MPAEE: A Multipath Adaptive Energy-Efficient Routing Scheme for Low Earth Orbit-Based Industrial Internet of Things

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***Abstract*—The low Earth orbit (LEO) constellation has great potential for global coverage and high-capacity transmission. However, poor reliability and high energy consumption can severely affect the routing transfer performance. In this article, a multipath adaptive energy-efficient (MPAEE) routing scheduling scheme for LEO constellations is designed. A static weight multipath (SWM) routing scheme is proposed initially, extending single-path routing to multipath routing to simulate route scheduling in large-scale constellations accurately. To further address the limitations of static weight allocation in adapting to dynamic network changes, a particle swarm optimization-based dynamic weight multipath (PSODWM) routing scheme is proposed, considering transmission delay, energy consumption, capacity, and packet loss rate, thereby achieving an optimal multipath load distribution without additional resource consumption. Finally, leveraging the neural population dynamics optimization algorithm (NPDOA) and digital twin technology, the MPAEE scheme is developed, providing real-time feedback for path selection and optimizing the system performance. Simulation results demonstrate that the MPAEE scheme significantly reduces propagation delay, packet loss, hop count, and interruption probability while improving satellite energy efficiency and extending satellite lifetime.**

***Index Terms*—Digital twin (DT), energy conservation, low Earth orbit (LEO) constellation, multiobjective optimization, multipath routing.**

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I. Introduction

A. Background

INDUSTRY 5.0 promotes the global development of a "sustainable digital economy," for which the satellite Internet is an essential underpinning. The low Earth orbit (LEO)-based industrial Internet of Things (IoT) is strategically important in applications, such as global communications, disaster monitoring, and military warfare [1], [2]. The LEO-based industrial IoT can overcome geographical limitations, enabling extensive remote monitoring, intelligent scheduling, and efficient network support for industrial equipment in remote or harsh environments [3]. Satellites are expensive, have high launch costs, and batteries cannot be replaced during orbit. Their limited battery life pose great challenges to developing IoT carbon intelligence based on the LEO constellation industry [4], [5]. With the increasing number of satellites and the growing diversity of application scenarios, reliability, load balancing capabilities, and energy efficiency of satellite network communications have become critical concerns [6].

B. Related Work

With the development of the LEO satellite network and industrial IoT, optimizing intersatellite routing has become a key technology of satellite network communication. Yang et al. [7] built a LEO network model focused on satellite link communication performance as the key metric. Tsuchida et al. [8] applied Q-learning to optimize the power allocation in LEO satellite-to-ground communication, effectively reducing the battery strain and extending satellite lifetimes by balancing workloads among satellites. In addition, [9] and [10] proposed an application of adaptive routing and MDP-based distributed angular routing to intersatellite routing to improve performance further. Chen et al. [11] proposed reducing the average hop count for the entire network and users in specific regions by selecting the optimal path.

These studies have achieved fruitful results for the intersatellite routing optimization problem. However, they mainly focus on a single-path intersatellite route optimization. Under high load or sudden network failures, a single path can easily lead to congestion, disconnection, and a single failure point, making it difficult to ensure reliable data transmission. To solve these problems, the development of multipath routing has become a hot research topic. To improve the transmission efficiency, Ding et al. [12] proposed a model of multipath routing with two heuristic path discovery algorithms, i.e., iterative path discovery algorithm and parallel path discovery algorithm. Wang et al. [13] discussed theoretically the mode selection of device-to-device pairs and the path selection of video streams. In addition, Zhang et al. [14] constructed a combined satellite routing algorithm that considers bandwidth and delay. But these developed algorithms rely on manually defined constraints, which are insufficiently comprehensive and thus degrade the system performance. In contrast, recent research has increasingly focused on the use of deep reinforcement learning (DRL) and federated learning-based approaches to enhance the efficiency and adaptability of LEO satellite networks, as evidenced by studies [15], [16], [17], [18]. Kuperman and Modiano [19] designed a multipath selection algorithm for wireless disjoint path protection to minimize the delay variance by rationally selecting multiple paths.

Significant progress has been made in addressing the multipath routing scheduling problem in the above studies. However, managing real-time states and dynamic changes of intersatellite links (ISLs) in complex satellite communication networks remains challenging. To solve the above problems, researchers have proposed various optimization schemes to cope with the challenges of dynamic network environments. Zhang et al. [20] proposed an improved routing algorithm based on ISL state information. This algorithm can be decided based on link status and satellite network topology. In addition, the classical Dijkstra's algorithm used to solve the single-source shortest path problem and extensively used for route optimization in satellite networks [21]. Zhang et al. [22] constructed an on-demand task model using a storage time aggregation graph to ensure the quality of service of tasks. Furthermore, Wang et al. proposed a multipath collaborative routing algorithm based on source and destination nodes to accelerate data transmission [23]. Furthermore, Li et al. [24] constructed a grid-based routing method to locate satellites by discrete grids instead of coordinates to search for optimal paths in space debris networks. A shortest path priority routing method based on path prediction was proposed by Pan et al. [25]. In addition, analyzing from the perspective of how battery energy affects the satellite's operational lifetime, the authors in [26] proposed an energy-efficient routing scheme based on DRL to save energy.

C. Motivations

Energy consumption has a direct impact on the stability and reliability of LEO satellite networks. Excessive energy use can lead to premature battery depletion, resulting in critical service interruptions in real-time applications. Therefore, optimizing energy consumption is crucial for ensuring consistent and reliable connectivity across the LEO constellation. Multipath routing selection in satellite Internet improves network reliability and enhances data transmission efficiency. However, the rational and efficient use of multipath routing while ensuring satellite lifetime and reducing energy consumption remain challenging.

First, single-path routing has limitations in satellite networks under high load or malfunction. Data transfer cannot be effectively shared, or redundancy guarantees provided by single-path routing, resulting in unreliable data transmission and low energy efficiency. To address this problem, existing technologies are mainly solved by intersatellite routing optimization. However, in the case of high load or sudden network failure, it faces difficulties, such as easy congestion, disconnection, and a single point of failure. Therefore, optimizing data stability and reliability through multipath selection becomes a key challenge in a dynamic network environment.

Second, there are dynamic changes in LEO-based satellite networks, meaning that static weight allocation methods traditionally lead to suboptimal transmission efficiency [27]. Coping with sudden changes caused by faults or congestion is difficult, leading to poor energy efficiency. Therefore, dynamically adjusting the weight allocation to adapt to changes in the network state is the key to improving the performance of multipath routing.

Finally, traditional multipath routing schemes typically rely on simple optimization frameworks [28], which struggle to select paths accurately, leading to high computational complexity, increased energy consumption, and reduced energy efficiency. Existing heuristic algorithms are complex to adapt to the dynamic network environment and cannot achieve optimal path selection, affecting transmission efficiency and system stability. Therefore, designing efficient optimization algorithms to select paths and reduce energy consumption accurately has become a key challenge that needs to be addressed urgently.

A new idea is proposed to solve the problem of optimal path selection in a dynamic network environment based on digital twin (DT) technology. DT has found extensive use in areas like intelligent transportation and healthcare, yet research on its integration with satellite routing remains limited [29]. In addition, the routing scheduling scheme based on intelligent optimization algorithms has become the core direction of research [30], [31], [32], [33]. Therefore, combining DT with the neural population dynamics optimization algorithm (NPDOA) is considered a promising way to solve the limitations of traditional routing scheduling methods.

