Traffic Prediction Based Capacity Pre-assignment Scheme for Low Latency in LEO Satellite Communication Systems

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Abstract. Low latency is an important index in LEO satellite communication systems, while the satellite capacity "application-assignment" scheme based on the DVB-RCS2 standard in the return channel causes a long round-trip delay. To improving the quality of experience (QoE), in this paper, a more aggressive capacity pre-assignment scheme combining traffic prediction and free capacity assignment (FCA) is proposed. The network control center (NCC) predicts traffic for every return channel satellite terminal (RCST) and assigns capacities in advance without capacity requests. Several FCA strategies based on multi-frequency time division multiple accesses (MF-TDMA) in the physical layer are analyzed as a compensatory capacity assignment method to deal with the inaccuracy of traffic prediction. Simulation results show that the proposed FCA strategies have better performance than existing FCA strategies.

Keywords: LEO satellite communication systems · Low latency · Network traffic · Traffic prediction · Self-similar model · Free capacity assignment · FARIMA · ARIMA

1 Introduction

As a part of the upcoming sixth-generation (6G) mobile communication network, the low earth orbit (LEO) satellite communication network will play an important role in the future for providing global coverage [1]. According to the 6G white paper [2], 6G will focus on the quality of experience (QoE), which has higher requirements in latency. However, satellite communication has inherent inferiority in latency, even it is the LEO satellite system. Generally speaking, the transmission delay in packet-based networks including access delay, propagation delay, and processing delay. The processing delay is relative to the processing performance and congestion control, which accounts for a tiny minority of the whole transmission delay when the traffic load is low. The propagation delay in LEO satellite communication systems is shortened by routing optimization in the inter-satellite link (ISL) [3]. In this paper, the access delay is what we are interested in.

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The second-generation digital video broadcasting return channel via satellite (DVB-RCS) protocol [4] defines the medium access scheme for the return channel (uplink channel) via satellite adopts a multi-frequency time division multiple access (MF-TDMA) approach. As shown in Fig. 1, the return channel satellite terminals (RCSTs) need to apply to the network control center (NCC) for capacity. The NCC periodically processes all the capacity requests (CR) received from RCSTs and runs the dynamic capacity allocation (DCA) algorithm to form a terminal burst time plan (TBTP) which is broadcasted to all the RCSTs through forwarding link. The RCSTs receive the TBTP and transmit signal in the specified time–frequency interval according to the TBTP. This round-trip delay may up to hundreds of milliseconds in LEO satellite communication systems depend on the distance between the RCST and the NCC. One of the problems caused by the round-trip delay is the mismatch between capacity requests and capacity assignments. Capacity assignments always lag behind capacity requests by a round-trip time (RTT). To tackle with the latency, the traffic prediction is used in the DBA for DVB-RCS2 systems [5]. The traffic prediction methods can be roughly divided into two categories: one is relying on proper statistical traffic modeling [6, 7] and the other is using a time series prediction model including ARIMA [8, 9], LSTM [10], BPNN [11], and so on.

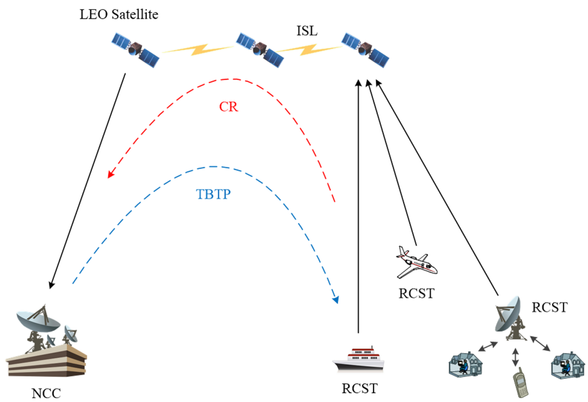

Fig. 1. The return channel via LEO satellites for capacity requests

However, the traffic prediction is inevitably inaccurate, especially when the traffic is relatively random, there will be a large deviation between the predicted traffic and the real traffic. A compensatory capacity assignment must be carried to satisfy the real capacity requests. The DVB-RCS2 standard provides five CR types including continuous rate assignment (CRA), rate-based dynamic capacity (RBDC), volume-based dynamic capacity (VBDC), absolute volume-based dynamic capacity (AVBDC) and free capacity assignment (FCA). Noticing that the FCA is not a true CR and it is trying to allocate the unused capacity to RCSTs. It seems that the FCA can be the compensatory capacity assignment method that assigns additional capacities on the basis of predicted capacity requests to RCSTs to satisfy the real capacity requests. As far as we know, there is no research on combining the traffic prediction and the FCA in the MF-TDMA structure, even the research on the strategy of FCA is rare.

