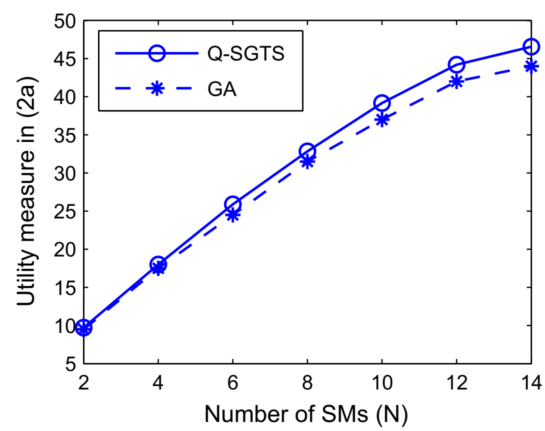

Fig. 9 The utility measure of FS traffic scheduling in stage two

bandwidth allocation in (16), the allocated bandwidth to each FS queue n at each time slot t is $w_n^{FS}(t) = \frac{a_n}{\sum_{n=1}^{N} a_n} w_{rest}(t)$. Following the assumed ED traffic arrival rates, weights a_n's can be considered as $a_1 = 1, a_2 = 2, \ldots, a_8 = 8$.

One the feasibility of ED traffic scheduling model in (1), in Sect. 3.1, we have proposed a lower bound on required w_{tot} in order to have a feasible problem. To evaluated the performance of this lower bound, we perform a simulation. Consider a SG communication system consisting of a number of SMs, all with the same channel gains of 3dB and the same arrival rate of 4 kbps for ED traffic. The average required bandwidth for ED traffic from the algorithm and that from the proposed lower bound is shown in Fig. 7 for different number of SMs. The figure discerns that the required bandwidth by the Q-SGTS and that by the proposed lower bound mostly match with each other for several number of SMs. But, the difference increases linearly for adding more SMs.

Finally, it is interesting to evaluate the cost and utility measures defined in (1a) and (2a) as objective functions for the first and the second stages, respectively. With $d = 100$ ms and $w_{tot} = 100$ kHz in all instances, these measures are shown in Figs. 8 and 9 versus the number of SMs. In these figures, we extend the time horizon to $T = 1000$ time slots at each instance. As shown, the cost measure increases when N increases. This is the cost of satisfying the determined latency $d = 100$ ms for all SMs. As N increases, the more bandwidth is needed, which results in higher costs. However, as N increases, the rest bandwidth in the second stage is utilized more efficiently. This fact results in a higher utility measure for larger number of SMs, which is shown in Fig. 9.

For the aim of comparison, Figs. 8 and 9 also show the results of applying the genetic algorithm (GA) to the given problems in stages one and two. In GA, in contrast to our proposed algorithm Q-SGTS, it is assumed that the whole data of SMs instant arrival rates and channel gains are known in the beginning of the time horizon. The results are remarkably comparable, which verify the performance of Q-SGTS.

5 Conclusion

In this paper, we discussed two-stage traffic scheduling model, and we used the model to design a new algorithm, Q-SGTS for SG communication system. The model prioritizes ED packets over the FS traffic. Thus, it provides latency requirement of ED traffic, which results in stable queues for ED traffic. Moreover, the proposed lower bound on the required bandwidth in the model well underestimates that achieved from the proposed algorithm. Additionally, a weighed utility-based resource allocation approach for FS traffic results a weighted bandwidth allocation for FS traffic. Finally, the results verified high performance of Q-SGTS and it outperformed GA algorithm.

Appendix

Convergence of the Stochastic iteration

Without loss of generality, consider the problem

$$\min_{x} \mathbb{E}_r \left[f(x, r) \right] \tag{17}$$

where r is a random variable and $f(x,r)$ is a convex function in x. To find the optimal solution x^* and optimal value $p^* = \mathbb{E}_r \left[f(x^*, r) \right]$, the following gradient iteration is used.

$$x(t+1) = x(t) - \alpha g(t) \tag{18}$$

where α is a step size and $g(t)$ is the gradient of $f(.)$ with respect to $x(t)$, i.e., $g(t) \triangleq \nabla f_x(x(t), r(t))$. Taking *norm-2* of $(x(t+1) - x^*)$, we derive

$$\begin{aligned} \left\| x(t+1) - x^* \right\|^2 &= \left\| x(t) - \alpha g(t) - x^* \right\|^2 \\ &= \left\| x(t) - x^* \right\|^2 - 2\alpha g(t)(x(t) - x^*) + \alpha^2 \left\| g(t) \right\|^2 . \end{aligned} \tag{19}$$

Due to the convexity of $f(x(t), r(t))$ in $x(t)$, the following inequality holds [27].:

$$f(x^*, r(t)) \geq f(x(t), r(t)) + g(t)(x^* - x(t)). \tag{20}$$

Applying this inequality to (19), it is written as

$$\begin{aligned} &\left\| x(t+1) - x^* \right\|^2 \leq \\ &\left\| x(t) - x^* \right\|^2 - 2\alpha \left\{ f(x(t), r(t)) - f(x^*, r(t)) \right\} \\ &\quad + \alpha^2 \left\| g(t) \right\|^2 . \end{aligned} \tag{21}$$

Taking a similar recursive approach from $x(t)$ to $x(0)$ as an initial value, we derive

$$\begin{aligned} \left\| x(t+1) - x^* \right\|^2 \leq \left\| x(0) - x^* \right\|^2 + \alpha^2 \sum_{i=0}^{t} \left\| g(i) \right\|^2 \\ - 2\alpha \sum_{i=0}^{t} \left\{ f(x(i), r(i)) - f(x^*, r(i)) \right\} . \end{aligned} \tag{22}$$

Since the left-hand side is always non-negative, then

$$\begin{aligned} &2\alpha \sum_{i=0}^{t} \left\{ f(x(i), r(i)) - f(x^*, r(i)) \right\} \\ &\leq \left\| x(0) - x^* \right\|^2 + \alpha^2 \sum_{i=0}^{t} \left\| g(i) \right\|^2 . \end{aligned} \tag{23}$$

Now consider the following two assumptions:

- $\| g(i) \| \leq G$, for all i.
- $\| x(0) - x^* \|^2 \leq R^2$.

With reference to the system model in Sect. 2, these assumptions are reasonable and can be provided in the model. Dividing both sides of (23) by $2\alpha t$, it is concluded that

$$\frac{1}{t} \sum_{i=0}^{t} \left\{ f(x(i), r(i)) - f(x^*, r(i)) \right\} \leq \frac{R^2}{2\alpha t} + \frac{\alpha^2 t G^2}{2\alpha t}. \tag{24}$$

If $t \to \infty$, by the law of large numbers

$$\overline{f(x,r)} - p^* \leq \frac{\alpha}{2} G^2. \tag{25}$$

where $\overline{f(x,r)} = \frac{1}{t} \sum_{i=0}^{t} f(x(i), r(i))$ and $p^* = \mathbb{E}_r \left[f(x^*, r) \right] = \frac{1}{t} \sum_{i=0}^{t} f(x^*, r(i))$.

Since $f(.)$ is a convex function, by the Jensen's inequality [24] we have $\overline{f(x,r)} \geq f(\bar{x}, r)$, and consequently

$$f(\bar{x}, r) - p^* \leq \frac{\alpha}{2} G^2. \tag{26}$$

Choosing step size α small enough, we conclude that the gradient iteration (18) converges statistically. In other words, as t goes to infinity, the solution derived from gradient iteration (18), i.e. $f(\bar{x}, r)$, converges to the optimal value p^*.

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