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LLM-Inspired Decomposition Multi-Objective Evolutionary Algorithm for Joint BDS-3 Resource Allocation

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Abstract. With the BeiDou-3 Global Navigation Satellite System (BDS-3) now attaining worldwide coverage, the rapid expansion of digital services has triggered an unprecedented surge in operational demands. However, limited spectral resources and onboard energy reserves are insufficient to meet this growing demand, which restricts further improvement in system efficiency. To optimally allocate constrained resources and elevate system performance, this paper introduces a coordinated power and bandwidth allocation strategy for BDS-3, grounded in a large language model (LLM)-inspired decomposition multi-objective evolutionary algorithm (MOEA). The proposed method adaptively tunes power and bandwidth assignments according to the channel conditions and service requirements of each link, with the dual objective of harmonizing energy efficiency and communication rate within the system. Specifically, we develop an LLM-inspired decomposition multi-objective evolutionary algorithm (LEDMA) to tackle the highly non-convex multi-objective optimization problem. A decomposition approach is first employed to partition the original problem into multiple scalar subproblems. Subsequently, the LLM serves as a black-box search operator and is seamlessly incorporated into the MOEA framework via carefully designed prompt engineering, enabling concurrent resolution of these subproblems. Simulation results validate that LEDMA effectively reconciles energy efficiency and communication rate, yielding Pareto fronts and convergence characteristics that surpass those of benchmark multi-objective evolutionary algorithms.

Keywords: BeiDou-3 System, Inter-satellite Links, Multi-objective Optimization, Large Language Model.

1. Introduction

With the full deployment and global operation of the BeiDou-3 Navigation Satellite System (BDS-3), it has now entered a new era marked by dynamic network topologies and large-scale constellation coordination. Inter-Satellite Links (ISLs), as a pivotal technological component, enable direct communication among satellites, significantly strengthening autonomous navigation capabilities and accelerating data update frequencies [21,10]. Nonetheless, in the context of contemporary digital applications, global service requests are characterized by uneven spatiotemporal distribution and exponential growth. This

leads to a pronounced supply–demand disparity concerning onboard spectral and energy resources across different time slots and communication links. Therefore, efficiently allocating limited onboard resources has become essential for satisfying heterogeneous service demands and improving resource utilization within the BeiDou system.

Power and bandwidth are two fundamental resources that govern the efficiency of satellite navigation systems [16]. Due to inherent payload constraints, the solar power capacity of BDS-3 satellites is relatively constrained, and repeated charge–discharge cycles may adversely affect satellite longevity. At the same time, inter-satellite link conditions undergo continuous fluctuations, while individual satellites face ever-increasing service loads. Conventional resource allocation strategies tend to treat power and bandwidth independently, often disregarding their intrinsic coupling, which can result in inefficient resource usage. Recent studies [20] suggest that jointly optimizing power and bandwidth allocation can substantially improve system performance and promote more rational resource exploitation. However, the nonlinear interdependence between these two resources renders the joint allocation problem a typical non-convex Multi-objective Optimization Problem (MOP). Such problems are frequently hindered by local optima entrapment and prohibitive computational expense, making it challenging to obtain globally optimal solutions in a timely manner.

To tackle these issues, this study proposes a joint power and bandwidth allocation framework for BDS-3 based on the LEDMA algorithm. The proposed method allocates resources adaptively according to link-level traffic loads and time-varying channel conditions. Specifically, for links experiencing high traffic demand and poor propagation environments, the system preferentially assigns broader bandwidth while compensating with elevated transmission power. In terms of solving the underlying MOP, we introduce an LLM-inspired Decomposition Multi-objective Evolutionary Algorithm (LEDMA). This algorithm first applies a decomposition strategy to reformulate the original multi-objective problem into a collection of scalar subproblems. The Large Language Model is then employed as a search operator embedded within the evolutionary computation framework. Through carefully designed prompts, the LLM generates high-quality offspring solutions that markedly outperform randomly generated counterparts, thereby accelerating convergence and achieving a more favorable balance between computational efficiency and solution accuracy. The principal contributions of this work are outlined as follows:

- We formulate a joint power and bandwidth allocation problem for BDS-3 inter-satellite links, where link-specific service requirements and channel attenuation are jointly considered under limited onboard power and spectral resources.
- We establish a constrained multi-objective optimization model that simultaneously maximizes the total channel capacity and the system energy efficiency. Practical constraints, including total power budget, total bandwidth budget, per-link resource bounds, and minimum service-rate requirements, are incorporated into the model.
- We propose an LLM-inspired decomposition multi-objective evolutionary algorithm, namely LEDMA, to solve the formulated optimization problem. By decomposing the original problem into scalar subproblems and using the LLM as a guided offspring-generation operator, LEDMA improves the search process in the constrained power-bandwidth allocation space.

2. Related Work

The optimal allocation of Inter-Satellite Link (ISL) resources plays a pivotal role in enhancing the service performance of the BeiDou Navigation Satellite System. Existing research in this domain can be broadly categorized into three streams: single-resource optimization, joint resource allocation, and the adoption of advanced intelligent algorithms.

