Traffic Characteristic and Overhead Analysis for Wireless Networks Based on Stochastic Network Calculus

Lishui Chen[1], Dapeng Wu[2], and Zhidu Li[2](✉)

[1] Science and Technology on Communication Networks Laboratory, The 54th Research Institute of CETC, Shijiazhuang 050081, Hebei, People's Republic of China
[2] School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China

Abstract. With the rapid development of communication technology, impacts of various service characteristics on the performance of wireless networks draw numerous studies. However, few from such studies take into account the impacts of the overheads which always arise due to traffic influx. Stochastic network calculus is a newly but promising queuing theory, and its concept has proved to be a good tool for performance analysis in the field of communication networks. In this paper, we investigate the impacts of packet size and their overheads on wireless network performance. A wireless network model that comprises data channels and control channels is introduced. An optimization problem is then formulated with the objective to minimize the transmission rates under different probabilistic delay constraints in both data and control channels. Thereafter, we apply stochastic network calculus to solve the optimization problem. Finally, numerical results of minimum transmission rate, overhead arrival rate and packet loss probability are presented, wherein the impacts of packet size and their overheads are analyzed and discussed.

Keywords: Performance analysis · Packet size · Overheads · Probabilistic delay constraint · Stochastic network calculus

1 Introduction

With the development of communication technology, various mobile data services, such as video service, instant messaging service and so on, are loaded in high speed wireless networks, which have greatly enriched our daily lives [1–3]. Mobile terminals are now good alternatives to home television for watching videos and personal computers for electronic messages. Sometimes, the network seems quite affluent for users to enjoy a good time, but sometimes it seems too choky to be tolerated. This phenomenon is relevant to the traffic characteristics and the capacity of channels [4].

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Recently, numerous studies have paid attention to the impacts of traffic characteristics on the performance of wireless networks. For example, work [5] shown that the data burst from delay-sensitive uplink services can have significant impacts on the network performance, and work [6] proposed a detailed performance assessment of VoIP traffic by carrying out experimental trials across a real LTE-A environment. To the best of our knowledge, few studies take into account the traffic characteristics and their overheads which may arise due to the traffic influx. However, these overheads do have significant impacts on the performance of wireless networks especially when data service is extracted from the real mobile networks. For example, WeChat service (a kind of instant messaging service) may cause congestions in wireless networks because of large amounts of control signaling. Therefore, comprehensive study on different traffic characteristics and their corresponding overheads is of great importance for the research of wireless resource allocation and quality of service guarantee provisioning.

Stochastic network calculus is one branch of network calculus which is an emerging queuing theory first proposed by Cruz in 1991 [7,8]. Nowadays, stochastic network calculus has evolved into a powerful and promising tool in analyzing network performance especially in delay and backlog analysis [9,10]. Compared with traditional queuing theories, stochastic network calculus deals with problem by giving probabilistic bound instead of deterministic mean value. Hence, it has great advantage on performance analysis in the situation where deterministic characteristics cannot be ascertained or the performance guarantee is flexible. Furthermore, stochastic network calculus has been widely used in many fields, such as performance analysis of cognitive radio [11,12], energy consumption analysis in wireless networks [13–15] just to mention a few.

Hence, this paper applies stochastic network calculus to study the traffic delay performance by taking the traffic characteristics and control overheads into account. Data channels and control channels are first modeled and an optimization problem is then formulated with the objective to minimize the transmission rates under different probabilistic delay constraints in both data and control channels. Finally, numerical results of minimum transmission rate, overhead arrival rate and packet loss probability are presented and discussed.

The remainder of this paper is organized as follows. Section 2 introduces the system model, where some assumptions are given. After that, an optimization problem is formulated, with the objective to minimize the transmission rates under different probabilistic delay constraints. Section 3 demonstrates the derivation of the relationship between the minimum transmission rate and the probabilistic delay constraint using stochastic network calculus. The solution of the optimization problem is also achieved at the end of this section. Then, numerical results about the impacts of packets size and their overheads are presented and discussed in Sect. 4. Finally, Sect. 5 concludes the paper.