D. Contributions

To enhance the satellite lifetime and reduce the energy consumption, we introduce three key innovations. First, we propose a multiobjective optimization model that integrates four essential metrics: 1) propagation delay; 2) energy consumption; 3) capacity utilization; and 4) packet loss rate into a unified framework. This comprehensive model enables balanced decision-making by dynamically adjusting the trade-offs between competing objectives. Second, we present the proposed particle swarm optimization-based dynamic weight multipath (PSODWM) scheme based on the particle swarm optimization (PSO) algorithm. This scheme dynamically updates path weights in response to real-time network topology changes, improving the routing adaptability and ensuring an optimal load distribution without increasing the computational complexity. Finally, we develop a multipath adaptive energy-efficient (MPAEE) routing scheme, which integrates the NPDOA with the DT technology. This approach allows the system to simulate and evaluate routing decisions in a virtual environment before applying them to the physical satellite network. This ensures proactive path optimization and reduces the risk of link failures. The proposed MPAEE scheme enhances routing efficiency, improves network reliability, and extends satellite operational lifetimes by integrating intelligent algorithms into both the multiobjective evaluation and path planning processes. These innovations collectively address the limitations of existing methods and provide a robust solution for dynamic, energy-efficient routing in LEO satellite networks.

The main contributions of this article are outlined as follows.

1) A routing algorithm based on multipath optimization is proposed to extend single-path routes to multipath routes to improve the network reliability and load-balancing capability. The static weight multipath (SWM) routing scheme is used to effectively improve the transmission performance of the network and reduce the interruption probability.
2) A dynamic weighted routing scheme is constructed to reduce the path disruption and decrease the communication delay for multipath optimization when the network topology changes frequently. Specifically, the PSO algorithm is employed to dynamically determine the weights in the multipath routing. Candidate nodes and links that meet the multiobjective constraints are then identified based on the requirements of path scheduling.
3) The MPAEE routing scheme is constructed to identify the most efficient routing path. The resources of different paths are fully utilized to improve the transmission reliability, extend the satellite life, and reduce the energy consumption.

E. Structure

The remainder of this work is organized as follows. Section II describes the construction of the system model and the associated problems. Section III provides the proposed solution. Section IV provides a simulation and analysis of the results. Finally, we summarize this article in Section V.

II. System Model and Problem Formulation

This work aims to develop an MPAEE routing scheme that dynamically adjusts data transmission paths and optimizes resource utilization. The MPAEE routing scheme is designed to enhance the reliability and energy efficiency of the LEO satellite network.

A. System Model

We utilize a routing and transmission model for LEO satellite networks based on the Iridium constellation, which consists of 66 satellites and their ISLs, as illustrated in Fig. 1. Here, intersatellite communication is established through ISLs

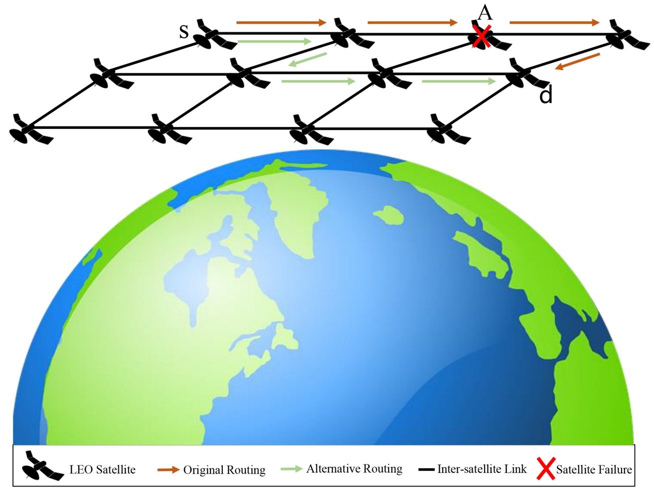

Fig. 1. Low-orbit satellite network routing.

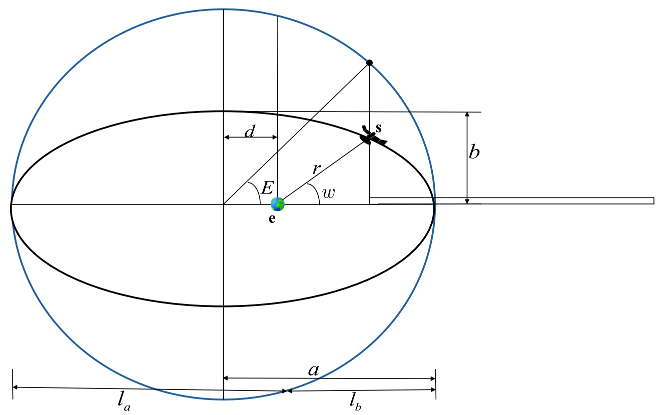

Fig. 2. Position of the satellite in orbit.

to relay data across the network. Each satellite operates under strict energy constraints, primarily relying on onboard batteries for power. The routing model proposed in this study evaluates the path quality in terms of the expected delay of the path. The probability of successfully transmitting data decreases after the failure of node A in Fig. 1 by constructing a dynamic scheduling scheme for multipath routing to find the globally optimal path that meets several constraints. An energy-efficient multipath routing and scheduling scheme ensures data transmission reliability and minimizes energy consumption, offering a sustainable solution for satellite communication networks with limited resources.

According to the proposed satellite network model, communication links and internode relationships are further portrayed through topology modeling to describe and analyze the network characteristics accurately. A satellite orbital position directly affects the connection status of interplanetary links and key performance parameters. Therefore, the satellite's in-orbit position must be determined before network topology modeling. The key orbital parameters, relative position, and orbital period are defined in Fig. 2.

In this figure, a and b denote the semi-long and semi-short axis of the elliptical orbit of the satellite. Correspondingly, w is the true perigee angle, which is the angle formed between the

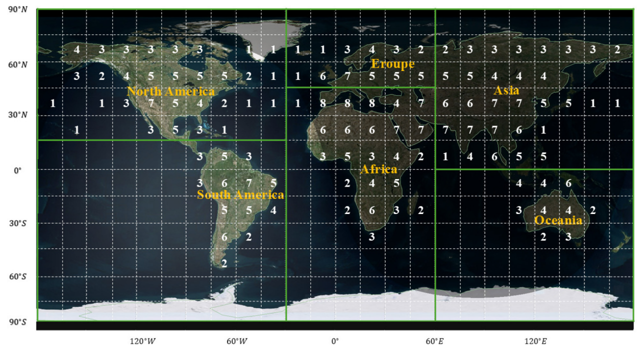

Fig. 3. Regional division and user density.

satellite on the ellipse and the perigee on the ellipse concerning the Earth at its center of the Earth. r is the distance from the Earth's center to the satellite.

Based on the presented satellite network topology model, the dynamic characteristics of data transmission in the network are further portrayed through traffic modeling. It is used to analyze the network performance and optimize the resource allocation strategies comprehensively. The data traffic in this work is generated based on historical data [34], combined with the actual Internet usage and the proposed model [35], [36]. Fig. 3 shows the Earth's surface segmented into 288 (12×24) zones. In this case, the size of the each region by latitude and longitude is $15^\circ\times15^\circ$, and the number of each marker in the region indicates the user density level u_j in region j.