The traffic prediction for DVB-RCS systems mentioned previously is generally carried out by the RCSTs and still need to send CR to the NCC. In this paper, based on the demand assigned multiple access (DAMA) protocol in the link layer and MF-TDMA structure in the physical layer, we propose a more aggressive capacity pre-assignment scheme for low latency in the LEO satellite communication system. The traffic prediction is implemented by the NCC and doesn't need the RCSTs' CR. Several FCA strategies are introduced to satisfy different performance requirements.

The rest of this paper is organized as follows: Sect. 2 introduces the FARIMA model for network traffic simulation and the ARIMA model for traffic prediction. In Sect. 3, several FCA strategies are analyzed from different points of view. Section 4 presents and analyzes the simulation results. Section 5 concludes the paper.

2 Traffic Prediction

2.1 Self-similar Traffic Model

The LEO satellite communication network provides Internet access services. It has been proved that the network traffic is self-similar [12] which has the nature of long-range dependence (LRD). That is to say, when the traffic flow is measured in a large range of time scales, the traffic flow will show self-similar characteristics. The common models for simulating the network traffic including the ON/OFF model [13], FARIMA model [14], FBM model [15], and so on. In fact, in our scheme, the traffic prediction operates in a short range of time scales. Therefore, the traffic model is required to describe both long-range and short-range dependence (SRD) simultaneously. The FARIMA model has better performance in that aspect, hence, we adopt the FARIMA model for its applicability in our simulations to simulate the network traffic. The FARIMA model generates self-similar traffic by driving an ARMA (p, q) process by a fractionally differenced noise FARIMA (0, d, 0), where d is a fractal coefficient and $0 < d < 0.5$. The details of the FARIMA model can refer to [14]. The steps to generate a FARIMA (p, d, q) by definition are as follows:

Step 1: Generating a white noise sequence ε_t with zero mean and variance equal to σ^2.

Step 2: Choosing an approximate value of d and doing fractional differencing on ε_t, we obtain fractional noise ω_t. The fractional differencing filter's unit impulse response is

$$h(n) = (-1)^n \binom{-d}{n} \tag{1}$$

where

$$\binom{-d}{n} = \frac{\Gamma(1-d)}{\Gamma(n+1)\Gamma(1-d-n)} = \frac{-d(-d-1)\cdots(-d-n+1)}{n!} \tag{2}$$

Step 3: Determining the approximate (p, q) combination and driving the ARMA (p, q) by the fractional noise ω_t. Finally, we obtain a FARIMA (p, d, q) series X_t which can simulate the self-similar traffic.

2.2 Traffic Prediction Model

The traffic prediction in our scheme is implemented on the NCC side. The NCC can record the traffic volume from each RCST over a period of time. Therefore, the only information the NCC needs to predict traffic is the previous traffic volume and the traffic prediction belongs to the time series prediction. As mentioned before, the time series prediction model including ARIMA, LSTM, BPNN, and so on. In the scheme we proposed, there are two points we have to note. Firstly, the traffic prediction method should be simple with less computation. The NCC needs to predict traffic for every RCST which leads to a huge computational burden for the NCC. Secondly, even though the network traffic has the LRD, the SRD affects the traffic prediction result much more because of the traffic prediction operates in a short range of time scales. Therefore we adopt the classical ARIMA model for the traffic prediction. Many papers preprocess the traffic before the ARIMA model to predict traffic for more accuracy. Such as Han and Li et al. combine wavelet transform and ARIMA [8, 9], Huang et al. combine ARIMA and artificial neural network (ANN) to deal with the linear part of the historical load data by ARIMA and the nonlinear part of historical load data by ANN [16]. Under the computing power allows, the more prediction accuracy the better. But in this paper, we just use the ARIMA model as long as the model extracts enough information from the traffic time series, and the residual error between real data and predicted data obeys normal distribution which means there is little information that can be extracted from the residual error.