2 System Model

In this paper, we consider a wireless network model depicted in Fig. 1, control channels, data channels as well as data flows and overheads are all taken into account. The data traffic and overheads are all transmitted as packets. Furthermore, all packets obey the scheduling rule of first in first out (FIFO). The data channels provide a constant total transmission rate of C_1 to transmit both data packets and their extra data overheads. Data overheads are the extra information which are generated and transmitted with data packets. The control channels provide a constant total transmission rate of C_2 to transmit the control overheads. In this paper, we only consider the control overheads which mainly arise whenever a session is setup to transmit data packets.

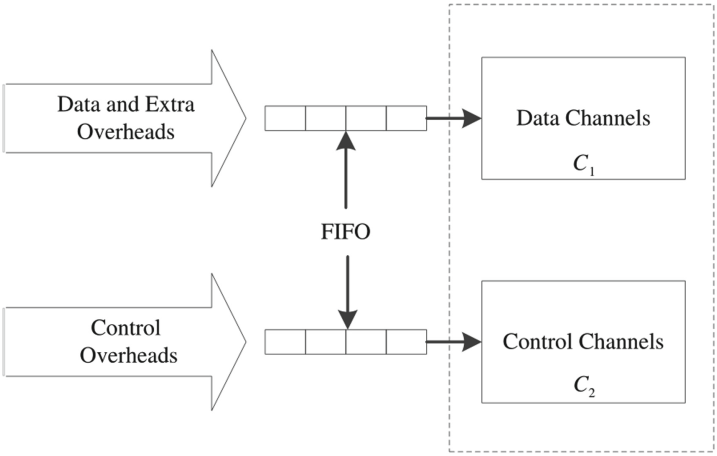

Fig. 1. System model

There are three steps for a successful data packet transmission: firstly, whenever there is a data packet to be transmitted, the system will generate a control overhead and transmit it through the control channels to the target system to setup a session; subsequently, the system generate a data overhead and pack it into the data packet; lastly, the data packet and its data overhead await their time slot to get transmitted through the data channels. For ease of expression and with the focus on the impacts of packet size and overheads, the transmission channels are assumed to be error free and only timeout packets are discarded. Therefore, a data packet is successfully transmitted if and only if the packet and its corresponding overheads are both successfully transmitted under a probabilistic delay constraint.

Transmission delay in the data channels and control channels are denoted by $D_1(t)$ and $D_2(t)$ respectively. Moreover, the transmission in the data channels has a delay requirement, represented by a probabilistic delay constraint (t_1, p_0), which means the probability of the delay $D_1(t)$ exceeding a delay time t_1 should be bounded by p_0, i.e. $\Pr\{D_1(t) > t_1\} \leq p_0$. Similarly, the transmission in control channels also has a probabilistic delay constraint $\Pr\{D_2(t) > t_2\} \leq p_0$.

For analyzing the impacts of packet size and overheads on the minimum transmission rate and packet loss probability under a probabilistic delay constraint, it is necessary to find the relationship between the minimum transmission rate and the probabilistic delay constraint. In addition, it is also required that the upper bound of the mean traffic arrival rate should not be larger than the transmission rate for the sake of ensuring stability in the system. Therefore, if the probabilistic delay constraint is given, an optimization problem which minimizes the transmission rates under probabilistic delay constraints in the data channels and the control channels respectively can be expressed as:

$$\begin{aligned} &\min \mathrm{C}_1(D_1(t)) \text{ and } \min \mathrm{C}_2(D_2(t)) \\ &\text{s.t. } \rho_1(\theta_1) \leq \mathrm{C}_1, \Pr\{D_1(t) > t_1\} \leq p_0, \\ &\quad\;\; \rho_2(\theta_2) \leq \mathrm{C}_2, \Pr\{D_2(t) > t_2\} \leq p_0 \end{aligned} \tag{1}$$

where $\rho(\theta_1)$ denotes the upper bound of mean traffic arrival rate for the data channels, $\rho(\theta_2)$ denotes the upper bound of mean arrival rate for the control channels, θ_1 and θ_2 are both optimization parameters to be used to determine the minimum of C_1 and C_2 respectively.

