TYPE Brief Research Report
PUBLISHED 01 December 2025
DOI 10.3389/fcomp.2025.1659616

OPEN ACCESS

EDITED BY
Shancheng Zhao,
Jinan University, China

REVIEWED BY
Ahmad Bazzi,
New York University Abu Dhabi, United Arab Emirates
Hilal Nuha,
Telkom University, Indonesia

*CORRESPONDENCE
Ziyang Xing
jingqs@yeah.net

RECEIVED 04 July 2025
ACCEPTED 30 October 2025
PUBLISHED 01 December 2025

CITATION
Xing Z (2025) AIICN: a 7G multi-path transmission based on information-centric network. *Front. Comput. Sci.* 7:1659616. doi: 10.3389/fcomp.2025.1659616

AIICN: a 7G multi-path transmission based on information-centric network

Ziyang Xing*

Shanghai Donghai College, Shanghai, China

The 7G network refers to the seventh generation of mobile communication standards, which will integrate satellites, airships, and base stations to achieve data transmission with longer coverage. It can also be deeply integrated with artificial intelligence, big data, and other technologies. Multi-path transmission achieves bandwidth aggregation by establishing multiple paths between the sender and the receiver, improving transmission reliability and data accessibility. Therefore, it is of great significance to apply multi-path transmission to 7G networks. However, traditional multi-path transmission technologies (MPTCP/MPQUIC) cannot cope with the new features emerging in 7G networks, such as path selection, low latency, and protocol incompatibility, which require lower complexity. The Information-Centric Network (ICN) offers the advantages of strong mobility and bandwidth efficiency and has been widely adopted in integrated networks. Therefore, this study proposes an artificial intelligence multi-path transmission mechanism based on the ICN and mathematically models the entire transmission process as a mixed-integer linear programming model to solve the problem of multi-path transmission path conflicts in 7G networks (called AIICN). Experiments demonstrate that the proposed AIICN multi-path transmission offers advantages of high throughput, low complexity, and fast algorithm convergence, with a transmission throughput approximately 21% higher than that of traditional multi-path transmission. AIICN can be well applied to 7G networks to achieve efficient multi-path transmission.

KEYWORDS

7G network, multi-path transmission, artificial intelligence, throughput, ICN

1 Introduction

With the large-scale popularization of mobile communications, 7G is a further upgrade and expansion of the current 5G and 6G networks (Chamola et al., 2025). Its communication speed has also been significantly improved. In addition, the 7G network has been more deeply integrated with technologies such as artificial intelligence and blockchain. Besides communication, its core network can also self-learn and innovate (Chamola et al., 2025). Therefore, some new features in the 7G network cannot be directly applied to traditional MPTCP and MPQUIC protocols (Alkasassbeh et al., 2024). While 6G technology facilitates large-scale data transmission, it is not well-suited for use in satellite networks. 7G networks use high-band technologies such as terahertz waves, and their peak transmission rates can reach 36 Gbit/s, far exceeding 5G and 6G networks. They can efficiently transmit huge data sets and model updates required by artificial intelligence (Kaushik et al., 2024). The data transmission capacity of a 6G network can reach up to 100 Gbps, which can meet the requirements of blockchain and live applications but cannot be effectively applied to artificial intelligence. However, the data transmission capacity of a 7G network can reach 300 Gbps, making it more meaningful to apply artificial intelligence to multi-path transmission in a 7G network (Chamola et al., 2025).

Multi-path transmission has been a part of people's lives for many years, as seen in the multi-path transmission of Apple mobile phones, which offers advantages such as improved reliability and throughput (Wei et al., 2025). The 7G network comprises a satellite network and a terrestrial network, making it highly suitable for implementing multi-path transmission, as shown in Figure 1. Since the 7G network is a three-dimensional network formed by integrating satellite networks, terrestrial networks, and other technologies, it also presents numerous challenges.

1. Poor transmission conditions. Due to the periodic orbit-changing characteristics of satellites, the number of available satellites for data transfer is limited, and the transmission link may change due to variations in the satellite's orbit.

Since the 7G network operates in a three-dimensional space that encompasses both terrestrial and satellite networks, multiple protocols coexist. The traditional multi-path mechanism cannot cope well with transmission under multi-protocol fusion.

2. Low transmission intelligence, limited adaptability, and high complexity. Since traditional multi-path transmission mainly relies on ground networks, it has low intelligence and high complexity, making it unsuitable for applications in satellite networks, including 7G networks.

ICN uses content instead of TCP/IP to transmit data (https://www.rfc-editor.org/info/rfc9508) and has been widely adopted in content delivery and other fields. It is also considered the network architecture of the future. It is a new type of network centered on content or data. It performs large-scale data transmission and delivery by decoupling content and location, abandoning the communication mode centered on IP addresses in traditional networks. It utilizes content caching to achieve efficient data transmission, and its content caching technology is particularly suitable for multi-path transmission (Nadeem Ali et al., 2025). The entire network comprises content providers, users (consumers), base stations, satellites, and other components. Users request data from content providers through interest packets via satellite links, and content providers respond to these requests according to the data packets specified by the users. Since ICN has the function of content caching and the satellite network has multiple transmission links, the entire 7G network forms multi-path transmission.

Based on the above analysis, this study employs artificial intelligence technology for 7G to facilitate multi-path transmission. The main contributions include

1. The 7G network multi-path transmission is mathematically modeled, and a calculation scheme for link transmission costs, including satellite networks, is proposed. By calculating link transmission costs, it is beneficial to transmit data on high-value links. The path transmission problem of 7G network multi-path transmission is mathematically modeled as a mixed-integer linear programming problem, and reinforcement learning is used to solve it, thereby realizing low-complexity, highly intelligent multi-path transmission.

