A Random Access Scheme for Aggregate Traffic Based on Deep Fusion of Supermartingale and Improved SSA

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Abstract. *The network services present diversity as the continuous evolution of communication scenarios, which brings a great challenge to the efficient utilization of resources. The ALOHA access mechanism is considered as an effective solution to deal with multi services for its feature of shared bandwidth. However, the collision problem of ALOHA degrades the quality of service (QoS) seriously. The multi packet reception (MPR) technology could mitigate collision and improve network performance. Considering ALOHA mechanism with MPR capability, we propose a novel random access scheme for aggregate traffic based on deep fusion of supermartingale and improved sparrow search algorithm (SSA) to provide delay QoS guarantee. Firstly, we construct a complicated queuing model with heterogeneous arrivals and ALOHA-type service. Secondly, we derive the tighter delay-violation probability bound relying on supermartingale theory, and the optimization problem is constructed with the goal of minimizing the service rate and the constraint of supermartingale bound. Finally, we improve the SSA by combining Circle chaotic map, nonlinear inertia weight and Lévy flight strategy, then the scheme is designed by applying the improved SSA and supermartingale constraint. Simulation results show that the proposed algorithm has faster convergence speed and the scheme is more bandwidth-saving.*

Keywords

Supermartingale, improved sparrow search algorithm, quality of service, multi packet reception, aggregate traffic

1. Introduction

In future wireless communication networks, it is foreseeable that the number of terminals will continue to increase, and the types of services will increasingly be various [1], [2]. The evolution brings more difficulties for the effectiveness of spectrum resources and poses more significant challenges for the guarantee of quality of service (QoS). The traffic in the networks usually has a random characteristic, so reserving bandwidth for individual terminal is bound to wasting resources. It is more suitable to utilize the access mode of shared bandwidth for the services with random traffic. The ALOHA mechanism is widely used in the random access of wireless communications for its simpleness and easy realization [3], [5]. For ALOHA access process, the packet collision is easy to occur since it does not listen to the channel, which reduces the utilization of network resources. By introducing multi packet reception (MPR) technology, the signals of multiple terminals can be decoded simultaneously, and the collision is alleviated effectively. However, it is not an easy work to model and analyze the random service with MPR capability. At the same time, the network traffic may be different and sporadic, and the efficient guarantee of QoS is difficult to achieve.

It is the key to realize efficient QoS guarantee that the bandwidth requirements and the service capability are estimated accurately. The effective bandwidth and effective capacity have introduced statistical QoS into the evaluation of bandwidth requirements and service capacity, which provides an available methodology for QoS analysis and guarantee. The effective bandwidth refers to the minimum service rate that the system needs to provide under given statistical QoS requirements [6]. In [7], a corresponding formula is proposed to calculate the effective bandwidth of the generalized Markovian flow. For the Long Term Evolution (LTE) downlink, the authors of [8] propose a scheme to allocate resource blocks based on the estimation of the effective bandwidth of traffic. The effective capacity refers to the maximum arrival rate that the system can support under the given statistical QoS requirements [9]. The effective capacity of non-orthogonal multiple access (NOMA) is studied to guarantee the delay QoS in [10]. The authors of [11] employ the QoS exponent in the effective capacity theory to characterize delay QoS constraint for MPR-capable visible light communication (VLC) system. To guarantee the statistical QoS of heterogeneous traffic, the effective bandwidth and effective capacity theory is introduced into the slicing scheme in [12]. The effective bandwidth and effective capacity both come from the large deviation theory, which could result in a loose estimation for the delay performance bound, especially for the bursty traffic. The authors of [13], [15] innovatively put forward the concepts of arrival-martingale and service-martingale, and derive a tighter QoS performance

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bound. The authors of [16], [17] utilize supermartingale method to the delay performance analysis of multimedia heterogeneous high-speed train networks and multi hop vehicular ad hoc networks, and the simulations prove the compactness of the performance bound. The authors of [18] first apply the service-martingale model to the delay analysis of short packet transmission and propose D-ALOHA random access algorithm, which could not only achieve energy conservation but also meet the requirements of high reliability and low latency. Based on the delay bound of supermartingale analysis, the authors of [19] propose a task allocation scheme for heterogeneous networks under the constraint of the global delay-violation probability. These studies demonstrate the superiority and potential of supermartingale analysis to the efficient QoS guarantee.

In recent years, the development of optimization methods further assists QoS guarantee. In [20], for VLC-orthogonal frequency division multiplexing (OFDM) system, the subcarrier allocation problem is transformed into an optimization problem to maximize the effective capacity, and a bandwidth allocation strategy based on statistical delay QoS guarantee is proposed. Relying on the theory of effective bandwidth and effective capacity, the authors of [21] construct the optimization problem of multi-user scheduling to realize the QoS guarantee of indoor VLC multi-user. The authors of [22] formulate the problem to maximizing the average throughput under a minimum energy efficiency constraint and obtain the optimal power control policy. In solving optimization problems, the swarm intelligence algorithm plays an important role. Through simulating the foraging and anti-predatory behavior of the sparrow population, a new swarm intelligence optimization algorithm, namely sparrow search algorithm (SSA), is proposed in 2020 [23], and it has the advantage of simplicity and efficiency. However, there are also some deficiencies in SSA, such as uneven population distribution, slow convergence speed and easy to fall into local optimization.