Early investigations primarily focused on optimizing individual resource dimensions. In the context of bandwidth allocation, Jiang et al. introduced a traffic-prediction-based bandwidth allocation algorithm leveraging BP neural networks for broadband multimedia satellite networks. Despite its limited computational efficiency, the approach achieved notable latency reductions compared to conventional methods [11]. For multi-beam satellite configurations, Hong et al. applied gradient descent to solve the dual problem for bandwidth optimization; however, the performance improvements were constrained due to the convex approximation of the problem and the exclusion of power allocation considerations [8]. Of particular relevance to satellite navigation systems is the Optimized Bandwidth Equal Power (OBEP) algorithm proposed by Park et al., which reformulated the problem as a convex optimization based on Lagrange duality. Although OBEP enhanced channel capacity relative to traditional schemes, the gains attainable through bandwidth optimization alone remain insufficient for the operational demands of the BeiDou system [17].

With respect to power allocation, heuristic algorithms have progressively supplanted conventional greedy strategies. Destounis et al. [6] combined Lagrange multipliers with heuristic techniques for beam-level power allocation, yielding improvements in computational efficiency. Subsequently, Aravanis et al. [2] formulated the minimization of unsatisfied capacity and total power as a multi-objective optimization problem, solved via Simulated Annealing. Nevertheless, the inherent complexity of the multi-objective framework limited its practical applicability. Bousquet employed a Genetic Algorithm for power allocation in multi-beam systems, thereby validating the advantages of global optimization methods in multi-link scenarios [24]. Moreover, emerging paradigms such as Reinforcement Learning (RL) have demonstrated that refining the architecture of intelligent algorithms constitutes an effective pathway for enhancing solution quality in non-convex resource allocation problems [9].

Recognizing the inherent limitations of single-resource strategies, joint allocation has progressively become the dominant research direction. Stuber et al. [4] proposed a joint bit and power allocation scheme based on a greedy algorithm. While this approach offered low computational complexity, it compromised allocation performance and failed to accommodate the high traffic demands characteristic of satellite navigation systems. In contrast, swarm intelligence-based heuristics have exhibited greater robustness. Chai et al. [3] applied a Genetic Algorithm to solve joint allocation problems in heterogeneous networks, thereby confirming the suitability of evolutionary algorithms for such tasks. Zhu et al. [25] adopted a Clonal Immune Algorithm to enhance energy efficiency and reliability, although its performance deteriorated under conditions of extreme resource scarcity.

To systematically address the inherent performance trade-offs in complex networks, Multi-objective Optimization Problems (MOPs) have been widely formulated. A range of bio-inspired Multi-objective Evolutionary Algorithms (MOEAs) have been developed to tackle these problems, including the Decomposition-based Multi-objective Evolutionary

Algorithm (MOEA/D) [23], the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [7], and the Multi-objective Differential Evolution Algorithm (MODEA) [1]. Each of these methods offers distinct advantages: MOEA/D decomposes complex problems into more tractable subproblems; NSGA-II preserves solution diversity through non-dominated sorting and crowding distance mechanisms; and MODEA leverages differential evolution to efficiently explore the solution space.

Despite their efficacy, MOEAs are often hampered by high computational complexity. Recent breakthroughs in Large Language Models (LLMs) have demonstrated remarkable reasoning and predictive capabilities, prompting research into their integration with Evolutionary Algorithms (EAs) [13]. Prior work in this area has mainly focused on benchmark test problems with well-defined Pareto fronts. Extending these techniques to real-world ISL resource allocation remains an important research direction. Motivated by these developments, this paper investigates the application of an LLM-enhanced multi-objective evolutionary algorithm to the joint optimization of power and bandwidth in BeiDou ISLs.

Specifically, we adopt MOEA/D as the foundational framework, decomposing the multi-objective optimization problem into a series of scalar subproblems. The LLM is subsequently integrated as a black-box search operator within the evolutionary architecture. Through the design of customized prompts that incorporate multiple objective functions and constraint satisfaction criteria, the LLM is guided to explore the solution space more effectively, thereby overcoming the limitations of conventional algorithms in terms of both convergence speed and solution quality.

3. Materials and Methods

3.1. System Modeling

The system consists of N satellites, which communicate with each other via ISLs (as shown in Fig. 1). For clarity, the main variables used in the system model are defined before the formulation of the optimization problem. Let N denote the number of satellites and L denote the number of active inter-satellite links. For each link $l \in \{1, \ldots, L\}$, d_l, p_l, b_l, h_l, C_l, and N_0 denote the link distance, allocated transmission power, allocated bandwidth, link loss coefficient, channel capacity, and noise power spectral density, respectively. Each satellite i is equipped with communication and navigation functions and is located in a three-dimensional coordinate system. To facilitate the solution, this paper adopts the snapshot assumption: within a single resource allocation period, the distance of each link l remains approximately constant, although the transmission distances d_l for different links may vary and are calculated based on ephemeris/geometric relationships. In dynamic BDS-3 scenarios, the proposed method can be applied in a snapshot-based manner. That is, the link state is regarded as approximately constant within one resource allocation period, and the resource allocation scheme is updated periodically when the topology, link distance, or service demand changes.