3 Performance Analysis

3.1 Stochastic Network Calculus Basics

As highlighted earlier, stochastic network calculus is a newly developed queuing theory which has been widely used in performance analysis. There are two basic concepts in stochastic network calculus: stochastic arrival curve (SAC) and stochastic service curve (SSC), which are used to describe the arrival process of input traffic and the service process of server respectively. The concept and proof of the theorem can be found in [9]. For convenience, we provide basic definitions here for our subsequent analysis.

Definition 1 (Stochastic Arrival Curve). A flow $A(t)$ is said to have a stochastic arrival curve $\alpha(t)$ with the bounding function $f(x)$, if for all $t \geq s \geq 0$ and all $x \geq 0$, there holds

$$\Pr\{\sup_{0 \leq s \leq t} \{A(s,t) - \alpha(t,s)\} > x\} \leq f(x) \tag{2}$$

Here,$A(s,t)$ denotes the cumulative amount of packets during the time period $(s,t]$, and $A(t) = A(0,t)$.

Definition 2 (Stochastic Service Curve). A system is said to provide a stochastic service curve $\beta(t)$ with the bounding function $g(x)$, if for all $t \geq s \geq 0$ and all $x \geq 0$, there holds

$$\Pr\{A \otimes \beta(t) - A^*(t) > x\} \leq g(x) \tag{3}$$

Here, $\otimes$ is the operation of minimum plus $(\min; +)$ convolution, $A \otimes \beta(t) \equiv \inf_{0 \leq s \leq t} \{A(s,t) + \beta(s)\}$. And $A^*(t)$ denotes the cumulative amount of the output packets by time t.

Theorem 1 (Probabilistic Delay Bound). In a given system, if the input has a stochastic arrival curve as $\alpha(t)$ with the bounding function $f(x)$, and the system provides to the input a stochastic service curve as $\beta(t)$ with the bounding function $g(x)$. Then for all $t \geq 0$ and all $x \geq 0$, the delay $D(t)$ is bounded by:

$$\Pr\{D(t) > h(\alpha + x, \beta)\} < f \otimes g(x) \tag{4}$$

where $h(\alpha+x, \beta) = \sup_{s \geq 0}\{\inf\{\tau \geq 0 : \alpha(s)+x \leq \beta(s+\tau)\}\}$ denotes the maximum horizontal distance between $\alpha(t)+x$ and $\beta(t)$. Here, $h(\alpha+x, \beta)$ denotes the delay time t, the relationship between $h(\alpha + x, \beta)$ and transmission rate C is:

$$h(\alpha + x, \beta) = t = \frac{t}{C} \tag{5}$$

3.2 Solution of the Optimization Problem

As the system model describes, a data overhead and a control overhead arise if and only if there is a data packet to be transmitted. Therefore, the numbers of arrival of data packets and control overheads as well as data overheads are the same.

Also, suppose the traffic flow is Poisson distribution with the expectation of λ. Using the knowledge of stochastic network calculus, the arrival curves with the bounding functions for both data channels and control channels are deduced respectively as follows [16].

Arrival curve for the data channels with the bounding function:

$$\begin{cases} \alpha_1(t) = \frac{\lambda t}{\theta_1}(e^{\theta_1(L+\sigma_1)} - 1) \\ f_1(x) = e^{-\theta_1 x} \end{cases} \tag{6}$$

where, L and σ_1 denote data packet size and data overhead size respectively, and θ_1 is optimization parameters mentioned earlier.

Arrival curve for the control channels with the bounding function:

$$\begin{cases} \alpha_2(t) = \frac{\lambda t}{\theta_2}(e^{\theta_2 \sigma_2} - 1) \\ f_2(x) = e^{-\theta_2 x} \end{cases} \tag{7}$$

where σ_2 denotes control overhead size and θ_2 is optimization parameters.