We calculate the level of the terminal density by combining the number of internet-connected devices across each continent [35]

$$h_j = \frac{u_j N_h(k)}{\sum_i u_i} \tag{1}$$

where h_j represents the terminal density in region j. u_j represents the user density in region j, $N_h(k)$ represents the total number of terminals in continent k, $\sum_i u_i$ is the cumulative user density across all regions.

The flow matrix is calculated based on the terminal density level

$$T^{ij} = \frac{\left(u_i h_j\right)^{\alpha}}{d_{(i,j)}^{\beta}} \tag{2}$$

where parameters α and β are defined as 0.5 and 1.5 [37]. T^{ij} represents the data traffic from i to j. Additionally, $d_{(i,j)}$ is the distance.

B. Problem Formulation

When the number of satellites increases and the application scenario expands, establishing a connection from the source node to the destination node requires sequentially locating nodes. The four indicators for selecting the satellite energy efficiency are calculated as follows.

First, the propagation delay of the route established from s to d across multiple paths is calculated as

$$T_{s,d} = \frac{\sum_{h\in H} L(h, h+1)}{V} \tag{3}$$

where the unit of the transmission delay T is milliseconds (ms), V represents the speed of light, and $L(h, h+1)$ is the link distance from h to $h+1$.

Second, the energy consumption and harvesting of each satellite can be calculated as follow:

$$E = PT \tag{4}$$

where P denotes the power consumption associated with specific operations in the simulation, including data transmission, data reception, routine system tasks, and energy harvesting via solar panels, which are defined as 7 J/s, 3 J/s, 4 J/s, and 20 J/s, respectively.

Additionally, the energy consumption per satellite includes operating and transceiver energy consumption. The energy consumed by the satellite operation is shown in the as:

$$E_C(t) = E_R(t) - E_N(t) - E_{T'}(t) - E_{R'}(t) \tag{5}$$

where $E_C(t)$ is the residual energy at the end of the satellite mission. $E_R(t)$ is the battery energy at the beginning of the satellite mission. $E_N(t)$, $E_{T'}(t)$, and $E_{R'}(t)$ are the energy consumption of the satellite operating at the moment of representing t, the energy consumed by the satellite transmitting the data, and the energy consumed by the satellite receiving the data, respectively.

$E_R(t)$ is the energy at the beginning of the mission, as expressed by the following:

$$E_R(t) = \min\ \left\{W_{\max},\ E_R(t) + E_{\text{cap}}(t)\right\} \tag{6}$$

where $W_{\max}$ is the maximum energy of the battery, defined as 30 KJ in this study, $E_{\text{cap}}(t)$ represents the energy captured by the solar panels and stored in the satellite's battery during time interval t.

Subsequently, the path from the source node s to the destination node d passes through K links, and the total capacity consumption C is shown as

$$C = \sum_{k=1}^{K} r_k d_k \tag{7}$$

where r_k denotes the amount of data transmitted data for the kth link and d_k denotes the distance of the kth link.

Finally, the proportion of data packets that fail to reach the destination node d from the source node s during transmission is shown as

$$P = \frac{P_{\text{lost}}}{P_{\text{sent}}} \times 100\% \tag{8}$$

where P is the packet loss rate. P_{lost} the number of lost packets, i.e., the total number of packets that did not successfully reach the destination during transmission. P_{sent} the total number of packets sent, i.e., the total number of all packets sent by the source node.

In the design of LEO satellite networks, previous studies primarily focused on optimizing a single performance metric, such as minimizing the delay or maximizing the throughput. This single-objective approach often overlooks the tradeoffs between critical factors like energy consumption, packet loss rate, and link reliability, resulting in suboptimal routing decisions under dynamic network conditions. Existing multipath routing schemes, such as the SWM scheme, apply fixed-weight evaluations to multiple QoS dimensions. However, these methods lack the flexibility to adapt to real-time changes in network topology and do not consider the dynamic energy states of satellites, both of which are essential for prolonging satellite lifespans and ensuring sustainable network operations. Based on the above analysis, the optimal path that satisfies the satellite energy efficiency criteria is selected from the source node s to the destination node d. We model the problem of choosing an optimal path of the satellite as a multiobjective optimization problem, which is presented as follows:

$$\begin{aligned} \min \quad & Q_{x,y} = \omega_1 \frac{T_{x,y} - T_{\min}}{T_{\max} - T_{\min}} + \omega_2 \frac{E_{x,y} - E_{\min}}{E_{\max} - E_{\min}} \\ & \quad + \omega_3 \frac{C_{x,y} - C_{\min}}{C_{\max} - C_{\min}} + \omega_4 \frac{P_{x,y} - P_{\min}}{P_{\max} - P_{\min}} \\ \text{s.t.} \quad & T \geq 0 \\ & E \geq 0 \\ & C \geq 0 \\ & P \geq 0 \end{aligned} \tag{9}$$

where $Q_{x,y}$ is the battery consumption of the LEO satellite in the eclipse region from node x to node y when maximizing the traffic demand is satisfied. $T_{x,y}$ is the transmission delay of the neighboring satellite nodes, where $T_{\min}$ and $T_{\max}$ denote the minimum and maximum transmission delay in the snapshot, respectively. $E_{x,y}$ is the energy consumption used to transmit the data between neighboring nodes. $C_{x,y}$ is the capacity of the link between the two nodes. $P_{x,y}$ is the packet loss rate of transmitted data between two nodes. The weight coefficients ω_1, ω_2, ω_3, and ω_4 are dynamically adjusted parameters that represent the relative importance of transmission delay, energy consumption, link capacity, and packet loss rate, respectively. These weights are dynamically adjusted in real-time according to the current state of the network, ensuring that path selection consistently remains optimal.

In high-latency environments, the PSO algorithm increases the weight of the transmission delay ω_1 to prioritize the low latency. This helps to reduce the data transmission delay and improve the communication efficiency. In scenarios with a high network load, the PSO algorithm increases the weight of the energy consumption ω_2 to prioritize the energy efficiency. This effectively reduces the energy consumption of individual satellites, thereby extending their operational lifespan. In cases where the link capacity is constrained, the PSO algorithm increases the weight of the link capacity ω_3 to ensure a smooth data transmission. In situations with a high packet loss rate, the PSO algorithm increases the weight of the packet loss rate ω_4 to prioritize the reliability of the data transmission.

In summary, the parameters-transmission delay, residual battery energy, storage capacity, and packet loss rate-are normalized and combined into a composite link cost through the application of weighted factors, which represents the battery consumption. Dynamically adjusts link weights to penalize links with satellites not meeting the minimum energy reserve threshold, while still permitting satellites below the threshold to handle data transmission. This results in fewer blocking sources, better traffic equalization, and effective reduction of energy consumption during network routing.

C. Algorithm Design

In this section, we formulate a multiobjective optimization problem to balance between different objectives while ensuring reliable data transmission. Then, we propose the MPAEE routing scheme to enhance the reliability and energy efficiency of LEO satellite networks by optimizing the selection of data transmission paths.