Considering the above aspects, we model a queuing system to characterize the communication scenario of the aggregate traffic under ALOHA-type mechanism. Through the construction and analysis of supermartingale, the tighter bound of delay-violation probability is obtained and the minimization problem of service rate is set up. We improve SSA and fuse supermartingale to solve the problem more effectively. The main contributions can be summarized as follows:

- Considering the ALOHA service with MPR capability and hybrid arrivals, we model a complicated queuing system to carve the communication scenario. By utilizing supermartingale theory, a stricter delay-violation probability bound is derived.
- Relying on the supermartingale analysis, we construct the optimization problem with the constraint of supermartingale bound. To handle the optimization problem more efficiently, we improve SSA by combining Circle chaotic map, nonlinear inertia weight and Lévy flight strategy, which helps to ameliorate the shortcomings of standard SSA and compute the optimal parameters faster.
- Ingeniously combining improved SSA and supermartingale analysis, the resource optimization algorithm is proposed to solve the service parameters that guarantee delay QoS. Simulation results show the performance of supermartingale-based improved SSA is favorable and saves bandwidth effectively.

The rest of the paper is organized as follows. The model of queuing system is established and analyzed in Sec. 2. In Sec. 3, we introduce the supermartingale theory to derive delay-violation probability bound and formulate the optimization problem. The improved SSA along with supermartingale rate estimation (SRE) is utilized to solve the problem. The simulation results and discussions are demonstrated in Sec. 4. Finally, the conclusion is drawn in Sec. 5.

2. System Model

In our work, we consider the communication scenario that consists of one access point (AP) and N terminals. The terminals send packets to AP by ALOHA-type mechanism with MPR ability. We consider the aggregation of N_1 Poisson flows that are relatively stable and N_2 Markov modulation on/off (MMOO) flows that are bursty. The research scheme of this paper is not limited to the specific arrival process. The packets are served according to the regulation of first input first output (FIFO), and the queuing model of this system is shown in Fig. 1.

We assume that each terminal sends packets to the AP with a certain probability p. The AP has MPR capability M, that is, it can decode M terminal signals at the same time. Referring to [11], the instantaneous service $s(n)$ of the system at time slot n ($n \geq 0$) can be expressed as:

$$s(n) = \begin{cases} kR_s, & 1 \leq k \leq M, \\ 0, & k = 0 \text{ or } k > M \end{cases} \tag{1}$$

where k denotes the number of terminals being transmitted in the time slot and R_s is the service rate. We use $\Pr\{s(n) = kR\}$ $(1 \leq k \leq M)$ to indicate the access probability of k terminals transmitting data packets to the AP, and the probability is:

$$\Pr\{s(n) = kR_s\} = C_N^k p^k (1-p)^{N-k}. \tag{2}$$

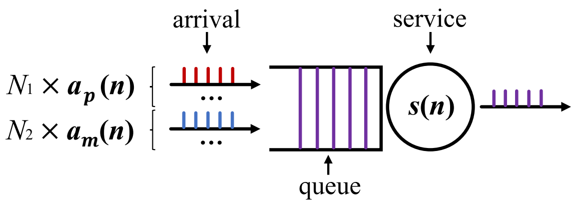


Fig. 1. The model of queuing system.

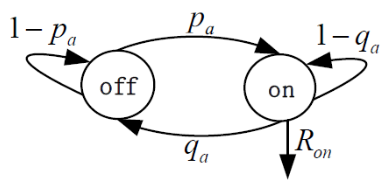


Fig. 2. The Markov chain of MMOO arrival.

The accumulated service process is denoted as $S(n)$.

The single Poisson arrival process is described as:

$$\Pr\left\{a_{\mathrm{p}}(n)=r\right\}=\frac{\lambda^r \mathrm{e}^{-\lambda}}{r!}, r=0,1,2\ldots \tag{3}$$

where $\Pr\{a_{\mathrm{p}}(n) = r\}$ represents the probability that r packets will arrive in the time slot n. λ denotes the average arrival rate, and the accumulated Poisson arrival process is represented as $A_{\mathrm{p}}(n)$.

The Markov chain of single MMOO arrival is shown in Fig. 2. The arrival rate is R_{on} at state on, and the arrival rate is zero at state off. p_{a} describes the transition probability from off state to on state, and q_{a} denotes the transition probability from on state to off state. The instantaneous and accumulated MMOO arrival process are represented as $a_{\mathrm{m}}(n)$ and $A_{\mathrm{m}}(n)$, respectively.

The accumulated aggregate traffic $A(n)$ is represented as:

$$A(n)=N_1 A_{\mathrm{p}}(n)+N_2 A_{\mathrm{m}}(n). \tag{4}$$

Then, we analyze the buffer behavior in the queuing system. Let $Q(n)$ represent the queue length. The evolution trend of the queue length can be expressed as:

$$Q(n+1)=\max\{0,(Q(n)+A(n)-S(n)\}. \tag{5}$$

According to Little's law [24], the delay $d(n)$ can be expressed as:

$$d(n)=\frac{Q(n)}{\mu} \tag{6}$$

where μ represents the average arrival rate of mixed services.

