Genetic Algorithm-Based Inter-Satellite Link Establishment and Routing Scheme for Satellite Networks

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Abstract. In recent years, because of their advantages in coverage and throughput compared to traditional fiber and mobile networks, satellite networks have garnered increasing attention. However, satellite networks have limited resources such as storage, power, and frequency bands. Therefore, how to maximize network transmission capacity under limited communication resources is a key to the practical application of satellite networks. To enhance the throughput of the satellite network, we have devised a multicast satellite network that incorporates network coding. Additionally, we have further bolstered the network capacity by optimizing its topology and refining the routing of information flow. In order to find a better topology structure, we design a Genetic Algorithm based topology construction method which decode the topology as the chromosome and finding topologies with higher performance by mimicking biological genetic meritocracy. Ultimately, the simulation outcomes demonstrate that the introduced method substantially outperforms traditional approaches in augmenting the network's capacity.

Keywords: Network Coding · Inter-Satellite Link(ISL) Establishment · Genetic Algorithm · Satellite Network · Routing Scheme

1 Introduction

During the past few years, satellite networks have received more focus and attention due to their ability to provide greater coverage and throughput compared

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to traditional fiber and mobile networks, especially in remote locations, including mountainous regions and vast oceans, without incurring additional deployment costs. As a result, satellite networks have become an integral part of next-generation communication networks. However, satellite networks have limited resources such as storage, power, and frequency bands, while high-bandwidth transmission tasks like streaming video, VR/AR, and large language models are essential services provided by current and future networks. Therefore, how to maximize network transmission capacity under limited communication resources is a current research hotspot within the realm of satellite communication and a key to the practical application of satellite networks.

Traditional methods often improve network capacity by optimizing the allocation of communication resources, such as the author in [1] craft a gain function for multi-service characterization and devise a multi-beam resource allocation scheme to boost satellite network capacity. Although these studies have achieved some capacity optimization by investigating resource allocation issues, they lack consideration of the dynamic characteristics of satellite networks. In actual transmission scenarios, due to the continuous changes in environment and tasks, resource optimization strategies also need to be updated in real-time. However, most of the optimization algorithms used in these studies take too long to compute and occupy significant memory in larger constellations, making it difficult to maintain high real-time performance. Therefore, improving the characteristics of the network itself is a more practical research direction.

Network coding is an effective tool for enhancing network performance in multicast scenarios, with numerous studies demonstrating its ability to improve network capacity. In [2], author proposes a co-oprative multicast scheme for content delivery in the integrated terrestrial-satellite networks which is further enhanced by network coding, and the experimental data show that network throughput was enhanced. The random linear network coding (RLNC) was used to improve the sceurity and performance of data transmission in [3]. According to current research, the network topology has a significant impact on the effectiveness of network coding in improving network capacity, such as the authors in [4] analyz the eddect of network topology on RLNC system and found that it may be having advantage in reducing the failure probability. Because of this, in the study [5], the authors utilized a topology construction technique rooted in the Lagrangian relaxation approach to optimize secure multicasting. This approach to topology construction serves as an effective means of enhancing the performance of network coding systems. However, the inherently dynamic nature of satellite systems necessitates a continuously evolving network topology over time. Adding the time dimension to the network model makes it difficult to represent and optimize. By using a time-expanded graph to describe the storage, communication, and other behaviors between satellites As demonstrated in [6,7], the time-varying network model is simplified into a directed graph.

Drawing from the preceding analysis, this paper represents the dynamic changes and network connections between satellites using a time-expanded graph and employs an improved genetic algorithm for topology optimization and flow allocation in satellite networks. This approach aims to enhance the multicast performance of satellite networks under the network coding mechanism by transmitting content from several source satellites to various multiple destination satellites, thereby improving network capacity from the fundamental network topology perspective. Simulation results show that when using the topology-optimized network coding scheme, network capacity is significantly increased.