We obtained the real network traffic which is the daily traces at the transit link of WIDE to the upstream ISP (Internet Service Provider) from the *MAWI Working Group of the WIDE Project* [17]. The real traffic packets are counted every 100 ms and it is assumed that all the packets are identical without loss of generality. Figure 2 shows the 200 points of real traffic time series prediction result by the ARIMA method. We can see that the real traffic has strong randomness that the traffic prediction is not enough

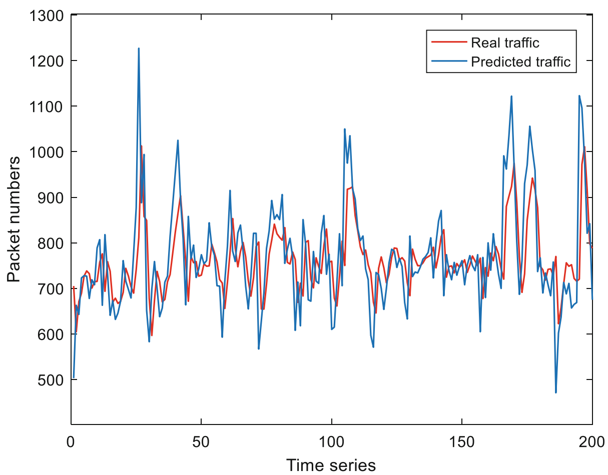

Fig. 2. The real traffic time series prediction result by the ARIMA method

to satisfy the traffic demand. Figure 3 shows the normal distribution fitting of residual error about 1000 points of real traffic time series prediction results. The residual error basically accords with zero mean normal distribution which is a benefit for the analysis of FCA strategies introduced in the next section.

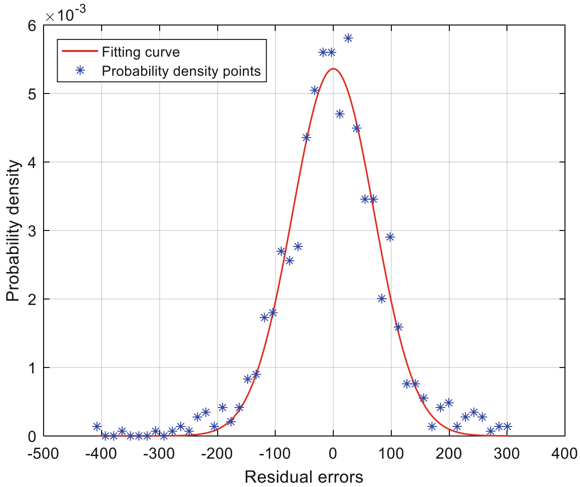

Fig. 3. The normal distribution fitting of residual errors

3 FCA Strategies

After the NCC predicted traffic for the RCSTs, the DCA algorithm calculates the capacity satisfying the predicted traffic demand for each RCST. More concretely, the capacity in the MF-TDMA approach is the timeslot. When there are timeslots remain unused, the unused timeslots can be appropriately assigned to each RCST. Assuming that the capacity assign cycle is a superframe period, for example, 265 ms. Let T_{tot} denotes the total timeslots in a superframe. N_T denotes the number of RCSTs. R_i denotes the average number of packets that the i th RCST can transmit per timeslot depends on channel conditions, where $1 \leq i \leq N_T$. C_i and C_i^* denote the real and predicted number of packets respectively that the i th RCST will transmit, where $\sum_{i=1}^{N_T} \frac{C_i^*}{R_i} < T_{tot}$. σ_i^2 denotes the variance of the residual error of the traffic prediction for the i th RCST and the corresponding residual error distribution is

$$g_i(c) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{c^2}{2\sigma_i^2}} \tag{3}$$

where $c = C_i - C_i^*$. The FCA strategy assigns the unused timeslots into N RCSTs, represented as $X = \{x_1, x_2, ..., x_{N_T}\}$.