To guarantee the statistical delay QoS requirements, the inequality should hold:

$$\Pr\left\{d(n)\geq D\right\}\leq\varepsilon \tag{7}$$

where ε denotes delay-violation probability threshold, D denotes the target delay. Equation (7) means that when the target delay is given, the delay-violation probability should be less than the delay-violation probability threshold.

3. Resource Optimization Algorithm

3.1 The Optimization Problem under Supermartingale Bound Constraint

In this section, we construct the supermartingale for arrival process and service process to analyze delay QoS performance. Based on the concepts of arrival-martingale [15], the supermartingale of single Poisson process can be constructed as:

$$M_{\mathrm{p}}(n)=h_{\mathrm{p}}\left(a_{\mathrm{p}}(n)\right)\mathrm{e}^{\theta(A_{\mathrm{p}}(n)-nK_{\mathrm{p}})}. \tag{8}$$

In particular, the Poisson process is independent identically distributed (IID). So, we can take h_{p} as constant 1. The value of K_{p} is determined by the following formula:

$$E(\mathrm{e}^{\theta A_{\mathrm{p}}(n)})=\mathrm{e}^{\theta K_{\mathrm{p}}}. \tag{9}$$

Therefore, we have:

$$K_{\mathrm{p}}=\frac{\lambda\left(\mathrm{e}^{\theta}-1\right)}{\theta}. \tag{10}$$

Referring to [15], the supermartingale of the single MMOO process can be constructed as:

$$M_{\mathrm{m}}(n)=h_{\mathrm{m}}\left(a_{\mathrm{m}}(n)\right)\mathrm{e}^{\theta(A_{\mathrm{m}}(n)-nK_{\mathrm{m}})}. \tag{11}$$

The probability transition matrix and exponential column transformation matrix of the MMOO process are defined as $\mathbf{V}$ and $\mathbf{V}^{\theta}$, separately. $\mathbf{V}^{\theta}$ is expressed as:

$$\mathbf{V}^{\theta}=\begin{pmatrix}1-p_{\mathrm{a}} & p_{\mathrm{a}}\mathrm{e}^{\theta R_{\mathrm{on}}}\\ q_{\mathrm{a}} & (1-q_{\mathrm{a}})\mathrm{e}^{\theta R_{\mathrm{on}}}\end{pmatrix}. \tag{12}$$

We set $sp(\mathbf{V}^{\theta})$ as the spectral radius, and the parameter h_{m} is determined by the right eigenvector of matrix $\mathbf{V}^{\theta}$. The value of K_{m} is determined according to the following formula:

$$K_{\mathrm{m}}=\frac{\log sp(\mathbf{V}^{\theta})}{\theta}. \tag{13}$$

Based on the concepts of service-martingale [15], the supermartingale of a service process can be constructed as:

$$M_{\mathrm{s}}(n)=h_{\mathrm{s}}\left(s(n)\right)\mathrm{e}^{\theta(nK_{\mathrm{s}}-S(n))}. \tag{14}$$

For the service process also obeys IID, h_{s} can take as 1. K_{s} is taken as:

$$K_{\mathrm{s}}=-\frac{\log E\left(\mathrm{e}^{-\theta s(n)}\right)}{\theta}. \tag{15}$$

To analyze the delay performance of the queuing system with aggregate traffic, we further construct a supermartingale about queue length, and then we analyze the evolution trend of queue length in the supermartingale domain. The supermartingale has the mathematical property that the product of two independent supermartingales is still a supermartingale. In our model, the arrival processes and service process are independent. Through (8), (11) and (14), we could construct supermartingale $M_{\mathrm{L}}(n)$ relative to queue length as:

$$\begin{aligned}M_{\mathrm{L}}(n)=&\left\{h_{\mathrm{p}}\left(a_{\mathrm{p}}(n)\right)\right\}^{N_1}\left\{h_{\mathrm{m}}\left(a_{\mathrm{m}}(n)\right)\right\}^{N_2}\\ &\times h_{\mathrm{s}}\left(s(n)\right)\mathrm{e}^{\theta\left(N_1A_{\mathrm{p}}(n)-nN_1K_{\mathrm{p}}+N_2A_{\mathrm{m}}(n)-nN_2K_{\mathrm{m}}+nK_{\mathrm{s}}-S(n)\right)}.\end{aligned} \tag{16}$$

The values of K_p, K_m, K_s and h_p, h_m, h_s all depend on θ, so we set special value of θ to θ*:

$$\theta^* := \sup\{\theta > 0 : N_1K_\mathrm{p} + N_2K_\mathrm{m} = K_\mathrm{s}\}. \tag{17}$$

Then, the supermartingale $M_L(n)$ can be simplified as:

$$M_\mathrm{L}(n) = \{h_\mathrm{p}(a_\mathrm{p}(n))\}^{N_1}\{h_\mathrm{m}(a_\mathrm{m}(n))\}^{N_2} \times h_\mathrm{s}(s(n))\mathrm{e}^{\theta^*(N_1A_\mathrm{p}(n)+N_2A_\mathrm{m}(n)-S(n))}. \tag{18}$$