2 System Model and Problem Formulation

2.1 System Model

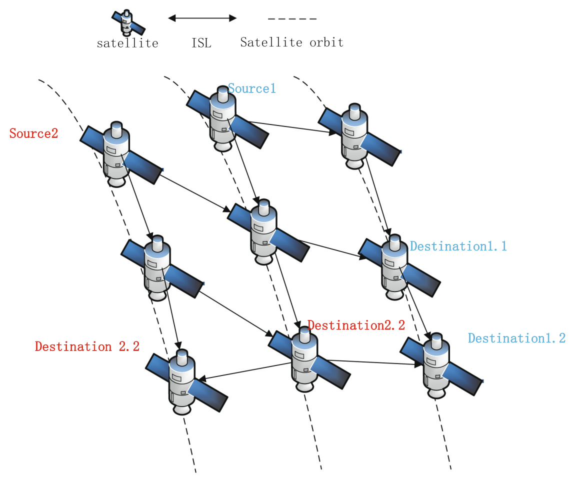


Fig. 1. Multicast satellite network model, Source1 transmits data to Destination1.1 and Destination1.2, Source2 transmits data to Destination2.1 and Destination2.2.

This paper considers a wireless multicast satellites network model depicted in Fig 1. It is composed of multiple communications satellites, every satellites can build several wireless inter satellite links (ISL) with other satellites and thus become a network node. Every node is fully equipped with communication and computation functions and can be a source, relay or destination node as required. During a multicast transmission with network coding, several source satellites are first encode and transmit the information to the relay satellite which is connected by the builded link, the relay satellites are tasked with eoncoding once more and relaying these packets, the destination satellites that want to acquire data from one of the source satellite collect the packets from the relay satellites and decode them to get the orginal information.

Consider the dynamic characterization of the satellites, the period motion of the satellites will cause the periodic and predictable performance changes of

ISLs, even wheteher it exists or not over time. For ease of analysis, we consider the network over a short period as a static. Therefore, we divided the total transmission timeframe T into N time slots, each time slot lasts for $\tau = T/N$. When τ is small enough that the change of the character of ISLs can be ignored. Thus, The satellite network's topology can be structured as a time expanded graph $G = (V, E)$ representation. Where $V = \{v_i^{(t)} | v_i^{(t)} \in ST, t \in N\}$ is a set representing vertices, $v_i^{(t)}$ represents i-th satellite nodes in the time slot t and $ST = S \cup R \cup D$ where S is a collection comprising source satellite nodes, R is composed of relay satellite nodes, and D is composed of destination satellite nodes. E is composed of edges that contain the communication edges between two satellites in one slot and the storage edges between two slots in one satellite. The capacity of communication edges is defined as the data transfer rate achievable through the ISL connecting two satellites. The representation of edge $e(v_i^{(t)}, v_j^{(t)})$'s capacity is as follows:

$$C_{i,j}^{(t)} = \tau B \log(1 + \frac{p_{i,j}^{(t)} G_{i,j}^{(t)}}{n}) \tag{1}$$

B signifies the bandwidth of the ISL, $p_{i,j}^{(t)}$ indicates the transmission power utilized by i-th satellite, $n_{i,j}^{(t)}$ represents the average noise power and $G_{i,j}^{(t)}$ is the gain of ISL between i-th satellite and j-th satellite, that can be calculated as

$$G_{i,j}^{(t)} = \frac{\lambda^2 G^{tr} G^{re}}{(4\pi d_{i,j}^{(t)})^2} \tag{2}$$

$$n = \kappa B \Gamma \tag{3}$$

Where κ and Γ represent the Boltzmann constant and noise temperature, respectively. λ represents the wavelength used for ISLs, the transmit gain and receive gain during communication can be represented by G^{tr} and G^{re}, respectively. $d_{i,j}^{(t)}$ represents the straight-line distance between i-th satellite and j-th satellite.

For the storage edge which is presented as $e(v_i^{(t)}, v_i^{(t+1)})$, it's capacity is the storage capacity STO_i of the i-th satellite.

