Hindawi
Wireless Communications and Mobile Computing
Volume 2019, Article ID 1257150, 11 pages
https://doi.org/10.1155/2019/1257150

Research Article

A Data Transmission Strategy with Energy Minimization Based on Optimal Stopping Theory in Mobile Cloud Computing

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Received 22 May 2019; Accepted 4 August 2019; Published 21 November 2019

Academic Editor: Juan F. Valenzuela-Valdés

Considering the widespread use of mobile devices and the increased performance requirements of mobile users, shifting the complex computing and storage requirements of mobile terminals to the cloud is an effective way to solve the limitation of mobile terminals, which has led to the rapid development of mobile cloud computing. How to reduce and balance the energy consumption of mobile terminals and clouds in data transmission, as well as improve energy efficiency and user experience, is one of the problems that green cloud computing needs to solve. This paper focuses on energy optimization in the data transmission process of mobile cloud computing. Considering that the data generation rate is variable, because of the instability of the wireless connection, combined with the transmission delay requirement, a strategy based on the optimal stopping theory to minimize the average transmission energy of the unit data is proposed. By constructing a data transmission queue model with multiple applications, an admission rule that is superior to the top candidates is proposed by using secretary problem of selecting candidates with the lowest average absolute ranking. Then, it is proved that the rule has the best candidate. Finally, experimental results show that the proposed optimization strategy has lower average energy per unit of data, higher energy efficiency, and better average scheduling period.

1. Introduction

The popularity of mobile devices such as smartphone and tablet PC has enabled people to communicate not only anytime, anywhere, but also through various applications on mobile devices to access online shopping, online social networking, news, and other services. It is a great convenience. However, mobile devices have the characteristics of limited computing power and storage capacity. In addition, the capacity of mobile devices is severely limited by battery power limitations. Mobile devices cannot be charged anytime, anywhere in a mobile scene, and the user experience is affected by limited battery power. To address the above shortcomings, mobile devices offload computing tasks to cloud platforms through high-speed wireless communications to reduce computing overhead and save energy, extending battery life and speeding up applications. Mobile devices also alleviate storage shortages by periodically sending data on the device as a backup to the cloud. This has led to the birth of a computing paradigm—mobile cloud computing (MCC)—that leverages resources in the cloud to help mobile devices collect, store, and process data, extending the capabilities of resource-constrained mobile devices. Data communication between mobile devices and the public clouds is shown in Figure 1. Due to the widespread use of mobile devices, data traffic has increased dramatically in recent years. According to IDC's forecast, the total global mobile data will reach 40,000 EB in 2020, with a compound annual growth rate of 36%. As a result, the energy efficiency of mass data transmission between mobile devices and cloud has become a key issue in MCC. Studying this problem is conducive to building a green mobile network environment.

Researchers have done a lot of research on energy-saving issues in MCC and proposed different mechanisms and methods. For example, in [1, 2], energy-saving issues are

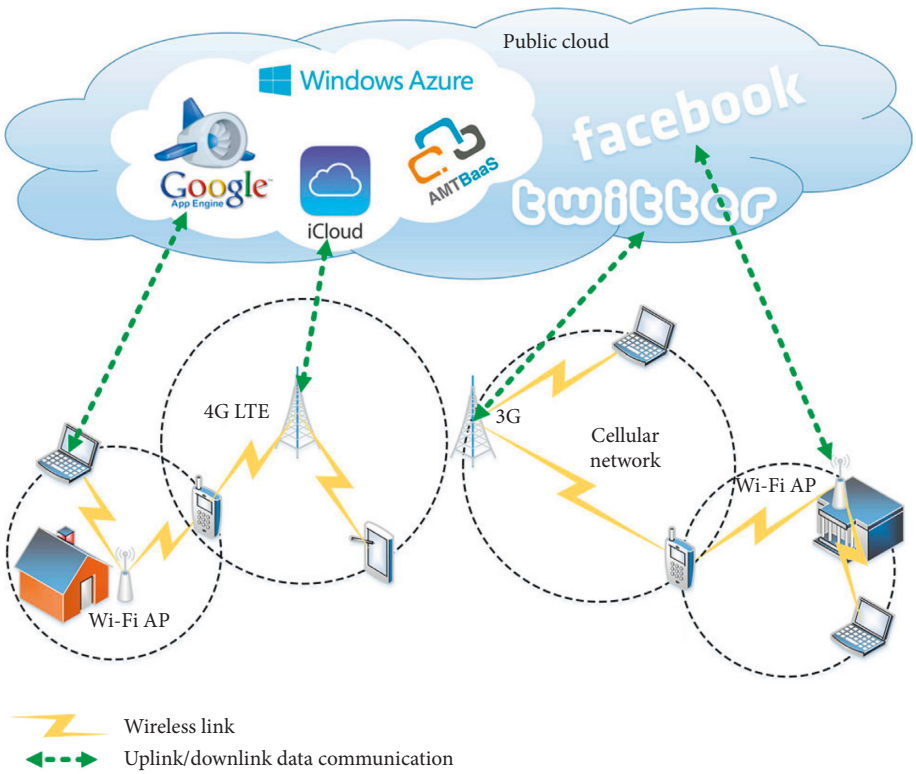


Figure 1: Data communication between mobile devices and the public clouds [1].

proposed. In [1], the problem of energy-saving data transmission between mobile devices and cloud is achieved by dynamically selecting an energy-efficient link and delaying poorly connected data transmission. The goal is to minimize the time-average energy consumption of mobile devices while ensuring the stability of both device-side and cloud-side queues. In [3, 4], a new online task scheduling or control algorithm is proposed for mobile device optimization on the throughput-energy trade-off using the Lyapunov optimization framework, without requiring any statistical information of traffic arrivals and link bandwidth. In [5], a novel data transmission optimization method, called DTM based on mobile agent deployed between mobile device layer and cloud service layer, is proposed to optimize large volume data transmission for mobile clients in MCC, which helps to reduce energy consumption and decrease waiting time. In [6], a layered heterogeneous mobile cloud architecture for high data rate transmission is proposed. Then, an energy efficiency scheme based on joint data packet fragmentation and cooperative transmission is designed, and the energy efficiency corresponding to different packet sizes and the cloud size is analyzed. In [7], the authors proposed eTime, an energy-efficient data transmission strategy between cloud and mobile devices, based on Lyapunov optimization. The eTime relies solely on current state information to make global energy-delay trade-off decision and can actively and adaptively seize the timing of good connectivity to prefetch frequently used data while deferring delay-tolerant data in bad connectivity. Similarly, as described in [7], inspired by the popularity of prefetch-friendly or delay-tolerant apps, Liu et al. [8] designed and implemented the application-layer transmission protocol, AppATP, which leverages cloud computing to manage data transmissions for mobile apps, transferring data to and from mobile devices in an energy-efficient manner in cloud computing. In [9], an online control algorithm based on Lyapunov optimization theory is proposed to optimize the data transmission between mobile devices and cloud. The algorithm can make control decisions for application scheduling, interface selection, and packet dropping to minimize the combined utility of network energy cost and packet dropping penalty. In summary, researchers have done a lot of research on the energy efficiency of data transmission between mobile devices and cloud. Despite this, many factors have not been considered, such as data dynamic arrival and transmission delay. Therefore, based on factors such as energy consumption, bandwidth, delay, and dynamic arrival of data, this paper proposes a strategy to realize the minimum transmission energy consumption of unit data by using secretary problem in optimal stopping theory.