The transmission quality of ISLs is primarily affected by free-space path loss. In this paper, the free-space path loss of each inter-satellite link is first characterized according to the link distance, antenna gains, and carrier wavelength. Based on the path loss, the equivalent channel gain is obtained and used in the subsequent capacity calculation. Specifically, a larger transmission distance leads to higher path loss and a smaller equivalent channel gain, which reduces the received signal-to-noise ratio. For a given link,

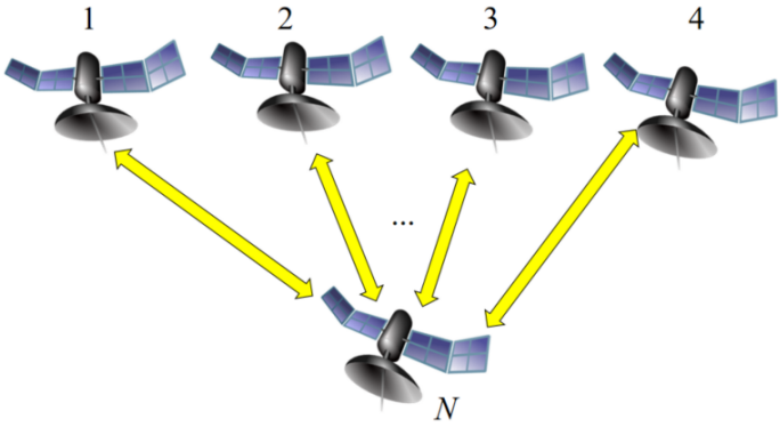


Fig. 1. System model of ISLs

the achievable capacity is jointly determined by the allocated transmission power, the allocated bandwidth, the equivalent channel gain, and the noise power spectral density. Therefore, power and bandwidth allocation must be considered together with link attenuation when evaluating the communication performance of BDS-3 inter-satellite links. To maintain consistency with the subsequent Shannon capacity formula, this paper denotes the equivalent link gain as h_l. For example, it can be written as

$$h_l = \frac{G_t G_r \lambda^2}{(4\pi d_l)^2}\,, \tag{1}$$

where G_t and G_r are the transmit and receive antenna gains respectively, λ is the carrier wavelength, and d_l is the link distance, which is treated as a constant within one resource allocation period. As d_l increases, h_l decreases, leading to a decline in both link capacity and energy efficiency.

In the system, the signal y transmitted from satellite i to satellite j can be expressed as:

$$y = \sqrt{p_l}\, h_l\, s(t-\tau) + n(t)\,, \tag{2}$$

where s is the signal sent from satellite i to satellite j, p_l is the transmission power of satellite i on link l, h_l is the loss coefficient of signal transmission which depends on the inter-satellite distance, $s(t)$ is the radar waveform emitted by satellite, τ is the signal propagation delay representing the transmission time from satellite i to satellite j, and $n(t)$ is the noise signal. The signal transmission process is influenced by multiple factors such as distance, loss, noise, and bandwidth. For each link, the signal attenuates during transmission, and the signal quality of the link (i.e., channel capacity) is directly related to power, bandwidth, and transmission loss.

Channel capacity is a key indicator for measuring link performance. On each inter-satellite link, the link's channel capacity C_l can be calculated using the Shannon capacity

formula:

$$C_l = b_l \log_2 \left(1 + \frac{p_l h_l}{N_0 b_l}\right), \tag{3}$$

where C_l is the channel capacity of the link between the i-th satellite and the j-th satellite, b_l is the bandwidth allocated to link l, p_l is the power on link l, h_l is the link loss coefficient, and N_0 is the noise power spectral density.

The calculation of channel capacity indicates that signal transmission on each link is affected by power, bandwidth, and loss. Furthermore, capacity increases with the increase of power and bandwidth; however, due to signal attenuation, there are limits to increasing power and bandwidth.

3.2. Problem Formulation

To balance the Quality of Service (QoS) and energy consumption of the satellite communication system, this paper constructs a multi-objective optimization framework. To simplify subsequent notation, we unify the numbering of all L active links in the system, denoted as $l = 1, \ldots, L$. To satisfy the growing data transmission demands of the BeiDou system, our first objective is to maximize the total channel capacity of the entire network:

$$\max_{\mathbf{p},\mathbf{b}} \; f_1(\mathbf{p}, \mathbf{b}) = \sum_{l=1}^{L} C_l = \sum_{l=1}^{L} b_l \log_2 \left(1 + \frac{p_l h_l}{N_0 b_l}\right). \tag{4}$$

Maximize Total System Energy Efficiency: Considering the limited energy of the satellite platform, the second objective is to maximize the system's energy efficiency. Energy efficiency is defined as the number of bits transmitted per unit of energy (bits/Joule):

$$\max_{\mathbf{p},\mathbf{b}} \; f_2(\mathbf{p}, \mathbf{b}) = \frac{\sum_{l=1}^{L} C_l}{\sum_{l=1}^{L} (p_l + p_c)}, \tag{5}$$

where p_c is the constant basic circuit power consumption of the link (including the fixed power consumption of the RF chain excluding the power amplifier).