The MPAEE scheme consists of three main components: First, we extend single-path routing to multipath routing for more flexible and reliable path selection. Second, dynamically adjusts the weights of multiple paths based on real-time network conditions to achieve optimal load distribution.

Algorithm Steps:

1) Initialize particle swarm with random positions and velocities.
2) Calculate fitness values and update the regional and global best candidate node.
3) Continuously update particle velocities and positions to adjust multipath weights.
4) Determine the global optimal position and final optimal solution after numerous iterations.

Finally, NPDOA and DT technologies are integrated for real-time feedback and optimization, ensuring reliable and energy-efficient data transmission.

Algorithm Steps:

1) Initialize required variables for path information.
2) Calculate the initial shortest paths.
3) Iteratively generate remaining paths while avoiding path repetitions.
4) Use DT to model changes in the real system and provide real-time feedback.
5) Select appropriate paths to update the result set.

III. Solution Approach

This section describes the solution for dynamic weighted multipath routing and the multipath routing scheduling scheme. The PSO algorithm is employed to adjust weights in real-time, dynamically ensuring an optimal multipath load distribution without any additional resource consumption. The strength of PSO lies in its ability to adapt to frequent network changes, ensuring that each path undertakes appropriate transmission tasks based on prevailing network conditions. Additionally, NPDOA and DT technologies are developed to provide real-time feedback and adaptation capabilities. The NPDOA utilizes neural population dynamics to model changes in the real system and optimize path adjustments in response to dynamic network conditions. This combination effectively addresses the challenges of dynamic network changes, energy efficiency, and optimal path selection in LEO satellite networks.

Fig. 4 illustrates the MPAEE routing scheme with the help of the NPDOA and DT technology. The MPAEE routing scheme is a MPAEE routing scheduling scheme that dynamically adjusts data transmission paths and optimizes the resource utilization. Specifically, Fig. 4(a) and (b): the path selection process from the

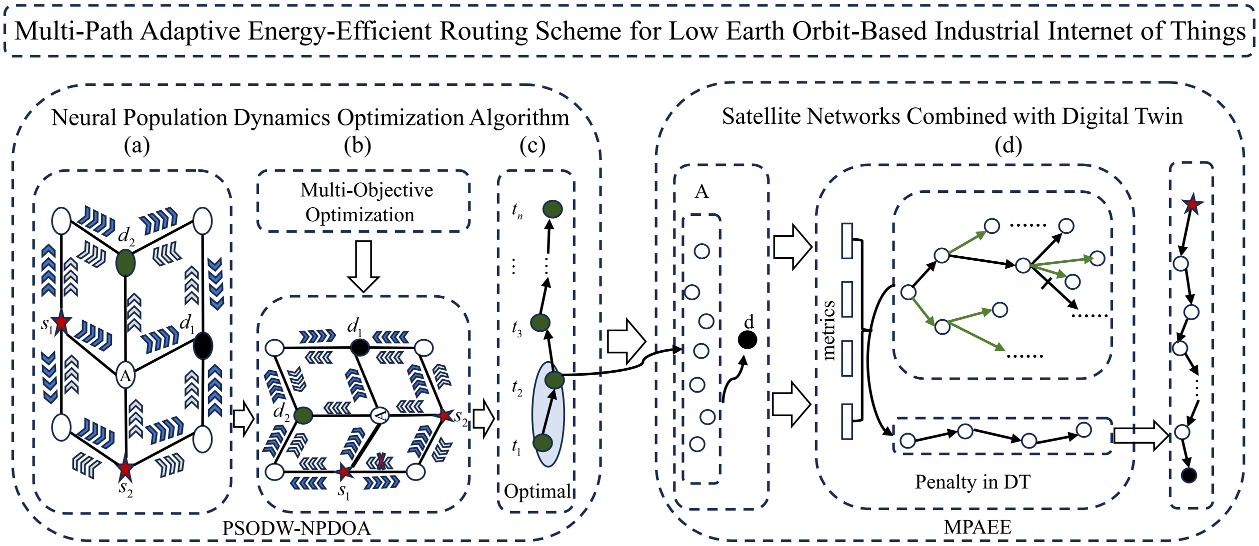

Fig. 4. Schematic of LEO-based MPAEE route scheduling scheme. (a) and (b) Path selection process from the source node to the destination node. (c) Selecting optimal paths that satisfy satellite energy-efficient targets. (d) Objective of the DT-assisted routing scheme is to select the optimal path from all possible routing paths and implement it in the physical satellite network.

source node to the destination node. Fig. 4(c): selecting optimal paths that satisfy satellite energy-efficient targets. Fig. 4(d): the objective of the DT-assisted routing scheme is to select the optimal path from all possible routing paths and implement it in the physical satellite network. Using the NPDOA, an optimal path from the source node to the destination node is determined to minimize the battery energy consumption. The primary goal of this study is to enhance the reliability and energy efficiency of LEO satellite networks, particularly aiming to extend the operational lifetime of LEO satellites. To achieve this, we propose an adaptive method for satellite energy-efficient metrics. This method balances the traffic load across constellation links under minimum battery power constraints and considers the propagation delay, energy consumption, capacity utilization, and packet loss rate.

We further introduce the DT technique to mitigate satellite dynamics and frequent topology changes, which lead to duplicate ISL paths, increased communication delays, and excessive battery energy consumption. By applying the dynamic weighting algorithm with the help of NPDOA and DT technologies, we optimize the multipath intersatellite routing and improve routing efficiency and reliability.

The DT networks (DTNs) are spatially constructed based on the real-time state of the satellite network, as shown on the right side of Fig. 4. We assume that neighboring satellites collaborate to establish distributed computing services for implementing DTNs, mirroring the real satellite network in terms of entities (satellites) and related information. The DT continuously monitors and replicates the current state of the satellite network, including satellite positions, link status, and traffic load. This real-time replication enables the DTN to accurately reflect dynamic changes in the network topology. Adjacent satellites collaborate to establish distributed computing services, allowing the DTN to perform complex computations and simulations that mirror the real satellite network. This collaboration ensures that the DTN can handle large-scale data processing and provide an accurate feedback.

The periodic movement of satellites enables the prediction of satellite trajectories and the identification of alternative satellites for subsequent paths in DTNs. Simultaneously, using the NPDOA, the DTN selects the optimal candidate satellites and plans the paths to be applied in the physical satellite network. In addition, the prediction method is employed to construct the DTNs, which model the future network state and provide additional valuable features. During the intersatellite content delivery phase, satellite dynamics and timeslot visibility can create numerous loops, leading to a low link utilization and increased delays. By performing advanced virtual routing within the DTNs, the network topology is optimized through the energy-efficient routing to identify optimal paths. These paths are computed and validated before assigning multipath routes to the physical satellite network, thereby minimizing communication delays and reducing the battery energy consumption.

A. Dynamic Weight Multipath Routing

In multipath routing, static weights struggle to accommodate the frequent topology changes in satellite networks, often leading to path interruptions and increased transmission delays. To address this, we employ the PSO algorithm, which dynamically adjusts link weights by mimicking the foraging behavior of bird flocks. Each particle represents a candidate solution for path weights, and the particles iteratively adjust their positions in the search space to find the optimal solution, achieving optimal load distribution without additional resource consumption. Algorithm 1 presents the pseudocode for a multipath routing scheme that utilizes the PSO algorithm to adjust path weights dynamically.