As shown in Figure 1, the service data delivered by the mobile terminal to the cloud processing need to be transmitted through the wireless channel first. In a wireless environment, the channel conditions are time variant [10]. The transmission rate varies randomly with the quality fluctuation of the wireless channel. When the transmission power of the mobile terminal is given, in order to cope with the randomness and unpredictability of the wireless connection, the mobile terminal selects a channel with good quality, that is, the transmission rate is large to transmit data,

which is beneficial to reducing the average energy consumption of the transmission data. In fact, when the channel state changes randomly, the mobile terminal selects a better time to transmit data according to the temporary channel condition information, which is a distributed opportunistic scheduling problem [11]. The distributed opportunistic scheduling problem can be solved by the optimal stopping theory [12, 13]. Optimal stopping theory is that the decision-makers choose a suitable moment to stop observing and execute the given behavior based on the continuously observed random variables so as to maximize the interests of the decision-makers. Optimal stopping theory has been studied in the field of wireless communications. For example, in [10], communication is deferred to an acceptable time deadline based on optimal stopping theory until the best expected channel conditions are found to minimize the energy consumption of the wireless device and extend its battery life. In [14], building on optimal stopping theory, the fundamental trade-off between the throughput gain from better channel conditions and the cost for further channel probing is characterized in ad hoc networks. In [15], the authors quantify power consumption of heartbeats of real-world mobile instant messaging (IM) apps through extensive measurements. Furthermore, the authors propose a device-to-device- (D2D-) based heartbeat relaying framework for IM apps in order to reduce energy for heavy signaling traffic transmission in [16]. In fact, 5G is a new paradigm that brings new technologies to overcome the challenges of the next generation wireless mobile network. The heterogeneous environment (such as network functions virtualization (NFV), software-defined networking (SDN), and cloud computing) of 5G will cause frequent handoff in small cells where users join and leave frequently; besides transmission performance, the security and privacy of cloud and wireless networks is also important for users, such as in [17]. Furthermore, outsourcing service fair payment based on blockchain has been studied in cloud computing in [18].

This paper mainly studies the energy-saving optimization problem of data transmission with time delay requirement and variable data generation rate in MCC. A data transmission energy optimization strategy based on optimal stopping theory is proposed. Optimal stopping theory is adopted so that the mobile terminal stops detecting the channel and obtains the time when the wireless channel transmission rate is large so as to minimize the energy consumption of data transmission. The specific research ideas are as follows: first, a data transmission queue model with multiple applications is constructed, and the data generation rate is dynamic because it is more realistic. Considering comprehensively the energy consumption and delay in the transmission process, the goal is to minimize the average energy consumption per unit of data. Based on secretary problem in optimal stopping theory, a rule is proposed to abandon the first k candidates, from $(k+1)$th candidate; if he is better than the top k candidates, then he is hired. At this time, the average absolute ranking of the selected candidate is the smallest.

The remainder of this paper proceeds as follows: Section 2 presents the system model and related theory; Section 3 proposes our strategy of minimizing expected energy consumption based on secretary problem. In Section 4, simulation results and analysis are given; Section 5 concludes the paper.

2. Theoretical Background and Problem Description

2.1. System Model. The research goal of this paper is to optimize the energy consumption generated by mobile terminals transmitting data to the cloud in MCC under the condition of satisfying transmission delay. Figure 2 is a data transmission queue model diagram of a mobile terminal and assumes that the mobile terminal has M applications simultaneously transmitting data to the cloud.

In the model shown in Figure 2, M different types of applications need to transmit data with the cloud. In each discrete time slot $t\,(t \in \{0, 1, 2, \ldots\})$, the data to be transmitted of each application enter the corresponding queue and are awaiting transmission, represented by $Q^{(t)} \cong (Q_1^{(t)}, Q_2^{(t)}, \ldots, Q_M^{(t)})$. $Q_m^{(t)}$ is a queue in which application m needs to transmit data with the cloud at the beginning of time slot t. The rate c at which the transmitting terminal generates data to be transmitted is dynamic and cannot be kept constant, such as the cause of network instability. For the convenience of processing, it is assumed that the number of transmitted packets obeys the probability distribution of $f_B(b)$, and the capacity of each packet is α. In Figure 2, $A_m^{(t)}$ represents the newly generated data to reach the $Q_m^{(t)}$ queue, where the vector $A^{(t)} \cong (A_1^{(t)}, A_2^{(t)}, \ldots, A_M^{(t)})$. In each time slot t, $U_m^{(t)}$ represents the data that the system is about to process, and $A_m^{(t)} - U_m^{(t)}$ represents the data that the system will not process immediately but will process in the future, so it is temporarily stored in a cache space. In this model, no assumptions are made about the prior knowledge of $A_m^{(t)}$ statistics. The change of $A_m^{(t)}$ can be described as a Markov process, and the probability of conversion between different states is unknown. Therefore, the above queue model describes time-varying and unpredictable data transmission between mobile terminals and the cloud. Each time slot t transmits data over a wireless link (e.g., Wi-Fi, 3G, 4G, or even 5G).