3.1 The Strategy of Fairness

A fair FCA strategy is assigning the unused timeslots to the RCSTs to make every RCST has an equal expected satisfaction rate $E[R_s]$. The satisfaction rate for the ith RCST is defined as

$$R_s^i = \begin{cases} 0, & x_i R_i + C_i^* < C_i \\ 1, & x_i R_i + C_i^* \geq C_i \end{cases} \tag{4}$$

Let $x = C_i - C_i^*$ we have

$$E\left[R_s^i\right] = \int_{-\infty}^{x_i R_i} g_i(x)dx \tag{5}$$

Let $E\left[R_s^i\right] = E\left[R_s^j\right]$, we have

$$\frac{x_i R_i}{\sigma_i} = \frac{x_j R_j}{\sigma_j} \tag{6}$$

The X is subjected to

$$\sum_{i=1}^{N_T} \frac{C_i^*}{R_i} + x_i = T_{tot} \tag{7}$$

Combining (6) and (7) we have

$$x_i = \left(T_{tot} - \sum_{j=1}^{N_T} \frac{C_j^*}{R_j} \right) \frac{\frac{\sigma_i}{R_i}}{\sum_{j=1}^{N_T} \frac{\sigma_j}{R_j}} \tag{8}$$

3.2 The Strategy of Minimizing Wasted Timeslots

When the assigned timeslots are far more than the RCSTs require, redundant timeslots are wasted. The more redundant timeslots for some RCSTs, the more likely the assigned timeslots are unsatisfied with other RCSTs. Hence, reducing wasted timeslots is equal to increasing the satisfaction rate. We hope the wasted timeslots to be minimized.

The timeslots waste function is constructed as

$$W(X) = \sum_{i=1}^{N_T} \max\left\{ x_i + \frac{C_i^*}{R_i} - \frac{C_i}{R_i}, 0 \right\} \tag{9}$$

The expected value $W(X)$ is

$$E[W(X)] = \sum_{i=1}^{N_T} \int_{-\infty}^{x_i} (x_i - x) f_i(x) dx \tag{10}$$

where $f_i(x) = g_i(xR_i)$. The problem of minimizing wasted timeslots can be modeled as

$$\begin{aligned} & opt.\ \min_X \sum_{i=1}^{N_T} \int_{-\infty}^{x_i} (x_i - x) f_i(x) dx \\ & s.t.\ \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} + x_i = T_{tot} \end{aligned} \tag{11}$$

Obviously, this problem can be solved by convex optimization method, and the Lagrange function of problem (11) is

$$U(X;\lambda) = \sum_{i=1}^{N_T} \int_{-\infty}^{x_i} (x_i - x) f_i(x) dx + \lambda \left(T_{tot} - \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} - x_i \right) \tag{12}$$

Let the partial derivative of $U(X;\lambda)$ being zero, we obtain

$$\begin{cases} \int_{-\infty}^{x_i} f_i(x) dx - \lambda = 0 \\ T_{tot} - \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} - x_i = 0 \end{cases} \tag{13}$$

Combining (13) and $f_i(x) = g_i(xR_i)$ we have

$$x_i = \left(T_{tot} - \sum_{j=1}^{N_T} \frac{C_j^*}{R_j} \right) \frac{\frac{\sigma_i}{R_i}}{\sum_{j=1}^{N_T} \frac{\sigma_j}{R_j}} \tag{14}$$

Noticing that the result of minimizing expected wasted timeslots is the same as the result of an equal expected satisfaction rate.