The supermartingale threshold H is set as:

$$H := \min\left\{\begin{matrix}\{h_\mathrm{p}(a_\mathrm{p}(n))\}^{N_1}\{h_\mathrm{m}(a_\mathrm{m}(n))\}^{N_2} \\ \times h_\mathrm{s}(s(n)) : N_1\, a_\mathrm{p}(n) + N_2\, a_\mathrm{m}(n) - s(n) > 0\end{matrix}\right\}. \tag{19}$$

Capitalizing on the stopping time theory of supermartingale, we obtain the delay-violation probability bound as:

$$\Pr\{d(n) \ge D\} \le \frac{\{E[h_\mathrm{p}(a_\mathrm{p}(0))]\}^{N_1}\{E[h_\mathrm{m}(a_\mathrm{m}(0))]\}^{N_2}E[h_\mathrm{s}(s(0))]}{H}\mathrm{e}^{-\theta^*\mu D}. \tag{20}$$

According to (7) and (20), we acquire the further delay-violation probability constraint as:

$$\frac{\{E[h_\mathrm{p}(a_\mathrm{p}(0))]\}^{N_1}\{E[h_\mathrm{m}(a_\mathrm{m}(0))]\}^{N_2}E[h_\mathrm{s}(s(0))]}{H}\mathrm{e}^{-\theta^*\mu D} \le \varepsilon. \tag{21}$$

With the goal of minimizing service resource and the constraint of supermartingale bound, the optimization problem is formed as:

$$\begin{aligned}&\min_p\ R_\mathrm{s}(p),\\ &\text{s.t. C1: } \frac{\{E[h_\mathrm{p}(a_\mathrm{p}(0))]\}^{N_1}\{E[h_\mathrm{m}(a_\mathrm{m}(0))]\}^{N_2}E[h_\mathrm{s}(s(0))]}{H}\mathrm{e}^{-\theta^*\mu D} \le \varepsilon,\\ &\quad\ \text{C2: } 0 < p \le 1,\\ &\quad\ \text{C3: } R_\mathrm{s}(p) > 0.\end{aligned} \tag{22}$$

Theorem 1: The service rate $R_s(p)$ has the minimum value at the optimal access probability p*.

Proof: For the proof of Theorem 1, see Appendix A.

Although there is a minimum value for service rate, the solution is not easy to obtain. The nonlinear constraint C1 contains two maximum functions: the upper bound of θ and the maximum eigenvalue of $\mathbf{V}^\theta$, so the optimization problem is difficult to solve by general mathematical analysis. We take the swarm intelligence optimization algorithm as an alternative method.

3.2 The Improved Sparrow Search Algorithm for Optimization Scheme

The idea of the standard SSA focuses on simulating the foraging and anti-predatory behavior of a sparrow population in nature. The individual species of sparrow population can be divided into three parts: producer, scrounger and alerter. The producer provides the region and direction for the population to search for food, and the scrounger follows the producer to get food. The producer and scrounger are dynamic. The alerter simulates the behavior that sparrows will give an alarm and move to a safe position when they are attacked by predators. Although sparrow search algorithm has the advantages of simplicity and efficiency, it still has some shortcomings. In the iteration process, it may encounter the problems such as nonuniform distribution of sparrow population, falling into local optimization and slow convergence speed.

To enhance the efficiency of the standard SSA, we make the following improvements. Firstly, for increasing the diversity of the initial population, the Circle map is used to initialize the sparrow search location. Then, to adaptively adjust the convergence ability, an exponential form of nonlinear inertia weight is introduced into the producer position update. Finally, the Lévy flight strategy is used for strengthening the global search ability in updating the scrounger position.

A. Circle Chaotic Map

In the standard SSA, the sparrow population is initialized by random generation, which will make the sparrow distribution nonuniform and the ergodicity low. The remarkable characteristics of Circle mapping include regularity, ergodicity and randomness [25]. We use Circle function mapping to generate the initial population and increase the diversity of population location. Circle chaotic map is defined as:

$$x_{i+1} = \mathrm{mod}\left(x_i + 0.2 - \left(\frac{0.5}{2\pi}\right)\sin(2\pi x_i), 1\right) \tag{23}$$

where x_i and x_{i+1} represent the values of the i-th and (i+1)-th sparrow in the sequence generated by the Circle chaotic map respectively.

B. Nonlinear Inertia Weight

To boost the convergence speed of the basic sparrow search algorithm, the nonlinear inertia weight is introduced in updating the location of the producer. In this way, the algorithm can adjust the convergence ability adaptively [26]. After improvement, the location of the producer is updated as:

$$x_{i,d}^{t+1} = \begin{cases} x_{i,d}^t \cdot \omega, & A_2 < ST \\ x_{i,d}^t + Q \cdot L, & A_2 \ge ST \end{cases} \tag{24}$$

where $x^t_{i,d}$ denotes the position of t-th iteration of the i-th sparrow in the d-th dimension. Q is a random number that obeys normal distribution. L denotes the matrix $1 \times d$, and the elements are all 1. A_2 denotes the alarm value within the range of [0, 1]. ST denotes the security threshold within the range of [0.5, 1]. The nonlinear inertia weight ω is calculated as:

$$\omega = \exp\left(1 - \frac{T_{\max} + t}{T_{\max} - t}\right) \quad (25)$$

where $T_{\max}$ denotes the maximum number of iterations.

