End-to-End Stochastic QoS Performance Under Multi-Layered Satellite Network*

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Abstract: To meet the growth of real-time and multimedia traffic, the next generation of satellite networks with a guarantee of quality of service (QoS) is indeed, urgent. In this paper, we support the multi-layered satellite network as the scenario, owing to dynamic topology and distinct classification of the generated traffics. We map the satellite network system into a tandem queuing model, which the purpose is devoted to use a mathematical tool for evaluating the performance bounds of per-flow end-to-end networks. For delay-sensitive traffics, we compare two different arrival models–Poisson process and self-similar process. Meanwhile, we apply traditional scheduling strategy to MEO nodes while considering link impairment between a pair of satellites. Finally, we analyze, in a numerically way, which parameters (and how they) influence the perflow end-to-end performance bounds. Our analysis can be used as a reference to China's future satellite topology and routing algorithms designed and, optimization given a network with performance requirements and constraints.

Key words: quality of service, multi-layered satellite network, tandem queue model, transmission path.

I. Introduction

With the widespread adoption of multimedia applications in the Internet, how to guarantee quality of service (QoS) for those applications has become a urgent issue in the current research. However, the restriction of geography and technical makes traditional terrestrial wireless network difficult to satisfy users demands. In some particular areas, like islands and isolated mountainous, may not easily deploy adequate infrastructure, even worse in the disasters. Given the advantages of significantly wide coverage and flexible deployment and networking, satellite network plays an essential role in providing better service and worldwide communication environments.

Recently, according to the altitude of orbits, satellites are classified into Geostationary Earth Orbit (GEO) satellites, Medium Earth Orbit (MEO) satellites and Low Earth Orbit (LEO) satellites. Combining to GEO satellite, LEO and MEO satellite networks have overwhelming advantages, such as small signal attenuation and shorter round trip delays. They are more suitable for real-time service [1]. But there is a case with some delay-sensitive traffics, if the arrival traffics is long distance traffic (LDT) at the LEO layer, because of the increase of hops of the inter-satellite transmission, it will occur congestion easily, higher queueing delay and packet loss [2]. When MEO is regarded as relay node, it will help business flow reducing the exchange of nodes and processing delay. Therefore, the overall network performance, a Multi-Layered Satellite Network (MLSN) has much better than these orbits individually.

Several factors can be found to account for the performance of the MLSN. Apparently, uncertainties and time variances in the spatial environment may be liable to cause various forms of end-to-end performance degradation such as random changes in service properties and space magnetic storms. Under such circumstance, it can generate the impaction of whether the traffics can send successfully. Besides that, the link of a pair of satellites will occur congestion while satellites above hot spot areas are aggregated a huge amount of traffic. Meanwhile, multiple data flows will compete for satellite service resources simultaneously, so that the performance of target flow will be influenced to some extent. Particularly, it is attractive for real-time applications to need a short delay. Thus, on the one hand, it is essential to establish a realistic traffic model for real-time traffics. On the other hand, how to optimize the transmission path and improve the QoS is a pressing problem.

Among existing analysis tools, queueing theory has been proved to be a useful method to deal with traffic model problems in satellite networks. [3] analyzes packet delivery delay in multi-layered satellite networks based on M/M/1 model; [4] employs the stochastic Petri net to evaluate the performance of the double-layered satellite network, but those scheme can lead complex network topologies and heavy traffic load; To avoid traffic congestion, a routing strategy is proposed in [5] to balance the traffic load by using a traffic distribution model. Through these efforts, the satellite network model has been simplified to some extent. Additional research efforts focus on the optimization and design of routing algorithms to meet the QoS requirement for delay and other performances. In

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the [2], [6], a new topological and routing protocol is proposed to evaluate the performance of long-distance traffic; [1] proposes a novel adaptive routing protocol for quality of service (ARPQ) in two-layered satellite network which improves the system performance for delay-sensitive traffic; And in the [7], a unified mathematical framework is proposed to analyze the relationship between network capacity and associated parameters. However, no analytical research considers the end-to-end backlog bound for per-flow and on which parameters (and how they) directly influence the network performances in MLSN.

To better optimize the satellite network performance and improve the data utilization, an effective way to meet the QoS demand is particularly urgent as the current queuing theory can hardly describe the stochastic behavior of a real satellite network.

Network Calculus (NC) is a new mathematical tool for quantitative performance analysis of computer networks. Based on min-plus algebra and max-plus algebra, this theory is expected to transform a complex network system into an analytically tractable system. The NC concept, originally proposed two decades ago [8, 9], has evolved into two branches: Deterministic Network Calculus (DNC) [10] and Stochastic Network Calculus (SNC)[11, 12]. Of them, the former mainly focuses on the worst case and cannot address the statistical nature of traffic flow. To tackle this challenge, the latter introduces the probability knowledge into DNC, and thus expands the application of network calculus from deterministic problems to stochastic problems. It can better provide stochastic QoS guarantee to network.

SNC has been widely used to analyze the performance of networks and channels, such as packet switching network [13], LTE network [14], high-speed railway communication network [15], Gilbert-Elliott (G-E) channel [16], Rayleigh fading channel [17], finite Markov-chain channel [18], MIMO wireless channel [19, 20], and cognitive radio network [21]. To our knowledge, this is the first work to apply SNC to evaluate the end-to-end performances of MLSN. In this paper, based on the analysis of the MLSN satellite network architecture, the network system is mapped into a tandem queuing system. According to consider the characteristic of spatial traffic flow, we establish a stochastic arrival curve by comparing two different arrival model. Also, we choose the latency-rate scheduling algorithm to provide the MEO nodes services with the impairment of the channel. It aims to build a stochastic service curve. Clearly, the end-to-end performance bounds can be obtained by combining the first two curves with the basic features of SNC. Finally, the numerical analysis shows that this tool can clearly depict the functional relations between these parameters and performance bounds. This paper is just to provide a reference for the design and optimization of topological structure and routing algorithms in the future satellite network.

The rest of this paper is organized as follows. Section II maps the multi-layered network system into tandem queue model and presents a description of the channel model.The basic knowledge of SNC is introduced in Section III, including a stochastic arrival curve and stochastic service curve. In Section IV that combine the first two curves with min-plus algebra to derive probabilistic performance bounds, such as end-to-end delay bound and end-to-end backlog bound and so on. Numerical results are discussed in Section V. Finally, Section VI makes a conclusion of the whole paper.

II. System Model

2.1 Multi-Layered Satellite Network (MLSN)

In the Fig.1, the MLSN, including a MEO layer and a LEO layer, is illustrated.

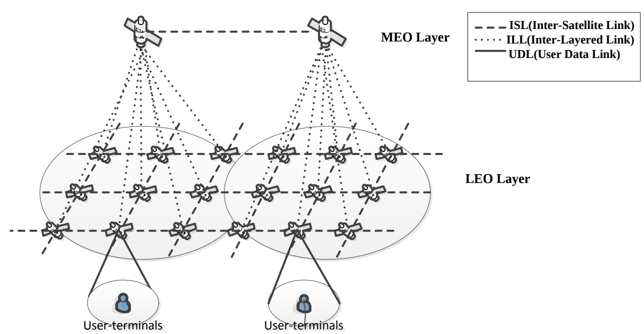


Fig.1. The multi-layered network system

ISL (Inter-Satellite Link): Data can be transmitted at the same layer through ISL. Each satellite is connected with its neighboring nodes via four ISLs, including intra-orbit links and inter-orbit links. The two satellites in an intra-orbit link are on the same orbit plane, while the two satellites in an inter-orbit link are in different orbits.