2.2 Problem Formulation

After establishing the graph G that represents the time-varying topology of the satellite network, we can convert the programming issue of multicasting data from several source satellite nodes to their respective multiple destination satellite node into a problem of allocationg flows in the time expanded graph G between the vertex set S and D that represent source satellite nodes and destination satellite nodes respectively. In order to introduce the network topology into G, we define a binary set $\mathbf{A} = \{a(v_i^{(t)}, v_j^{(t)}) = \begin{cases} 1, if\ establish\ e(v_i^{(t)}, v_j^{(t)}) \\ 0, otherwise \end{cases}\}$ to describe whether the ISL $e(v_i^{(t)}, v_j^{(t)})$ will be established. Taking into account the finite number of antennas available on each satellite node, we have the constraint as

$$\sum_{v_j^{(t)} \in \mathcal{ST}} a(v_i^{(t)}, v_j^{(t)}) \leq A_{out} \tag{4}$$

$$\sum_{v_j^{(t)} \in \mathcal{ST}} a(v_j^{(t)}, v_i^{(t)}) \leq A_{in} \tag{5}$$

Unlike traditional transimission modes, due to the information packets has been encoded by source satellite and relay satellites, the information packets has been compressed and harmonized. Thus the common flow balance constraint, which stipulates that in each relay satellites, inflow and outflow must be equal, does not hold true in the context of our problem. But we can still figure that the inflow and outflow of data destined for the same destination satellite node remain equal at each relay satellites. To represent the information flow that has been transmitted from source satellite $\tilde{s}$, through relay satellites $v_i^{(t)}$ nad $v_j^{(t)}$ and finally collected by destination satellite $\tilde{d} \in D_s$, the $D_s \in D$ is the set of destination satellites receiving data from $\tilde{s}$, we define $x(v_i^{(t)}, v_j^{(t)}, \tilde{s}, \tilde{d})$. Now we can express the flow balance constraint of each relay satellite as

$$\begin{aligned}
&\sum_{v_j^{(t)} \in \mathcal{ST}} x(v_i^{(t)}, v_j^{(t)}, \tilde{s}, \tilde{d}) + x(v_i^{(t)}, v_i^{(t+1)}, \tilde{s}, \tilde{d}) \\
&= \sum_{v_j^{(t)} \in \mathcal{ST}} x(v_j^{(t)}, v_i^{(t)}, \tilde{s}, \tilde{d}) + x(v_i^{(t-1)}, v_i^{(t)}, \tilde{s}, \tilde{d}), v_i^{(t)} \notin S, t \in \mathcal{N}
\end{aligned} \tag{6}$$

In addition, all information is sent by the source satellite and collected by destination in a given time, thus we have another flow constraint as follow:

$$\sum_{v_j^{(t)} \in \mathcal{ST}} x(v_i^{(t)}, v_j^{(t)}, \tilde{s}, \tilde{d}) = R_{\tilde{s},\tilde{d}}, v_i^{(t)} = \tilde{s}, t = 1 \tag{7}$$

$$\sum_{v_j^{(t)} \in \mathcal{D}} x(v_j^{(t)}, v_i, \tilde{s}, \tilde{d}) = R_{\tilde{s},\tilde{d}}, v_i = \tilde{d} \tag{8}$$

Based on the characteristics of linear network coding [8], during the transmission over ISL $e(v_i^{(t)}, v_j^{(t)})$, The total quantity of data transmitted precisely matches the maximum allowable flow volume over this ISL to all disparate destination satellites, remaining within the ISL's capacity limits. Thus, we have

$$\sum_{\tilde{s} \in \mathcal{S}} \max_{\tilde{d} \in \mathcal{D}_s} x(v_i^{(t)}, v_j^{(t)}, \tilde{s}, \tilde{d}) \leq a(v_i^{(t)}, v_j^{(t)}) C_{i,j}^{(t)} \tag{9}$$

Likewise, for an edge $e(v_i^{(t)}, v_i^{(t+1)})$ which representing the data has been stored by satellite i instead of being transmitted, the total quantity is less than the maximum cache capacity carried by this satellite. Thus, we have

$$\sum_{\tilde{s} \in \mathcal{S}} \max_{\tilde{d} \in \mathcal{D}_s} x(v_i^{(t)}, v_j^{(t)}, \tilde{s}, \tilde{d}) \leq STO_i \tag{10}$$