This paper aims to simultaneously optimize the two conflicting objectives mentioned above by jointly optimizing the power vector $\mathbf{p} = (p_1, \ldots, p_L)$ and bandwidth vector $\mathbf{b} = (b_1, \ldots, b_L)$ for each link, subject to resource constraints. Therefore, this problem is modeled as a constrained Multi-Objective Optimization Problem (MOP). To adapt to the characteristic that optimization algorithms typically solve for minimum values, although the problem is one of maximization, we actually minimize the negative values of the objective functions when solving with the algorithm. We transform the maximization problem into a problem of minimizing negative objective functions:

$$\min_{\mathbf{p},\mathbf{b}} \quad -f_1(\mathbf{p}, \mathbf{b}), \tag{6}$$

$$\min_{\mathbf{p},\mathbf{b}} \quad -f_2(\mathbf{p}, \mathbf{b}), \tag{7}$$

subject to

$$
\begin{aligned}
&\text{C1:} \quad \sum_{l=1}^{L} p_l \le P_{\text{tot}} \,, \\
&\text{C2:} \quad \sum_{l=1}^{L} b_l \le B_{\text{tot}} \,, \\
&\text{C3:} \quad p_l^{\min} \le p_l \le p_l^{\max} \,, \quad \forall l \,, \\
&\text{C4:} \quad b_l^{\min} \le b_l \le b_l^{\max} \,, \quad \forall l \,, \\
&\text{C5:} \quad C_l \ge R_l^{\min} \,, \quad \forall l \,.
\end{aligned}
$$

Constraints C1 and C2 indicate that the total allocated power and total bandwidth cannot exceed the satellite system's maximum available resources P_{tot} and B_{tot}. Constraints C3 and C4 specify the physical boundaries for power and bandwidth. Constraint C5 ensures that each link meets the minimum service rate requirement $R_l^{\min}$.

Since objective f_1 tends to consume more resources while objective f_2 tends to improve the ratio by reducing power, there is a significant Pareto conflict between the two. Furthermore, this problem is non-convex and non-linear.

To solve this complex MOP, we employ the Tchebycheff decomposition method to decompose formula (6)–(7) into M scalar optimization sub-problems. The m-th sub-problem can be described as:

$$
\min_{\mathbf{x}} \; g^{\text{te}}(\mathbf{x} \mid \boldsymbol{\lambda}^m, \mathbf{z}^*) = \max_{1 \le i \le 2} \left\{ \lambda_i^m \middle| f_i(\mathbf{x}) - z_i^* \middle| \right\} \,, \tag{8}
$$

where $\boldsymbol{\lambda}^m$ is the weight vector, and $\mathbf{z}^*$ is the ideal reference point. This decomposition modeling allows us to utilize an LLM as a black-box operator to co-evolutionarily solve this set of sub-problems, thereby approximating the system's Pareto front.

3.3. Proposed Algorithm

Traditional Multi-Objective Optimization Algorithms (e.g., NSGA-II) often struggle to maintain population diversity and suffer from slow convergence when facing high-dimensional decision variables. LEDMA adopts a Decomposition-based framework, breaking the original bi-objective problem into M scalar sub-problems. Each sub-problem is defined by a specific weight vector, guiding the population to distribute uniformly in the objective space and approximate the Pareto Front.

For the m-th sub-problem g^{te}, the optimization objective is constructed based on the Tchebycheff Approach:

$$
g^{\text{te}}(\mathbf{x} \mid \boldsymbol{\lambda}^m, \mathbf{z}^*) = \max_{1 \le i \le 2} \left\{ \lambda_i^m \middle| f_i(\mathbf{x}) - z_i^* \middle| \right\} \,, \tag{9}
$$

where $\mathbf{z}^*$ is the ideal reference point, representing the optimal values found so far for each objective. The ideal reference point is initialized by evaluating the objective values of the initial population and selecting the best (minimum) value achieved for each objective. During the evolutionary process, this reference point is continuously updated whenever

a better objective value is obtained. The algorithm seeks the optimal solution set by co-evolving these M sub-problems.

Traditional evolutionary algorithms rely on random Crossover and Mutation operators. Such "blind" perturbations are inefficient when dealing with complex power-bandwidth coupling constraints. The introduction of the LLM is not intended to merely replace conventional crossover and mutation operators. In the considered BDS-3 joint power and bandwidth allocation problem, feasible solutions are strongly constrained by the coupled relationship among link loss, transmission power, bandwidth, and minimum service requirements. Random perturbation-based evolutionary operators may generate candidate solutions that satisfy the numerical bounds but fail to reflect meaningful physical allocation patterns. By contrast, the LLM is employed as a guided solution-generation operator. Through in-context examples selected from elite neighboring individuals, the LLM can infer implicit allocation trends, such as assigning more resources to links with poorer channel conditions or higher service demands, while maintaining awareness of the overall power and bandwidth constraints. Therefore, the LLM contributes to the evolutionary process by providing constraint-aware and pattern-guided offspring generation, rather than functioning only as a conventional recombination or mutation operator.

LEDMA utilizes the LLM as an LLM-guided evolutionary operator. By observing the allocation patterns of elite individuals in the current neighborhood and considering the physical constraints of the resource allocation problem, the operator generates candidate offspring solutions for subsequent feasibility correction and population updating.

Specifically, for the m-th sub-problem, we select T elite individuals from its Neighborhood as context Demonstrations to construct a Prompt for the LLM (as shown in Fig. 2). Upon receiving the prompt, the LLM combines physical constraints with contextual patterns to generate a new candidate solution $\mathbf{x}'$. This generation method is essentially a form of guided recombination, capable of converging to efficient regions of the feasible domain faster than random operators.