Assume that the time that the application m detects the channel bandwidth is T. The quality of the wireless channel varies randomly, and the quality retention time is τ. The mobile terminal detects the channel with period τ. The detection duration is much less than τ, and the detection energy consumption is E_D. The mobile terminal transmits data after detecting the channel quality of $n\,(n = 1, 2, \ldots)$ times. The dynamic queue model of the amount of data to be transmitted of application m is $Q_{m_n}^{(t+1)} = \max\{Q_{m_n}^{(t)} - r_{m_n}^{(t)}, 0\} + U_{m_n}^{(t)}$, where $r_{m_n}^{(t)}$ represents the data transmission rate at the current time, $U_{m_n}^{(t)}$ represents the newly generated data to be transmitted on the nth detection channel, and $U_{m_n}^{(t)} = c \cdot (T + \tau)$. Transmission time $t = \min\{Q_{m_n}^{(t)}/r_{m_n}^{(t)}, \tau\}$.

When the mobile terminal selects a transmission time with a large transmission rate, the amount of transmission data in the transmission delay can be increased, and the average energy consumption of the transmission unit data

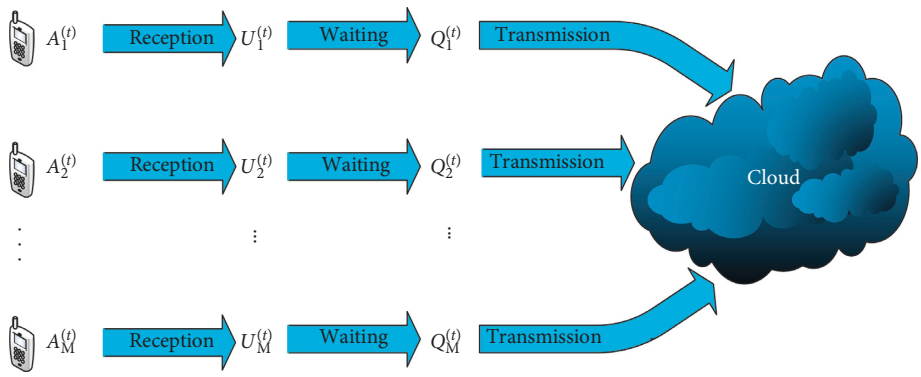


Figure 2: Queue-based data model.

can be reduced, thereby improving energy utilization. According to the Shannon formula $R = W \log_2 (1 + ((g \cdot P)/(N_0 \cdot W)))$, the channel transmission rate R is determined by the channel bandwidth W, the channel gain g, the transmission power P, and the noise power spectral density N_0. When the values of the channel bandwidth W, the transmission power P, and the noise power spectral density N_0 are determined, the transmission rate R is proportional to the channel gain g. The mobile terminal selects a time when the transmission rate is large, that is, a time when the channel gain value is large and the channel quality is good. In this paper, secretary problem in optimal stopping theory is utilized to obtain the optimal transmission time.

2.2. Secretary Problem. Optimal stopping theory is that decision-makers aim to maximize the reward or minimize the expected cost based on the continuously observed random variables and decide to choose a suitable moment to take the given behavior. Secretary problem is the most representative problem in optimal stopping theory. The method introduced in this paper is based on the criterion of minimizing the absolute ranking of selected candidates in secretary problem. Assume that 1 is the best candidate's ranking, 2 is the second best ranking, ..., N is the worst ranking. The mathematical description of secretary problem is as follows: let $\Omega = \{(a_1, a_2, \ldots, a_N)\}$. $J = J(\Omega)$, that is, Ω is the whole of all subsets. For all sample points, the assigned probability is $1/N!$ and Ω is an equal probability profile. y_n is the number less than or equal to a_n in $(a_1, a_2, \ldots, a_n)$, which is the relative position of a_n. Normally we always observe the value of a random variable sequentially $y_1, y_2, \ldots, y_n$, and $J_n = \sigma(y_1, y_2, \ldots, y_n)$ is a list of increasing sub-σ algebras of J.

A stop time t is a random variable, and t is taken from $\{1, 2, \ldots, n\}$, and $\{t = n\} \in \sigma\{y_1, y_2, \ldots, y_n\}$. This indicates that the stopping moment depends on the observations to date. The interviewer hopes to hire the most rewarding candidate when he stops the interview. The standard of employment is to minimize the average of the applicant's absolute rankings. However, the best standard in practice is difficult to grasp, so choose an average optimal candidate. Take the reward function $X_n = -E(a_n \mid J_n)$, $n = 1, 2, \ldots, N$ to measure the priority of the candidate. For any stopping rule t, $EX_t = -E(a_t)$, where $E(a_t)$ is the average absolute ranking, according to this criterion, and then the problem can be transformed into

$$\max EX_t = -E(a_t). \tag{1}$$

Therefore, the optimal stopping rule for the criterion that minimizes the mean value of the absolute position of candidates is

$$s = \inf\{n \geq 1 : y_n \leq s_n\}, \tag{2}$$

where

$$\begin{aligned} s_n &= \left\lfloor -\frac{n+1}{N+1} V_{n+1} \right\rfloor, \quad n = N-1, N-2, \ldots, 1, \; S_N = 0, \\ V_N &= -\frac{N+1}{2}, \\ V_n &= -E\left[\frac{N+1}{n+1} y_n \wedge (-V_{n+1})\right], \quad 1 \leq n \leq N-1, \end{aligned} \tag{3}$$

where $a \wedge b = \min(a, b)$.

There are limitations to this standard: (1) dependent on N and sensitivity; (2) complex rules and invariant applications; (3) regardless of the time cost. Therefore, this paper proposes an admission rule that is superior to the former k candidate, so the applicant's mean average absolute position is the smallest. That is, k candidates in the first round interview would not be hired; starting with the $k+1$ th candidate, if he is better than the top k candidates, then the candidate will be hired; otherwise, the next one will be interviewed until the last one.

3. Data Transmission Energy Consumption Optimization Strategy

3.1. Energy Consumption Optimization Problem. The transmitting terminal determines to transmit data only when it detects that the channel quality is good. Assuming that the transmission power of the mobile terminal is P, the energy consumption of data transmission by the application m is $P \cdot t$. If the number of times that application m performs one round of channel detection is N, then the total energy consumption of one round of channel bandwidth detection and data transmission is $E_{m_N} = N \cdot E_D + P \cdot t$.