ILL (Inter-Layered Link): ILLs are the links connecting the satellites in different layers. The ILL between a LEO satellite and a MEO satellite can be established when the former enters the latter's coverage, otherwise, switched out. Through ILL, different types of data flows can be transferred between LEO satellites and MEO satellites. The link between source node and terminal node must go through one or more end-to-end nodes for data retransmission, whose number, in our view, equals the hop counts[22].

GSL (Ground-Satellite Link): The terrestrial users transmit messages to LEO through the ground-satellite Links.

In this paper, main consideration is given to the satellite network between LEO and MEO layers, except for

GSL. The combination of these two layers realizes wireless global coverage, as well as full LEO satellites coverage by MEO satellites. In such a context, we shall guarantee the QoS of this satellite network, whose end-to-end performance shall be achieved through links and reliable connectivity.

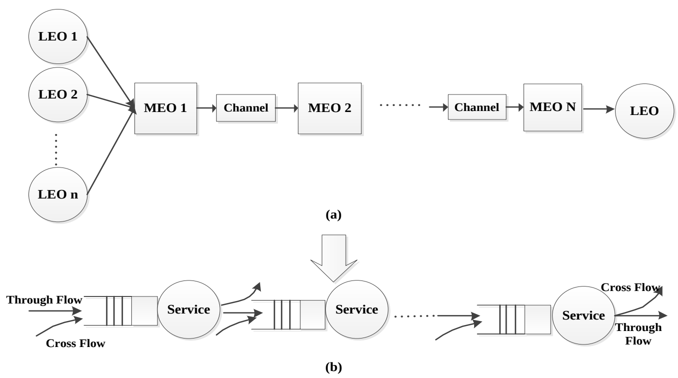


Fig.2. System model

Although the MLSN under the current research can provide a lot of network resources, traffic congestion still exists in hot spots [23]. To balance the traffic load, as shown in Fig. 2(a), we assume that one LEO satellite can only be linked to one MEO satellite, and that a group of LEO satellites covered by a MEO satellite can directly transfer the generated data flows to the served MEO, where multiple data flows will meet. Here we take no account of link switching and routing. After receiving the aggregated flows, the MEO satellite will send information to terminal node through one or more hops. Between every pair of MEO satellites, there is a wireless channel.

In the Fig. 2(b), we map the above satellite architecture into a tandem queuing model. The data flows arriving here can be divided into two types: target flow and cross flow. The former is the flow extending from source node to the destination, while the latter is the aggregated flow from other LEO satellite nodes except target flow, and may seriously impact the propagation delay of target flow. The target flow leaving from the source node will pass through multiple nodes before finally arriving at the destination. But beyond that, the arrival and departure of a cross flow can be found in every queue. For the arriving flows, we store them in the corresponding buffer and output them in a first-in-first-out (FIFO) manner. Then a specific scheduling algorithm is provided at the nodes until the flows are successfully transferred to the terminal. We assume that the buffer capacity is infinite so that no overflow exists.

Generally speaking, both the arrival and service processes of an arriving flow are stochastic, so traditional queuing theory can no longer deal with such stochastic performance. Therefore, we apply the SNC in the paper.

2.2 Gilbert-Elliott channel model

A satellite channel consists of three main components: transmitting antenna, receiving antenna, and propagation channel. The transmitting antenna sends mass data to the receiving antenna via a wireless satellite channel. The main influencing factor of channel fading is free space loss [24]. In this paper, For the satellite channel, we describe the impairment process as Rayleigh fading channel with a fixed threshold ξ. When the channel is in fading state, the traffic can't be successfully transmitted to the receiver,i.e., $|h(t)| \le \xi$, otherwise successful at a constant rate, i.e., $|h(t)| > \xi$,where $|h(t)|$ is the envelope process with a Rayleigh probability distribution function and the phase being uniform over $[0, 2\pi)$. To describe the fading channel more correctly, we have mapped it into Gilbert-Elliott (G-E) channel model, as shown in the Fig.3.

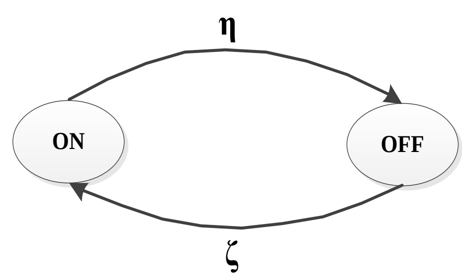


Fig.3. Two-state Channel Model

A continuous-time G-E Markov Chain model has two states: ON and OFF, then a peak service rate can be achieved when the model is in good condition. That is, with the channel ON, the workload is processed at the rate of R_{on}, and the transition rate from OFF to ON is ζ. Likewise, the transition rate from ON to OFF is η. So, the generated matrix Q for GE channel chain can be given as [16],

$$Q = \begin{pmatrix} -\zeta & \zeta \\ \eta & -\eta \end{pmatrix} \tag{1}$$

If the Rayleigh fading channel has an exponential decay rate κ, then, we must have $\eta + \zeta = \kappa$. Through the relationship, we can determine ζ and η as

$$\zeta = \kappa e^{-\xi^2}, \eta = \kappa(1 - e^{-\xi^2}) \tag{2}$$

Consequently the average transmission rate R is:

$$R = \frac{1}{2\theta}(\sqrt{(\zeta - \eta + R_{on}\theta)^2 + 4\zeta\eta} - \zeta - \eta + R_{on}\theta). \tag{3}$$

where $\theta > 0$ is a free parameter.

III. Stochastic Network Calculus

As a basis, SNC contains three processes: the arrival process, service process and departure process in the queuing model, where can be modeled as a traffic model and service model from the first two processes. There are two basic tools including arrival curve and service curve. Arrival curve can be regarded as a constraint to the behaviour of traffic flow, in addition, service curve is an abstract description of service strategy and scheduling strategy, which is exactly provided service lower bound to meet the business QoS requirements, both of curves with min-plus algebra derive probabilistic performance bounds: delay and backlog.

In this paper, we use a series of processes to model an assumed lossless network. Cumulative functions $A(t)$ and $D(t)$ represent the data arrival and departure processes respectively. Of them, $A(\mathrm{s},t)$ is defined as the amount of arriving data accumulated in the period $(\mathrm{s},t]$, while $D(\mathrm{s},t)$ is the amount of arriving data departing from the receiver in the period $(\mathrm{s},t]$. We assume that arrival and service are stationary random processes that are statistically independent. Therefore, $A(\mathrm{s},t) = A(t) - A(s)$ and $D(\mathrm{s},t) = D(t) - D(s)$. $A(t)$ and $D(t)$ are non-negative and increasing on t, and $A(t,t)=0$,$D(t,t)=0$,$\forall A(t), D(t) \in \mathcal{F}, t \geq 0$[25].