The detailed steps of the Large Language Model-based Evolutionary Decomposition Multi-objective Algorithm (LEDMA) are as follows:

Initialization Phase: First, initialize the algorithm's basic parameters, setting population size M and neighborhood size T. The core lies in constructing the decomposition framework: using Tchebycheff Decomposition to generate M uniformly distributed weight vectors $\boldsymbol{\lambda}^1, \ldots, \boldsymbol{\lambda}^M$, decomposing the complex bi-objective optimization problem into M parallel scalar optimization sub-problems. Next, construct a cooperative neighborhood for each sub-problem. For any m-th sub-problem, calculate the Euclidean distance between its weight vector $\boldsymbol{\lambda}^m$ and all other vectors, selecting the T closest vector indices to form its neighborhood set $B(m)$. In the neighborhood selection process, the k closest weight vectors are selected according to the Euclidean distance between weight vectors. When multiple weight vectors have identical or very close distances, a deterministic tie-breaking rule is applied to ensure a unique and consistent neighborhood structure during the evolutionary process. This ensures that in subsequent evolution, sub-problems only exchange information with their "neighbors," balancing exploration and exploitation. Randomly generate an initial population $\{\mathbf{x}^1, \ldots, \mathbf{x}^M\}$ within the physical constraints of power and bandwidth. Simultaneously, evaluate the channel capacity and energy efficiency objectives for each individual, initializing the ideal reference point $\mathbf{z}^*$, where z_i^* represents the best (minimum negative objective) value found so far for the i-th objective.

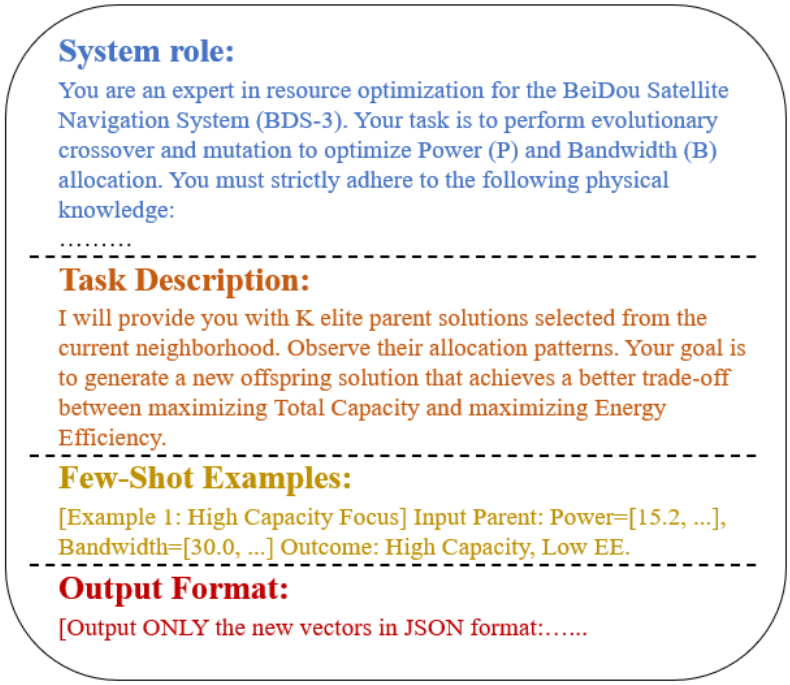


Fig. 2. Example of the prompt

Iterative Evolution Phase: Upon entering the evolutionary loop, the algorithm processes each sub-problem m sequentially. This phase introduces the Large Language Model as a black-box evolutionary operator. It randomly selects T high-quality individuals from the current neighborhood $B(m)$ as "In-context Examples." Combined with physical constraint descriptions, a Prompt is constructed and input to the LLM to guide the model in inferring and generating a new candidate solution $\mathbf{x}'$. To address potential numerical deviations in the generated solution, the system immediately performs normalization correction, forcing $\mathbf{x}'$ to satisfy the total power constraint $\sum p_l \leq P_{\text{tot}}$ and total bandwidth constraint $\sum b_l \leq B_{\text{tot}}$. To ensure feasibility, each LLM-generated candidate solution is processed through a constraint-correction step before population updating. First, the power and bandwidth values of each link are clipped to their corresponding lower and upper bounds. Then, the solution is normalized to satisfy the total power and total bandwidth constraints. Finally, the channel capacity of each link is recalculated to verify whether the minimum service-rate requirement is satisfied. Candidate solutions that still violate the minimum service-rate constraint after correction are discarded and do not participate in the neighborhood replacement process. After normalization to satisfy the total power and total bandwidth constraints, each decision variable is further checked against its per-link lower and upper bounds. If any value exceeds the predefined limits, it is clipped to the corresponding boundary. Moreover, solutions that still violate the minimum service-rate requirement after correction are discarded and excluded from the population update pro-