2. The proposed AIICN is simulated and validated using network simulation tools. The results demonstrate that AIICN possesses high intelligence and strong versatility, making it applicable to 7G networks, including terrestrial and satellite networks.

The rest of the article is organized as follows: In Section II, we review existing proposals for multi-path in 7G. In Section III,

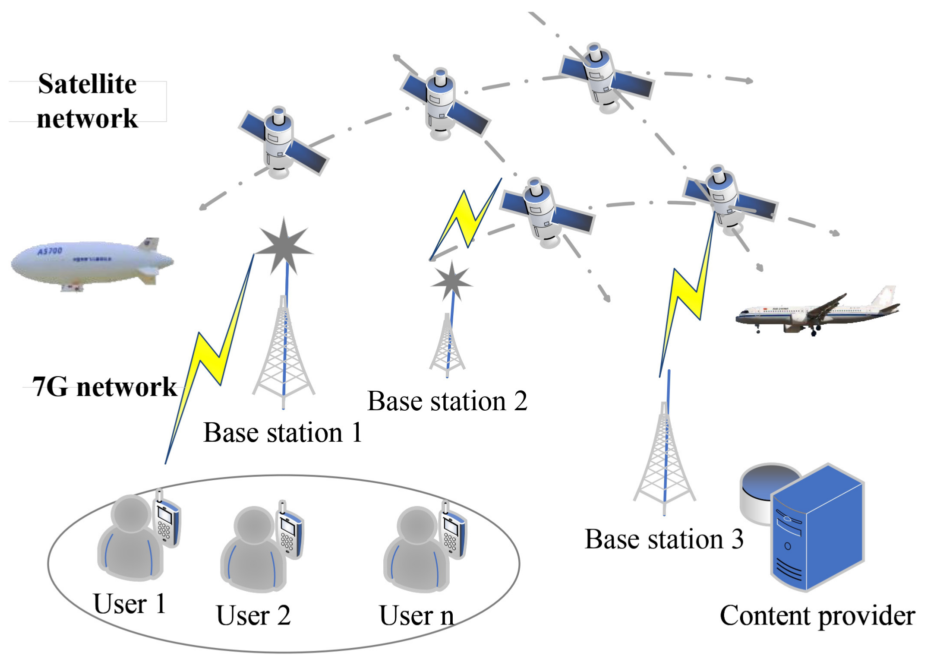

FIGURE 1
Multi-path transmission scenario composed of 7G network.

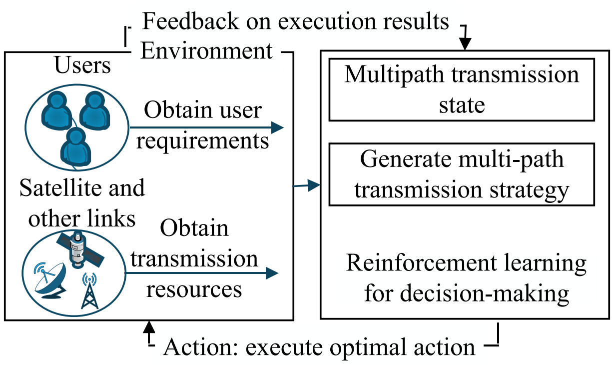

FIGURE 2
Schematic diagram of strengthening learning to solve multi-path transmission.

we introduce the proposed system model and its implementation process. Section IV covers performance evaluation and result analysis, providing a detailed comparison of the performance with other methods. In Section V, we summarize the findings of this study.

Next, we will further discuss the multi-path transmission for the 7G network based on artificial intelligence proposed in this study.

2 Related research

Currently, scholars have conducted extensive research on multi-path transmission, focusing on improving transmission throughput and reliability, as well as preventing network congestion (Karimah et al., 2021). Since there are few studies on 7G networks, we can refer to the research on 5G and 6G networks for guidance. MPTCP and MPQUIC are traditional multi-path protocols (Kusuma and Putri, 2020). For example, in 2024, Zhao et al. (2024) proposed an MPTCP scheduling algorithm for bandwidth allocation in 5G edge networks that cannot meet the transmission requirements of multiple virtual reality streams. Hikmaturokhman (2023) studied the relationship between spectrum and tariffs in 5G networks, noting that the new characteristics of 5G networks will impact the determination of tariffs. By integrating cross-layer information between the application end and the wireless end to predict latency, better user experience quality can be achieved. Gao et al. (2020) designed multi-path transmission for transmitting game videos in 6G vehicle networks, effectively solving the data transmission quality download problem caused by link switching. At the same time, some scholars also studied multi-path transmission in satellite networks. Yang et al. (2024a) proposed a multi-path traffic model to address the link interruption problem caused by the high-speed movement of satellites in integrated networks, thereby aiding the avoidance of network congestion and enhancing throughput. In 2025, Nassef and other scholars (Nassef et al., 2025) proposed a transmission mechanism based on the QUIC protocol to distinguish between reliable and unreliable data packets in 5G networks, aiming to address the problem of network congestion caused by data packets transmitted across multiple protocol layers, which is conducive to reducing network congestion. Hilal and other scholars proposed multi-path transmission by reducing the number of sub-streams to address the problem of bottleneck links affecting data transmission, and experimental results have shown that it is beneficial for avoiding congestion and enhancing throughput (Hilal H et al., 2023).

6G and 7G networks are very suitable for application in artificial intelligence data transmission (Bazzi et al., 2025). Yang et al. (2025) also proposed a quality of service-driven commuting framework based on MPQUIC to address the issue of video streaming performance degradation caused by link switching in 6G wireless networks. It can intelligently select access networks and adapt to varying throughputs. Experiments have verified that it can prevent video interruptions. (Yang et al., 2024b) also studied mobile perception in wireless networks. They used ACK packets in QUIC to transmit mobile information, allowing them to select the optimal transmission path based on the real-time status of the link and achieve efficient multi-path transmission. Elhachi et al. (2025) expanded the functionality of MPQUIC in satellite networks, enabling the elimination of unreliable transmission data, thereby avoiding any impact on reliable transmission data packets and improving the quality of video transmission.