After find the constraints, we can build the optimization problem for our model. The optimization problem is optimizing the plan of establishment ISLs $\mathbf{A} = \{a(v_i^{(t)}, v_j^{(t)})\}$, the flow ditribution $\mathbf{X} = \{x(v_i^{(t)}, v_j^{(t)}\}$ and the data requirements $\mathbf{R} = \{R_{\tilde{d}}\}$ to maximize the coding capacity $\sum_{\tilde{s}\in\mathcal{S}} \underset{\tilde{d}\in\tilde{D}}{min} R_{\tilde{s},\tilde{d}}$which is in accordance with the linear network coding theory. Overall, we have the optimization problem as

$$\begin{aligned} &\max_{\mathbf{A},\mathbf{X},\mathbf{R}} \sum_{\tilde{s}\in\mathcal{S}} \min_{\tilde{d}\in\mathcal{D}_s} R_{\tilde{d}} \\ &s.t.(4) - (10) \\ &\quad a(v_i^{(t)}, v_j^{(t)}) \in \{0, 1\} \end{aligned} \tag{11}$$

This problem is a integer linear programming, which is obviously a NP-hard problem, therefore, this optimization problem is difficult to effectively solve through traditional methods. So, we design an efficient algorithm to obtain sub optimal solutions. We will divide this problem into two sub-problems, namely a topology construction problem and a maximum flow problem. The second sub problem is easy to be solved, therefore we need to find a method to construct a efficient topology $\mathbf{A}$.

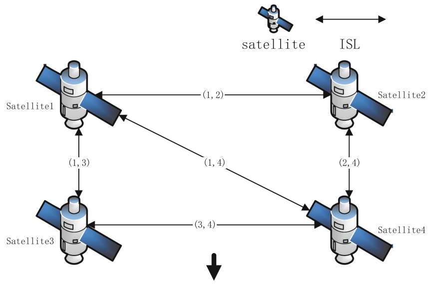
3 GA-Based ISLs Construction Method

In this section, we design a Genetic Algorithm (GA) based ISLs construction method that is a search algorithm inspired by the theory of natural evolution, which searches for high-quality solutions by simulating the processes of biological evolution in nature.

Individuals with different chromosomes are randomly generated to form the initial population. By evaluating the transmission performance of the network topology represented by each individual as its fitness function, we determine which individuals can reproduce. The chromosomes of these individuals are crossed to simulate sexual reproduction in nature, thus searching for other better solutions under the premise of retaining the partial advantages of the current network topology. At the same time, the population is randomly updated periodically to simulate genetic mutations, encouraging the search in unknown regions of the solution space and preventing the algorithm from falling into local optimal solutions. The above process is repeated iteratively, and after the population characteristics tend to be stable or the algorithm has completed M iterations, reaching its predefined maximum, the individual with the highest fitness is selected, and the set $\mathbf{A}$ of ISL establishment it represents is the solution obtained by this algorithm. Specifically, A GA encompasses the subsequent stages:

1) Generating the initial cohort of candidates. The initial population is a randomly selected set of individuals that represent acceptable proposals for selection. Every individuals have different chromosomes which are randomly generated. We need to build a complete topology to get the optimization variable $\mathbf{A}$.

If and only if both satellites are visible to one another, we build the ISL and add the ISL as a element into set $\mathbf{A}$, and encode $\mathbf{A}$ into chromosomes g_i as shown in Fig. 2. If we have P individuals, we have the population $\mathbf{G} = \{g_i | i \in P\}$.



edge	(1, 2)	(1, 3)	(1, 4)	(2, 1)	(2, 3)	(2, 4)	(3, 1)	(3, 2)	(3, 4)	(4, 1)	(4, 2)	(4, 3)
establishment	1	1	1	1	0	1	1	0	1	1	1	1

1	1	1	1	0	1	1	0	1	1	1	1

Fig. 2. Traverse a network topology into a set $\mathbf{A}$ and then into a chromosomeg_i^j.