3.3 The Strategy of Maximizing Throughput

The throughput for the ith RCST is $\min\{x_i R_i, C_i\}$. We construct the throughput function as

$$M(X) = \sum_{i=1}^{N_T} \min\{C_i^* + x_i R_i, C_i\} \tag{15}$$

The expected value $M(X)$ is

$$E[M(X)] = \sum_{i=1}^{N_T} \left[\int_{-\infty}^{x_i} x R_i f_i(x) dx + \int_{x_i}^{+\infty} x_i R_i f_i(x) dx + C_i^* \right] \tag{16}$$

The problem of maximizing throughput can be modeled as

$$\begin{aligned} & opt. \quad \max_{X} \sum_{i=1}^{N_T} \left[\int_{-\infty}^{x_i} xR_if_i(x)dx + \int_{x_i}^{+\infty} x_iR_if_i(x)dx \right] \\ & s.t. \quad \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} + x_i = T_{tot} \end{aligned} \tag{17}$$

It also can be proved that (17) is a convex problem, and the Lagrange function of problem (17) is

$$V(X;u) = \sum_{i=1}^{N_T} \left[\int_{-\infty}^{x_i} xR_if_i(x)dx + \int_{x_i}^{+\infty} x_iR_if_i(x)dx \right] + u\left(T_{tot} - \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} - x_i \right) \tag{18}$$

Let the partial derivative of $V(X;u)$ being zero, we obtain

$$\begin{cases} R_i \int_{x_i}^{+\infty} f_i(x)dx - u = 0 \\ T_{tot} - \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} - x_i = 0 \end{cases} \tag{19}$$

Combining (19) and $f_i(x) = g_i(xR_i)$ we have

$$\begin{cases} x_i = F_i^{-1}\left(1 - \frac{u}{R_i}\right) \\ \sum_{i=1}^{N_T} F_i^{-1}\left(1 - \frac{u}{R_i}\right) = T_{tot} - \sum_{i=1}^{N_T} \frac{C_i^*}{R_i} \end{cases} \tag{20}$$

where $F_i^{-1}(\cdot)$ is the inverse function of $F_i(\cdot)$ and $F_i(\cdot)$ is the cumulative distribution function of $f_i(\cdot)$.

4 Performance Evaluations

The FCA strategies analyzed in Section III can be integrated into two categories. For simplicity, in this paper, the strategies of fairness and minimizing wasted timeslots are abbreviated as FCA-F, and the strategy of maximizing throughput is abbreviated as FCA-MT. For comparison, another two FCA strategies used in the Combined Free/Demand Assignment Multiple Access (CFDAMA) protocol which is a TDMA based access scheme are introduced. In CFDAMA protocols, after demand assignment, the unused timeslots can be assigned to all the ground terminals in round-robin fashion [18] or weighted free assignment fashion [19]. We abbreviate the round-robin fashion FCA as FCA-RR and the weighted free assignment fashion FCA as FCA-WFA. To simulate various network traffics, we generate different FARIMA (p, d, q) sequences plus different traffic mean values C_m to represent the packets sequences the RCSTs transmit. The simulation parameters are shown in Table 1. In the simulations below, we adopt the time average substitute for statistical expectation. The average traffic load is defined as the mean value of timeslots that the RCSTs request and the average traffic load divides total timeslots per superframe T_{tot} for normalization.

Table 1.

Parameter	Value
Network traffic parameter	
White noise sequence variance σ^2	50–500
Fractal coefficient d	0–0.5
ARMA parameter p	0.6–0.9
ARMA parameter (q_1, q_2)	(0.3–0.5, 0.1–0.3)
Traffic mean value C_m	500–5000
Satellite system parameter	
RCSTs number N_T	10, 30, 80
Superframe period	265 ms
Total timeslots per superframe T_{tot}	848
Packets transmitted per timeslot R_i	40–80

Figure 4 compared the expected satisfaction rate of four FCA strategies with the RCSTs number is 10. The min SR and max SR denote the minimum and maximum average satisfaction rate in 10 RCSTs, respectively. The smaller difference between max SR and min SR, the fairer. As we can see, in terms of fairness, the two FCA strategies we proposed significantly better than the FCA-RR and the FCA-WFA. The FCA-F is the fairest that almost all the RCSTs have the same expected satisfaction rate.

Figure 5 compared the throughput of three FCA strategies with the RCSTs number is 10. As analyzed before, the FCA-MT has maximum throughput compare to the other three FCA strategies. In terms of throughput, the FCA-MT > FCA-F > FCA-WFA > FCA-RR.