C. Lévy Flight Strategy

When the scroungers in the standard sparrow search algorithm move to the optimal position, the population may gather rapidly in a short time, which increases the probability of falling into local optimization. The Lévy flight strategy could strengthen the local escape ability [27]. To improve the performance of the algorithm, the improved scroungers apply the Lévy flight strategy and the position is updated as:

$$x_{i,d}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{x_{\mathrm{w},d}^{t} - x_{i,d}^{t}}{i^2}\right), & i > \dfrac{G}{2} \\ x_{\mathrm{b},d}^{t+1} + x_{\mathrm{b},d}^{t+1} \otimes Levy(d), & i \le \dfrac{G}{2} \end{cases} \quad (26)$$

where x_b and x_w denotes the global best and worst position of the sparrow respectively. G denotes the total number of sparrows. The flight mechanism of Lévy is:

$$Levy(d) = 0.01 \cdot \frac{r_{1,d} \cdot \sigma}{\left|r_{2,d}\right|^{(1/\xi)}} \quad (27)$$

where $r_{1,d}$ and $r_{2,d}$ are random numbers within the range of [0, 1] with d dimensions, and the value of ξ can be taken as 1.5. The calculation method of σ is:

$$\sigma = \left(\frac{\Gamma(1+\xi) \cdot \sin(\pi\xi / 2)}{\Gamma((1+\xi)/2) \cdot \xi \cdot 2^{((\xi-1)/2)}}\right) \quad (28)$$

where $\Gamma(c) = (c-1)!$.

The standard location of alerters is updated as:

$$x_{i,d}^{t+1} = \begin{cases} x_{\mathrm{b},d}^{t} + \beta \cdot \left|x_{i,d}^{t} - x_{\mathrm{b},d}^{t}\right|, & f_i \ne f_\mathrm{b} \\ x_{i,d}^{t} + K \cdot \left(\dfrac{\left|x_{i,d}^{t} - x_{\mathrm{w},d}^{t}\right|}{(f_i - f_\mathrm{w}) + \delta}\right), & f_i = f_\mathrm{b} \end{cases} \quad (29)$$

where β is a random number satisfying the standard normal distribution. δ is a minimal constant, which prevents the denominator from appearing 0. K is random number within the range of [–1, 1]. f_i denotes the fitness value of the i-th sparrow, f_b and f_w are the best and worst fitness values of the current sparrow population, separately.

3.3 The Solution of Optimization Algorithm

To obtain the optimal access probability p^* and the optimal service rate R_s^*, the solution that combines the improved SSA with supermartingale rate estimation (SRE-ISSA) is devised. The whole framework of the algorithm is presented in Algorithm 1.

Algorithm 1 The SRE-ISSA algorithm	
1:	According to (23), initialize location of the sparrows: $x_i = p_i$.
2:	**While** ($t < T_{\max}$)
3:	**For** each sparrow x_i **do**
4:	Calculate the lower and higher bound of service rate R_{low}, R_{high}.
5:	**While** ($R_{\mathrm{low}} < R_{\mathrm{high}}$)
6:	$R_{\mathrm{mid}} = (R_{\mathrm{low}} + R_{\mathrm{high}}) / 2$;
7:	Substitute R_{mid} and x_i to the formula of supermartingale rate estimation, and calculate delay $d(n)$.
8:	**If** $\lvert d(n) - D \rvert < \gamma$
9:	$R_i = R_{\mathrm{mid}}$; **Break**;
10:	**Else**
11:	update R_{mid}.
12:	**End if**
13:	**End while**
14:	**End for**
15:	According to R_i, rank sparrows X, and find the current best location x_b and the current worst location x_w.
16:	Calculate the nonlinear inertia weighting factor ω by (25).
17:	Generate A_2.
18:	**For** $i = 1 : PD$
19:	Use (24) to update the producer's location.
20:	**End for**
21:	**For** $i = (PD + 1) : G$
22:	Use (26) to update the scrounger's location.
23:	**End for**
24:	**For** $i = 1: SD$
25:	Use (29) to update the alerter's location.
26:	**End for**
27:	Sparrows X get the current new location;
28:	If the new location is better than before, update it;
29:	$t = t + 1$
30:	**End while**
31:	**Return** x_b (p^*) and R_s^*

The search process starts with creating a sparrow population of G sparrows: $X = \{x_i,\ i = 1,...,G\}$ by Circle chaotic map. Over the course of iterations, the position of producer, scrounger and alerter are updated according to A_2, ST and fitness values R_i to achieve foraging and anti-predatory behavior. Through the binary search algorithm (BSA), the service rate R_i is gained by supermartingale bound constraint. Specifically, we calculate the lower and higher bound of theoretical service rate R_{low}, R_{high} according to the system parameters at first (Line 4). Then, we set mid value $R_{\mathrm{mid}} = (R_{\mathrm{low}} + R_{\mathrm{high}})/2$ and calculate supermartingale-based delay $d(n)$ according to R_{mid} and x_i (Lines 6–7, x_i represents the access probability). If the delay value is close to the target delay value, the value of mid R_{mid} is selected as the required bandwidth R_i (Lines 8–9, γ is an acceptable error). Otherwise, continue to execute the binary search algorithm until the value of the required bandwidth R_o is obtained (Lines 5–13). Finally, the SRE-ISSA is ended by satisfying the max iterations $T_{\max}$ and returns x_b (p^*), R_s^*.