3.1 Basic Knowledge

In SNC, there are several different categories in the definition of stochastic arrival curve and stochastic service curve. In this paper, we mainly apply the v.b.c. Stochastic Arrival Curve and Weak Stochastic Service Curve. Definitions are as follows:

Definition 1 (v.b.c. Stochastic Arrival Curve) A flow denoted by $A(t) \sim_{vb} < f, \alpha >$ has a v.b.c. stochastic arrival curve $\alpha \in \mathcal{F}$ with a boundary function $f \in \bar{\mathcal{F}}$, if for all $t > 0$ and all $x > 0$ there has

$$P\{\sup_{0 \leq \mathrm{s} \leq \mathrm{t}} \{A(s,t) - \alpha(t-s)\}\} \leq f(x).$$

where $\mathcal{F}$ is non-negative increasing function and $\bar{\mathcal{F}}$ is non-negative non-increasing function.

Definition 2 (Weak Stochastic Service Curve) A system S denoted by $S \sim_{wb} < g, \beta >$ has a weak stochastic service curve $\beta \in \mathcal{F}$ with a boundary function $g \in \bar{\mathcal{F}}$, if for all $t > 0$ and all $x > 0$ there has

$$P\{\sup_{0 \leq \mathrm{s} \leq \mathrm{t}} \{A \otimes \beta(s) - D(s) > x\}\} \leq f(x).$$

Now we introduce the formula of min-plus convolution:$A \otimes B(x) = \inf_{0 \leq x \leq y} [A(x) + B(y-x)]$.

The following basic properties are an essential part within our work, presented in[26, 27].

Theorem 1 (Superposition Property) Consider the aggregation of N arriving flows with $A_i(t)$,$i = 1, 2, ..., N$. We denote the aggregate arrival process $A_i(t)$, or $A(t) = \sum_{i=1}^{N} A_i(t)$. If $\forall i$, $A_i \sim_{vb} < f_i, \alpha_i >$, then $A(t) \sim_{vb} < f, \alpha >$, where $f(x) = f_1 \otimes \ldots \otimes f_N(x)$,$\alpha(t) = \sum_{i=1}^{N} \alpha_i(t)$.

Theorem 2 (Concatenation Property) Regard as a flow through N tandem nodes one by one in a single tandem queue. Each node $i, i = 1, 2, ..., N$ has a stochastic service curve $S^i \sim_{wb} < g^i, \beta^i >$. The overall stochastic service curve obtained by multiple nodes is $S \sim_{wb} < g, \beta >$, where $\beta(t) = \beta^1 \otimes \beta^2 \otimes \ldots \otimes \beta^N(t)$.

Theorem 3 (Per-flow Service Property) Suppose the aggregated arriving flow A is composed of two data flows C target flow A_1 and cross flow A_2. The system provides the aggregated flow A with a stochastic service curve $S \sim_{wb} < g, \beta >$.If $A_2 \sim_{vb} < f_2, \alpha_2 >$, $\beta_1 \in \mathcal{F}$,then A_1 can obtain the stochastic service curve $S_2 \sim_{wb} < g_1, \beta_1 >$, where $\beta_1 = \beta(t) - \alpha_2(t)$, $g_1(x) = g \otimes f_2(x)$.

Theorem 4 (Delay Bound) If for all $t > 0$ and all $x > 0$, the service of network element provides stochastic service curve $S \sim_{wb} < g, \beta >$ and the arrival flow has v.b.c. stochastic arrival curve $A(t) \sim_{vb} < f, \alpha >$. The delay bound $D(t)$ is denoted by

$$P\{D(t) > h(\alpha + x, \beta)\} \leq f \otimes g(x).$$

where $h(\alpha, \beta) = \sup_{s \geq 0} \{inf\{\tau \geq 0, \alpha(s) \leq \beta(s+\tau)\}\}$ denotes the maximum horizontal distance between the two function $\alpha(t)$ and $\beta(t)$.

Theorem 5 (Backlog Bound) If for all $t > 0$ and all $x > 0$,service of network element provides stochastic service curve $S \sim_{wb} < g, \beta >$ and the arrival flow has v.b.c. stochastic arrival curve $A(t) \sim_{vb} < f, \alpha >$, then the backlog bound $B(t)$ is denoted by

$$P\{B(\mathrm{t}) > v(\alpha + x, \beta)\} \leq f \otimes g(x)$$

where $v(\alpha, \beta) = \sup_{s \geq 0} \{\alpha(s) - \beta(s)\} \equiv \alpha \oslash \beta(0)$ denotes the maximum vertical distance between the two function $\alpha(t)$ and $\beta(t)$.

In order to better apply SNC to multi-layered satellite network and improve stochastic service guarantees, the next section will introduce a specific stochastic arrival curve and stochastic service curve to model the traffic arrival and node service process.

3.2 Stochastic Arrival Curve

The next generation of satellite network system designed to support multimedia application. This faces a huge challenges to QoS guarantee, as different data flows are expected to meet different performance demands. For example, some real-time applications, such as voice and video, require a low end-to-end delay; and some best-effort traffics, such as email without any specific requirements. Hence it is more and more important to establish different arrival models according to different traffic flows and to meet the QoS demand. In the previous studies, traditional traffic models were Poisson model and ON/OFF model. However, it is fully evidenced in massive current studies that multimedia traffics are characterized by bursty and long range dependence, which can be correctly depicted by self-similarity model [28]. In this paper, we consider the use of two arrival models, traditional Poisson model and self-similarity model, to describe the arrival process in a real-time application, and then compare their influences in the QoS performance analysis.

1)Poisson Process

The Poisson process, a classical model, is described in the probability distribution of the number of events in per unit interval. $N(\mathrm{t})$, a stable and independent increment, is the number of data arriving at a queuing system during $[0,t]$. The counting process $\{N(\mathrm{t}), t \geq 0\}$ can be regarded as a Poisson process. If $N(\mathrm{t}) = 0$, the Poisson distribution function will be $P\{N(\mathrm{t}) = k\} = e^{(-\lambda t)}(\lambda t)^k/k!$, where λ is the mean arrival rate.

Theorem 6 (Poisson process) If the arrival process $A_i(t)$ of aggregated flow is given, the stochastic arrival curve with violation probability ε can be expressed as:

$$a_n(t) \approx N\lambda t + \sqrt{N\lambda t} ln\frac{1}{4\varepsilon}$$

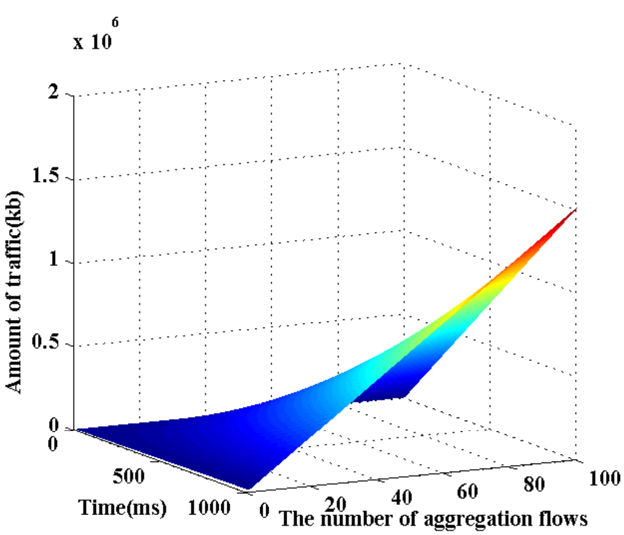


Fig.4. The relation between the amount of traffic and aggregated flows with the time

As shown in the Fig.4, we can determine the relations about the amount of total traffic between time interval and aggregation traffic numbers. By making some assumptions such as time $t \in [0, 1000]\,ms$, the number of aggregated flows N is from 1 to 100, and some fixed parameters are set, for example, arrival rate $\lambda = 15Kb/ms$, and violation probability $\varepsilon = 10^{-3}$. From the Fig.4, we can observe that, the amount of arriving data will increase sharply if $\mathrm{N} \geq 20$, but quite steadily if $\mathrm{N} < 20$.