Since current artificial intelligence technology has made significant progress in many fields, many scholars have also used artificial intelligence to solve problems in multi-path transmission and to improve the service quality of multi-path transmission.

3 System modeling and implementation

3.1 Mathematical model

First, we model the 7G network transmission path selection problem, determining the objective function and constraints. The objective function can be to maximize the transmission throughput, minimize the path cost, etc. The constraints include the number of paths, location restrictions, link capacity restrictions, etc. The principle is shown in Figure 2. It consists of a user demand acquisition module, an artificial intelligence decision module, and a link status acquisition module. The system first obtains the user's demand information and the specific status of the transmission link. Then the artificial intelligence decision module calculates the optimal multi-path strategy based on the above information, including path selection and data volume allocation. Finally, the generated decision information is sent to the transmission link to execute the multi-path transmission strategy. To better generate real-time strategies, the results of the entire multi-path execution will also be input into the artificial intelligence decision module, improving the artificial intelligence algorithm.

Next, the above multi-path transmission framework is described in detail.

3.2 Time model

Suppose the time slot set is: $T = \{t_1, t_2, \ldots\}$, the elements in the set T are called a transmission time slot, which satisfies the following relationship:

$$T = \sum_{i=1}^{|T|} t_i, t_i < t_{i+1}, i \in [1, 2, \ldots] \tag{1}$$

T is the total transmission time. It is assumed that the network topology is stable and unchanged during a time slot t. In practical applications, the air-ground connection can last for several minutes. In this study, it is assumed that the duration is 10 s, and the dynamic network topology is characterized within a time slot.

3.3 Network topology model

Network topology refers to a disjoint graph G in a time slot $G^t = \{V^t, E^t\}$, where V is the set of network nodes and E is the set of edges in a connected state in 7G. In particular, the entire network is a three-dimensional network comprising satellite node sets, ground stations, base stations, flying machines, airships, and users, among others. The bandwidth between transmission node m and node n is $B_{m|n}$. In a data process, the bottleneck bandwidth of the entire path is:

$$B_{m|n} = min\{B_{m|1}, B_{1|2}, \ldots, B_{(h-1)|h}, B_{h|n}\} \tag{2}$$

$m|n$ represents the transmission path between node m and node n. The bandwidth value is calculated by obtaining the number of data packets in real time through the sketch algorithm installed on each satellite node (Li et al., 2024). Sketch is a type of probabilistic data structure widely used in the field of network measurement. It is used to record the frequency of elements in multiple sets or streams. It possesses the characteristics of low overhead and high precision, and has been widely used in cloud computing and satellite networks (Cao et al., 2024). One of the calculation methods of the sketch vector is the product of flow and its unit.

$$\begin{bmatrix} f_{11} & \cdots & f_{1g} \\ \vdots & \ddots & \vdots \\ f_{g1} & \cdots & f_{g1} \end{bmatrix} \times \begin{bmatrix} tr_1 & tr_2 \\ tr_3 & tr_4 \end{bmatrix} = \text{one sketch vector} \tag{3}$$

f is a hash function. tr is the historical traffic value of 4 nodes.

The calculation method for transmission delay is:

$$d_{m|n} = \frac{L_{m|n}}{v} \tag{4}$$

Among them, $L_{m|n}$ represents the distance between two nodes, and its specific value can be determined based on the regularity and predictability of satellite operations. v is the transmission speed of light, which is a known value.

Similarly, the transmission delay D between the transmission paths from node m to node n is given as follows:

$$D_{m|n} = \{d_{m|1} + d_{1|2} + \cdots + d_{(q-1)|q} + d_{q|n}\} \tag{5}$$

Then, in a single data processing step, the transmission delay for the entire path is as follows:

$$D_{m|n} = max\{D_{m|1}, D_{1|2}, \ldots, D_{(h-1)|h}, D_{h|n}\} \tag{6}$$

3.4 Link transmission cost

Link transmission cost refers to the construction, resource, and time costs involved in the data transmission process. For example, the construction costs of satellite nodes and drones are significantly higher than those of ground networks.

One satellite node functions as a switch and a router during transmission, and it can calculate and save data. The calculation method for the data buffer area at node m is as follows:

$$U_m = \sum(u_1 + u_2 + \ldots) \tag{7}$$

The above formula illustrates that the calculation method for the transmission data buffer is the sum of all data packets (i.e., the sum of the queue lengths). u_m is the real-time queue length. U is the total amount of buffer.

Based on the above analysis, the cost function of a transmission link is as follows:

$$C_{m|n} = C_c \cdot (1 - \frac{B_{p(m|n)}}{B_{Total}}) \cdot D_p(m|n) \cdot max\{\frac{u_m}{U_m}, \frac{u_n}{U_n}\} \tag{8}$$

Among them, C_c is the construction cost, which is a known value. For example, the construction cost of an unmanned aerial vehicle is higher than that of ground-wired networks. B_{Total} is the total bandwidth in the network. The transmission path must choose a lower-cost link.

3.5 System architecture and implementation

According to the above sections, the path selection in the multi-path transmission of the entire 7G network is a mixed-integer linear programming (MILP) (Fard Moshiri et al., 2025), and its optimization objectives and constraints are as follows. By defining satellite selection variables as integer types, the model can accurately describe the discrete decision-making process. Maximize network throughput:

$$\max\min \sum_{m=1}^{M}\sum_{n=1}^{N}(\frac{Data}{\Delta t} \cdot |p|) \tag{9}$$

In the above formula, p represents the total number of transmission paths, Δt denotes the time interval of each transmission, and $Data$ represents the total amount of data that the user needs to transmit.