In the following, we analyze the complexity of the proposed SRE-ISSA algorithm. ISSA is the core of the algorithm, whose evolution process is determined by the maximum iterations and sparrows population scale. The evolutionary complexity is $O_1(T_{max} \times (G+SD))$, where SD is the number of alerters in the sparrow population. For the fitness function SRE, BSA is the central part, and the search complexity is $O_2(\log_2 \zeta)$, where ζ is the number of minimum search intervals. Therefore, the complexity of the whole algorithm is $O(O_1 \times O_2) = O(T_{max} \times (G+SD) \times \log_2 \zeta)$.

4. Simulation Results and Analysis

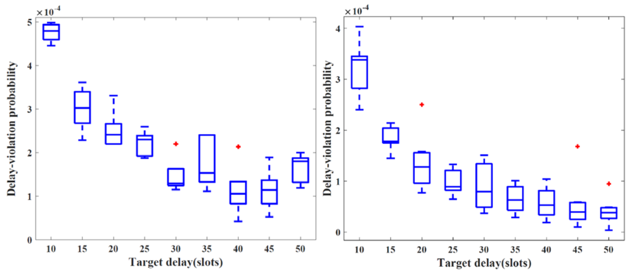
In this section, we verify the validity of the proposed random access scheme and then evaluate the performance of the SRE-ISSA. The network system is simulated and the delay-violation probability for two sets of different aggregate traffic are calculated. The experimental parameters of delay-violation probabilities are listed in Tab. 1. The parameters such as λ, p_a, q_a, R_{on}, and ε are set by referring to the order of magnitudes in [12, 15, 18]. The following simulations are adjusted relying on the parameters of Tab. 1. All simulations are implemented on MATLAB.

Firstly, we investigate the availability of our proposed scheme. The total number of flows is set as $N = N_1 + N_2 = 5$. The value of target delay D takes from 10 to 50 time slots. The simulations span 10^6 time slots and are done 10 times. The experimental results are as box-plots form in Fig. 3 where the symbol "+" indicates an outlier. It can be seen that the delay-violation probabilities are all below the setting probability threshold ε, which illustrates that the proposed random access scheme works well for different aggregate traffic.

Next, to reflect the high efficiency of the improved SSA, we select two algorithms for comparison, i.e., standard SSA and particle swarm optimization (PSO), which are used to solve optimization problems in reference [28] and [29] separately. The simulation results are taken average value through multiple experiments. As is shown in Fig. 4, it demonstrates that the improved SSA iterates to the optimal solution faster and enhances the search ability for the optimal solution significantly.

Parameters	Notations	Values
λ	The arrival rate of Poisson flow	4(packets/slot)
p_a	The transition of off-on state probability of MMOO flow	0.2
q_a	The transition of on-off state probability of MMOO flow	0.3
R_{on}	The arrival rate of MMOO flow	10 (packets/slot)
N_1	The number of Poisson flows	[2, 3]
N_2	The number of MMOO flows	[2, 3]
M	MPR capability	2
ε	The threshold of delay-violation probability	10^{-3}

Tab. 1. The table of experimental parameters configuration.



(a) $N_1 = 2$, $N_2 = 3$ (b) $N_1 = 3$, $N_2 = 2$

Fig. 3. The delay-violation probability of different aggregate traffic under delay constraints.

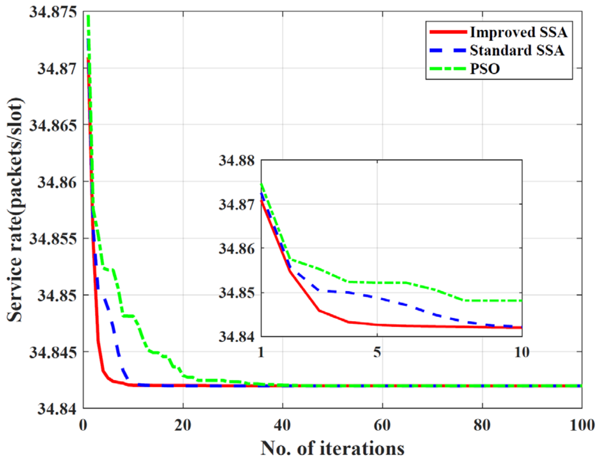


Fig. 4. The comparison diagram of various algorithms.

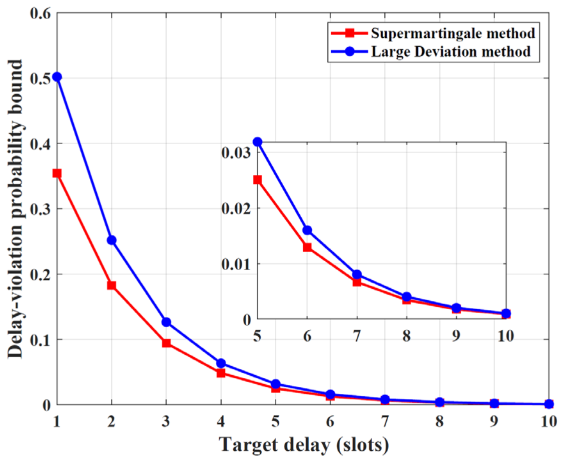


Fig. 5. The comparison of delay-violation probability bound between the supermartingale method and the large deviation method.