The v.b.c stochastic arrival curve for Poisson process $a_i(t)$ with boundary function $f_i(x)$ is:

$$P\{\sup_{0\leq s\leq t}\{A_i(s,t) - a_i(t-s)\}\} \leq a_{f_i}e^{-b_{f_i}x} \quad (4)$$

Here:

$$\begin{cases} \alpha_i(t) = \lambda_i t, \\ f_i(x) = a_{f_i}e^{-b_{f_i}x}. \end{cases}$$

where the average arrival rate $\lambda_i = \frac{\rho_i}{\theta}(e^{\theta\sigma_i} - 1) + \theta_1$, $\alpha_{f_i} = e^{-\theta\theta_1}$ and $b_{f_i} = \theta$. ρ is the packets arrival according to Poisson process with mean rate, and σ is the packet lengths, for $\forall\theta, \theta_1 > 0$.

2)Self-Similarity Process

Fractional Brownian motion (FBM) is widely described as a self-similarity service flow model of aggregated flows with correlated Gaussian increments. It is used to analyze the impact of long range dependence in the network. Self-similarity parameter H is the only similarity standard in the self-similarity process. In case of $H \in (0.5, 1)$, the self-similarity process will be long-range dependent, and the standard form of FBM traffic in the arrival process will be:

$$A(t) = mt + \sqrt{\sigma m} Z_H(t).$$

where the average arrival rate of FBM $m > 0$, σ is the coefficient of dispersion, $Z_H(t)$ is standard FBM process.

The v.b.c stochastic arrival curve for self-similar process $a_i(t)$ with boundary function $f_i(x)$ is:

$$P\{\sup_{0\leq s\leq t}\{A_i(s,t) - a_i(t-s)\}\} \leq a_{f_i}e^{-b_{f_i}x^{2(1-H)}}. \quad (5)$$

Here:

$$\begin{cases} \alpha_i(t) = m_i t + \sqrt{\sigma_i m_i} t^H, \\ f_i(x) = a_{f_i}e^{-b_{f_i}x^{2(1-H)}}. \end{cases}$$

where $\alpha_{f_i} = e^{-\theta\theta_1}$ and $b_{f_i} = \theta$, for $\forall\theta, \theta_1 > 0$.

3.3 Stochastic Service Curve

We have developed the Latency-Rate (LR) Server, a universal model, to analyze the traffic scheduling algorithms in the broadband packet network. Some famous scheduling algorithms, such as weighted fair queuing, VirtualClock, self-clocked fair queuing, weighted round robin, and deficit round robin, are all LR servers. To describe the node service process, we use the LR server model with a week stochastic service curve to describe the feature of node service $\beta(t) = R(t-T)$, where T is the maximum processing latency at the node and R is the minimum service rate (depending upon the channel capacity). From this equation, the relation between for a work-conserving constant rate server counting the effect of packetization can be obtained, that is, $T = L/R$, where L is the maximum packet size, and the boundary function is $g(x) = a_g e^{-b_g x}$ $(a_g = 1,\ b_g = \theta_2)$.

According to Theorem 2 and Theorem 3, at the node N_i of a MEO satellite, the weak stochastic service curve β^i is available for the target flow A_i aggregated with other cross flows. Thus we can obtain a new stochastic service curve $\beta^i(t)$ and boundary function $g^i(x)$, which are:

$$\beta^i(t) = \beta_i(t) - \alpha_i(t),$$

$$g^i(x) = f_i \otimes g_i(x).$$

The stochastic service curve for MLSN system is:

$$P\{A \otimes \beta^i(t) - D(t) > x\} \le \alpha_{g_i} e^{-b_{g_i} x}. \quad (6)$$

Here:

$$\begin{cases} \beta^i(t) = R_i(t - T_i), \\ g_i(x) = a_{g_i} e^{-b_{g_i} x}. \end{cases}$$

Now we begin to consider the relationship between the service rate and the fading channel:

The fading channel is governed by Rayleigh fading characteristic [29], as shown below:

$$y(t) = x(t)h(t) + n(t). \quad (7)$$

where $x(t)$ is input signal, $y(t)$ is output signal of satellite system at t, $h(t)$ denotes the channel fading coefficient, $n(t)$ is complex additive white Gaussian noise (AWGN).

In the G-E channel model, the transmission rate R_{on} as the channel is ON can be related to transmission power in the following way:

$$R_{on} = W \log_2(1 + \frac{P\xi^2}{N_o W}). \quad (8)$$

where W is the channel bandwidth, $N_o/2$ is noise power spectral density; P is transmission power; and ξ is a fixed threshold that maps the channel gain $|h(t)|$ into transmission rate.

Then state of G-E channel model depends on channel capacity $C(t)$ and actual transmission rate R_c, which, in turn, depends on AMC (adaptive modulation and coding) in the channel. If $R_c < C(t)$, the channel will be in the ON state, where the transferred data can be received successfully, otherwise, in the OFF state. With the channel ON, the threshold ξ can be expressed as:

$$|h(t)| > \xi = \sqrt{\frac{N_o W}{P}(2^{\frac{R}{W}} - 1)}. \quad (9)$$

The transmission rate R_{on} can be determined by the fixed threshold in (8). For the signal-to-noise ratio γ, there is $\gamma = P/N_O W$. From the above equation, the effect of SNR on service rate R can be seen.

IV. Performance Analysis

In the previous chapter, we describe the arrival and service processes of MLSN and obtain a stochastic arrival curve and a stochastic service curve respectively. In this chapter, we will analyze per-flow end-to-end performance parameters.

Corollary 1 (End-to-end delay and backlog bounds) The arriving flow is sent to a MEO node according to a specific scheduling strategy, and then transferred to $N_2, ..., N_n$ before arriving at the destination. This flow is characterized by the stochastic arrival curve $A_i \sim_{vb} < f_i, \alpha_i >$ and the stochastic service curve $S_i \sim_{wb} < g_i, \beta_i >$. So the end-to-end delay and backlog bounds can be expressed as:

$$P\{D_{end} > h(\alpha_1 + x, \beta^{net})\} \le \underset{1 \le i \le n}{\otimes} [f_i \otimes g_i(x)],$$

$$P\{B_{end} > v(\alpha_1 + x, \beta^{net})\} \le \underset{1 \le i \le n}{\otimes} [f_i \otimes g_i(x)].$$

where: $\beta^{net} = \beta_1 \otimes (\beta_2 - \alpha_2) \otimes \ldots \otimes (\beta_N - \alpha_N)(t)$.