The service curve in the data channels with the bounding function is:

$$\begin{cases} \beta_1(t) = C_1 t \\ g_1(x) = 0 \end{cases} \tag{8}$$

Similarly, service curve in the control channels with the bounding function is:

$$\begin{cases} \beta_2(t) = C_2 t \\ g_2(x) = 0 \end{cases} \tag{9}$$

Let $t_1 = h(\alpha_1 + x, \beta_1)$, according to (4) and (5), the probabilistic delay bounding function for the data channels is derived as follows:

$$\Pr\{D_1(t) > t_1\} = \Pr(D_1(t) > h(\alpha_1 + x, \beta_1)) \leq f \otimes g(C_1 t_2) = e^{-\theta_1 C_1 t_1} \tag{10}$$

Similarly, the probabilistic delay bounding function for the control channels is derived as:

$$\Pr\{D_2(t) > t_2\} \leq f \otimes g(C_2 t_2) = e^{-\theta_2 C_2 t_2} \tag{11}$$

Hence, the optimization problem in (1) is clear, there holds

$$\begin{cases} \rho_1(\theta_1) = \frac{\lambda}{\theta_1}(e^{\theta_1(L+\sigma_1)} - 1) \leq C_1 \\ \Pr\{D_1(t) > t_1\} \leq e^{-\theta_1 C_1 t_1} = p_0 \\ \rho_2(\theta_2) = \frac{\lambda}{\theta_2}(e^{\theta_2 \sigma_2} - 1) \leq C_2 \\ \Pr\{D_2(t) > t_2\} \leq e^{-\theta_2 C_2 t_2} = p_0 \end{cases} \tag{12}$$

By simplifying (12), we can get:

$$\begin{cases} C_1 \geq \frac{(L+\sigma_1)\log(1/p_0)}{t_1 \log(\frac{\log(1/p_0)}{\lambda t_1}+1)} \\ C_2 \geq \frac{\sigma_2 \log(1/p_0)}{t_2 \log(\frac{\log(1/p_0)}{\lambda t_2}+1)} \end{cases} \tag{13}$$

where the condition of equality holds if and only if

$$\begin{cases} \theta_1 = \frac{\log(\frac{\log(1/p_0)}{\lambda t_1}+1)}{L+\sigma_1} \\ \theta_2 = \frac{\log(\frac{\log(1/p_0)}{\lambda t_2}+1)}{\sigma_2} \end{cases} \tag{14}$$

Therefore, the optimization problem in (1) is solved. The minimum transmission rates for both data channels and control channels are achieved, there holds:

$$\begin{cases} C_{1,\min} = \frac{(L+\sigma_1)\log(1/p_0)}{t_1 \log(\frac{\log(1/p_0)}{rt_1/L}+1)} \\ C_{2,\min} = \frac{\sigma_2 \log(1/p_0)}{t_2 \log(\frac{\log(1/p_0)}{rt_2/L}+1)} \end{cases} \tag{15}$$

where $r = \lambda L$, denotes the mean traffic arrival rate.

4 Numerical Results and Analysis

In the preceding sections, the arrival processes of data packets and their overheads as well as service process are introduced and modeled. The considered model is applicable to different wireless network systems, such as Wi-Fi, LTE and NR. Afterwards, the relationships between the minimum transmission rate and the probabilistic delay constraint in both data channels and control channels are derived based on the theory of stochastic network calculus.

In this section, two types of mobile data services are considered, which are video service and instant messaging service (representing service with large size packets and service with small size packets respectively). The size of video packet is set to 5 Mbits whereas instant messaging (IM) packet is set to 5 kbits. Overheads of data packets for the data channels are set to 1 kbits while for the control channels are set to 0.5 kbits (i.e., $\sigma_1 = 1$ kbits,$\sigma_2 = 0.5$ kbits).