In [5] and [12], the scheme of QoS guarantee is explored based on the typical large deviation method. To illustrate the advantage of the supermartingale, we perform the performance bound comparison for delay-violation probability depending on the analysis of supermartingale and large deviation. In Fig. 5, the results reveal that the supermartingale-based bound is tighter than the large deviation-based bound under the same delay QoS constraint. It means the supermartingale-based results would be smaller in the estimation of the required service rate, which could improve resource utilization.

Then, we analyze the performance of the scheme in terms of delay QoS parameters (D, ε). In Fig. 6, the delay-violation probability thresholds ε are set as 10^{-3} and 10^{-4}, respectively. The results show that the required service rate declines with the increasing of target delay D, and the downward trend gradually becomes smooth. When QoS constraint weakens to a certain degree, the required service rate gradually converges to the lower bound. Additionally, it is observed that the strict delay-violation probability threshold ε leads to an increase of the required service rate. To further demonstrate the superiority of the improved SSA combined with supermartingale analysis for our scheme, we use the method in the reference [5] and [12] to achieve our scheme for comparison. Obviously, the values obtained using the SRE-ISSA are smaller than those obtained by the solution that combines the improved SSA with large deviation rate estimation (LDRE-ISSA). Thus, the SRE-ISSA could save bandwidth resources.

In Fig. 7, we set the MPR capabilities M as 2 and 3 respectively. The simulation results depict that the stronger the MPR capability, the smaller the required service rate. Since the more powerful MPR capability represents that the AP could decode more packets at the same time, the de-

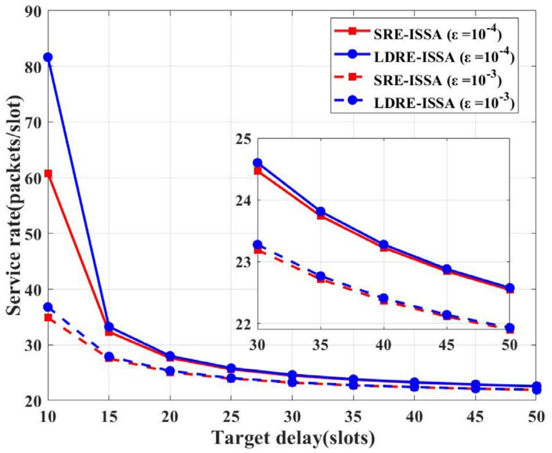


Fig. 6. The influence of delay QoS parameters (D, ε) on service rate.

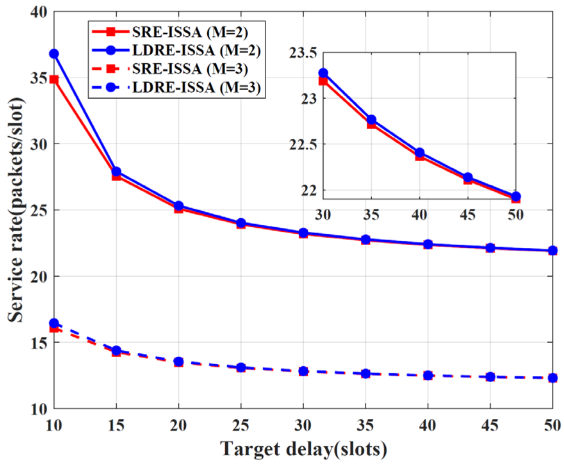


Fig. 7. The influence of MPR capability on service rate.

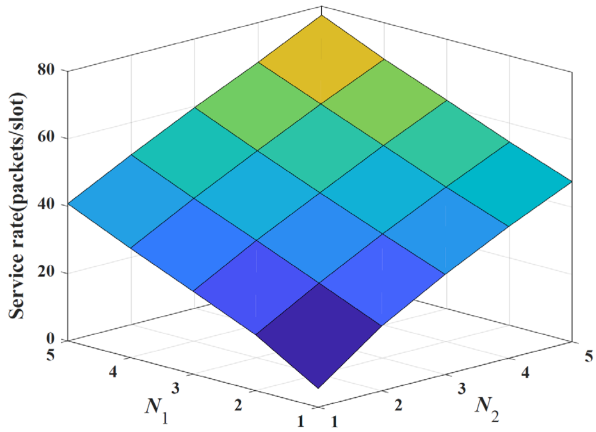


Fig. 8. The influence of different aggregate traffic on the service rate.

mand for service rate would be reduced. For fixed MPR capabilities, the impact of increasing target delay on the service rate is less and less obvious. For the same target delay, we also observe that the service rate calculated by SRE-ISSA is smaller than that calculated by LDRE-ISSA, and the advantage of the proposed scheme is proven again.