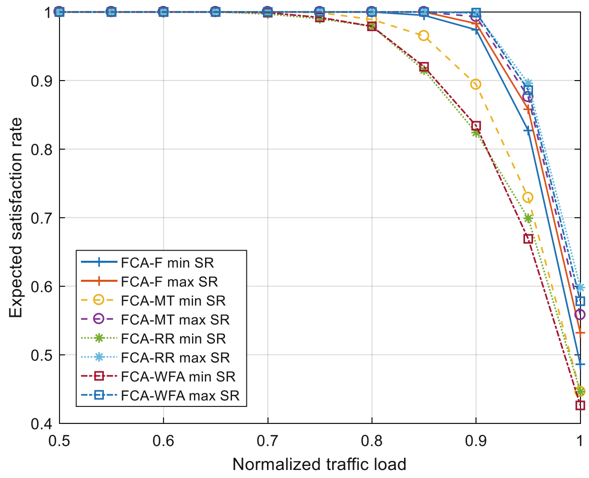

Fig. 4. Fairness comparison between three FCA strategies

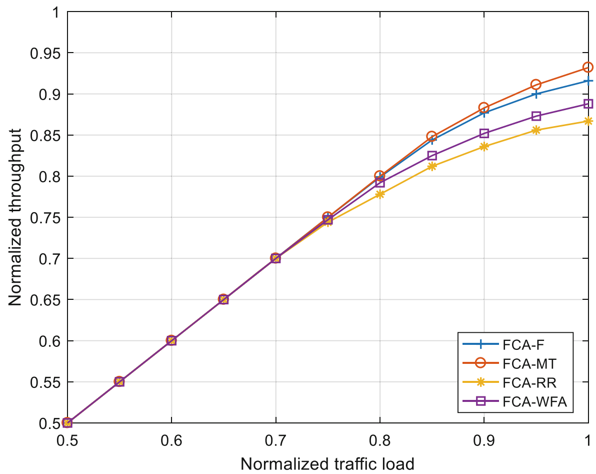

Fig. 5. Throughput comparison between four FCA strategies

Another interesting data is the influence of the number of RCSTs. Figure 6 compared the throughput uses the FCA-MT when the number of RCSTs is 10, 30, and 80. As the number of RCSTs increases, the throughput is descending with the same traffic load. Therefore, to obtain a higher satisfaction rate and throughput, the free capacity must be sufficient and the number of RCSTs should be limited, which means that the scheme we proposed is more suitable for non-high-load scenarios.

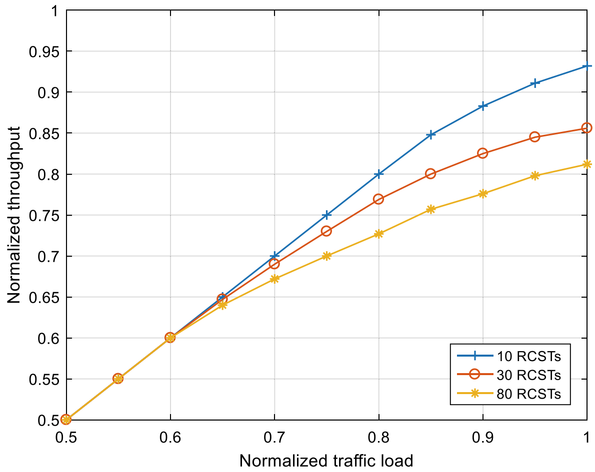

Fig. 6. Throughput comparison between different RCSTs numbers

5 Conclusion

In this paper, a novel capacity pre-assignment scheme combines traffic prediction and FCA is proposed. We adopt the FARIMA model for network traffic simulation and the ARIMA model for traffic prediction. Several FCA strategies are analyzed to appropriately assign unused timeslots based on MF-TDMA in the physical layer. Simulations show that our scheme can achieve a high expected satisfaction rate in non-high-load scenarios, but the throughput is limited in high-load scenarios. In our future work, the traffic will be further classified to make the traffic prediction more accurate which makes our scheme available for high-load scenarios.