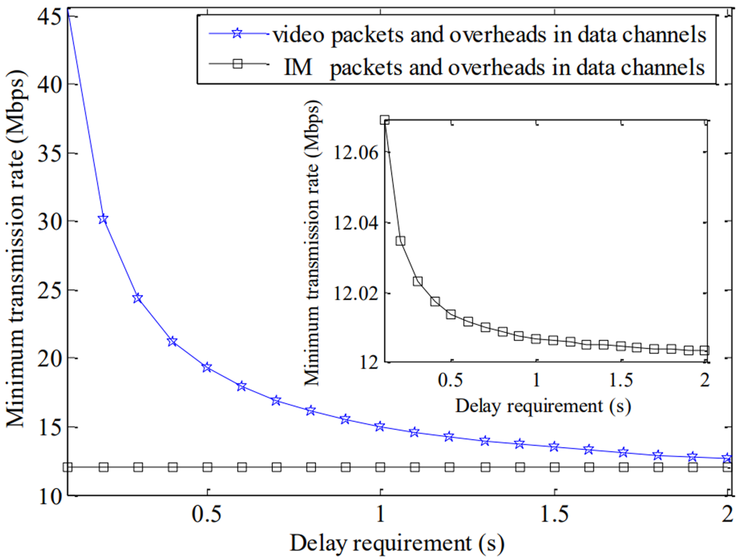

Fig. 2. Minimum transmission rate-delay requirement curves in data channels

4.1 Impacts of Packet Size on the Minimum Transmission Rate and Overhead Arrival Rate

In this subsection, impact of packet size on the minimum transmission rate is investigated. Probabilistic delay constraint is set to 0.1 (i.e. $p_0 = 0.1$) and traffic arrival rate is assumed to be 10 Mbps (i.e. $r = 10^7$bps). The minimum transmission rate requirement for the two traffics in the data channels and control channels are shown in Fig. 2 and Fig. 3 respectively.

Firstly, it is intuitive that every delay requirement is mapping to unique minimum transmission rate, which implies the optimization problem in (1) has unique solution. In addition, Fig. 2 and Fig. 3 also show that: the minimum transmission rate decreases as the delay requirement increases and will converge to a certain value when delay requirement increases largely enough (e.g. larger than 1.8 s). This is because larger delay requirement means looser delay constraint, which needs lower minimum transmission rate to guarantee it.

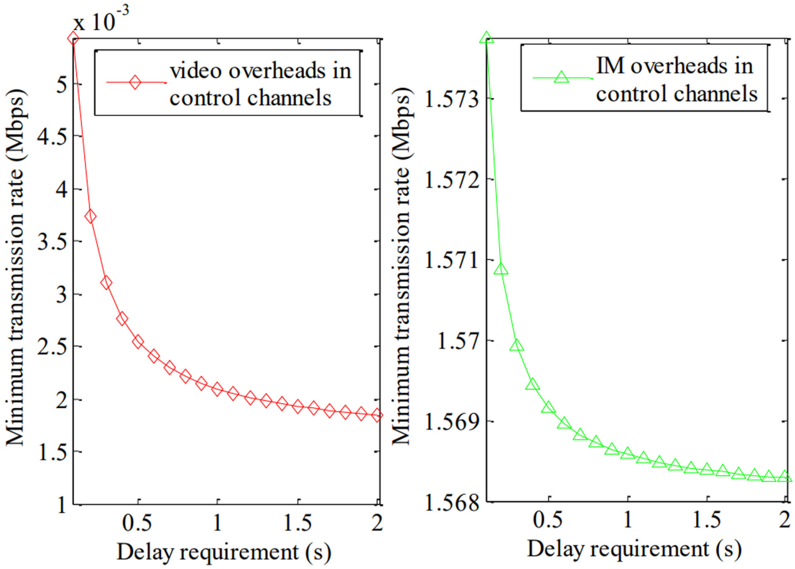

Fig. 3. Minimum transmission rate-delay requirement in control channels

Secondly, as demonstrated in Fig. 2, the minimum transmission rate for video packets changes more aggressively than the one for IM packets as the delay requirement changes. Besides, comparing video packets with IM packets, though they have the same traffic arrival rate, we found that higher transmission rate is needed to transmit larger packets while delay requirement is small (e.g. smaller than 1.5 s). For instant, when delay requirement is limited to 0.1 s, the minimum transmission rate for video packets to guarantee the probability delay constraint reaches to 45 Mbps, which is too high. We intuit that larger packets may have more stochastic characteristics in real arrival rate when other conditions are the same. It can also be mathematically explained that the upper bound of mean arrival traffic is an increasing function for packet size L when delay requirement is small according to (6).