Now let's derive from the boundary function in the Poisson arrival process with the help of min-plus algebra. At first, we consider two nodes:

$$\begin{aligned} &\beta_1 \otimes (\beta_2 - \alpha_2)(t) = R_1(t - T_1) \otimes [R_2(t - T_2) - \lambda_2 t] \\ &= \underset{0 \le s \le t}{inf} [(R_1 - R_2 + \lambda_2)s + (R_2 - \lambda_2)t - (R_1 T_1 + R_2 T_2)]. \end{aligned}$$

It is clear that, only with the theory of $R_1 + \lambda_2 \ge R_2$, sufficient service flows can be guaranteed and the best results may be yielded. We use $s = 0$ to obtain the minimum value:

$$\begin{aligned} &\beta_1 \otimes (\beta_2 - \alpha_2)(t) \otimes (\beta_3 - \alpha_3)(t) \\ &= \underset{0 \le s \le t}{inf} [(R_2 - \lambda_2 - R_3 + \lambda_3)s + (R_3 - \lambda_3)t - \sum_{i=1}^{3} R_i T_i]. \end{aligned}$$

Next, we consider three nodes:

$$\begin{aligned} &\beta_1 \otimes (\beta_2 - \alpha_2)(t) \otimes (\beta_3 - \alpha_3)(t) \\ &= \underset{0 \le s \le t}{inf} [(R_2 - \lambda_2 - R_3 + \lambda_3)s + (R_3 - \lambda_3)t - \sum_{i=1}^{3} R_i T_i]. \end{aligned}$$

When $(R_2 - \lambda_2)t > (R_3 - \lambda_3)t$, we set $s = 0$, thus:

$$\beta_1 \otimes (\beta_2 - \alpha_2)(t) \otimes (\beta_3 - \alpha_3)(t) = (R_3 - \lambda_3)t - \sum_{i=1}^{3} R_i T_i.$$

When $(R_2 - \lambda_2)t \le (R_3 - \lambda_3)t$, we set $s = 0$, thus:

$$\beta_1 \otimes (\beta_2 - \alpha_2)(t) \otimes (\beta_3 - \alpha_3)(t) = (R_2 - \lambda_2)t - \sum_{i=1}^{3} R_i T_i.$$

In this way, we can obtain the stochastic service curve of the whole network:

$$\beta^{net} = \underset{2 \le i \le N}{inf} [(R_i - \lambda_i)t] - \sum_{i=1}^{N} R_i T_i. \quad (10)$$

Similarly, we can obtain the stochastic service curve in the self-similarity arrival process:

$$\beta^{net} = \inf_{2 \le i \le N} [(R_i - m_i)t - \sqrt{\sigma_i m_i} t^{H_i}] - \sum_{i=1}^{N} R_i T_i. \quad (11)$$

With (10) or (11), apply β^{net} to Corollary 1, the maximum horizontal distance can be readily obtained.

To analyze the boundary functions of the whole network, we adopt the following lemma:
Lemma 1 For any positives a_k, b_k,$(k = 1,...,K)$and $x > 0$, the following equation is:

$$\inf_{x_1+\cdots x_k=K} \sum_{k=1}^{K} a_k e^{-b_k x_k} = e^{-\frac{x}{w}} \prod_{k=1}^{k} (a_k b_k w)^{\frac{1}{b_k w}}$$

where $w = \sum_{k=1}^{K} \frac{1}{b_k}$, the related content is given in[27].

With the lemma above, the boundary function can be expressed as:

$$\underset{1\le i\le N}{\otimes} \{f_i \otimes g_i(x)\} = \underset{1\le i\le N}{\otimes} \inf_{0\le y\le x} \{\alpha_{f_i} e^{-b_{f_i} y} + \alpha_{g_i} e^{-b_{g_i}(x-y)}\}$$

$$= \underset{1\le i\le N}{\otimes} \alpha_i e^{-b_i x}$$

$$= e^{-\frac{x}{w}} \prod_{i=1}^{N} (a_i b_i w)^{\frac{1}{b_i w}}$$

where $a_i = (\alpha_{f_i} b_{f_i} w_i)^{\frac{1}{b_{f_i} w_i}} \times (\alpha_{g_i} b_{g_i} w_i)^{\frac{1}{b_{g_i} w_i}}$, $b_i = \frac{1}{w_i}$, $w_i = \frac{1}{b_{f_i}} + \frac{1}{b_{g_i}}$, $w = \sum_{i=1}^{N} \frac{1}{b_i} = \sum_{i=1}^{N} (\frac{1}{b_{f_i}} + \frac{1}{b_{g_i}})$.

Finally, we can derive the end-to-end delay and backlog performance bounds from SNC.

If the arrival model is Poisson distribution, then:

$$\left(P\{D_{end} > h(\alpha_1 + x, \inf_{2\le i\le N} [(R_i - \lambda_i)t] - \sum_{i=1}^{N} R_i T_i)\}\right) \left(\le e^{-\frac{x}{w}} \prod_{i=1}^{N} (a_i b_i w)^{\frac{1}{b_i w}}\right) \tag{12}$$

$$\left(P\{B_{end} > v(\alpha_1 + x, \inf_{2\le i\le N} [(R_i - \lambda_i)t] - \sum_{i=1}^{N} R_i T_i)\}\right) \left(\le e^{-\frac{x}{w}} \prod_{i=1}^{N} (a_i b_i w)^{\frac{1}{b_i w}}\right) \tag{13}$$

where $a_1 = \lambda_1 t$, $w = \sum_{i=1}^{N} \frac{1}{b_{g_i}}$.

If the arrival model is self-similarity, then:

$$P\{D_{end} > h(\alpha_1 + x, \inf_{2\le i\le N} \left[(R_i - m_i)t - \sqrt{\sigma_i m_i} t^{H_i}\right] - \sum_{i=1}^{N} R_i T_i)\} \le (\underset{1\le i\le N}{\otimes} a_{f_i} e^{-b_{f_i} x^{2(1-H)}}) \otimes (e^{-\frac{x}{w}} \prod_{i=1}^{N} (a_{g_i} b_{g_i})^{\frac{1}{b_{g_i} w}}). \tag{14}$$

$$P\{B_{end} > v(\alpha_1 + x, \inf_{2\le i\le N} \left[(R_i - m_i)t - \sqrt{\sigma_i m_i} t^{H_i}\right] - \sum_{i=1}^{N} R_i T_i)\} \le (\underset{1\le i\le N}{\otimes} a_{f_i} e^{-b_{f_i} x^{2(1-H)}}) \otimes (e^{-\frac{x}{w}} \prod_{i=1}^{N} (a_{g_i} b_{g_i})^{\frac{1}{b_{g_i} w}}). \tag{15}$$

where $\alpha_1 = m_1 t + \sqrt{\sigma_1 m_1} t^{H_1}$, $w = \sum_{i=1}^{N} \frac{1}{b_{g_i}}$.