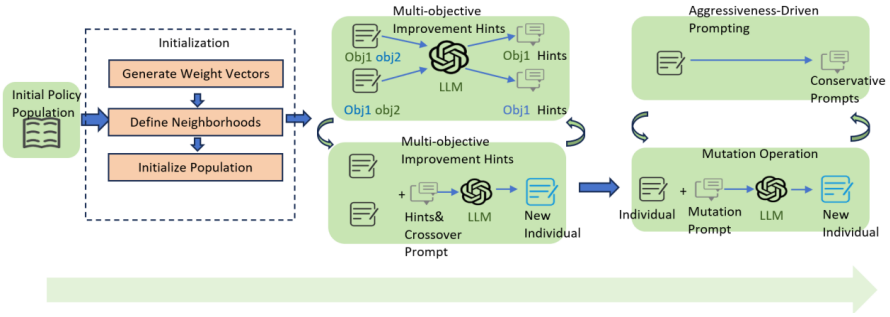


Fig. 3. Algorithm framework

cess. During the population update, if any objective value of the new solution $\mathbf{x}'$ is better than the global reference point $\mathbf{z}^*$, $\mathbf{z}^*$ is updated immediately. Simultaneously, iterate through every index j in neighborhood $B(m)$ and evaluate using the Tchebycheff aggregate function. If $g^{\text{te}}(\mathbf{x}' \mid \boldsymbol{\lambda}^j, \mathbf{z}^*) \leq g^{\text{te}}(\mathbf{x}^j \mid \boldsymbol{\lambda}^j, \mathbf{z}^*)$, replace the original individual $\mathbf{x}^j$ with the new solution $\mathbf{x}'$, thereby promoting the propagation of superior genes within the neighborhood. Notably, although the time cost of LLM inference is higher than traditional mathematical crossover operators, traditional operators often produce offspring that are largely infeasible or of poor quality, wasting computational resources on invalid Fitness Evaluations. By generating high-quality offspring with "strong potential," LEDMA trades operator complexity for convergence speed, which is highly advantageous in complex constrained optimization problems where evaluation is costly.

Termination & Output: The aforementioned "Select-Generate-Update" iterative process continues until preset stopping criteria are met. The algorithm typically sets a maximum number of iterations $G_{\max}$ as the primary termination condition. Alternatively, the Hypervolume indicator of the population can be monitored; convergence is declared once the rate of change of the indicator over consecutive generations falls below a preset threshold. Upon termination, the algorithm outputs the final population. The Non-dominated Solutions within it constitute an approximation of the Pareto Front for the ISL resource allocation problem, providing decision-makers with a series of configuration schemes that achieve the optimal trade-off between system capacity and energy efficiency.

To overcome the "hallucination" problem of LLMs in continuous numerical optimization, this paper proposes a Physics-Semantics-based Prompt Construction Strategy. Unlike general numerical optimization prompts, we explicitly embed a Physics-Constraint Descriptor and a Trend-Guided Chain of Thought (CoT) into the Prompt. This enables the algorithm to not only search for numerical values but also learn physical strategies for resource allocation. As shown in Fig. 3, this framework combines decomposition-based multi-objective evolutionary strategies with Large Language Models [5,15,22]. By initializing weight vectors and neighborhoods, the algorithm utilizes the LLM as an intelligent black-box operator and guides population iteration through Physics-Informed Prompt Engineering (including refinement, crossover, and mutation prompts) to generate high-quality offspring solutions.

Table 1. Parameter settings for the simulation environment and the proposed algorithm

Parameter	Value
Total Power	200 W
Total Bandwidth	500 MHz
Orbit Altitude	21518 Km
Noise Power Spectral Density	−174 dBm/Hz
Antenna Gain	69.83 dB
Distance	20000∼60000 Km
Transmission Loss	210∼220 dB
Service Demand	15 Mbps
Number of Links	12

Table 2. Parameter settings for the simulation environment and the proposed algorithm

Parameter	Value
Total Power	200 W
Total Bandwidth	1085 MHz
Orbit Altitude	21518 Km
Noise Power Spectral Density	−174 dBm/Hz
Antenna Gain	69.83 dB
Distance	20000∼60000 Km
Transmission Loss	210∼220 dB
Service Demand	15 Mbps
Number of Links	27

4. Results and Discussion

To comprehensively evaluate the proposed algorithm's performance under different conditions, two typical constellation scenarios—MEO and GEO—were selected for analysis. Since the energy efficiency maximization algorithm operates on the premise of relatively low traffic demand that can be fully satisfied by available resources, the performance metrics for this evaluation focus on the average energy efficiency of the links and the total system power consumption. The specific environmental parameters are detailed in Tables 1 and 2.

To clearly illustrate the details of resource allocation for specific links and conduct an in-depth analysis within the space constraints, MOEA/D and NSGA-II were selected as representative benchmark algorithms for the subsequent detailed comparison of physical quantities [18,19,14].

Figure 4 demonstrates that the Hypervolume (HV) metric of the proposed algorithm rises rapidly during the initial iterations, exhibiting the fastest convergence rate. It ultimately stabilizes at the highest level, indicating the superior quality of the solution set. For intuitive visualization, the Pareto front in Figure 5 utilizes the original positive values of channel capacity and energy efficiency. The Pareto front of the proposed algorithm is located at the outermost layer, occupying a dominant position. This indicates that, under identical conditions, it achieves a superior trade-off between power and bandwidth.