If application m repeatedly uses a given rule to detect channel Y rounds, then the sequence of stop times generated by Y rounds is $\{N_1, N_2, \ldots, N_i, \ldots, N_Y\}$, and the total energy consumption sequence is $\{E_{N_1}, E_{N_2}, \ldots, E_{N_i}, \ldots, E_{N_Y}\}$. Here, N_i is the stop time number of i-th round. E_{N_i} is the total energy consumption of i-th round stopped at N_i. At this time, the total time spent by the mobile terminal is the detection time $\Delta T_{N_i} = T \cdot N_i$ and the transmission time t, that is, $\Delta T_{N_i} + t$. The amount of data to be transmitted is $Q_{m_n}^{(t+1)}$. Then the amount of data $L_{m_{N_i}}$ that are not transmitted in this round is

$$\begin{aligned} L_{m_{N_i}} &= \left(Q_{m_n}^{(t+1)} - r_{m_n}^{(t)} t\right)^+ \\ &= \begin{cases} Q_{m_n}^{(t+1)} - r_{m_n}^{(t)} t, & Q_{m_n}^{(t+1)} > r_{m_n}^{(t)} t, \\ 0, & Q_{m_n}^{(t+1)} \le r_{m_n}^{(t)} t. \end{cases} \end{aligned} \tag{4}$$

Energy efficiency ζ is defined as the average energy consumption of data transmitted by M applications, and then

$$\zeta = \sum_{i=1}^{M} \xi_i = \sum_{i=1}^{M} \frac{\sum_{i=1}^{Y} E_{m_{Ni}}}{\sum_{i=1}^{Y} \left(Q_{m_{Ni}}^{(t+1)} - L_{m_{Ni}}\right)}, \tag{5}$$

where N is the optimal stop time if the minimum average energy consumption per unit data is obtained after N times of observation. The mobile terminal detects the channel bandwidth at least once, and the optimal stop time is $N \ge 1$. The maximum transmission delay of the data to be transmitted is D_m. Defining $Z = \lfloor D_m/\tau \rfloor$, there is $1 \le n \le N \le Z$, and $\lfloor \cdot \rfloor$ indicates rounding down.

According to the large number theorem, equation (5) converges to $(ME[E_N])/(E[Q_N^{(t+1)} - L_N])$. Therefore, a stop time $1 \le N \le Z$ is constructed to minimize $(ME[E_N])/(E[Q_N^{(t+1)} - L_N])$. The rule originates from the channel transmission rate r_N during the interval period T and the detection time sequence ΔT_N. It also generates an energy consumption sequence E_N, a data quantity sequence to be transmitted Q_N, and a data quantity sequence L_N which cannot be transmitted. These sequence values can all be obtained by measurement.

3.2. Solving the Secretary Problem of Energy Minimization. The goal of this paper is to minimize the average energy consumption of data transmitted from the mobile terminal to cloud, that is, to select the time at which the transmission rate is maximized. The moment when the transmission rate is maximized is solved by using secretary problem. That is, following the rule after giving up the top k candidates, when he is better than the first k candidates, he is hired. This section details how to choose the k value.

Let V denote the absolute ranking of selected candidates according to the proposed rule. Let X denote the step size at which the decision is made. $P_{r,s}^{k,N} = P(V = r, X = s)$ is the probability that the absolute rank of the applicant is r, and the step length is s when the decision is made. $P_r^{k,N} = P(V = r)$ is the probability that the absolute rank of the candidate selected is r when the decision is stopped.

Lemma 1. *When* $1 \le k \le N-1$, $k+1 \le s \le N$,

$$P_1^{k,N} = \frac{k}{N} \sum_{s=k+1}^{N} \frac{1}{s-1}. \tag{6}$$

Lemma 2. *When* $1 \le k \le N-1$, $k+1 \le s \le N, r \ne 1$,

$$P_r^{k,N} = \begin{cases} \displaystyle\sum_{s=k+1}^{N-r+1} \frac{(N-r)!(N-s)!}{N!(N+1-r-s)!} \\ \displaystyle \cdot \frac{k}{s-1} + \frac{k(N-2)!}{N!}, & r+k \le N, \\ \displaystyle\frac{k(N-2)!}{N!}, & r+k > N. \end{cases} \tag{7}$$

By using the admission rule that is superior to the top k candidates, when $k = k^* = \lfloor \sqrt{N} \rfloor - 1$, the average absolute ranking of applicants recruited can be minimized.

Proof. Let $E(k)$ be the average absolute position of candidates, then

$$\begin{aligned} E(k) &= \sum_{1}^{N} r \cdot P_r^{k,N} \\ &= \frac{k}{N} \sum_{s=k+1}^{N} \frac{1}{s-1} + \sum_{r=2}^{N-k} r \left[\sum_{s=k+1}^{N-r+1} C_{N-r}^{s-1} \frac{k}{N!} (s-2)!(N-s)! \right] \\ &\quad + \sum_{r=2}^{N} r \cdot \frac{k(N-2)}{N!} \\ &= k \cdot \frac{N+2}{2N} + \sum_{r=1}^{N-K} r \sum_{s=k+1}^{N-r+1} \frac{k}{s-1} \cdot \frac{(N-r)!(N-s)!}{N!(N+1-r-s)!}. \end{aligned} \tag{8}$$

In the above formula, r and s are transposed to obtain

$$E(k) = k \cdot \frac{N+2}{2N} + \sum_{s=k+1}^{N} \sum_{r=1}^{N-s+1} \frac{k}{s-1} \cdot \frac{r(N-r)!(N-s)!}{N!(N+1-r-s)!}. \tag{9}$$

Let

$$G(s) = \sum_{r=1}^{N-s+1} \frac{k}{s-1} \cdot \frac{r(N-r)!(N-s)!}{N!(N+1-r-s)!},$$

$$E(k) = k \cdot \frac{N+2}{2N} + \sum_{s=k+1}^{N} G(s),$$

$$\begin{aligned} G(s) &= \frac{(N-s)!}{N!(s-1)!} \sum_{r=1}^{N-s+1} r \frac{(N-r)!}{[(N-r)-(s-1)]!(s-1)!}(s-1)! \\ &= \frac{(N-s)!(s-2)!}{N!} \sum_{r=1}^{N-s+1} r C_{N-r}^{s-1} \\ &= \frac{(N-s)!(s-2)!}{N!} \sum_{r=0}^{N-s} (r+1) C_{N-r-1}^{s-1} \\ &= \frac{(N-s)!(s-2)!}{N!} \sum_{r=0}^{N-s} C_{r+1}^{1} C_{r+1}^{1} C_{N-r-1}^{s-1} \\ &= \frac{N+1}{(s+1)s(s-1)}. \end{aligned} \tag{10}$$