Let the right side of (12),(13),(14)and(15) equal to violation probability ε, then:

When the arrival model is Poisson process:

$$d_{end} = \frac{NRT}{R-\lambda} - \frac{N(\frac{1}{b_f} + \frac{1}{b_g})}{R-\lambda} \times \ln \frac{\varepsilon}{Nab(\frac{1}{b_f} + \frac{1}{b_g})}. \tag{16}$$

$$b_{end} = \lambda t + NRT - N(\frac{1}{b_f} + \frac{1}{b_g}) \times ln \frac{\varepsilon}{Nab(\frac{1}{b_f} + \frac{1}{b_g})}. \tag{17}$$

When the arrival model is self-similarity process:

$$d_{end} \approx \frac{[-\frac{\ln \varepsilon}{\theta} - \theta_1]^{\frac{1}{2(1-H)}} + NRT}{R - m - \sqrt{\sigma m}}. \tag{18}$$

$$b_{end} \approx mt + \sqrt{\sigma m} t^H + NRT + [-\frac{\ln \varepsilon}{\theta} - \theta_1]^{\frac{1}{2(1-H)}}. \tag{19}$$

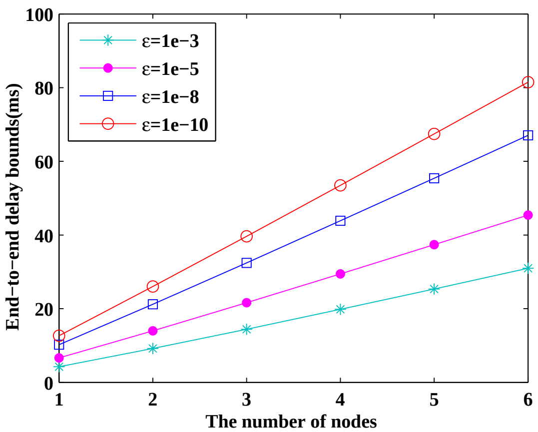
V. Numerical Analysis

In this chapter, we derive the numerical results of per-flow end-to-end delay and backlog bounds in the MLSN, while contrasting two different types of arrival model: Poisson process and self-similar process. The consequences are achieved based on the previous sections, after discussion. Finally, we draw a conclusion that can provide insights into the influence of different parameters on QoS performances in the MLSN.

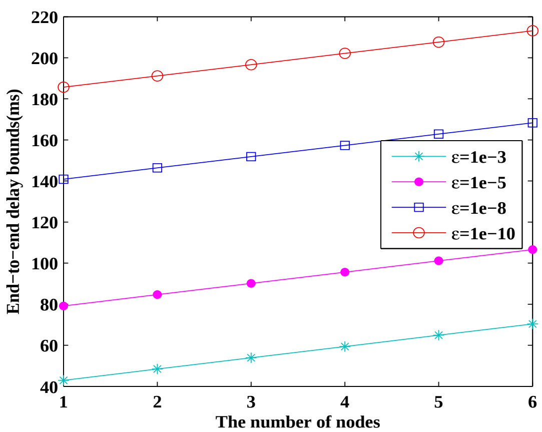
We use MATLAB simulation tool to implement analytical results. During the simulation, we set the following fixed parameters at first: number of aggregated flows is 20; maximum packet size is 10^4 bytes; exponential decay rate κ= 100; and θ, θ_1 and θ_2 , which can make the performance bounds as tight as possible after being adjusted.

From the Fig.5, we can visually find that, in different traffic models, the delay performance will become worse as the number of nodes increases. That is, the more hops, the greater influence on performance bounds. We also examine the effect of delay bound and violation probability. Violation probability is defined as the probability that the packet delay exceeds the stochastic delay bound. Once the violation probability varies, the delay will increase. When the traffic model is Poisson or self-similarity process, the results are shown in Fig.5(a)or Fig.5(b) respectively. It can be seen that, under the constraints of the same parameters, the stochastic delay of Poisson model is smaller than that of self-similarity traffic model.

It is demonstrable that, for real-time communications, the well-known Poisson model is more efficient than self-similarity. In the real network, we can choose an efficient path for a certain topological structure to achieve the best performance.



(a)Poisson process



(b)Self-similar process

Fig.5. End-to-end delay bounds vary from the number of nodes and different violation probability under SNR as $\gamma = 25dB$ and the arrival rate in different models $m = \rho = 15Kb/ms$

As shown in the Fig.6, in the self-similarity model, the end-to-end delay bound increases with H parameter under the condition of the self-similar model. When H rises to 0.9, the delay bound will increase rapidly. It indicates that the self-similar traffic model can reduce delay.

We first discuss the sub-graph in Fig.7. If the traffic model is a Poisson process, the horizontal axis will represent the arrival rate from 0 to $45Kb/ms$ and the vertical axis will indicate the end-to-end delay bound. Obviously, the delay will increase rapidly when the arrival rate goes up to $40Kb/ms$, otherwise level off. It can be seen from the Fig.7(a) that, in the future network design, the maximum arrival rate cannot exceed 40, or else excessive delay will be resulted in to degrade the performance. Likewise, from the Fig.7 (b), we can also observe that the change in arrival rate influences the performance. The comparison between the two pictures shows that, the end-to-end delay bound in the Poisson arrival process is lower than that in the self-similar process.

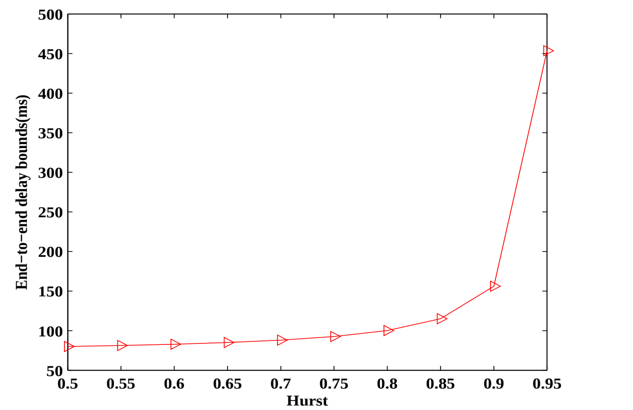
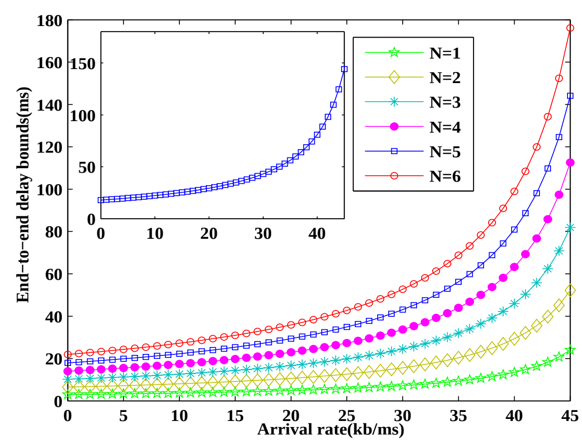
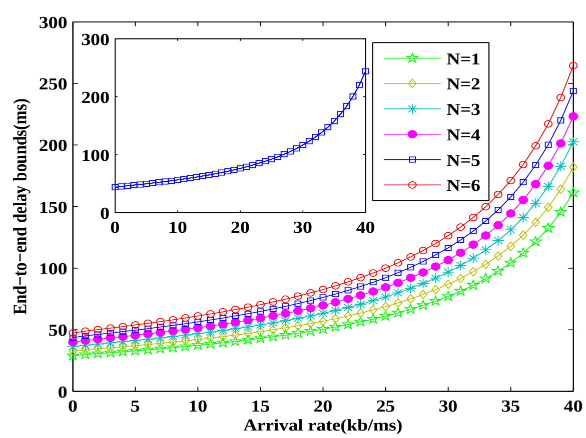