Minimize the path-transmission cost:

$$\min \sum_{m=1}^{M}\sum_{n=1}^{N} C_{m|n} \tag{10}$$

The following are the constraints.

1. During multi-path transmission, data are transmitted reliably, and time slots are continuously advanced. *Data* represents the total amount of data transmitted through the path.

$$Data(t) > Data(t+1) > \ldots \tag{11}$$

2. Since it is a multi-path transmission, at least two paths are involved in data transfer. p represents the number of the transmission path.

$$|p| \geq 2 \tag{12}$$

3. In a time slot, the total buffers of all transmission satellite nodes exceed the amount of data to be transmitted on the working path.

$$U(t) > Data(t) \tag{13}$$

4. During multi-path transmission, the transmission direction is forward, and no data loops are formed. m is the work path number.

$$Data(n) \rightarrow Data(m), m > n \tag{14}$$

The path selection problem in multi-path transmission is a Markov decision process (MDP). The task to be solved in a time slot t can be represented by a four-tuple $\langle t, St, Re, Ac \rangle$, where St is the state, Re is the reward obtained, and Ac is the action generated according to the strategy, as shown in Figure 2. Figure 2 illustrates the relationships between each entity in multi-path transmission.

The state St refers to the environmental information perceived by the agent in the entire 7G network. Since the state will change with the change of transmission during the 7G multi-path transmission process, its definition is $St = \langle Data_{user}, \langle State_{links}, node \rangle \rangle$, where $\langle State_{links}, node \rangle$ is the state information of the transmission link and node, such as bandwidth, packet loss rate, delay, and other key information.

Action Ac refers to the action performed by the agent in state St, which specifically selects the path used as the data transmission link. The action set includes the following:

$$Ac = \{link|(1, 2, \ldots), Data\} \tag{15}$$

Among them, $link|(1, 2, \ldots)$ is the set of path numbers that are in the working state (selected by the algorithm). *Data* is the amount of data allocated on the working path.

The reward Re refers to the reward function that guides the agent's actions. If an action is beneficial for improving throughput and load balancing, it is encouraged; otherwise, it is discouraged.

Since there is usually no unique optimal solution to a multi-objective optimization problem, the *Epsilon* constraint method provides an effective approach to solving such problems. The idea is to introduce a very small positive real number *Epsilon* and convert the multi-objective optimization problem into a single-objective one by treating all but one objective function as constraints, each bounded by a corresponding *Epsilon* value. By continuously varying the value of *Epsilon*, a set of Pareto optimal solutions can be obtained (Saber et al., 2025).

In addition, to improve the stability of the algorithm and prevent updates from occurring too rapidly, soft updates are applied to gradually approach the target value, as follows:

$$\begin{aligned} \theta^{Q'} &\leftarrow \theta^{Q} \cdot \omega + \theta^{Q'} \cdot (1-\omega) \\ \theta^{\mu'} &\leftarrow \theta^{\mu} \cdot \omega + \theta^{\mu'} \cdot (1-\omega) \end{aligned} \tag{16}$$

Among them, ω is a very small number.

The entire algorithm utilizes the deep deterministic policy gradient (DDPG) method, a deep reinforcement learning algorithm suitable for solving problems in continuous action spaces, such as continuous motion in driverless cars. It combines deterministic strategies and deep neural networks, is a model-independent reinforcement learning algorithm, and belongs to the actor-critic framework. It leverages both DQN and PG (policy gradient) (Zhang et al., 2024b) (Zhang et al., 2024a) (Fan et al., 2025). DDPG uses the Bellman equation to update the target value Q' of the critic network Q, and the value network is μ', that is:

$$Re + \gamma \cdot Q'(St', \mu'; \theta^{Q'}) \tag{17}$$

$\gamma \in [0, 1]$ is a discount factor: The larger the γ, the more steps the agent will consider ahead, but the higher the difficulty of training. The smaller the γ, the more the agent will focus on immediate interests, and the easier it will be to train.

The loss function is used to estimate the degree of inconsistency between a model's predicted value and the true value. The smaller the loss, the better the model's robustness, and it is the loss function that guides the model's learning. Our loss function is as follows:

$$\left| \sum \left(Re + \gamma \cdot Q' \left(St', \mu'; \theta^{Q'} \right) - Q \left(St, Ac \mid \theta^{Q} \right) \right) \right| \tag{18}$$

In the DDPG algorithm, the weight update rule involves two main steps: empirical replay and deterministic policy gradient update.

The experience replay pool can break down samples, which is beneficial for training. In deterministic policy gradients, the weights of the policy network are updated by maximizing the Q-value function. The Q-value function represents the expected cumulative reward of the current state and action and is used to evaluate the effectiveness of the strategy.

During deterministic policy gradient updating, a batch of experiences is randomly sampled from the experience replay pool, and then the Q value and the current Q value are calculated separately. The gradient is then calculated, and finally, gradient descent is used to update the weights of the policy network.

