Traffic Prediction-based Load-Balanced Routing Strategy for Mega LEO Satellite Optical Networks

Yajun Li
Zhengzhou University
Zhengzhou, China
liyajun@gs.zzu.edu.cn

Ruijie Zhu
Zhengzhou University
Zhengzhou, China
zhuruijie@zzu.edu.cn

Yudong Zhang
Zhengzhou University
Zhengzhou, China
zhang_zyd@163.com

Qiancheng Zhao
Zhengzhou University
Zhengzhou, China
1603765617@qq.com

Chao Xi
Space Star Technology CO., LTD.
Beijing, China
xichaofh@163.com

Bo Yang
Space Star Technology CO., LTD.
Beijing, China
bagoiyb@126.com

***Abstract*—We propose a Traffic Prediction-based Load-Balanced Routing (TPLBR) strategy for satellite optical networks solving the satellite node overload problem. Simulation results show that TPLBR can result in less packet loss and balanced queue occupancy.**

Keywords—traffic prediction, load-balanced routing, satellite optical networks, overload problem, node selection

I. Introduction

With the advent of satellite communication technology, the mega Low Earth Orbit (LEO) satellite networks are carrying an increasing volume of services. An effective routing strategy is particularly crucial. However, transport demand in LEO with global coverage is non-uniform [1]. Satellites have higher communication loads in developed areas than in rural areas. In the traditional shortest-path routing strategy, satellites accumulate traffic through developed areas, which is prone to overload and congestion problems at the satellite nodes [2]. To relieve network congestion at network nodes, it is crucial to address the issue of uneven traffic distribution.

The extraction of state and traffic features in satellite networks has been an important research direction. In recent years, the development of machine learning techniques has provided a new approach to automatically extract state and traffic features in satellite networks [3]. Machine learning techniques can learn complex features from large amounts of data in satellite networks and predict future traffic. However, existing algorithms still face several challenges. Extreme Learning Machine based Distributed Routing (ELMDR) only considers the traffic distribution density on the surface but does not consider network historical information [4].

In this paper, we design a traffic prediction-based load-balanced routing strategy (TPLBR) that satisfies load balancing to address the network congestion problem in the routing process. The federated learning traffic prediction model obtains nonlinear traffic. Satellite nodes only transmit model parameters update information instead of real traffic data, which reduces the network information transmission overhead. The optimal path is computed by considering the traffic prediction results and link delays comprehensively.

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II. System Description

A. LEO Satellite Constellation Modeling

LEO satellite optical network mainly consists of satellite nodes and inter-satellite links (ISLs). The satellite network is modeled as an undirected graph $G(N, L)$, where $Node$ is the set of satellite nodes and $Link$ is the set of ISLs [5]. The topology modeling considers the highly dynamic problem of the high-speed motion of a network of low-orbit satellites.

The satellite operation cycle is divided into multiple short time slices $G^T(N^T, L^T)$, where T is the set of time slices. The satellite $node_i^t \in Node^t$ can establish two intra-orbit links with two neighboring satellites in the same orbital plane at time $t \in T$ [6], and two ISLs with two neighboring satellites $< node_{i-orb}^t, node_{i+orb}^t >$ in the adjacent orbital plane, where orb is the number of satellites per orbit.

Designing a satellite load-balanced routing strategy is crucial to solving the problem of link congestion and load imbalance in satellite networks. First collect the historical traffic information in the network $< ISL_i^t, ground_i^t >$, where ISL_i^t is the set of 4 ISL traffic information between satellite $node_i^t \in Node^t$ and neighboring nodes [7], and $ground_i^t$ is the traffic information of the geographic area where $node_i^t$ is located.

B. Federated learning traffic prediction model

To address the problem of topological flow in satellite networks, we adopt a federated learning approach to predict historical traffic patterns, as illustrated in Fig. 1. The ground station acts as the server for updating the global model parameters, while the satellite node is chosen as the client for updating the local model parameters [8]. Each satellite node holds a set of local parameters, denoted as w_i, to train the prediction model. A federated learning model is constructed for each satellite $node_i^t \in Node^t$, with model parameters denoted as w_i.