Finally, we evaluate the scheme performance under different aggregate traffic. It can be clearly seen from Fig. 8, the service rate demand gains as the increasing number of Poisson flows or MMOO flows. The reason is that the heavier traffic requires more service rate to guarantee the QoS requirement. Furthermore, the growth in the number of MMOO flows is sharper on the impact of service rate. It could be explained that the packets tend to accumulate when the aggregate traffic reveals bursty characteristics, and more service resources should be allocated.

5. Conclusion

In this paper, upon considering the MPR-aided network to mitigate the collision of ALOHA mechanism, we explored a random access scheme that combines supermartingale and improved SSA for aggregate traffic to guarantee delay QoS more efficiently. We modeled a queuing system for heterogeneous arrivals and random access service. Based on the supermartingale theory, we derived the tighter delay-violation probability bound. Moreover, we formulated the optimization problem with the goal of minimizing the service rate and the constraint of supermartingale bound. To settle this optimization problem, we fused the improved SSA and supermartingale-based estimation to obtain the optimal access probability and the minimum service rate. This analysis framework could also be extended to other communication scenarios, and we will continue to investigate the applications in the future work.

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Appendix A: Proof of Theorem 1

The parameters R_s and p are integrated in (15) and the formula can be simplified as:

$$\begin{aligned} K_s &= -\frac{1}{\theta}\log\left\{\sum_{k=1}^{M}[C_N^k p^k (1-p)^{N-k} \times e^{-\theta k R_s}] + (1-\sum_{k=1}^{M} C_N^k p^k (1-p)^{N-k})\right\} \\ &= -\frac{1}{\theta}\log\left(1-\sum_{k=1}^{M}[C_N^k p^k (1-p)^{N-k} \times (1-e^{-\theta k R_s})]\right). \end{aligned} \quad \text{(A1)}$$

K_s is used for solving θ^*, and θ^* is:

$$\theta^*(\theta, p, R_s) := \sup\left\{ \begin{aligned} &\theta > 0 : N_1 \times \frac{\lambda\left(e^{\theta}-1\right)}{\theta} + N_2 \times \frac{\log sp(\mathbf{V}^{\theta})}{\theta} \\ &= -\frac{\log(1-\sum_{k=1}^{M}[C_N^k p^k (1-p)^{N-k} \times (1-e^{-\theta k R_s})])}{\theta} \end{aligned} \right\}. \quad \text{(A2)}$$

For the determined θ, we can obtain the following formula according to (A2):

$$\sum_{k=1}^{M}[C_N^k p^k (1-p)^{N-k} \times (1-e^{-\theta k R_s})] = C(\theta) \quad \text{(A3)}$$

where $C(\theta)$ is constant for the fixed θ. Take $\varphi(p,R_s)$ as:

$$\varphi(p, R_s) = \sum_{k=1}^{M}[C_N^k p^k (1-p)^{N-k} \times (1-e^{-\theta k R_s})]. \quad \text{(A4)}$$

If there exist $\frac{d^2}{dp^2}R_s(p) > 0$ and $\frac{d}{dp}R_s(p) = 0$ in $p \in (0,1)$, $R_s(p)$ has the minimum value at the optimal p.

Differentiating $\varphi(p,R_s)$ with respect to R_s and p, we get $\frac{d}{dp}R_s(p)$ as:

$$\begin{aligned} \frac{d}{dp}R_s(p) &= -\frac{\varphi'_p}{\varphi'_{Rs}} \\ &= \sum_{k=1}^{M}\frac{kC_N^k p^{k-1}(1-p)^{N-k}(1-e^{-\theta k R_s}) + (N-k)C_N^k p^k (1-p)^{N-k-1}(1-e^{-\theta k R_s})}{-k\theta C_N^k p^k (1-p)^{N-k} e^{-\theta k R_s}} \\ &= \sum_{k=1}^{M}\frac{(e^{\theta k R_s}-1)(Np-k)}{k\theta p(1-p)}. \end{aligned} \quad \text{(A5)}$$

Furthermore, we get $\frac{d^2}{dp^2}R_s(p)$ as:

$$\frac{d^2}{dp^2}R_s(p) = \sum_{k=1}^{M}\frac{(e^{\theta k R_s}-1)[(k-2pk+Np^2)+(k^2+N^2p^2-2Npk)e^{\theta k R_s}]}{k\theta p^2 (p-1)^2}. \quad \text{(A6)}$$

The denominator of (A5) and (A6), and $(e^{\theta k R_s}-1)$ are always positive. Let $f(p) = (Np-k)$ and $g(p) = [(k-2pk+Np^2)+(k^2+N^2p^2-2Npk)e^{\theta k R_s}]$. For $k \in [1,\dots,M]$ $(N > M)$, we have $f(p) < 0$ when $p < 1/N$, $f(p) > 0$ when $p > M/N$, and $g(p) > 0$ when $0 < p < 1$. Since $\frac{d}{dp}R_s(p)$ is continuous in $p \in (0, 1)$, there exists a $p^* \in (1/N, M/N)$ to make $\frac{d}{dp}R_s(p) = 0$ based on the zero point theorem. Also, we have $\frac{d^2}{dp^2}R_s(p) > 0$ for $p \in (0, 1)$. Therefore, $R_s(p)$ has a minimum value at p^*.

From the above analysis, we can conclude that the service rate $R_s(p)$ has the minimum value at the optimal access probability p^*.