The discount factor affects the current value of future rewards. A higher discount factor indicates that the algorithm places greater value on long-term returns, whereas a lower discount factor implies that the algorithm prioritizes short-term returns. For tasks that require long-term planning, a higher discount factor should be chosen. For tasks that prioritize immediate rewards, it is advisable to choose a lower discount factor.

```
Input: Initialize network status, actions, and
    experience replay pool Bu, Critic network Q, Actor
    network μ, and initialize network Q'.
Output: An optimal action is to select the path list
    set path.
Repeat
  Generate random noise for exploration ℕ.
  Initialize a state St.
  Repeat
     Select an action Ac based on the current ℕ
    and strategy.
     Execute actions and get rewards, as well as
    obtain new states St'.
     Put the result ⟨St, St', Ac, Re⟩ in Bu.
     Calculate the minimum loss with formula 18.
     Update the target network with formula 16.
  Until (episode = 1, 2, 3, ...)
Until (iteration = 1, 2, 3, ...)
return path list set path.
```

Algorithm 1. DDPG-based multi-path transmission algorithm

The complexity of Algorithm 1 mainly depends on two loops. When training the Critic, using the target actor and the target critic can reduce the variance and overestimation problems during training. Additionally, using the target network can prevent the critic from being overly sensitive to the current strategy, thereby reducing overfitting. The time complexity is $O(\sum_{\mathcal{D}=1}^{\mathcal{I}} \mathcal{T}_{\mathcal{D}}^2 * \mathcal{S}^2 * \mathcal{Y})$. $\mathcal{I}$ is the depth of the network, the number of convolutional layers in a neural network. $\mathcal{T}$ is the edge length of the features output by the convolution kernel. $\mathcal{Y}$ is the product of the number of channels in each convolutional kernel and the total number of convolutional kernels in the current convolutional layer.

4 Performance evaluation and result analysis

In this section, we utilize Mininet v2.3 (https://www.mininet.org/) and NS-3 to construct and simulate a 7G network environment (Perdana et al., 2022) - (Larasati et al., 2020). We design experiments to evaluate the performance of the proposed algorithm and compare its throughput, transmission delay, and other metrics. Based on the experimental method described in the study (Chang and Lin, 2024), we designed an experiment utilizing 7G network transmission, which involved 72 consecutive hours of data requests from 16 users, and the server was located on the ground.

The compared algorithms include:

The proposed method refers to the algorithm introduced in this study.

vStreamPth refers to an algorithm that ensures high-quality real-time video streaming by designing deadline satisfaction and applying multi-path transmission. For details, see the study (Han et al., 2025).

ODS is a multi-path algorithm based on software definition and network slicing used in 5G networks. For details, see the study (Chang and Lin, 2025).

CAMP refers to an algorithm used in the underwater Internet of Things to enhance reliability through multi-path routing. For details, see the study (Xu et al., 2025).

APROR refers to a multi-path transmission scheme used in 5G multi-path transmission. It minimizes carrying costs and energy consumption through the multi-path 5G network, adaptively distinguishing the collision domains of different types of flows, thereby minimizing the collision probability. For details, see the study (Chang and Lin, 2024).

MDQ refers to a QoS congestion-aware deep reinforcement learning method for multi-path routing in dynamic SDN networks. It uses deep reinforcement learning to intelligently select the best multi-path and allocate traffic according to traffic demand. For details, see the study (Aguirre Sanchez et al., 2025).

MP: In cloud networks, a multi-path protection method is designed to reduce the reserved bandwidth on backup paths by distributing traffic across multiple non-intersecting working paths, thereby improving overall network reliability. For details, see the study (Madani et al., 2025).

DGCN-ACO is applied in satellite networks and proposes a learning-based swarm intelligence method for deterministic flow scheduling in dynamic satellite networks. It includes an algorithm that combines a dynamic graph convolutional network with an adaptive ant colony optimization algorithm to achieve deterministic flow scheduling, thereby facilitating the overcoming of the dynamic nature of satellite networks. For details, see the study (Wang et al., 2025).

In order to eliminate the influence of objective factors on the experimental results, the average value of 50 experiments in each group is included in the final result. To intuitively reflect the data from the experiment and eliminate differences between features, all data are normalized. After all experimental data are normalized, the features are scaled to [0, 1]. The normalization formula is as follows:

$$\frac{V - V_{min}}{V_{max} - V_{min}} \tag{19}$$

In the above formula, V represents the original data, while V_{max} and V_{min} denote the maximum and minimum values after characterization. After the experimental results are normalized, it is helpful to quickly identify any abnormal values.

4.1 Transmission throughput normalization

Transmission throughput is a key indicator of overall network performance. It refers to the total number of bytes successfully transmitted by different algorithms simultaneously. Network congestion, data retransmission, and so on will affect transmission throughput. The higher the value, the better the overall transmission performance of the network.

In the 7G network, the data transmission from the ground to the air is dynamic, so the transmission will be "intermittent." Figure 3 shows the throughput under different transmission conditions. The algorithm proposed in this study comprehensively