Fig.6. End-to-end delay bounds with the Hurst values under SNR as $\gamma = 25dB$ and the arrival rate of self-similar process $m = 15Kb/ms$

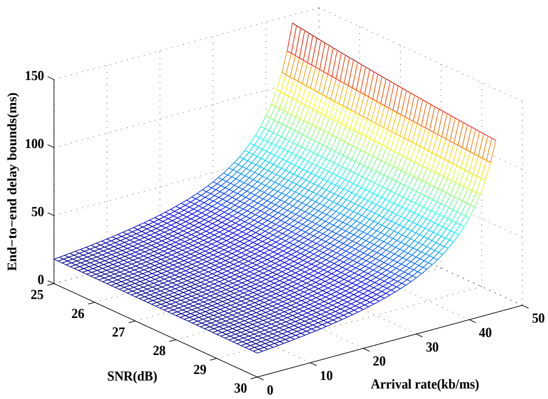


(a)Poisson process

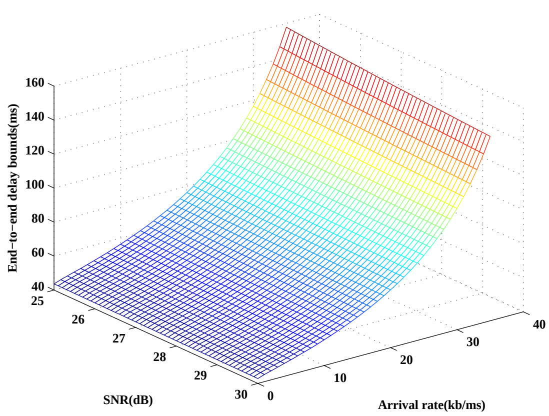


(b)Self-similar process

Fig.7. End-to-End delay bounds vary from arrival rate and different node numbers under SNR as $\gamma = 25dB$ and the violation probability $\epsilon = 10^{-3}$



(a)Poisson process



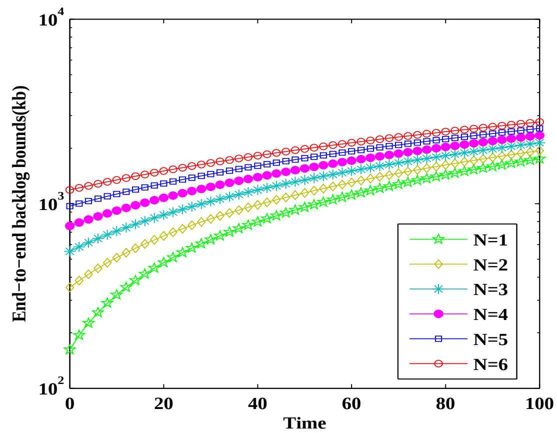
(b)Self-similar process

Fig.8. End-to-End delay bounds vary from different SNR and arrival rate under the number of nodes $N = 5$ and the violation probability $\epsilon = 10^{-3}$

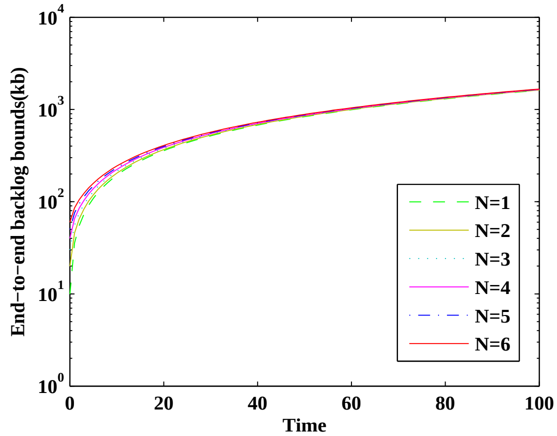
In the Fig.8, the 3D relationships among SNR, arrival rate and end-to-end delay bound are illustrated. We select several points from the picture for comparison. Obviously, as the SNR increases, the end-to-end delay bound will decrease with arrival rate. This is because that, with the increase of SNR, the satellite channel is more likely to be in better condition. The comparison between Fig.8(a) and Fig.8(b) shows that, an optimum delay bound can be obtained through the trade off between SNR and arrival rate under the Poisson constraint.

In the Fig.9, the impact of the number of nodes on end-to-end backlog bound is illustrated. At first, we set some fixed parameters: average arrival rate in Fig.9(a), $\rho = 15Kb/ms$; and $m = 15Kb/ms$ in Fig.9(b); and Hurst parameter $H = 0.5$. Obviously, the end-to-end backlog bound increases with the number of nodes. The comparison between Fig.9(a) and Fig.9(b) shows that, the impact of Poisson arrival process in Fig.9 (a) on backlog is worse than that in Fig.9 (b). This is because that, in the self-similar arrival process, the traffic is characterized by bursty and instability, and the nodes need more services to guarantee QoS. The final conclusion is that better backlog can be brought by choosing the self-similar arrival model and optimizing the number of nodes.

We can see from the Fig.10 that, the packet loss probability increases with time. After changing some parameters, for example, changing the number of nodes N from 1 to 6 or the arrival rate ($15Kb/ms$, $25Kb/ms$), the packet loss probability will be $P(B^{end}(t) > \mathrm{b}_{max})$,where the size of fixed buffer (bmax) is $\mathrm{b}_{max} = 2000$Kb. The Fig.10 shows that, if a given probability is reached, the number of nodes shall be optimized in addition to the reduction of arrival rate. Also, by considering both Fig.9 and Fig.10, we learn that the success rate of data transmission can be significantly improved when the arrival model is Poisson model.

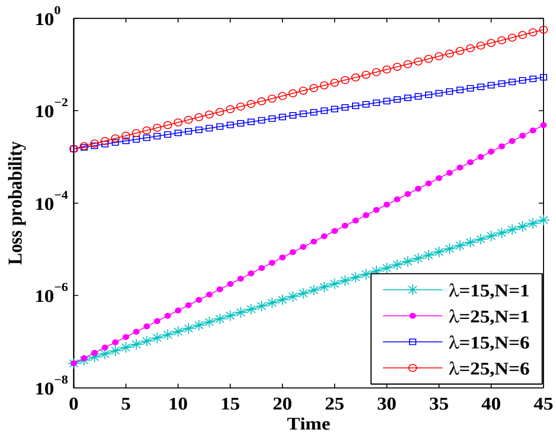


(a)Poisson process

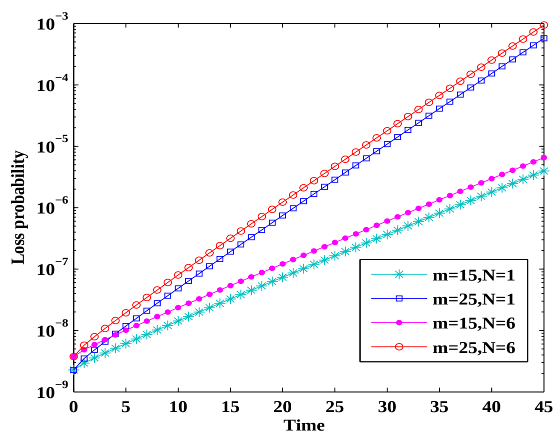


(b)Self-similar process

Fig.9. End-to-End backlog bounds vary from time and node number under SNR as $\gamma = 25dB$ and the violation probability$\epsilon = 10^{-3}$