Dynamic adjustment of multipath weights is the initial task of the energy-efficient scheduling scheme. This process involves initializing the particle swarm by randomly generating particle positions, setting their velocities, and assigning each particle's local optimal position as its initial position. First, the fitness is calculated by invoking the function and updating

Algorithm 1 PSO Dynamic Optimization Weights

Input: PSO_MultiObjective_Optimization_Dynamic (p, n, m, l, u, p_w)
Output: $W_{best}, f_{\min}$;

```
num_objectives = size(p, 2)
if isempty(p_w) then
    p_w = random
end if
p_p, p_v, p_best, f_best;
p_g = p_w, f_g = inf;
for iter = 1 to m do
    for i = 1 to n do
        Calculate the fitness values and record the optimal value
        if fitness < f_best(i) then
            f_best(i) = fitness;
            p_best(i,:) = p_p(i,:);
        end if
        if fitness < f_g then
            f_g = fitness;
            f_best = p_p(i,:);
        end if
        w, c1, c2
        for i = 1 to n do
            p_p(i, :) = max(min(p_p(i, :), u), l)
        end for
    end for
end for
return W_best, f_min
```

Algorithm 2 MPAEE Multipath Route Scheduling Scheme

Input: MPAEE kyensKShortestPaths_improved (G, O, D, K)
Output: *rota*

```
if ~ isa(G, 'digraph') then
    error('The input G must be a directed graph (digraph)');
end if
rota = cell(1, K); A = cell(1, K); B = {};
[S_p, S_c] = S_d(G, O, D);
if isempty(S_p) then
    error('No path exists from O to D');
end if
A{1} = S_p; rota{1} = struct('path', S_p, 'cost', S_c);
for k = 2 to K do
    for i = 1:length(A{k - 1}) - 1 do
        for j = 1 to k - 1 do
            if rootPath has the same prefix as A{j} then
                T_w(edgeIdx) = inf;
            end if
        end for
    end for
    [s, S_c] = S_d(tempG, N_s, D);
    if ~ isempty(s) then
        P_t = [P_r(1:end-1), s];
        B = [B; P_t, C_t];
    end if
    A{k} = B{idx}.path;
    rota{k} = struct('path', A{k}, 'cost', C_t);
end for
return rota
```

the regional and global best candidate nodes based on the fitness values. Then, within the main loop, the algorithm continuously updates each particle's speed and position to adjust the multipath weights dynamically. Setting the inertia, cognitive, and social factors modifies the particles' velocities relative to their local and global optimal positions and updates the best candidate nodes accordingly. Finally, after numerous iterations, the global optimal position and the final optimal solution are determined, resulting in dynamically adjusted weights. This algorithm improves the search efficiency of multiobjective optimization through the dynamic adjustment of particles.

B. Multipath Adaptive Energy-Efficient Routing

We design a MPAEE routing scheduling scheme to optimize path selection and task allocation. The MPAEE routing scheduling scheme is intended to optimize path selection and task allocation by integrating multipath load balancing, dynamic weight adjustment, and real-time feedback mechanisms. By extending single-path routing to multipath routing, MPAEE improves the network reliability and fault tolerance by distributing traffic across multiple paths, thereby reducing the energy consumption and prolonging the satellite lifetimes. The PSO technique is employed to adjust path weights in real-time dynamically, ensuring efficient load distribution based on current network conditions. The DT technology further enhances the system by simulating real-time path changes, enabling quick responses to topology variations and optimizing the path selection. The MPAEE routing scheme integrates the NPDOA and DT technologies to adjust multipath scheduling strategies dynamically, enhancing the data transmission reliability and the energy efficiency.

The NPDOA algorithm, inspired by biological population dynamics, continuously evaluates and updates path weights based on real-time metrics, such as energy consumption, transmission delay, and link conditions, ensuring an optimal path selection under multiobjective constraints. The DT generates updated path data when the physical network undergoes state changes. The NPDOA algorithm processes this data to identify the most efficient path, the optimal solution is subsequently implemented within the physical satellite network. This feedback loop ensures that the MPAEE routing scheme dynamically responds to network changes, delivering superior path optimization and energy savings. The MPAEE considers multiple performance metrics, including transmission delay, energy consumption, capacity utilization, and packet loss rate, to achieve optimal routing while ensuring reliable data transmission and minimizing resource consumption. The MPAEE also ensures reliable data transmission while minimizing the energy consumption. The scheduling scheme dynamically assesses the states of different paths and allocates traffic across multiple paths using an optimal strategy. The pseudocode of this process is presented in Algorithm 2.

IV. Simulation Results and Discussion

This section evaluates the performance of the proposed PSODWM routing scheme and the MPAEE routing scheme.

A. Simulation Settings

1) Parameter Settings: The MPAEE routing scheme is the critical component of the energy-efficient scheduling scheme. First, the required variables rota, A and B are initialized to store path information. Next, the constructed function is invoked to calculate the initial shortest paths. Efficient multipath planning is achieved by iteratively generating the remaining $k-1$ paths, starting from the second shortest path and avoiding path repetitions by assigning infinite weights to edges with repetitive prefixes. Finally, the DT serves as a virtual simulation system

TABLE I
PARAMETER VALUES FOR SIMULATION

Parameters	Value
Maximum energy capacity of the satellite battery(B_{max})	$30\,\mathrm{kJ} = 30,000\,\mathrm{J}$
Transmission power (P_t)	$P_t = 7\,\mathrm{W} = 7\,\mathrm{J/s}$
Reception power (P_r)	$P_r = 3\,\mathrm{W} = 3\,\mathrm{J/s}$
Nominal operation power (P_o)	$P_o = 4\,\mathrm{W} = 4\,\mathrm{J/s}$
Capture power (P_c)	$P_c = 20\,\mathrm{W} = 20\,\mathrm{J/s}$
Snapshot	$100\,\mathrm{s}$
Iridium constellation's orbital period	$100\,\mathrm{min}$
Total simulation duration (laps)	$36,000\,\mathrm{s}(6\,\mathrm{laps})$
ISL link capacity	$10\,\mathrm{Mbps}$
CBR rate of sources	$1\,\mathrm{Mbps}$
Terminal quantity	200
Battery charge threshold (L_B)	0.5
Weights	$\omega_1 = 0.2; \omega_2 = 0.3;$ $\omega_3 = 0.2; \omega_4 = 0.3.$

to model changes in the real system and provide real-time feedback to the algorithm, thereby enabling it to find the optimal solution more efficiently. By invoking DTUpdate to obtain real-time updated graph data, the algorithm dynamically calculates paths from branch nodes to destination nodes and stores the merged complete paths in a candidate set. It then selects appropriate paths from this set to update the result set, ultimately efficiently generating the shortest paths. By utilizing multipath resources, the MPAEE routing scheme enhances the overall reliability and reduces the energy consumption in the network transmission, providing a sustainable solution for satellite communication networks with limited resources.