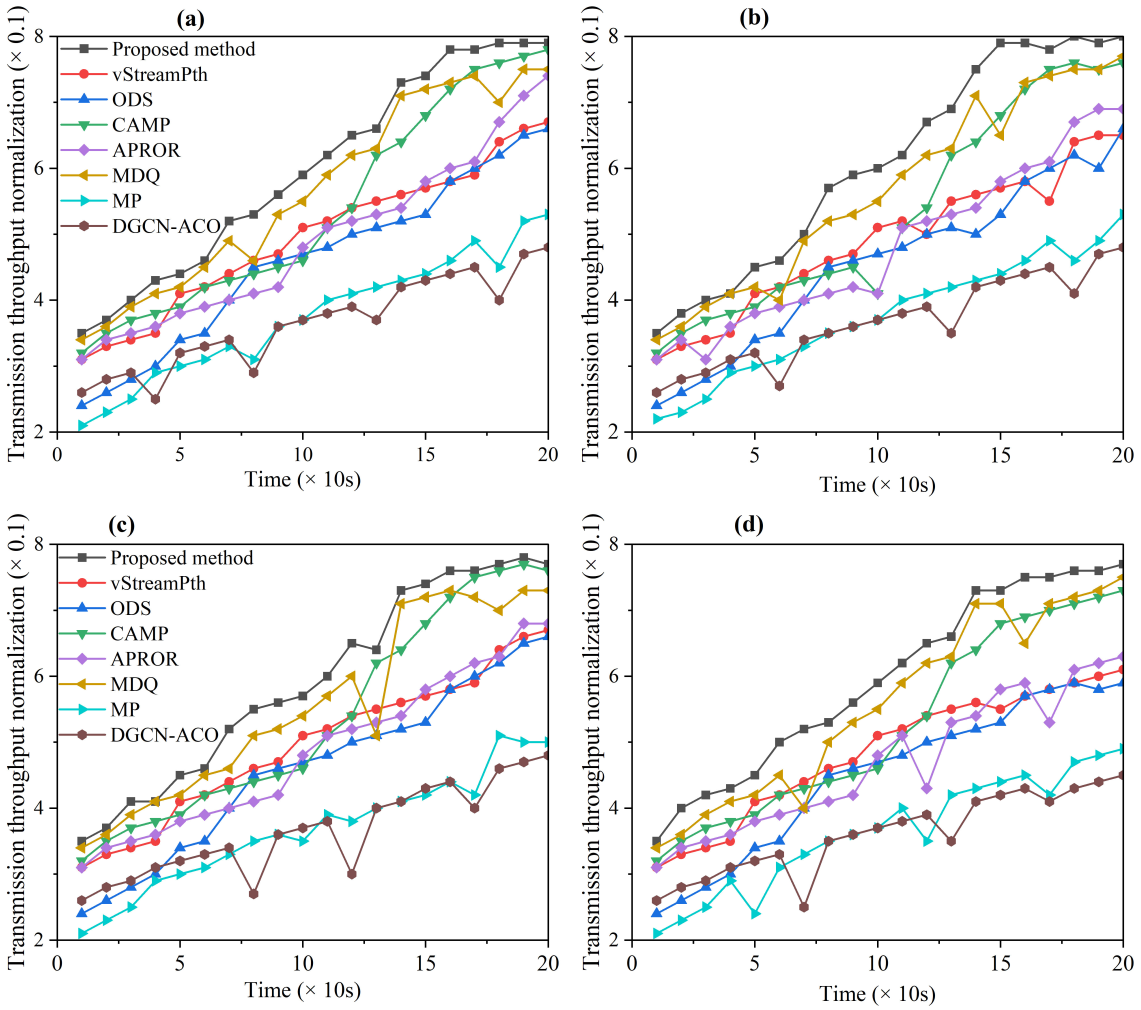

FIGURE 3
Normalized comparison of transmission throughput. **(a)** Normal transmission, **(b)** High load transmission, **(c)** High packet loss rate transmission, and **(d)** High delay transmission.

applies multi-objective optimization to achieve multi-path transmission. High throughput accounts for the largest proportion.

The algorithm proposed in this study utilizes artificial intelligence technology to solve multi-objective optimization problems, and it converges quickly. Figure 3b shows that from $x \in (14, 20)$, it has been in a stable state.

4.2 Number of satellites and throughput

In this experiment, the influence of the number of satellites on throughput was studied using the Iridium NEXT constellation. Due to the periodic on-off characteristics of satellites, transmission interruptions may occur. As shown in Figure 4a, as the number of satellites increases, throughput continues to increase. However, when $x = 70$, throughput remains basically unchanged. Thus, we can conclude that in the 7G network, due to the periodic orbit switching characteristics of satellites, the throughput is not directly determined by the number of satellites.

4.3 Load balance

Since the entire 7G network comprises multiple transmission nodes and complex links, there are multiple paths between the sender and the receiver; therefore, load balancing across these paths is crucial. If load balancing is achieved throughout the entire network, congestion can be effectively reduced. In this experiment, the flow values in multiple paths were measured using a sketch, and the statistical results are shown in Figure 4b. The data transmitted in paths 2, 4, 5, 6, and 8 are roughly equal, and the flow values between these paths do not fluctuate significantly. The traffic value between each path is less than 1. Therefore, the algorithm proposed in this article achieves load balancing between paths.

Artificial intelligence algorithms can integrate previous historical experience and the current path status to calculate the optimal reward function, select the optimal transmission path, and achieve load balancing between multiple paths.

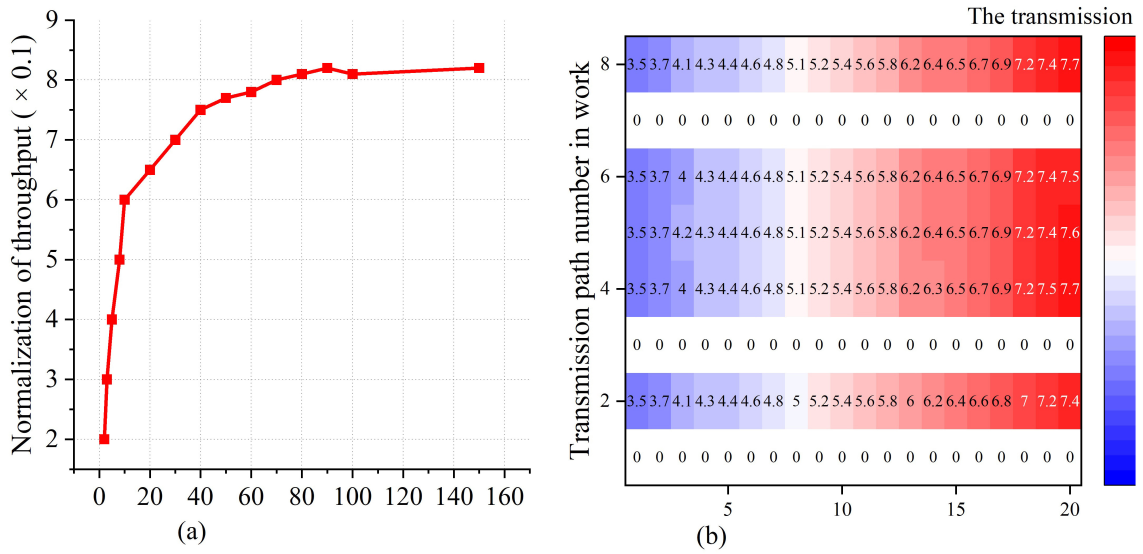

FIGURE 4
The transmission traffic and number of satellites in the work path. **(a)** Number of satellites, **(b)** Transmission time ×10s.