2) Calculating fitness. Each individual's suitability is assessed using the fitness function, initially for the entire starting population, and afterwards for every newly generated population following the application of genetic operators like selection, genetic recombination, and mutation. Given the independence of individual fitness assessments, the calculations can be efficiently executed in parallel, enhancing the overall performance of the process. With the aim of finding a solution to our problem, we use the optimization problem as the fitness function to obtain the maximum multicast capacity with network coding that can be achieved by the network topology represented by each individual chromosome, and to jude the value of an individual. Due to the variable $\mathbf{A}$ has benn given by chromosomes, the fitness function can be calculated as follow.

$$\begin{aligned} f(g_i) = \max_{\mathbf{X},\mathbf{R}} \sum_{\tilde{s} \in \mathcal{S}} \min_{\tilde{d} \in \mathcal{D}_s} R_{\tilde{d}} \\ s.t.(6) - (10) \\ a(v_i^{(t)}, v_j^{(t)}) \in \{0, 1\} \end{aligned} \tag{12}$$

This problem is difficult to solve directly, so we design a multi-source and multi-objective flow allocation method. The main idea of the method is first determine how to allocate information flows in order to maximize throughput, by solving the maximum flow problem, for each source node separately, and accumulate the solved flows to find the edges that overflow. A subgraph is created based on the maximum flows of different source nodes, and the capacity of the

Algorithm 1. Multi-source Flow Allocation Methods

Input: The set of source nodes $\mathcal{S}$, the set of destination nodes $\mathcal{D}$, the GVE G
Output: flow allocation result $\mathbf{x}$ and the sum of network coding capacity values

```
for s̃ in S do
    for d̃ in D do
        Solving the Maximum Flow Problem between s̃ and d̃
        Add the flow of s̃ and d̃ to the subgraph G_s̃ according to the formula (9)
    end for
    Accumulate the flow of subgraphG_s̃ on graph G
end for
for Iterate over the set of edges E of the graph G do
    if Constraint (9) Constraint (10) is not satisfied then
        Subtract the capacity of the corresponding edge in the subgraphs, Subtracted capacity value C_s̃ = (C_s̃ / Σ_{s̃∈S} C_s̃) C_overflow
    end if
end for
for s̃ in S do
    for d̃ in D do
        Solving the Maximum Flow Problem between s̃ and d̃
        Add the solution to the result x and R_d̃
    end for
end for
return x, Σ_{s̃∈S} min_{d̃∈D_s} R_d̃
```

corresponding edges in the subgraph is reduced according to the exceeded capacity. Finally, solve the maximum flow problem separately on the new subgraphs. The entire procedure can be encapsulated in Algorithm 1.

3) Selection, genetic recombination and mutation. Employing the evolutionary principles of selection, recombination, and mutation on a population leads to the emergence of a subsequent generation, optimized through the inheritance of favorable traits from the preceding generation's most fit individuals. Selection is aimming to choose the individuals that have advantages in current population. The probability that i-th individual's chromosome is selected for reproduction is proportional to its fitness $f(g_i)$. The set p_i is the probability that the i-th individual's chromosome is selected, we have:

$$p_i = \frac{f(g_i)}{\sum_{j=1}^{P} f(g_j)} \tag{13}$$

Genetic recombination progeny by blending the genetic information of chosen individuals, a process that is accomplished by two chosen individuals interchanging segments of their chromatids results in the formation of two distinct chromosomes, each serving as the genetic blueprint for a new individual. If the intersection is k and the chromosomes from parents are g_i and g_j, offspring g_new can be experessed as:

$$g_{new} = (g_{i1}, g_{i2}, ..., g_{ik}, g_{j(k+1)}, ..., g_{jn}) \tag{14}$$

To make it easier to understand, this process has been shown in Fig. 3.

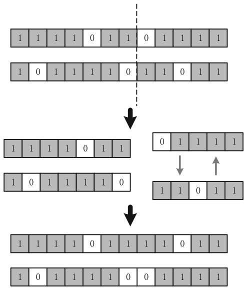


Fig. 3. Procedure for genetic recombination operations.

During the generation of new individuals, a mutation process is applied with a minute chance of randomly altering one or several genetic within their chromosomes. This mutation mechanism operates infrequently. We used the uniform mutation that replace the original chromosome at each locus in an individual with random numbers conforming to a uniform distribution within a certain range, respectively, with some smaller probability. The above process can be expressed as:

$$g'_{nk} = g_{nk} + \delta, \quad \text{with probability}\mu \tag{15}$$

Now we summarized the whole algorithm as Algorithm 2.