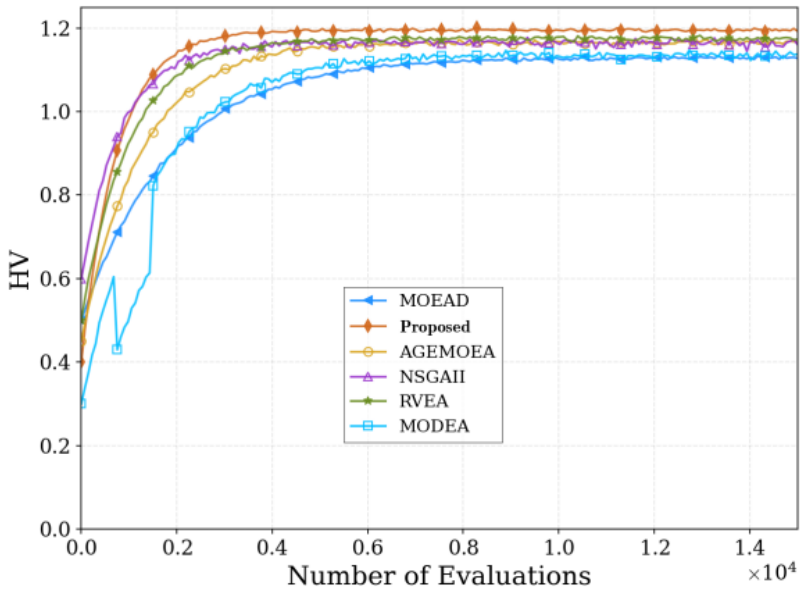


Fig. 4. Convergence curves of HV with respect to the number of evaluations

In conclusion, the proposed algorithm significantly outperforms benchmark algorithms, such as NSGA-II and MOEA/D [12], in terms of convergence speed, solution diversity, and the ability to approximate the true Pareto front. This validates that incorporating a LLM as an evolutionary operator effectively enhances optimization performance.

Subsequently, the MOEA/D, NSGA-II, and the proposed algorithm were applied to this scenario to evaluate their performance. Given that the performance fluctuation of the allocation schemes generated by the algorithms was negligible across thirty independent trials, a single allocation instance was arbitrarily selected for the comparative analysis.

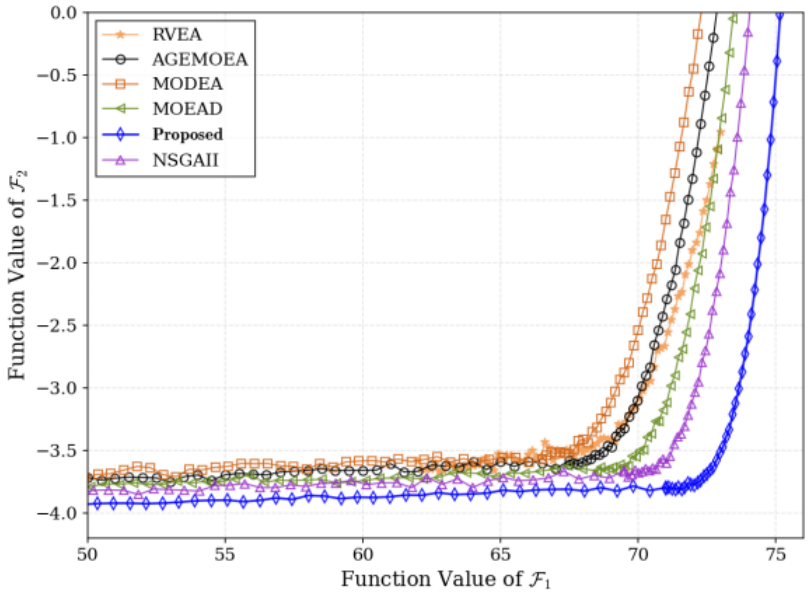


Fig. 5. Comparison of Pareto-optimal points distribution acquired by different algorithms

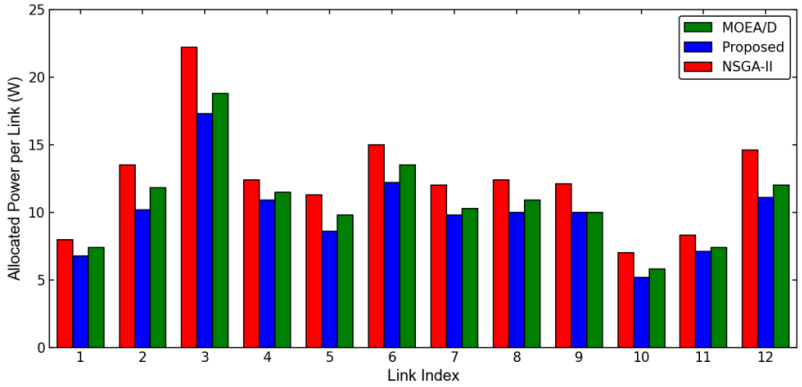


Fig. 6. Link power allocation under different optimization algorithms in the MEO scenario