In summary, the multi-path algorithm proposed in this study is well-suited for application in 7G networks and offers advantages in various aspects of multi-path transmission.

5 Conclusion

7G has been integrated with technologies such as artificial intelligence, satellite networks, and blockchain, making it a key next-generation network. Since traditional multi-path protocols cannot meet the requirements of 7G networks, this study proposes a multi-path transmission scheme based on artificial intelligence. First, the entire network is mathematically modeled, and a method for calculating link transmission costs is proposed. Then, the multi-path transmission mathematical model is transformed into a mixed-integer linear programming problem, which is solved using artificial intelligence techniques. After experimental simulation verification, it is shown that low-complexity, highly intelligent multi-path transmission can be achieved, characterized by high throughput and load balancing.

This study uses reinforcement learning to address multi-objective optimization, which results in a high demand for high-value samples and limits the application of the entire system. Therefore, in future work, further research will be conducted on using imitation learning and other techniques to solve multi-path transmission problems.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author: jingqs@yeah.net.

Author contributions

ZX: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This project was supported by Shanghai Donghai College Xi Jinping thought on socialism with Chinese characteristics for a new era education and teaching center with funding number is 25DYJZX004 and 2025 Shanghai ”Grand Neobay” university special fund.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

References

Aguirre Sanchez, L. P., Shen, Y., and Guo, M. (2025). Mdq: a qos-congestion aware deep reinforcement learning approach for multi-path routing in sdn. *J. Netw. Comput. Applic*. 235:104082. doi: 10.1016/j.jnca.2024.104082

Alkasassbeh, J., Al-Taweel, F., Alawneh, T., Al-Qaisi, A., Makableh, Y., and El-Mezieni, T. (2024). Advancements in wireless communication technology: a comprehensive analysis of 4g to 7g systems. *J. Wireless Mobile Netw*. 15:19. doi: 10.58346/JOWUA.2024.I3.006

Bazzi, A., Bomfin, R., Mezzavilla, M., Rangan, S., Rappaport, T., and Chafii, M. (2025). Upper mid-band spectrum for 6g: vision, opportunity and challenges. *Qeios* 1–6. doi: 10.32388/XNRU0A

Cao, Y., Feng, Y., Wang, H., Xie, X., and Zhou, S. K. (2024). Learning to sketch: a neural approach to item frequency estimation in streaming data. *IEEE Trans. Pattern Anal. Mach. Intell*. 46, 7136–7153. doi: 10.1109/TPAMI.2024.3388589

Chamola, V., Shall Peelam, M., Guizani, M., and Niyato, D. (2025). Future of connectivity: a comprehensive review of innovations and challenges in 7g smart networks. *IEEE Open Journal of the Communications Society* 6:3555–3613. doi: 10.1109/OJCOMS.2025.3560035

Chang, B.-J., and Lin, Y.-T. (2024). Adaptive flowing traffic prediction in contention random access for optimizing virtual/physical resource in b5g/5g new radio and core network. *IEEE Trans. Netw. Sci. Eng*. 11, 1934–1946. doi: 10.1109/TNSE.2023.3334744

Chang, B.-J., and Lin, Y.-T. (2025). Optimizing differentiated sfcs of slicing using virtual/physical network resources for sdn-based flowing and steering in b5g/5g networking. *Comput. Netw*. 259:111065. doi: 10.1016/j.comnet.2025.111065

Elhachi, H., Labiod, M.-A., Boumehrez, F., and Redadaa, S. (2025). Enhancing real-time mobile health video streams: a cross-layer region-of-interest based approach. *Comput. Netw*. 257:111014. doi: 10.1016/j.comnet.2024.111014

Fan, Q.-Y., Cai, M., and Xu, B. (2025). An improved prioritized ddpg based on fractional-order learning scheme. *IEEE Trans. Neural Netw. Learn. Syst*. 36, 6873–6882. doi: 10.1109/TNNLS.2024.3395508

Fard Moshiri, P., Simsek, M., and Kantarci, B. (2025). Joint optimization of completion ratio and latency of offloaded tasks with multiple priority levels in 5g edge. *IEEE Trans. Netw. Serv. Manag*. 22, 1357–1371. doi: 10.1109/TNSM.2024.3525004

Gao, K., Xu, C., Zhang, P., Qin, J., Zhong, L., and Muntean, G.-M. (2020). Gch-mv: game-enhanced compensation handover scheme for multipath tcp in 6g software defined vehicular networks. *IEEE Trans. Vehic. Technol*. 69, 16142–16154. doi: 10.1109/TVT.2020.3042987

Han, J., Liu, J., Xue, K., Sun, Q., and Lu, J. (2025). Toward high-quality real-time video streaming: An efficient multi-stream and multi-path scheduling framework. *IEEE Trans. Netw*. 33, 1–14. doi: 10.1109/TON.2025.3547278

Hikmaturokhman, A. (2023). A proposal for the regulation of the spectrum usage fee in 5g private network using fuzzy ahp. *J. Infotel* 15, 157–264. doi: 10.20895/infotel.v15i3.959