Algorithm 2. Genetic ISLs Construction Algorithm

Input: The satellites' visually represented and the ISL capacity
Output: The ISLs construction **A**

intialize the initial population
k=0
while $\max f(g_i)$ tends to be stable or $k < M$ **do**
  for $i = 1$ to P **do**
    evalute fitness of $f(g_i)$ by Equation 12
  end for
  for $i = 1$ to P **do**
    Select operation of g_i by Equation 13
  end for
  for $i = 1$ to P **do**
    Crossover operation of g_i by Equation 14
  end for
  for $i = 1$ to P **do**
    Mutation operation of g_i by Equation 15
  end for
  $k = k + 1$
end while
Converting $\arg\max f(g_i)$ into **A**
return A

4 Analysis and Interpretation of Simulation Outcomes

With the objective of assessing the efficacy of our ISLs construction algorithm, we have implemented a Walker-Delta satellite constellation with 3 robits of 20 LEO satellite each. We choose source satellites and destination satellites randomly from all satellites, and repeated the process for 50 rounds to obtain the average results. We will then evaluate the performance in terms of multi-source coding capacity, i.e., the sum of coding capacity from different sources. The parameters of the simulate environment are show in the Table 1.

Table 1. The parameters of the simulate environment.

Parameters	Value
Maximum number of iterations M	200
population size P	100
Channel bandwith B	20 MHZ
Wavelength λ	0.125 m
Length of a time slot ΔT	30 s
The temperature of noise Γ	354.81 K
Transimission antenna gain G^{tr}	10 dB
Receiving antenna gain G^{re}	10 dB
The upper limit of transmission antenna countA_{out}	2
The lower limit of receiving antenna count A_{out}	2
Orbital height of the satellite	1300 km
The orbital tilt of the satellite	60 deg

First, we choose two source satellites and two destination satellites for each source satellites randomly, set the transmission power to 80 W, and the storage capacity of satellite to 2000 Mbits and perform 200 iterations. The data in training is obtained as in Fig. 4.

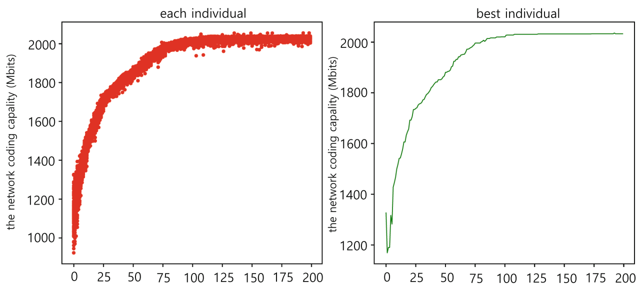


Fig. 4. Multi-source Network coding capacity versus iterations.

It is observable that the capacity rises gradually with the number of iterations and levels off after 125 generations and finally settles at 2032.437 Mbits at 150 generations. We can consider the population after 125 generations as a solution to the problem and apply it to the subsequent simulations. We can consider the population after 125 generations as a solution to the problem and apply it to the subsequent simulations.

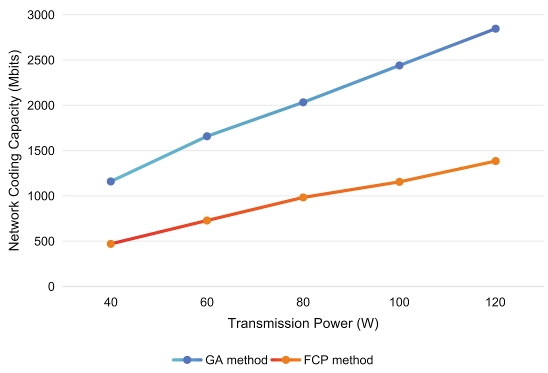


Fig. 5. Multi-source Network coding capacity versus transmission power

Figure 5 demonstrate a direct link between network coding capacity and the transmission power. Obviously, as the increasing transmission power increase the capacity of all ISLs, the network coding capacity also be increased. Compared with the baseline method, our method has obvious advantage.