There are

$$\frac{1}{(s+1)s(s-1)} = \frac{1}{2(s-1)} - \frac{1}{s} + \frac{1}{2(s+1)}. \tag{11}$$

And so

$$\begin{aligned} \sum_{s=k+1}^{N} \frac{1}{(s+1)s(s-1)} &= \frac{1}{2k} - \frac{1}{2(k+1)} - \frac{1}{2N} + \frac{1}{2(N+1)} \\ &= \frac{1}{2k(k+1)} - \frac{1}{2N(N+1)}. \end{aligned} \tag{12}$$

That is,

$$\begin{aligned} E(k) &= k\left[\frac{N+2}{2N} + \frac{N+1}{2k(k+1)} - \frac{1}{2N}\right] \\ &= \frac{N+1}{2}\left[\frac{k}{N} + \frac{1}{k+1}\right] \\ &\geq \frac{N+1}{2}\left[\frac{2}{\sqrt{N}} - \frac{1}{N}\right]. \end{aligned} \tag{13}$$

The above formula can achieve minimum if and only if $(k+1)/N = 1/(k+1)$. Therefore, when $k = \sqrt{N} - 1$, $E(k)$ can reach the minimum value, and the minimum value is $((N+1)/N)[\sqrt{N} - (1/2)]$. Let $k^* = \lfloor \sqrt{N} \rfloor - 1$, when $k = k^*$, the mean of the average absolute ranking of the employed applicant can be minimized.

The mobile terminal performs channel detection once at T intervals. After performing k times of detection, when detecting that the current rate r is greater than all previous rate values, the mobile terminal stops detecting and transmitting data to the cloud; otherwise, the mobile terminal continues to detect. If the mobile terminal does not transmit data for the first $Z-1$ detections, the data must be transmitted when the detection time reaches the maximum detection number Z. According to the strategy, the mobile terminal continuously performs channel detection and data transmission, thereby reducing the average energy consumption of the transmission unit data. □

4. Simulation Results and Analysis

In this section, the advantages of the proposed strategy will be demonstrated through simulation experiment. It is mainly verified by three indicators: average energy consumption, energy efficiency, and average scheduling period, and compared with the results of other related literature strategies.

Due to wireless network instability and communication bandwidth fluctuations, wireless channel has small-scale fading. Channel fading is usually considered in two cases: (1) Rayleigh fading and (2) Rician fading. In the experiment, the wireless channel is simulated by using these two fading distribution models, and the experimental parameter values are shown in Table 1.

This paper proposes an optimal transmission strategy based on secretary problem (OTSSP) of optimal stopping theory: following the rule that it is better than the top k candidates. In the experimental simulation, OTSSP is compared with the other two strategies. The two strategies for comparison are as follows:

(1) The sooner the better (TSTB): the mobile terminal sends data immediately after detecting the channel for the first time.

(2) Random transmission strategy (RTS): the mobile terminal randomly selects a certain time for data transmission. The maximum transmission delay D_m is divided into Z clocks, and the probability of being selected at each time is $1/Z$.

In order to weigh the average energy consumption and maximum transmission delay, etc., according to the literature [11], the maximum application number M of a mobile terminal in the experiment is 5; the number of packets EX of mobile terminal data generation rate c is 10, and the capacity of each packet is $\alpha = 512 * 8$ bit; the data detection period T is 1 s; data transmission time τ is 0.9 s; data transmission delay D_m is 10 s; and the data detection energy consumption E_D is 1×10^{-8} J. In addition, the effects of the number of data packets EX regarding the data generation rate of the mobile terminal and data transmission delay D_m on average energy consumption, energy efficiency, and average scheduling period are considered. The change factors EX range from 1 to 80, and D_m ranges from 1 to 30 s.

4.1. Average Energy Consumption. The average energy consumption reflects the energy consumed per bit of data in the successfully transmitted data. The total energy consumed

Table 1: Simulation parameters.

Parameters	Description	Value
W	Bandwidth (MHz)	1
N_0	Noise power spectral density (W/Hz)	10^{-6}
σ^2	Channel gain variance correlation value	1
g	Channel gain	0~4
P	Transmission power (mW)	100
A	Peak of main signal amplitude	1

includes the channel detection energy consumption E_{D} and data transmission energy consumption $P{\cdot}t$.

Figure 3 shows the average energy consumption comparison results for the three strategies when the Rayleigh and Rician distributions have different EX changes. As can be seen from Figure 3, the average energy consumption per unit data of OTSSP strategy is the smallest among the three strategies in Rayleigh and Rician distributions and is significantly smaller than that of the other two strategies. The maximum average energy consumption of OTSSP strategy does not exceed 0.005. The average energy consumption of TSTB strategy is the largest, and the fluctuation is the most obvious. The energy consumption value of RTS strategy is larger than that of OTSSP strategy, and the fluctuation range is also larger than that of OTSSP strategy. From the figure, we can also see that the average energy consumption of each strategy in the Rician distribution is less than that of the corresponding strategy in the Rayleigh distribution. The average energy consumption of the three strategies do not decrease significantly with the increase of EX, which shows that the three strategies are stable and not affected by the number of data packets in the data generation rate.

Figure 4 shows the average energy consumption comparison of the three strategies for different D_m changes under the Rayleigh and Rician distributions. It is observed from Figure 4 that, in both distributions, the OTSSP strategy has the lowest average energy consumption and the best energy efficiency. Moreover, the OTSSP strategy and the RTS strategy are related to D_m due to the data transmission time, and the average energy consumption value decreases with the increase of D_m. This is because when D_m increases, the generated data have more chances to be transmitted to the cloud before the maximum delay, and the energy consumed per unit of data is reduced, so the average energy consumption is decreasing. When the delay D_m is greater than 25 s, the energy consumption per bit of data is infinitely close to 0, but it is not equal to 0. At this time, although the average energy consumption is low, the user experience is not good.

4.2. Energy Efficiency. The energy consumption efficiency η reflects the energy consumed per unit time during the data transmission time, and the total consumption time includes the detection channel time T and data transmission time t. The smaller the energy efficiency η, the less energy is consumed per unit time.