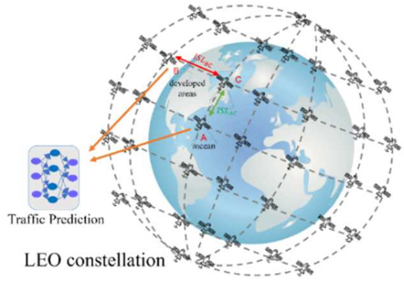

Fig. 1. Traffic prediction in LEO constellation.

Specifically, each satellite node maintains historical traffic data $< ISL_i^t, ground_i^t >$ locally. The ground station selects a set of visible satellite nodes, $< Clent_k^t, Clent_{k+1}^t, \dots, Clent_{k+j}^t >$, and randomly chooses satellite nodes $node_i^t \in < Clent_k^t, Clent_{k+1}^t, \dots, Clent_{k+j}^t >$, as the clients for local model parameter updates during each federated learning round. Meanwhile, the ground station employs the global model parameters w_a for parameter updates. As the number of iterations in federated learning increases, the local model parameters at each satellite node are continuously updated and improved, leading to a more accurate and stable predictive model [9]. This model leverages historical traffic information from ISL networks and geographically distributed traffic information to predict the traffic load of satellite nodes in advance at the beginning of each time slice. This approach enables nodes with lower load levels to be selected for data forwarding, accommodating the complex network topology and Quality of Service (QoS) requirements of the service [10].

III. Description of Traffic Prediction-based Load-Balanced Routing Strategy

Developing load-balanced routing strategies is essential to alleviate link congestion and load imbalance in satellite networks. To achieve this goal, the first step is to collect the historical traffic information in the network. Specifically, each satellite node in the LEO constellation collects the traffic load information from its coverage area, including the traffic from neighboring nodes in the ISL and the traffic from terrestrial users. This information is used to determine the traffic load at each node, which is a crucial factor for load-balanced routing. To predict the traffic load at each satellite node, this strategy proposes a satellite forwarding traffic prediction model using federated learning. The model consists of two stages: local training of nodes and global parameter aggregation. Each satellite node trains a local model using its traffic load information, and the global model is generated by aggregating the local models from all nodes. This federated learning approach ensures the privacy of the traffic data while enabling accurate traffic load prediction for each node.

All user traffic in the coverage area of a satellite node in LEO, together with the traffic from neighboring satellite nodes, determines its traffic load [11]. Firstly, satellite node i collects historical traffic load, including traffic from neighboring nodes ISL_i and traffic from terrestrial users $ground_i$. As shown in Fig. 2, a satellite forwarding traffic prediction model using federated learning [12], including node local training and global parameter aggregation.

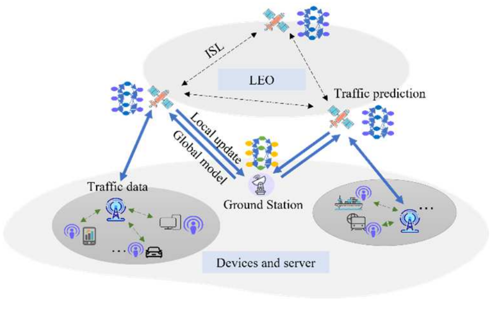

Fig. 2. Federated learning traffic prediction model training process.

Each satellite node client in the system is required to train a local network. The specific procedure for training the local model is as follows: the satellite client i receives the global model w_a from the server, and then initializes the local model parameters $w_0 = w_a$. The local state training data set consists of temporal information, which is denoted as $\{< ISL_i^{t-k}, ground_i^{t-k} >, \dots, < ISL_i^{t-1}, ground_i^{t-1} >\}$, and the training label is $< ISL_i^t, ground_i^t >$.

A model gradient descent algorithm is employed to optimize the local model and obtain the model parameters w_1 for a single local iteration of the node. After E rounds of local iterations, the satellite client obtains the local model parameters w_E. Then, $\Delta w_{a+1} = w_E - w_a$ is uploaded to the server by each client for parameter aggregation. The server aggregates the parameters from all satellite nodes, updates the global parameter model w_a for the next training round, and sends it back to each satellite client.