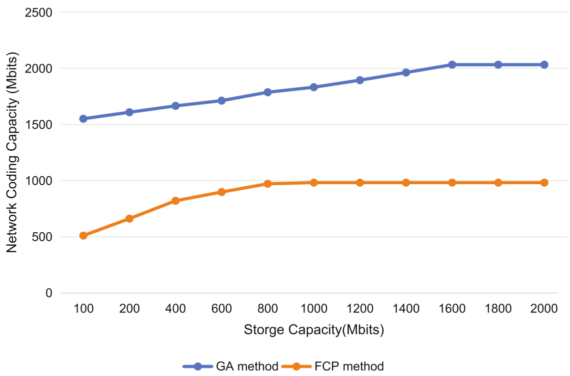


Fig. 6. Multi-source Network coding capacity versus storage capacity

As shown in Fig. 6, Obviously the storage capacity has a notable influence on network throughput when it is low. The reason of this is that not sufficient storage capacity forces some data packets that can't wait for more suitable time slots for transmission by be cached in relay satellites. In addition, as the storage capacity reaches a certain level, the network coding capacity becomes almost independent of the storage capacity, which can be interpreted that the ISLs' throughput became the weak link in improving the performance.

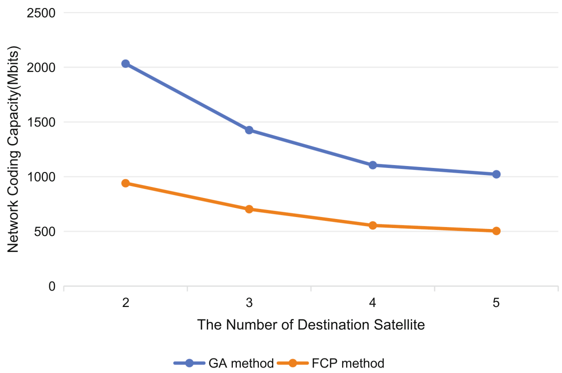


Fig. 7. Multi-source Network coding capacity versus destination number

As depicted in Fig. 7, When the quantity of destination nodes increases, the capacity decreases. We argue that this is because, according to coding theory, algorithms will tend to construct topologies that equalize the traffic of different destination satellites, resulting in a non-optimal traffic for each destination satellite.

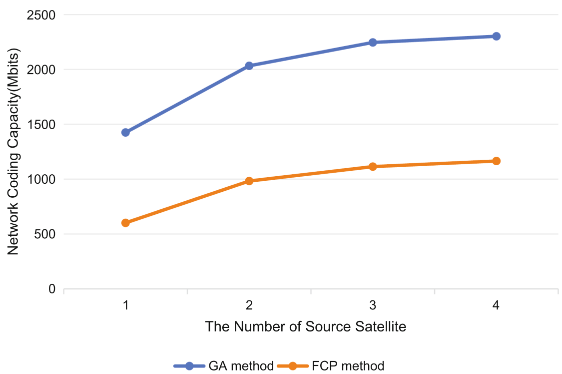


Fig. 8. Multi-source Network coding capacity versus source number

As depicted in Fig. 8, the number of source satellites increases, the total coding capacity of the multisource network rises, but at a significantly lower rate.

it is because that as the quantity of source satellites increases, the quantity of ISLs being used by multiple source satellites also increases. While the capacity of these ISLs remains constant, it can only reduce the traffic of each source satellite, so the rate of rise of the total coding capacity decreases.

Based on the above multiple comparisons, it can be seen that in almost any scenario, our method is significantly better compared to the baseline method.

5 Conclusions

This article explores how to enhance the throughput performance of satellite networks through network topology construction and network coding techniques. By leveraging the encoding process, we effectively compress multiple data streams transmitted via satellites, effectively enhances the utilization efficiency of on-satellite resources during the communication process. Additionally, we present a GA-based approach for network topology design and flow allocation, aimed at enhancing the efficacy of network coding. Our simulation results underscore the substantial augmentation in network capacity achieved through the optimization of topology construction..

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