Hilal H, N., Arif Y, F., et al. (2023). Enhanced multipath tcp to improve the mobile device network resiliency. *Int. J. Comput. Digit. Syst*. 16, 67–83. doi: 10.12785/ijcds/160106

Karimah, S. A., Susanto, F. M., and Putrada, A. G. (2021). Comparative analysis of qoe multipath tcp congestion control lia, cubic, and wvegas on video streaming. *Int. J. Inform. Commun. Technol*. 7, 31–39. doi: 10.21108/ijoict.v7i1.534

Kaushik, A., Singh, R., Dayarathna, S., Senanayake, R., Di Renzo, M., Dajer, M., et al. (2024). Toward integrated sensing and communications for 6g: key enabling technologies, standardization, and challenges. *IEEE Commun. Stand. Magaz*. 8, 52–59. doi: 10.1109/MCOMSTD.0007.2300043

Kusuma, F., and Putri, H. (2020). Increasing lte-advanced network capacity using the inter-band carrier aggregation (downlink side) method. *J. Infotel* 12, 52–59. doi: 10.20895/infotel.v12i2.474

Larasati, S., Yuliani, S., and Danisya, A. (2020). Outage performances of 5g channel model influenced by barometric pressure effects in yogyakarta. *J. Infotel* 12, 25–31. doi: 10.20895/infotel.v12i1.463

Li, F., Guo, K., Shen, J., and Wang, X. (2024). "Effective network-wide traffic measurement: a lightweight distributed sketch deployment," in *IEEE INFOCOM 2024 – IEEE Conference on Computer Communications* (Vancouver, BC), 181–190. doi: 10.1109/INFOCOM52122.2024.10621384

Madani, M. A., Zhou, F., and Meddahi, A. (2025). Deploying disaster-resilient service function chains using adaptive multi-path routing. *IEEE Trans. Netw. Serv. Manag*. 22, 1825–1840. doi: 10.1109/TNSM.2024.3520392

Nadeem Ali, M., Imran, M., Salah Ud Din, M., and Kim, B.-S. (2025). Ifcns: intelligent forwarding and computation node selection in icn mobile edge computing. *IEEE Sensors J*. 25, 22918–22940. doi: 10.1109/JSEN.2025.3564414

Nassef, O., Mahmoodi, T., Chiariotti, F., and Johnson, S. H. (2025). Drel: dynamically assigning per-packet reliability at the transport layer. *IEEE Trans. Netw. Serv. Manag*. 22, 1276–1294. doi: 10.1109/TNSM.2024.3509136

Perdana, D., Zaim, A., Hikmaturokhman, A., Irsyad, A., and Marthaliana, N. (2022). Analysis of greedy perimeter stateless routing protocol network simulation using bird flocking algorithm. *J. Infotel* 14, 15–19. doi: 10.20895/infotel.v14i1.706

Saber, H., Ranjbar, H., and Mazaheri, H. (2025). Multi-objective der planning framework as a tep alternative: an augmented epsilon-constraint approach. *IEEE Trans. Industry Applic*. 61, 1–11. doi: 10.1109/TIA.2025.3571870

Wang, Z., Yao, H., Mai, T., Li, Z., and Chen, C. L. P. (2025). Learning-driven swarm intelligence: enabling deterministic flows scheduling in leo satellite networks. *IEEE Trans. Mobile Comput*. 24, 3962–3978. doi: 10.1109/TMC.2024.3517618

Wei, D., Zhang, J., Liu, X., Li, H., Xue, Z., Huang, T., et al. (2025). Qoe-optimized multipath scheduling for video services in large-scale peer-to-peer cdns. *IEEE J. Select. Areas Commun*. 43, 563–576. doi: 10.1109/JSAC.2025.3528809

Xu, C., Song, S., Liu, J., Pan, M., Xu, G., and Cui, J.-H. (2025). Joint power control and multipath routing for internet of underwater things in varying environments. *IEEE Internet Things J*. 12, 15197–15210. doi: 10.1109/JIOT.2025.3527692

Yang, W., Cai, L., Shu, S., and Pan, J. (2024a). Mobility-aware congestion control for multipath quic in integrated terrestrial satellite networks. *IEEE Trans. Mobile Comput*. 23, 11620–11634. doi: 10.1109/TMC.2024.3397164

Yang, W., Cai, L., Shu, S., Pan, J., and Sepahi, A. (2024b). Mams: mobility-aware multipath scheduler for mpquic. *IEEE/ACM Trans. Netw*. 32, 3237–3252. doi: 10.1109/TNET.2024.3382269

Yang, W., Cai, L., Shu, S., Sepahi, A., Huang, Z., and Pan, J. (2025). Qos-driven contextual mab for mpquic supporting video streaming in mobile networks. *IEEE Trans. Mobile Comput*. 24, 3274–3287. doi: 10.1109/TMC.2024.3507051

Zhang, J., Tao, J., Hu, Y., and Ma, L. (2024a). An energy management strategy based on ddpg with improved exploration for battery/supercapacitor hybrid electric vehicle. *IEEE Trans. Intell. Transp. Syst*. 25, 3999–4008. doi: 10.1109/TITS.2023.3327105

Zhang, L., Peng, J., Yi, W., Lin, H., Lei, L., and Song, X. (2024b). A state-decomposition ddpg algorithm for uav autonomous navigation in 3-d complex environments. *IEEE Internet Things J*. 11, 10778–10790. doi: 10.1109/JIOT.2023.3327753

Zhao, B., Yang, W., Du, W., Ren, Y., Sun, J., Wu, Q., et al. (2024). A multipath scheduler based on cross-layer information for low-delay applications in 5g edge networks. *Comput. Netw*. 244:110333. doi: 10.1016/j.comnet.2024.110333