Thirdly, as illustrated in Fig. 3, the minimum transmission rate for video control overheads is much lower than the one for IM control overheads while arrival rates of the both traffics are the same. This is because the arrival rate of video control overheads are much less than the one of IM overheads according to the expression of arrival rate for the control channels given as $r\sigma_2/L$, which are also demonstrated in Fig. 4.

Lastly, as Fig. 4 shows, the overhead arrival rates of video traffic is quite lower than the ones of IM traffic, which means the system generate less overheads while transmitting larger packet traffic.

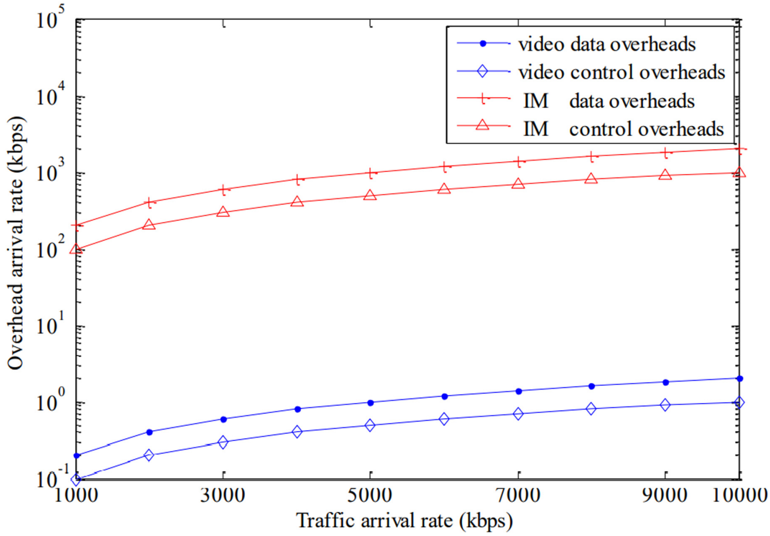

Fig. 4. Overhead arrival rate-traffic arrival rate for the two channels

Hence, packet size impacts greatly on the minimum transmission rate and the overhead arrival rate. The traffic of larger packets is more stochastic in real arrival rate. But large packets cause less overhead than small packets in both the data channels and the control channels when the arrival rates for the two traffics are the same.

4.2 Impacts of Control Overheads on Packet Loss Probability

In this subsection, we mainly focus on the impacts of control overheads on packet loss probability. As highlighted in the system model, a successful packet transmission holds if and only if the data packet and its corresponding overheads are transmitted under a probabilistic delay constraint. Otherwise, the timeout data packets will be discarded. Thus, packet loss probability and the probabilistic delay bound are equivalent in this paper.

For ease of analyzing, the network system is supposed to use OFDM technology with time slot of 0.5 ms. In every time slot, there are 7 OFDM symbols in time domain and 100 resource blocks (RB) in frequency domain. And there