References

1. Giordani, M., Zorzi, M.: Non-terrestrial communication in the 6G era: challenges and opportunities. Submitted to the IEEE (2019). https://arxiv.org/abs/1912.10226?context=cs.NI
2. Aazhang, B., Ahokangas, P., Alves, H., et al.: Key drivers and research challenges for 6G ubiquitous wireless intelligence (white paper) (2019)
3. Yan, D., Wang, L.: TPDR: traffic prediction based dynamic routing for LEO&GEO satellite networks. In: 2015 IEEE 5th International Conference on Electronics Information and Emergency Communication, pp. 104–107. IEEE, Beijing (2015)
4. ETSI EN 301 545–2 V1.2.1: Digital Video Broadcasting (DVB); Second Generation DVB Interactive Satellite System (DVB-RCS2); Part 2: Lower Layers for Satellite standard, April 2014
5. Priscoli, F.D., Pompili, D.: A demand-assignment algorithm based on a Markov modulated chain prediction model for satellite bandwidth allocation. Wireless Netw. **15**(8), 999–1012 (2009)
6. Chiti, F., Fantacci, R., Pecorella, T., Giacomelli, L., et al.: An improved dynamic bandwidth allocation scheme based on traffic prediction for DVB-RCS systems. In: The 1st International Conference on Advanced Satellite Mobile Systems ASMS, pp. 254–263. European Space Agency (Special Publication), Frascati (2003)

7. Lygizou, A., Xergias, S., Passas, N.: Video traffic prediction for improved scheduling in joint WiMAX/satellite networks. In: 8th International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 1017–1022. IEEE, Limassol (2012)
8. Han, Y., Li, D., Guo, Q., Wang, Z., Kong, D.: Self-similar traffic prediction scheme based on wavelet transform for satellite internet services. In: Huang, X.-L. (ed.) MLICOM 2016. LNICSSITE, vol. 183, pp. 189–197. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-52730-7_19
9. Li, C., Han, Y., Sun, Z.M., et al.: A novel self-similar traffic prediction method based on wavelet transform for satellite internet. EAI Endorsed Trans. Ambient Syst. **4**(14), 1–5 (2017)
10. Han, C., Liu, A.J., Huo, L., et al.: A prediction-based resource matching scheme for rentable LEO satellite communication network. IEEE Commun. Lett. **24**(2), 414–417 (2020)
11. Cheng, S.Y., Zhou, X.M.: Network traffic prediction based on BPNN optimized by self-adaptive immune genetic algorithm. In: International Conference on Mechatronic Sciences, Electric Engineering and Computer (MEC), pp. 1030–1033. IEEE, Shengyang (2013)
12. Na, Z., Gao, Z., Guo, Q.: performance analysis of self-similar traffic in LEO satellite network. In: International Conference on Machine Learning and Cybernetics, pp. 2649–2652. IEEE, Hong Kong (2007)
13. Marvi, M., Aijaz, A., Khurram, M.: On the use of ON/OFF traffic models for spatio-temporal analysis of wireless networks. IEEE Commun. Lett. **23**(7), 1219–1222 (2019)
14. Liu, J.K., Shu, Y.T., Zhang, L.F., et al.: Traffic modeling based on FARIMA models. In: IEEE Canadian Conference on Electrical and Computer Engineering, pp. 162–167. IEEE, Alberta (1999)
15. Tan, X., Huang, Y., Jin, W.: Modeling and performance analysis of self-similar traffic based on FBM. In: International Conference on Network and Parallel Computing Workshops, pp. 543–548. IEEE, Liaoning (2007)
16. Huang, H.Q., Tang, T.H.: Short-term traffic flow forecasting based on ARIMA-ANN. In: International Conference on Control and Automation, pp. 2370–2373. IEEE Guangzhou (2007)
17. MAWI Working Group Traffic Archive Homepage. https://mawi.wide.ad.jp/mawi/
18. Mitchell, P.D., Grace, D., Tozer, T.C.: Comparative performance of the CFDAMA protocol via satellite with various terminal request strategies. In: IEEE Global Telecommunications Conference, pp. 2720–2724. IEEE, San Antonio (2001)
19. Zhou, X., Wang, Z.J., Cao L.H., She, Y.: Performance of CFDAMA-CFA multiple access protocol via satellite. In: 1st International Symposium on Systems and Control in Aerospace and Astronautics, pp. 1038–1040. IEEE, Harbin (2006)