(a)Poisson process



(b)Self-similar process

Fig.10. Loss probability vary from different arrival rate and node number under SNR as $\gamma = 25dB$

VI. Conclusion

The main contribution of this paper is to use SNC to analyze the per-flow end-to-end performance bounds in the MLSN. In this paper, multiple data flows are aggregated and then arrive at a MEO satellite. The arrival process is simulated in two models: Poisson model and self-similar model. In addition, appropriate LR scheduling strategies are provided at the nodes. In the analysis, we map a complex network structure into a tandem queuing system, which, with SNC, is used to derive the functional relations between end-to-end delay/backlog bounds and other parameters. Finally, through numerical simulation, we can see more clearly that some parameters such as the violation probability, the number of nodes, SNR and arrival rate, have an impact on these performance bounds. The future improvement in this regard is to bring in simulation and numerical analysis for comparison, in order to better verify the applicability of SNC in the MLSN.

References

[1] Bayhan, S., G. Gr, and F. Alag02z, Performance of delay-sensitive traffic in multi-layered satellite IP networks with on-board processing capability [J]. International Journal of Communication Systems, 2007. 20(12): p. 1367–1389.

[2] Lee, J. and S. Kang. Satellite over satellite (SOS) network: A novel architecture for satellite network [C].Proceedings of Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies in INFOCOM 2000,IEEE.1:392-399.

[3] Kawamoto, Y., et al. Assessing packet delivery delay in multi-layered satellite networks [C]. 2012 IEEE International Conference on in Communications (ICC). 2012, 11(18):3311–3315.

[4] Wu, F.G., et al., Performance evaluation on a double-layered satellite network [J]. International Journal of Satellite Communications and Networking, 2005. 23(6): p. 359–371.

[5] Soret, B., M.C. Aguayo-Torres, and J.T. Entrambasaguas. Maximum delay-constrained source rate over a wireless channel [C]. Proceedings of the 2nd International Conference on PERFORMANCE Evaluation Methodolgies and Tools, Valuetools 2007, Nantes, France, October. 2007:1-9.

[6] Zhou, Y., F. Sun, and B. Zhang, A novel QoS routing protocol for LEO and MEO satellite networks [J]. International Journal of Satellite Communications and Networking, 2007. 25(6): p. 603-617.

[7] Runzi, L., et al. Capacity Analysis of Two-Layered LEO/MEO Satellite Networks [C]. Vehicular Technology Conference (VTC Spring), 2015 IEEE 81st. 2015

[8] Cruz, R.L., A calculus for network delay, Part I: Network elements in isolation [J]. IEEE Transactions on Information Theory, 1991, 37(1):114-131.

[9] Cruz, R.L., A calculus for network delay, Part II: Network analysis [J]. IEEE Transactions on Information Theory, 1991. 37: p. 132-141.

[10] Boudec J Y L, Thiran P. NETWORK CALCULUS Parts II and III - A Theory of Deterministic Queuing Systems for the Internet[J]. Lecture Notes in Computer Science Lncs, 2004.

[11] Fidler M, Rizk A. A Guide to the Stochastic Network Calculus[J]. IEEE Communications Surveys and Tutorials, 2015, 17(1):92-105.

[12] Jiang Y. Stochastic network calculus for performance analysis of Internet networks An overview and outlook[C]. IEEE International Conference on Computing, NETWORKING and Communications.2012:638-644.

[13] Geyer, Fabien. End-to-End Flow-Level Quality-of-Service Guarantees for Switched Networks[J].Network Architectures and Services, 2015.

[14] Chen Xin, Zhang Lei, Xiang Xu, Dong Wan. A Stochastic Network Calculus Approach for the End-to-End Delay Analysis of LTE Networks[J]. Chinese Journal of Computers, 2011, 35(1):30-35.

[15] Li Y, Lei L, Zhong Z, et al. Performance analysis for high-speed railway communication network using stochastic network calculus[C] IET International Conference on Wireless, Mobile and Multimedia Networks. 2013:100-105.

[16] Fidler, M.Fidler M. WLC15-2: A Network Calculus Approach to Probabilistic Quality of Service Analysis of Fading Channels[J]. 2006:1-6.

[17] She H, Lu Z, Jantsch A, et al. Modeling and analysis of Rayleigh fading channels using stochastic network calculus[C].Wireless Communications and Networking Conference (WCNC),IEEE, 2011, 34(17):1056-1061.

[18] Lin, S., et al. Finite state Markov modelling for high speed railway wireless communication channel [C]. IEEE in Global Communications Conference (GLOBECOM). 2012, 14:5421-5426.

[19] Mahmood, K., A. Rizk, and Y. Jiang. On the flow-level delay of a spatial multiplexing MIMO wireless channel [C]. IEEE International Conference on Communications (ICC),2011, 41(4):1-6.

[20] Mahmood K, Vehkapera M, Jiang Y. Delay Constrained Throughput Analysis of a Correlated MIMO Wireless Channel[C] IEEE International Conference on Computer Communications and Networks.2011:1-7.

[21] Gao, Y. and Y. Jiang. Performance analysis of a cognitive radio network with imperfect spectrum sensing [C]. INFOCOM IEEE Conference on Computer Communications Workshops.2010:1-6.

[22] Chen, C. and E. Ekici, A routing protocol for hierarchical LEO/MEO satellite IP networks [C]. Wireless Networks , 2005. 11(4): p. 507-521.

[23] Mohorcic, M., et al., Demographically weighted traffic flow models for adaptive routing in packet-switched non-geostationary satellite meshed networks [C]. Computer Networks, 2003. 43(2): p. 113-131.

[24] Patnaik, B. and P.K. Sahu, Inter-satellite optical wireless communication system design and simulation. Communications [C], IET, 2012. 6(16): p. 2561-2567.

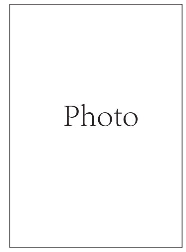
[25] Fidler, M. An End-To-End Probabilistic Network Calculus With Moment Generating Functions [C]. 14th IEEE International Workshop on Quality of Service.2005.

[26] Jiang Y. A basic stochastic network calculus[J]. Acm Sigcomm Computer Communication Review, 2006, 36(4):123-134.

[27] Jiang, Y. and Y. Liu, Stochastic Network Calculus [J]. 2010: Springer, Berlin. 1 - 6.

[28] Na, Z., et al., Research on Aggregation and Propagation of Self-Similar Traffic in Satellite Network [J]. International Journal of Hybrid Information Technology, 2015. 8(1): p. 325-338.

[29] Mahmood, K., M. Vehkaper, and Y. Jiang. Delay constrained throughput analysis of SISO [C]. 2012 3rd IEEE International Conference on Network Infrastructure and Digital Content (ICNIDC),2012.



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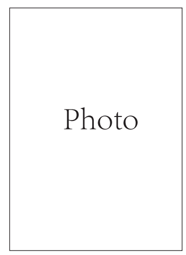

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