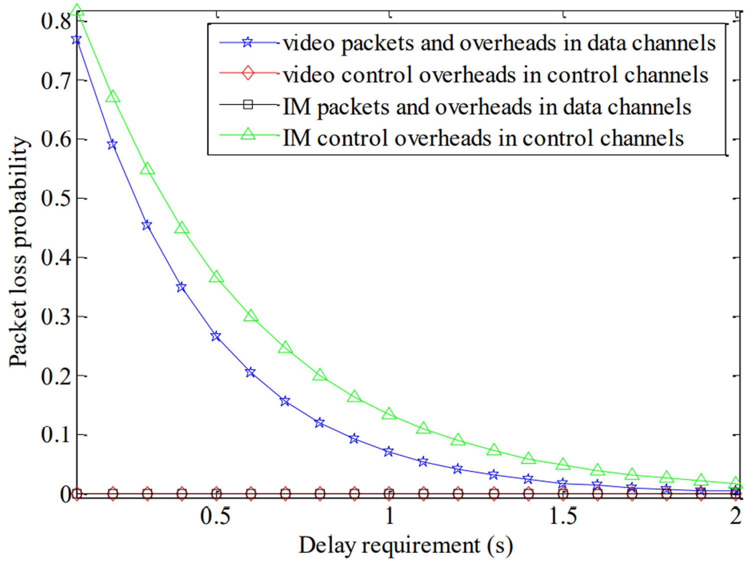

Fig. 5. Impact of control overheads on packet loss probability

are 12 sub-carriers in every RB. Besides, 16 QAM, 1/3 channel coding, single antenna are used as modulation, coding and transmission mode respectively. Then, the system channels can transmit 11.2 kbits flows per slot, which means the peak transmission rate is 22.4 Mbps. However, fixed overheads exist in RBs, such as PDCCH/PHICH/PSS overheads and so on, which are independent with the input traffic and provide other functions for the channels. These overheads are supposed to occupy 25.53% of RBs while the control overheads generated due to input packets in this paper are supposed to occupy 4.47% of RBs. Therefore, the peak transmission rate in the data channels is 15.68 Mbps, and in the control channels is 1.001 Mbps. Besides, the average arrival rate of data traffic is assumed to 10 Mbps. The packet loss probability-delay requirement curves of the four cases are shown in Fig. 5.

As Fig. 5 shows, while transmission rate and traffic arrival rate are definite, packet loss probability can be reduced at the expense of raising the delay requirement, which means the delay constraint turns loose. All curves converge to 0 when the delay requirement is large enough.

Moreover, an interesting phenomenon can be observed from Fig. 5. Packet loss probabilities of video control overheads and IM packets are close to 0 no matter what delay requirement is. However, packet loss probabilities of video packets and IM control overheads are greater than 0 when the delay requirement is not large enough. This indicates that packet loss probability for video service depends on the capacity of the data channels, while the one for IM service relies on the capacity of control channels. Now, we focus on the IM traffic. This is because the upper bound of arrival rate for the data channels is nearly 12.06 Mbps according to (6) and (14), which is quite less than the capacity of the data channels. On the other hand, the arrival rate of IM control overheads is large because the average arrival rate for control channels denoted by $r\sigma_2/L$ and its upper bound reaches up to 1.0005 Mbps according to (7) and (14), which may cause packet loss under a probabilistic delay constraint. Meanwhile, the packet loss probability in the control channels is much higher than the one in data channels. Thus, insufficient capacity of the control channels is the main factor that causes packet loss due to time out in this configuration while transmitting IM service. In contrast, the main factor of packet loss for video packet traffic is the insufficient capacity of the data channels and the impact of control overhead is negligible. Similar analysis for video traffic is omitted for saving space but could be inferred from IM analysis above.

In summary, we can verify that the results of our analysis in previous subsection that large packet traffic has less control overheads compare to small packet traffic if other conditions are the same. Even though the capacity of data channels is sufficient for traffic transmission, packet loss may occur due to timeout because of insufficient capacity of the control channels.

4.3 Impacts of Data Overheads on Packet Loss Probability

In this subsection, impacts of data overheads are discussed. And here, capacity of control channels is assumed to be infinite, which means packet loss does not occur in the control channels. As a result, whether a packet is transmitted successfully or not depends on the capacity of the data channels. Two types of packets are considered and transmission rate in data channels is set to 15.68 Mbps. For achieving the objective, three cases of traffic arrival rate are taken into account, e.g., case 1, case 2 and case 3. For case 1, mean arrival rate is set to 10 Mbps; for case 2, 13.06 Mbps; for case 3, 13.07 Mbps. Packet loss probability- delay requirement curves for these three cases are presented in Fig. 6.