After T rounds of training, the server obtains the final global model parameters by aggregating the received parameters from all satellite nodes. The aggregation process typically involves a weighted sum of parameters, where each node is assigned a weight proportional to its number of training samples or its computational capacity. The aggregated parameters represent the optimal model learned from the distributed data of all satellite nodes. The server can then use the global model to predict future traffic in the satellite network and design a load-balanced routing strategy. It is worth noting that the final global model parameters reflect the collaborative efforts of all satellite nodes, as each node contributes its local knowledge to the model without revealing its private data. As shown in Fig. 3, the proposed traffic prediction model enables efficient and privacy-preserving collaboration among distributed edge devices.

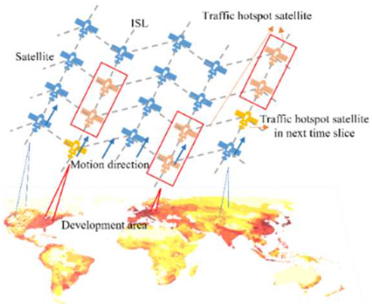

Fig. 3. Traffic condition in dynamic satellite topology.

ISL cost can be defined as $Cost_{s,v} = D_{s,v}/c$, $D_{s,v}$ is the distance from satellite s to satellite v, c is the speed of light [13]. The distance is stored at the satellite nodes based on the constellation parameters. Then the degree of loading of the satellite at the next instant is:

$$\xi(t) = \frac{(Q-q_t)\times avg_d + C\times\Delta t - (ISL_i^t + ground_i^t)}{B}, \tag{1}$$

where $ISL_i^t + ground_i^t$ is the predicted node service volume at the next moment, Δt is the time interval, avg_d denotes the average packet size, Q denotes the total satellite node queue length, q_t denotes the node queue occupancy length at moment t, B denotes the cache size and C denotes the satellite link capacity. The node load level is calculated using federated learning traffic prediction. The ISL cost adjustment factor is defined based on the node load level as:

$$\gamma = \frac{1}{1 + \exp(-\alpha\xi)}, \tag{2}$$

where a is the slope parameter. When users send service transmission requests, the ISL cost $Cost_{s,v}$ in the transmission process should be minimized. By minimizing the ISL cost during transmission, the proposed system enables efficient and reliable data transmission among satellite nodes. The use of traffic prediction and load-balanced techniques can further improve the system performance and ensure the optimal utilization of network resources.

The traffic prediction-based load-balanced routing strategy is designed to avoid congestion in satellite networks and ensure efficient utilization of network resources. To achieve this, the system employs a path selection strategy that prioritizes intermediate nodes with lower load levels. Specifically, the path cost from the source node s to the destination node d is calculated based on the ISL cost $Cost_{s,v}$ and the ISL cost adjustment factor γ, the path cost can be obtained as:

$$Path_{s,d} = \sum_{i=1}^{m} \frac{\gamma_{n_i} + \gamma_{n_i+1}}{2} * Cost_{n_i,n_{i+1}}, \tag{3}$$

where n_i is an intermediate node on the path, s is the source node and d is the destination node. The path cost is calculated as the sum of the product of the ISL cost adjustment factor and the corresponding ISL cost along the path from the source node to the destination node. The ISL cost adjustment factor γ is calculated based on the degree of loading of each intermediate node along the path. Path cost computation is thus a dynamic process that takes into account current network load conditions and adapts to changes in traffic patterns and network topology.

The satellite network topology map is updated based on the computed path cost, which reflects the relative weight of each link in the network. The weights of each link in the network are updated to reflect the path cost, and this information is used to guide the routing decisions made by the network nodes. By prioritizing intermediate nodes with lower load levels in the path selection process, the proposed system can effectively prevent congestion and ensure reliable data transmission in satellite networks.

The weights of the set of links in $G^t(N^t, L^t)$ are updated dynamically at the beginning of each time slice t based on the historical traffic data. Specifically, the link weights are updated by considering the congestion level and link quality, while the node weights are updated based on the link weights and node degree centrality. As shown in Fig. 4, the model can capture the dynamic changes in network traffic and adapt the weights accordingly, enabling load-balanced routing policies.

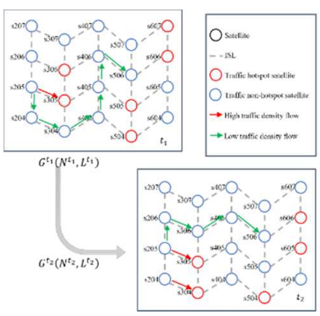

Fig. 4. Satellites s205 to s506 will rapidly switch path selections when time slices change because path cost computation is a dynamic process.