The simulation is conducted using the LEO satellite network simulator implemented in MATLAB R2022a, running on CentOS Linux 7.8 with a configuration of 256-GB RAM and an Intel 8358P processor. The simulator is adapted for this study, and the parameters for generating the traffic demand in the LEO satellite network are shown in Table I. The parameters and corresponding values in the simulation are used to simulate the Iridium constellation for six weeks of orbit around the Earth. The satellite orbital period is set to 100 min for each lap, snapshots are generated at 100-s intervals, and 360 snapshots are analyzed in the dynamic simulation. In this study, we simulate the Iridium constellation orbiting the Earth for six orbital periods, each lasting 100 min, and generate a snapshot every 100 s. This duration is sufficient for algorithm convergence, as key performance indicators stabilize within this timeframe. This is confirmed by stabilizing key performance indicators, such as latency, throughput, and handover frequency while capturing the dynamic characteristics of large-scale LEO satellite networks. Furthermore, although Iridium is used as the primary constellation for evaluation due to its well-structured and globally deployed topology, our simulation framework and algorithmic approach are designed to be constellation-agnostic. We have verified their adaptability across various LEO architectures (e.g., Walker-Delta and Starlink-like designs), where similar convergence behavior is observed, demonstrating our method's robustness and general applicability.

2) Evaluation Indicators: The key evaluation indicators are discussed, including end-to-end delay, satellite lifetime, remaining energy, throughput, hops, interruption probability, and packet loss rate. The average values of these indicators are also considered in the analysis.

The following equation gives the calculation of the average delay

$$\bar{D}_n = \frac{\sum_{(s,d)\in EF} D_n(s,d)}{Q_{Dn}} \;\; \forall n \in N \tag{10}$$

where $\overline{D}_n$ is the average transmission delay from all source nodes to destination nodes in snapshot n. EF represents the set of satellite pairs consisting of sources and destinations. D_n is the transmission delay from source node s to destination node d in snapshot n, in ms. Furthermore, Q_{Dn} is the nth snapshot number of the source-destination pairs.

The satellite's lifetime span is calculated by calculating the average life cycle (number of charge/discharge cycles) of the battery in one day (15 orbital cycles simulated) and multiplying it by the annual number of days. The following formula gives the calculation of the satellite battery life

$$\overline{L}_{t_1t_2} = \frac{\sum_{j=1}^{N}\sum_{i=1}^{M} L_{t_1t_2}(i,j)}{L_C\bar{Q}_S} \tag{11a}$$

$$\text{lifetime (year)} = \frac{1}{365\overline{L}_{t_1t_2}} \tag{11b}$$

where $L_{t_1t_2}$ is the life cycle of the satellite. N is the total snapshot count. L_C represents the total count of battery life cycles. M is the total satellites count. $\bar{Q}_S$ is the average number of satellites when forwarding traffic. $\bar{L}_{t_1t_2}$ is the average number of life cycles consumed by the satellite.

The residual energy of each satellite is determined by subtracting the initial battery energy from the energy consumed and adding the energy captured. The average residual energy is calculated as the weighted average of the residual energy across all satellites, obtained by dividing the total residual energy of all satellites by the overall number of satellites. The average satellite battery residual energy is shown as

$$\overline{E}_{Rn} = \frac{\sum_{i=1}^{M} E_{Rn}(i)}{B_{\max}M} \times 100\% \quad \forall n \in N \tag{12}$$

where $\overline{E}_{Rn}$ represents the proportion of the average remaining energy. $E_{Rn}(i)$ is the satellite's leftover energy i in n snapshots. $B_{\max}$ denotes the battery's total capacity. M is the total number of satellites.

We account for the traffic produced by all nonblocking source-destination pairs in every snapshot n. The average throughput of the satellite network is given as

$$\overline{T}_n = \frac{\sum_{(s,d)\ \in EF} T_n(s,d)}{Q_{T_n}} \quad \forall n \in N \tag{13}$$

where $T_n(s,d)$ denotes the total traffic volume (in Mbps) between the source-destination pair in the kth snapshot. Q_{T_n} denotes the count of satellite pairs with network traffic between sources and destinations in the nth snapshot.

The following equation gives the calculation of the average hop count of the satellite network

$$\overline{H}_n = \frac{\sum_{(s,d)\ \in EF} H_n(s,d)}{Q_{Hn}} \quad \forall n \in N \tag{14}$$

where $\overline{H}_n$ represents the average hop count in the satellite network. H_n represents the total number of hops between the source-destination pairs. Furthermore, Q_{Hn} denotes the count of source-destination satellite pairs associated with the established routes.

In satellite communication research, the outage probability refers to the likelihood that the communication link fails to transmit data properly during a certain period as a result of signal attenuation, interference, or occlusion, as shown as

$$P_{\text{out}} = \Pr(\gamma < \gamma_{\text{th}}) \tag{15}$$

where P_{out} is the outage probability, which indicates the probability that the communication link will be interrupted. Pr denotes the probability function, which indicates the probability that a particular event will occur. γ is the actual signal reception quality of the link (e.g., signal-to-noise ratio SNR or signal power). γ_{th} represents the minimum acceptable signal quality threshold (threshold) for the communication link. When the signal quality γ of the link falls below the threshold γ_{th}, the communication link is interrupted. In satellite communications, the lower the probability of interruption, the higher the reliability of the link.

The packet loss rate is the percentage of packets that do not successfully reach the target node during transmission, and (16) gives the equation of the packet loss rate for satellite networks

$$\text{PLR} = \frac{P_{\text{lost}}}{P_{\text{sent}}} \times 100\% \tag{16}$$

where PLR denotes the packet loss rate, which indicates the percentage of lost packets out of the total number of packets sent. P_{lost} is the number of lost packets, i.e., the total number of packets that do not successfully reach the destination during transmission. Furthermore, P_{sent} is the total number of packets sent, i.e., the total number of all packets sent by the source node. When the packet loss rate is high, the stability of the communication system is compromised, especially for environments, such as satellite communications where latency and packet loss are relatively high.

To better evaluate the proposed approach, we consider experiments under four scenarios: static weight single-path (SWS) routing scheme, SWM routing scheme, PSODWM routing scheme, and MPAEE routing scheme.

B. Simulation Results and Analysis

The simulation compares the average throughput and outage probability of the SWS and SWM routing schemes. The results in Figs. 5 and 6 show that the SWM routing scheme outperforms the SWS routing scheme in all evaluation indicators. At the same time, the SWM routing scheme significantly reduces the impact of a single node failure of the network transmission by dispersing data across multiple paths. This leads to a significant improvement in the outage probability, enhances the network reliability, and maximizes energy savings while ensuring the reliability of the data transmission.

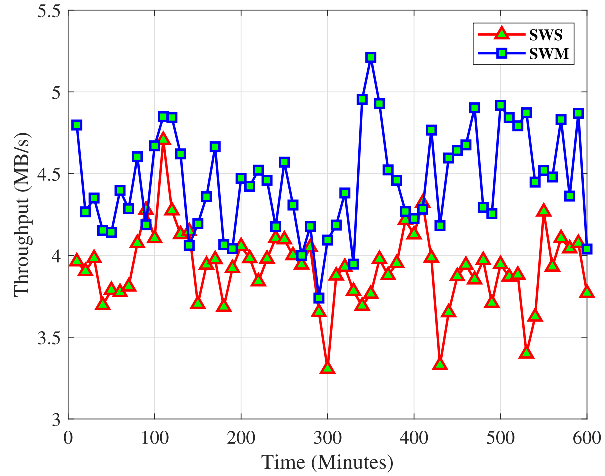

Fig. 5. Average throughput of SWS and SWM.