Figure 5 shows the comparison of the energy efficiency η values of the three strategies for different EX changes under the Rayleigh and Rician distributions. Because the three strategies cannot clearly express the change range in one graph, OTSSP strategy is shown as a single graph. And the energy efficiency values of TSTB strategy graphs are displayed on the left side of Y-axis, and the energy efficiency values of RTS strategy are displayed on the right side of Y-axis in Figures 5(b) and 5(d), respectively. From Figure 5, it is observed that in the Rayleigh and Rician distributions, the energy efficiency of OTSSP strategy is significantly lower than that of the other two strategies, which mainly changes between 1 and 7. In the Rayleigh distribution, the energy efficiency of TSTB strategy is mostly between 30 and 70, and that of RTS strategy is between 10 and 65. In the Rician distribution, the energy efficiency of TSTB strategy is between 10 and 65, and that of RTS strategy is between 10 and 35. It can be seen that the energy efficiency of the Rician distribution is better than that of the Rayleigh distribution.

Figure 6 shows the comparison of energy efficiency η of the three strategies for different D_m changes under Rayleigh and Rician distributions. As can be seen from Figure 6, OTSSP and RTS strategies have the same energy consumption efficiency value when D_m is equal to 1. Because the data transmission time of the OTSSP and RTS strategies is related to D_m, as the D_m increases, the accumulated data volume increases. The amount of data transmitted by the mobile terminal in a good channel condition increases. The η value of the OTSSP strategy and the RTS strategy gradually decrease, and η value of the OTSSP strategy is smaller than the RTS strategy. The transmission time of the TSTB strategy is independent of D_m, so the η value does not decrease as D_m increases. In the Rayleigh distribution, the energy efficiency of TSTB fluctuates around 0.33, and the energy efficiency value fluctuates by about 0.18 in the Rician distribution.

4.3. Average Scheduling Period. Average scheduling period refers to the average detection time of the mobile terminal in a given period of time. The larger the value, the longer the average detection time of the mobile terminal, and vice versa.

Figure 7 shows the average scheduling period comparison results of three strategies for different EX changes with the Rayleigh distribution and the Rician distribution. From Figure 7, it can be seen that the average scheduling period of OTSSP strategy is smaller than that of RTS strategy and larger than that of TSTB strategy. Because RTS always transmits data after the last delay arriving, the detection time of each round reaches the maximum. The average scheduling period of TSTB strategy is between 5 and 6, which is close to the expected value of all stopping times in the maximum transmission delay. The average scheduling period value of OTSSP strategy is slightly smaller than that of RTS strategy. The scheduling period of OTSSP strategy is related to its power threshold, so the average scheduling cycle is longer.

Figure 8 shows the comparison results of the average scheduling period of three strategies under the Rayleigh and Rician distributions with different D_m changes. From Figure 8, it can be seen that the average scheduling period of the three strategies shows an increasing trend in both distributions with the increase of D_m. Among them, OTSSP

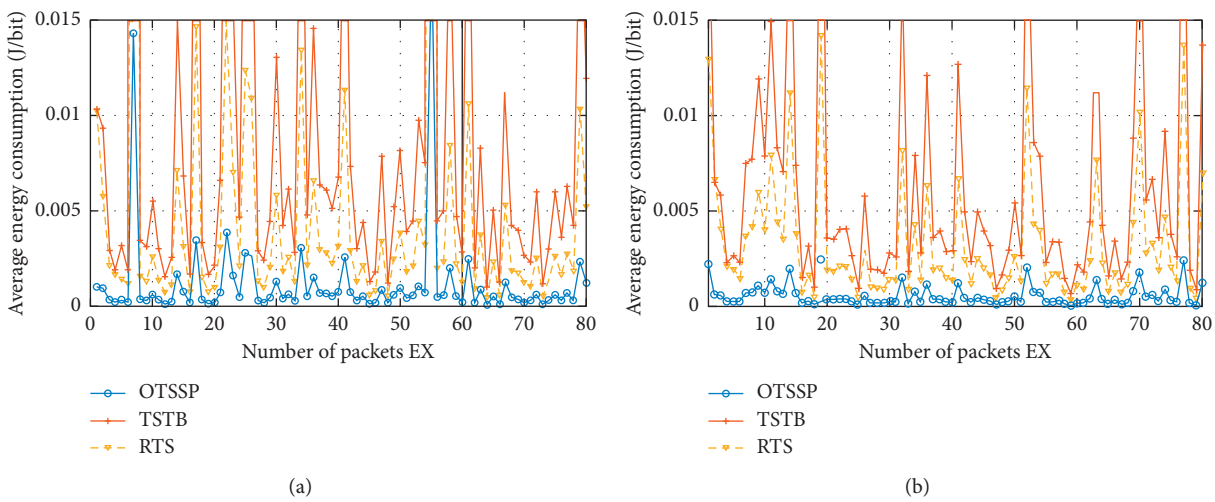


Figure 3: Comparison of average energy consumption with different *EX*. (a) Average energy consumption of the Rayleigh distribution. (b) Average energy consumption of the Rician distribution.

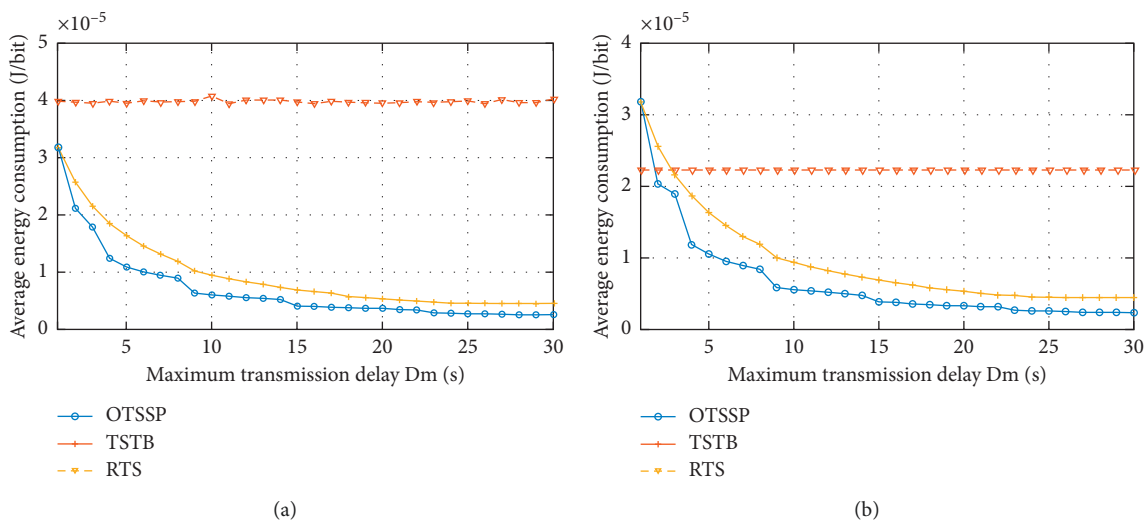


Figure 4: Comparison of average energy consumption with different D_m. (a) Average energy consumption of the Rayleigh distribution. (b) Average energy consumption of the Rician distribution.