When a user request arrives, the source node s and destination node d are identified and the available path between the two nodes is traversed using the Dijkstra algorithm. The routing cost is computed as the sum of the link weights along the path. The path with the minimum cost $Min(Path_{s,d})$ is selected as the optimal path for the user request. By dynamically updating the weights and selecting the optimal path, our model achieves load balancing and a low packet loss rate, which is critical for satellite communication systems.

IV. Simulation Results and Discussion

We compared the performance of TPLBR with Extreme Learning Machine-based Distributed Routing (ELMDR) and Dijkstra Short Path (DSP). One option to further enhance the performance of the satellite network is to adopt a Walker constellation as the topology of the satellite network. A Walker constellation has the advantage of providing better global coverage and less frequent satellite handovers than a Polar constellation. In this paper, we adopt the Walker constellation with an altitude of 550 km and an inclination of 57 degrees. The simulated satellite network is the Starlink constellation. The constellation consists of 1440 satellites and 72 orbits, where the same number of satellites are distributed in each orbit. The data source used in the experiments is generated from a Poisson distribution. The dataset is divided into a training and a test set with 4/5 and 1/5, respectively.

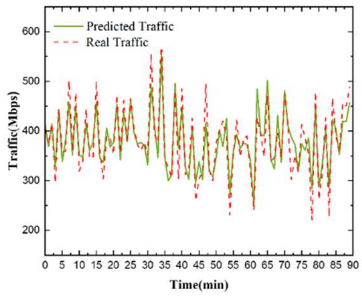

Fig. 5. Network traffic predicted results.

The traffic prediction result is shown in Fig. 5. It can be seen that the federated learning model can effectively predict future traffic and capture the complex nonlinear features of satellite communication traffic. This model exhibits high reliability and applicability by accurately predicting the trends and values of actual traffic. The proposed approach can effectively handle the nonlinear and volatile features of satellite communication traffic. Accurate traffic prediction is crucial for the subsequent computation of the minimum load path.

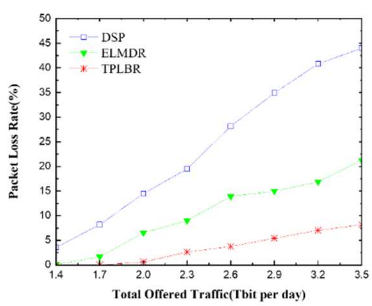

Fig. 6. Packet loss rate of different traffic.

Fig. 6 shows the results of the total packet loss rate for each scheme for different total traffic settings, and it can be seen that TPLBR has the lowest packet loss rate for all traffic volumes. When the total traffic volume is below 2.3 Tbit per day, the TPLBR packet loss rate is close to 0. However, DSP lacks satellite network load condition acquisition, which results in packet loss for heavily loaded satellites, which can occur at a rate of 5 to 15 percent. The ELMDR routing decision is based on the traffic prediction of the Earth's surface distribution density, which results in a lower packet loss rate than DSP. However, since it does not utilize network history information. The prediction is not valid and the packet loss rate is higher than TPLBR. The packet loss rate increases for all three algorithmic satellites when the total traffic exceeds 2.3 Tbit per day. TPLBR introduces a federated learning traffic prediction mechanism that reduces the priority of nodes if they are heavily loaded, such that the packet loss rate is always lower than DSP and ELMDR.

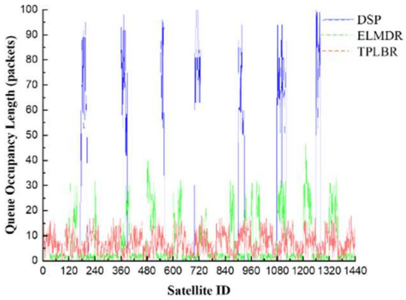

Fig. 7. Queue occupancy for each satellite.