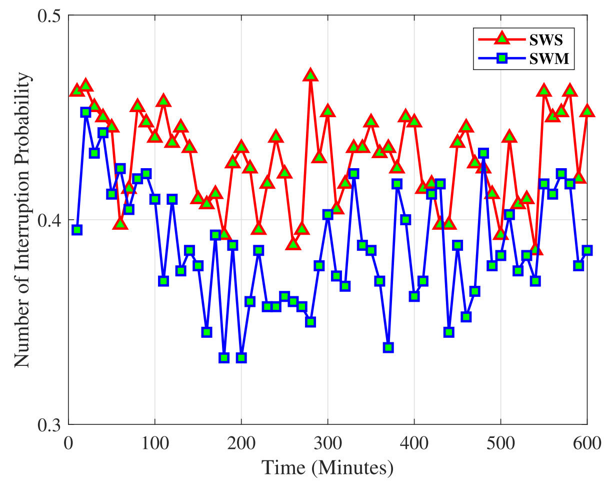

Fig. 6. Average interruption probability of SWS and SWM.

Fig. 5 illustrates the average throughput under the SWS and SWM routing schemes. The results show that the network's average throughput reaches 3.93 and 4.45 Mb/s for the SWS and SWM routing schemes, respectively. Therefore, the SWM routing scheme used in this study can effectively improve the network's transmission performance, improving the average throughput by 13.23% compared to the SWS routing scheme.

In the comparison between the SWM and the SWS routing schemes, the results show that the SWM outperforms the SWM considering the interruption probability. The average interruption probability of the SWS is 0.429, while that average interruption probability of the SWM routing scheme is 0.387. In comparison, the average interruption probability of the SWM routing scheme is reduced by 9.79%. This indicates that the SWM routing scheme transmission can more effectively distribute transmission risks, thereby reducing the likelihood of link interruptions. As a result, it enhances both the stability and reliability of the network, minimizes the energy consumption, and ensures a reliable transmission of data transmission.

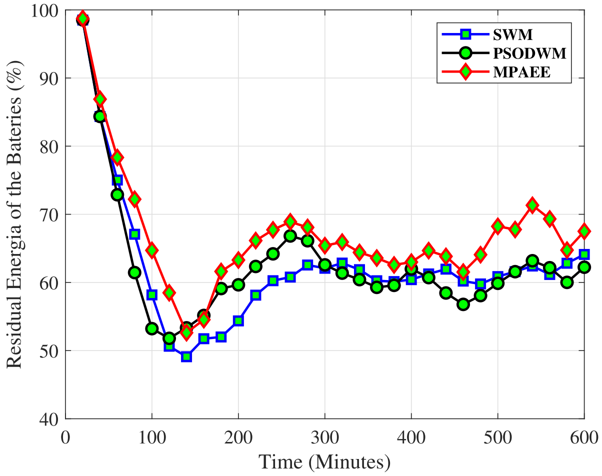

Fig. 7. Average residual energy of satellite batteries in SWM, PSODWM, and MPAEE.

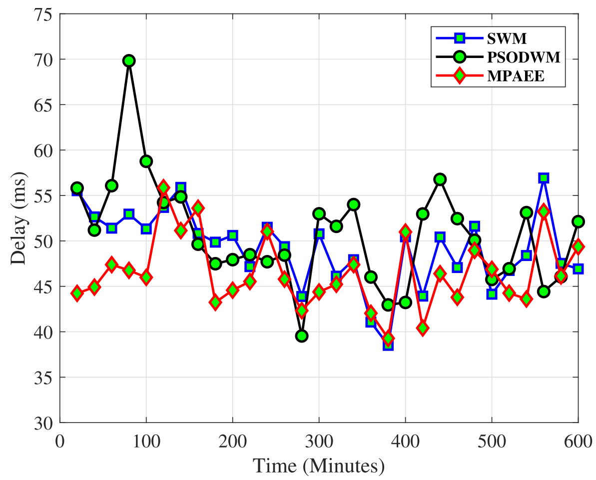

Fig. 8. Average propagation delay in SWM, PSODWM, and MPAEE.

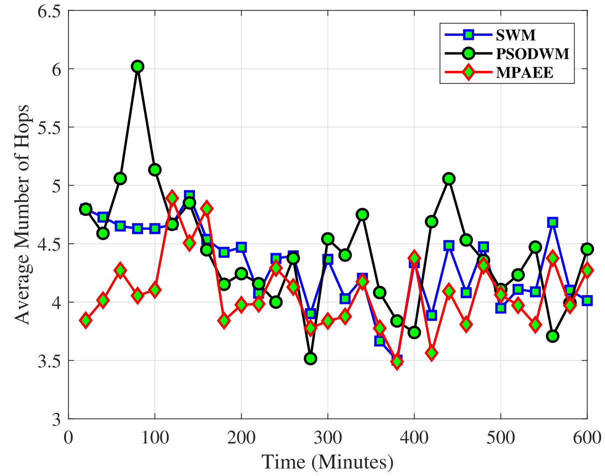

Fig. 9. Average number of hops in SWM, PSODWM, and MPAEE.

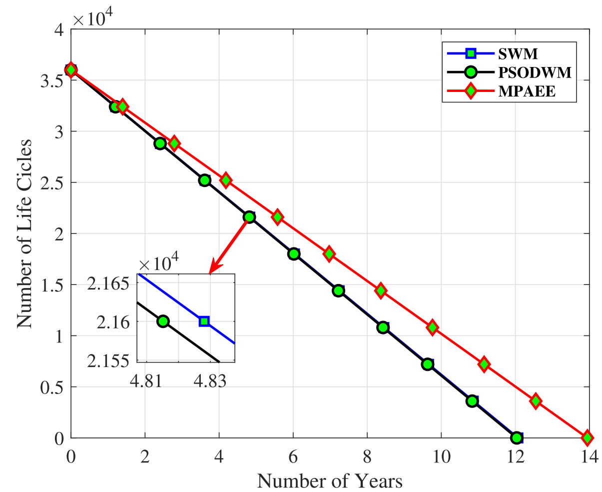

Fig. 10. Satellite battery lifetime in SWM, PSODWM, and MPAEE.

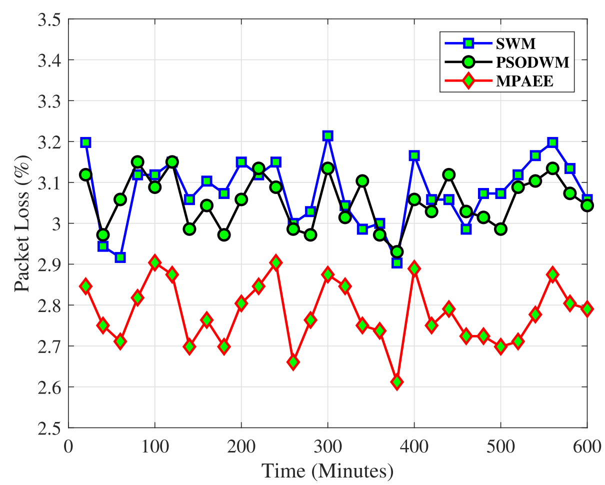

Fig. 11. Average packet loss rate in SWM, PSODWM, and MPAEE.