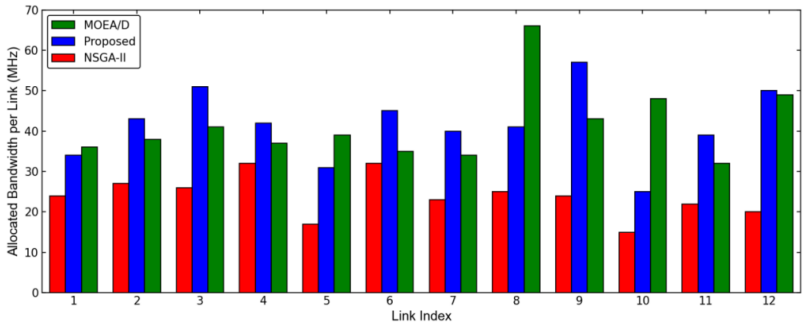


Fig. 7. Link bandwidth allocation under different optimization algorithms in the MEO scenario

Figures 6 and 7 further illustrate the specific power and bandwidth allocation schemes in the MEO scenario. Subject to the condition that all algorithms satisfy channel capacity constraints, the proposed algorithm effectively reduces the transmission power of each link and optimizes bandwidth configuration compared to NSGA-II.

Numerical results indicate that although the energy efficiency of the MOEA/D algorithm is comparable to that of the proposed algorithm, its total power consumption is approximately 2.8% higher. Furthermore, compared to the lower-performing benchmark algorithm, the proposed algorithm achieves a significant 11.4% improvement in energy efficiency and a 16.5% reduction in total system power consumption. Additionally, the proposed algorithm requires only about 50 generations to converge, and its computational efficiency during iteration surpasses that of NSGA-II. This confirms that, in the MEO scenario, incorporating a LLM as an evolutionary operator effectively enhances search efficiency and avoids local optima. Consequently, it generates high-quality joint allocation schemes without significant degradation in optimization performance.

Compared with scenarios where maximum channel capacity is the objective function, the volume of information transmitted between links in this design is significantly lower. Such a scenario is highly typical for the BeiDou system, which is characterized by dynamic link conditions and constantly changing navigation information. In this context, power consumption becomes a critical consideration. The following section presents the power and bandwidth allocation schemes of the three algorithms in the GEO scenario.

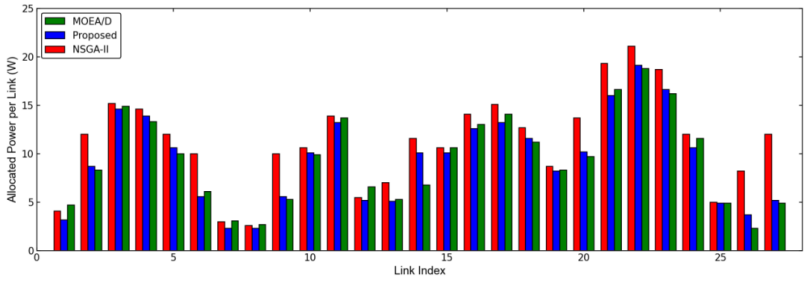


Fig. 8. Link power allocation under different optimization algorithms in the GEO satellite scenario

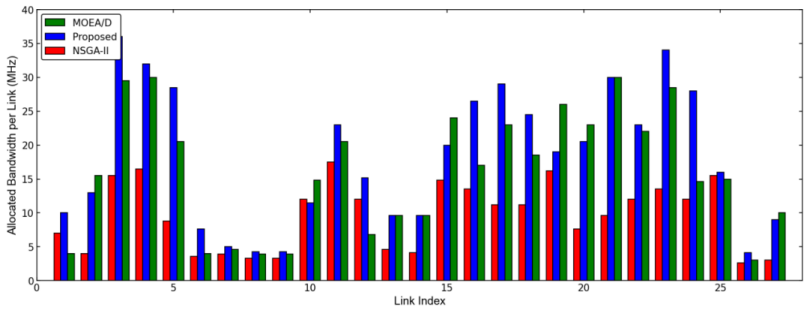


Fig. 9. Link bandwidth allocation under different optimization algorithms in the GEO satellite scenario

Verified by 30 simulation trials, the improved population generation structure effectively ensures initial individual diversity and algorithm stability; therefore, a representative result was selected for analysis. Figures 8 and 9 illustrate the resource allocation results in the GEO scenario.

In terms of power allocation, the performance of the proposed algorithm is comparable to that of MOEA/D, and both outperform NSGA-II. Although numerical statistics indicate that the total power consumption of the proposed algorithm is close to that of MOEA/D, by investing a small amount of additional power in critical links combined with optimized bandwidth allocation, it achieves a capacity gain that far outweighs the cost.

Consequently, despite a slightly higher absolute power consumption, the average link energy efficiency achieved by the proposed algorithm remains superior to that of MOEA/D. This demonstrates a successful realization of a better efficiency trade-off in a more rigorous communication environment.

5. Conclusions

This paper addresses the conflict between the limited BeiDou inter-satellite resources and the growing demand for communication services by proposing a joint power and bandwidth allocation method based on LEDMA for BDS-3. Our approach uses a Large Language Model (LLM) to guide the algorithm in efficiently searching for optimal power and bandwidth allocation schemes. Experimental results show that the proposed method converges faster and achieves better allocation outcomes than traditional optimisation algorithms across various orbital scenarios. Consequently, this method successfully strikes an optimal balance between system communication capacity and energy efficiency. This research significantly enhances the performance of the BeiDou system's integrated services and provides a novel approach to solving complex resource scheduling problems in large-scale satellite networks.

Data Availability. The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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