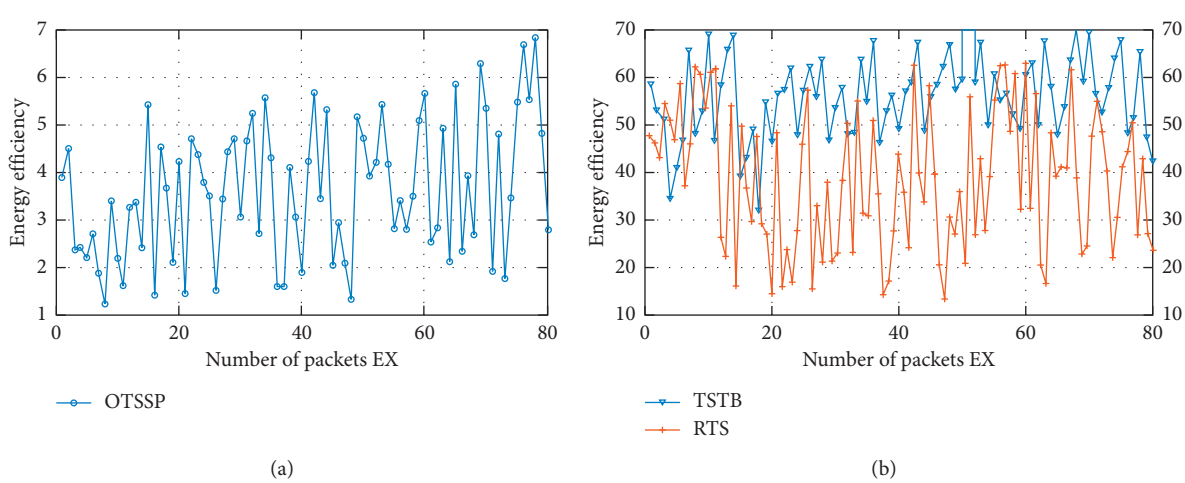
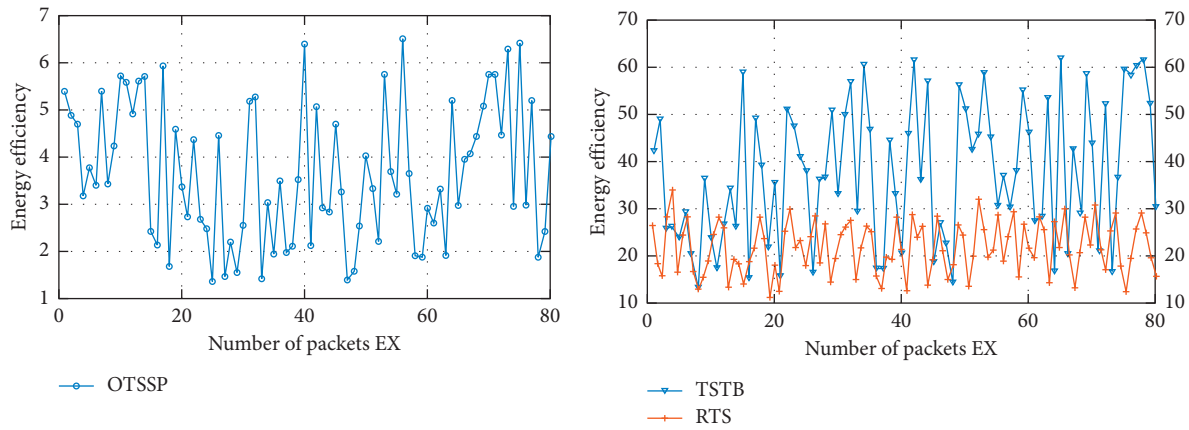
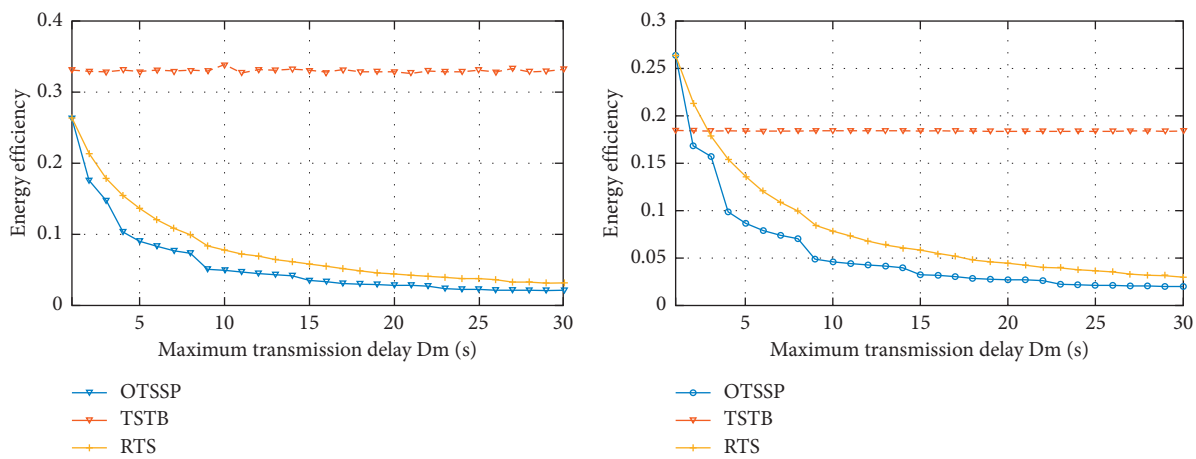


Figure 5: Continued.