It is obvious that the change of packet loss probability for IM packets is much more aggressively than the change of video packets as the traffic arrival rate changes. This implies that packet loss occurs more often as traffic arrival rate increases while transmitting small packet traffics. Typically, IM packets can be transmitted under a probabilistic delay constraint if mean traffic arrival rate is 13.06 Mbps but cannot be transmitted if the arrival rate reaches 13.07 Mbps. In contrast, the packet loss probabilities of video packets for the two arrival rates are similar.

The above phenomenon can be explained by centering on the data overheads in the data channels. Because overheads exist, the real arrival rate for the data channels is the sum of traffic arrival rate and data overhead arrival rate. Since the size of data overheads is fixed, according to the expression $r\sigma_1/L$, the actual mean arrival rate for the data channels is $(r + r\sigma_1/L)$. Note that, if the arrival rate of video packets is 13.06 Mbps or 13.07 Mbps, the actual mean arrival rates for data channels remain almost the same and less than the capacity of data channels. However, if the arrival rates of IM packets are the same as that of video packets, actual mean arrival rates reach up to 15.672 Mbps and 15.684 Mbps

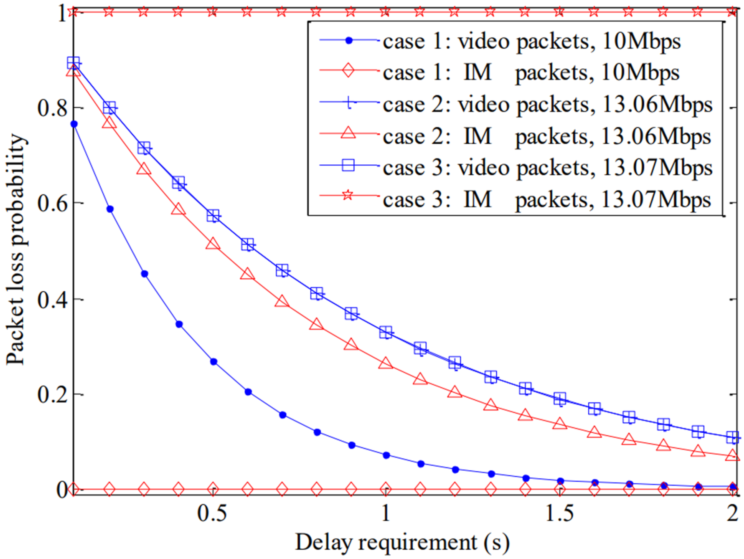

Fig. 6. Impact of control overheads on packet loss probability

respectively. And the later rate is larger than the channel capacity, which leads to packet loss due to timeout. In addition, IM packets can be transmitted under a probabilistic delay constraint, even if the actual mean arrival rate is quite close to but not beyond the channel capacity (e.g. 15.672 Mbps). This also verifies that small packet traffic is less stochastic than large packet traffic in arrival rate as mentioned earlier.

Therefore, we conclude that: compared with large packet traffic, small packet traffic generates more data overheads. And data overheads impact greatly on packet loss probability due to time out especially while transmitting small packet traffic. In addition, it also indicates that small packet traffic lowers the capacity of the data channels more severely.

5 Conclusions

In this paper, we use stochastic network calculus to investigate the impacts of traffic characteristics and overheads on wireless network performances. We formulate an optimization problem and solve it to find the minimum transmission rate which satisfies a given probabilistic delay constraint. Different types of traffics and their overheads are taken into account. The results of our analysis prove that packet size has great impacts on the minimum transmission rate as well as the arrival rate of overheads in both data channels and control channels. Meanwhile, both data overheads and control overheads have also great impacts on packet loss due to timeout, especially while transmitting small packet traffics.

Moreover, the idea of using stochastic network calculus to transform the complex traffic flows into linear flows and analyze the network performances with probabilistic bounds is generally awesome in performance analysis for different complex systems in wireless communications.

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