In the simulation, we compare the performance of three schemes, SWM, PSODWM, and MPAEE routing schemes, across key performance metrics, including residual energy, propagation delay, hop count, satellite lifetime, packet loss rate, and interruption probability. The results, shown in Figs. 7–12, demonstrate that the MPAEE routing scheme outperforms the other two schemes in all evaluation indicators, particularly in residual energy and satellite lifetime, while effectively reducing the packet loss rate and the interruption probability. By dynamically adjusting path weights and optimizing the path selection, the MPAEE routing scheme significantly reduces the propagation delay and hop count, improves the data transmission reliability, and minimizes the energy consumption. This scheme provides an effective multipath scheduling strategy tailored to resource-constrained satellite communication networks.

The percentage of the average remaining energy of the satellite battery, as obtained using the SWM, PSODWM, and MPAEE routing schemes, is shown in Fig. 7. In this figure, the square, circle, and diamond icons represent the SWM, PSODWM, and MPAEE routing schemes, respectively. The network's percentage of the average remaining energy of the satellite battery reaches 62.21%, 62.57%, and 67.00% for the SWM, PSODWM, and MPAEE schemes sequentially. In the simulation, a minimum energy threshold of 0.5 for the satellite battery was applied. As illustrated in the figure, the average

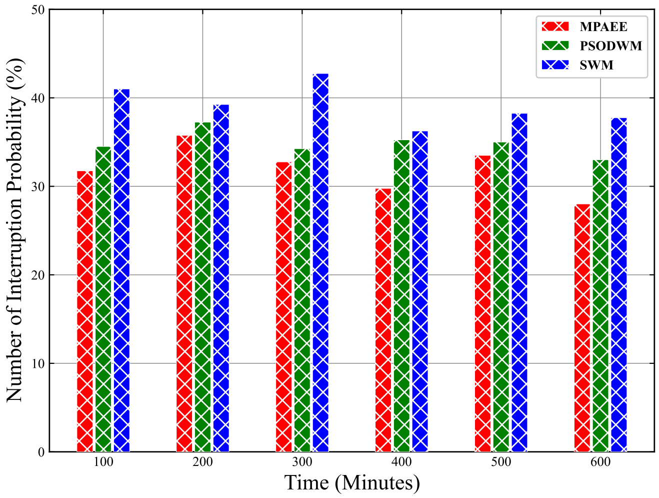

Fig. 12. Average interruption probability in SWM, PSODWM, and MPAEE.

remaining energy of the satellite battery increased by 7.70% for the MPAEE routing scheme and by 0.58% for the PSODWM routing scheme, compared to the SWM routing scheme.

Fig. 8 illustrates the average delay under the SWM, PSODWM, and MPAEE routing schemes. The network's average delay sequentially reaches 49.17, 50.71, and 46.49 ms for the SWM, PSODWM, and MPAEE routing schemes. As shown in the figure, the MPAEE routing scheme exhibits a significant advantage over both the SWM and PSODWM routing schemes in terms of the propagation delay. The average delay for the MPAEE routing scheme is 5.45% lower than that of the SWM routing scheme, indicating a superior delay performance. This demonstrates that the MPAEE routing scheme optimizes the path selection for the data transmission, thereby reducing the network delay, and is particularly suitable for satellite communication scenarios with stringent delay requirements.

Fig. 9 represents the average hop count for the satellite network with three different routing schemes. The network's average hop count reaches 4.31 hops, 4.43 hops, and 4.07 hops for the SWM, PSODWM, and MPAEE routing schemes, respectively. As shown, compared to the SWM scheme, the MPAEE routing scheme reduces the number of path hops by 5.57%, while the PSODWM routing scheme increases the average number of hops by 2.78%.

In Fig. 10, the network's satellite battery lifetime sequentially reaches 12.07 years, 12.04 years, and 13.95 years for the SWM, PSODWM, and MPAEE routing schemes. For both the PSODWM and MPAEE routing schemes, a lower energy threshold is imposed on the satellite battery. As the count of satellites charge/discharge cycles is restricted, fewer charge/discharge cycles lead to a longer satellite lifetime. Compared to the SWM routing scheme, the MPAEE routing scheme extends the satellite battery life by 15.58% in the simulation.

Fig. 11 represents the average packet loss rate for the satellite network. The network's average packet loss rate reaches 3.079%, 3.054%, and 2.780% for the SWM, PSODWM, and MPAEE routing schemes, respectively. As shown in the figure, the MPAEE routing scheme results in a 9.71% reduction in the average packet loss rate compared to the SWM routing scheme.

The average interruption probability of the satellite network under the three schemes is depicted in Fig. 12. The results show that the network's average interruption probability reaches 39.208%, 34.875%, and 31.917% for the SWS, PSODWM, and MPAEE routing scheme, sequentially. The MPAEE routing scheme reduces the average interruption probability by 18.596% compared to the SWM scheme. This indicates that the MPAEE scheme significantly optimizes the network stability and reduces link outages.

V. Conclusion

To address the high energy consumption and the low reliability in LEO-based industrial IoT, we propose the MPAEE routing scheme in this work. Specifically, a single-path routing is extended to a multipath routing, which enhances the network's load-balancing capability and fault tolerance and reduces the energy consumption. We dynamically optimize the weights of multipath routes to achieve an optimal load distribution. Moreover, we utilize the DT and the NPDOA for our MPAEE routing scheme, providing a real-time algorithm feedback. Simulation results indicate that the proposed MPAEE outperforms the other two routing schemes in key performance indicators, including residual energy, propagation delay, satellite lifetime, and outage probability. Specifically, the network's satellite battery lifetime sequentially reaches 12.04 years and 13.95 years for the PSODWM and MPAEE routing schemes. Compared to the PSODWM routing scheme, the MPAEE routing scheme extends the satellite battery life by 15.86% in the simulation. Additionally, the average packet loss rate for the PSODWM is 3.054%, whereas the MPAEE reduces it to 2.78%, resulting in an 8.97% decrease in the packet loss rate. The MPAEE achieves a 7.70% improvement in the average remaining battery energy percentage, underscoring its effectiveness in optimizing the energy consumption. This emphasis on energy efficiency is crucial for extending the operational lifetime of satellites and maintaining a reliable connectivity. Compared to existing energy-aware routing methods, the MPAEE offers a faster optimization speed, a more accurate path selection, and a greater energy efficiency, thereby significantly reducing the energy consumption and improving the reliability.

The MPAEE scheme can be widely applied in the future in fields, such as mobile networks and the Internet of vehicles. These applications highlight the broad practical significance of the MPAEE scheme, demonstrating its potential to contribute to energy savings and carbon reduction in various domains.

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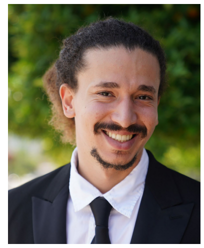

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Lei Shi, photograph and biography not available at the time of publication.