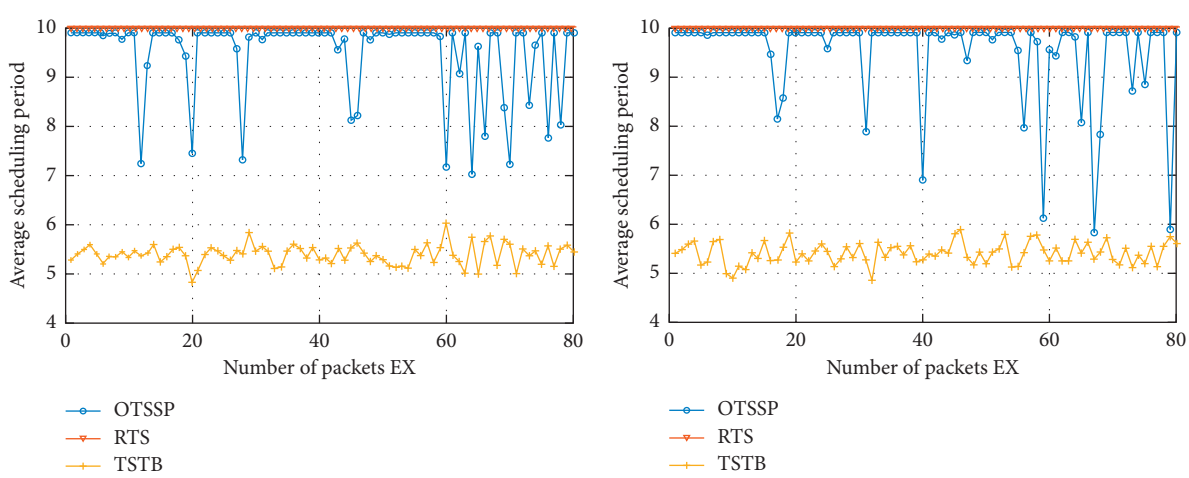
(c) (d)

Figure 5: Comparison of energy efficiency with different *EX*. (a) Energy efficiency of the Rayleigh distribution. (b) Energy efficiency of the Rayleigh distribution. (c) Energy efficiency of the Rician distribution. (d) Energy efficiency of the Rician distribution.



(a) (b)

Figure 6: Comparison of energy efficiency with different D_m. (a) Energy efficiency of the Rayleigh distribution. (b) Energy efficiency of the Rician distribution.



(a) (b)

Figure 7: Comparison of the average scheduling period with different *EX*. (a) Average scheduling period of the Rayleigh distribution. (b) Average scheduling period of the Rician distribution.

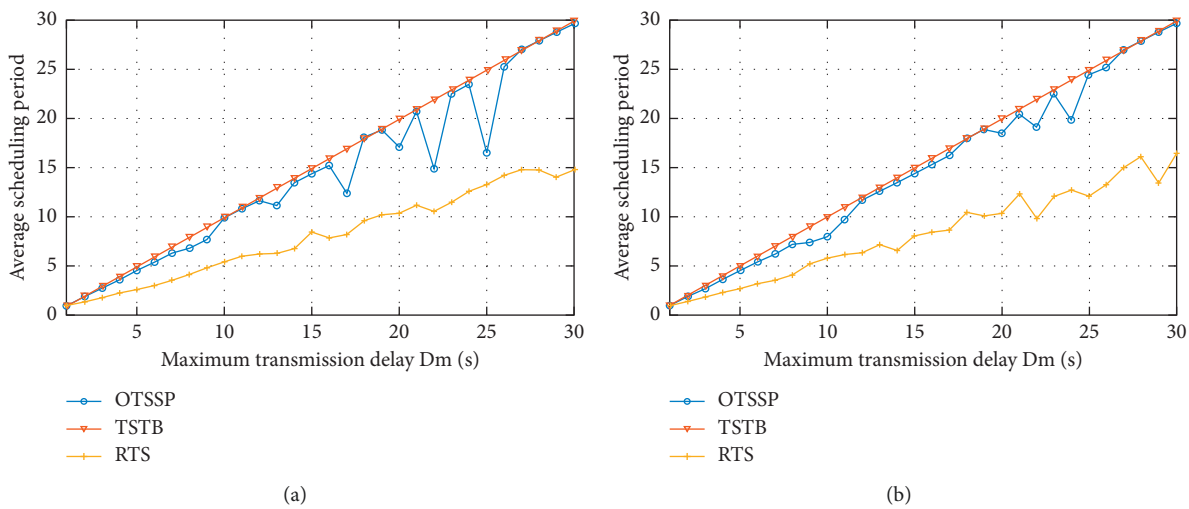


Figure 8: Comparison of the average scheduling period with different D_m. (a) Average scheduling period of the Rayleigh distribution. (b) Average scheduling period of the Rician distribution.

strategy and RTS strategy fluctuate in the growth process, while TSTB strategy shows a linear growth trend. Among the three strategies, RTS strategy has the smallest average scheduling period and TSTB strategy has the largest average scheduling period.

5. Conclusions and Further Work

With the rapid development of mobile networks and MCC, how to reduce the energy consumption of mobile terminals and cloud, improve energy efficiency, and improve users' QoE is a top priority. This paper mainly focuses on the optimization of energy consumption in MCC. Based on secretary problem with the lowest mean absolute ranking of the selected applicants, the paper proposes an admission rule that is superior to the top k candidates for energy consumption. Consider the maximum delay of data transmission and assume that the data generation rate is dynamic to build a data transmission queue model with multiple applications and an average energy consumption minimization model. In simulations, the proposed OTSSP strategy is compared with other related literature strategies. The OTSSP strategy has lower average energy consumption and higher energy efficiency. In addition, our strategy helps save decision-making time.

In the future work, the energy consumption model that is more in line with the actual situation of the network will be further constructed.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The simplified version is published in 2018 IEEE SmartWorld, https://ieeexplore.ieee.org/document/8560189/authors#authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

In this paper, each author participated sufficiently in the work to take public responsibility for appropriate portions of the content. Dr. Xin Zheng was responsible for the model proposed, Dr. Yu Nan, Dr. Ruiqing Song, and Dr. Gang-Zheng were responsible for the revised edition and supporting to publish, Dr. Fangsu Wang was responsible for writing the paper, Gaocai Wang was the supervisor, and Dr. Yuting Lu and Dr Qifei Zhao were responsible for simulation analysis and writing the paper.

Acknowledgments

This study was funded by the National Natural Science Foundation of China under Grant no. 61562006, in part by the Natural Science Foundation of Guangxi Province under Grant nos. 2013GXNSFGA019006 and 2016GXNSFBA380181, and in part by the Basic Ability Promotion Project for Young and Middle-aged Teachers in Universities of Guangxi under Grant no. 2018KY0640.

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