Fig. 7 shows that satellite nodes passing through high-load regions have large queue occupancy because the DSP does not account for the uneven traffic distribution. ELMDR takes into account the inhomogeneous traffic density distribution on the Earth's surface and reduces the inter-satellite forwarding task for satellites in highly loaded regions. As a result, the occupancy of these satellite cohorts is lower than that of the DSP. However, since historical traffic information is not taken into account, accurate prediction is not possible, and some satellite nodes still have high queue occupancy. The TPLBR satellite nodes have the lowest average queue occupancy. This indicates that the traffic prediction adjusts the ISL weights in real-time, which alleviates the network congestion.

V. Conclusion

In this paper, we propose a novel traffic prediction-based load-balanced routing strategy in satellite networks. Our proposed model exploits the distributed computing resources of edge devices and trains a global model via federated learning. Local models are trained using data generated by individual edge devices and only updated model parameters are transmitted to the server for aggregation. Simulation results demonstrate that the proposed model can effectively capture the complex and nonlinear features of satellite communication traffic and predict future traffic with high accuracy. Furthermore, our model achieves load-balanced routing with a low packet loss rate, which is important for designing and operating satellite communication systems. The proposed approach has significant potential for applications in other scenarios involving large-scale and dynamic network traffic.

References

[1] N. Torkzaban, A. Gholami, and J. S. Baras, "Joint satellite gateway placement and routing for integrated satellite-terrestrial networks." ICC 2020-2020 IEEE International Conference on Communications (ICC), pp. 1-6, June 2020.

[2] R. Zhu, S. Li, et al., "Energy-efficient Deep Reinforced Traffic Grooming in Elastic Optical Networks for Cloud-Fog Computing," *IEEE Internet of Things Journal*, vol.8, no.15, 2021.

[3] R. Zhu, A. Samuel, et al., "Survival Multipath Energy-aware Resource Allocation in SDM-EONs during Fluctuating Traffic," *IEEE Journal of Lightwave Technology*, vol. 39, no. 7, 2021.

[4] H. Al-Hraishawi, S. Chatzinotas, and B. Ottersten, "Broadband non-geostationary satellite communication systems: Research challenges and key opportunities." 2021 IEEE International Conference on Communications Workshops (ICC Workshops), pp. 1-6, June 2021.

[5] T. Ricker, K. Salehin, and Y. wang, "A Machine Learning Approach to Estimating Queuing Delay on a Router over a Single-Hop Path." ICC 2022-IEEE International Conference on Communications (ICC), pp. 2720-2725, May 2022.

[6] R. Secchi and A. Gotta, "Exploring Machine Learning for Classification of QUIC Flows over Satellite." ICC 2022-IEEE International Conference on Communications (ICC), pp. 4709-4714, May 2022.

[7] R. Goścień and P. Ksieniewicz, "Efficient dynamic routing in Spectrally-Spatially Flexible Optical Networks based on traffic categorization and supervised learning methods" Optical Switching and Networking, 2022.

[8] G. Ruan, T. Pan, C. Lu, "Lightweight Route Flooding via Flooding Topology Pruning for LEO Satellite Networks." ICC 2022-IEEE International Conference on Communications (ICC), pp. 1149-1154, May 2022.

[9] R. Zhu, L. Li, et al., "Multi-Agent Broad Reinforcement Learning for Intelligent Traffic Light Control," *Information Science*, vol.619, no.1, 2022.

[10] J. Li, N. Hua, and Y. Li, "Delay Advantage of Optical Satellite Networks (OSN) in Long-Distance Transoceanic Communication. " 2022 Optical Fiber Communications Conference and Exhibition (OFC), pp. 01-03, March 2022.

[11] R. Zhu, S. Wu, L. Li, P. Lv, M. Xu, "Context-Aware Multi-Agent Broad Reinforcement Learning for Mixed Pedestrian-Vehicle Adaptive Traffic Light Control," *IEEE Internet of Things Journal,* vol.9, no.20, 2022.

[12] Q. Yu, H. Wang, and D. Jin, "Network Traffic Overload Prediction with Temporal Graph Attention Convolutional Networks." 2022 IEEE International Conference on Communications Workshops (ICC Workshops), pp. 885-890, May 2022.

[13] R. Zhu, G. Li, Y. Zhang, et al., "Load-Balanced Virtual Network Embedding Based on Deep Reinforcement Learning for 6G Regional Satellite Networks," *IEEE Transactions on Vehicular Technology*, 2023.