A Survey of the Applications of Evolutionary Computation in Satellite Domain

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***Abstract*—Due to the swift progress of transmission technologies, the challenges faced by satellite systems are continually escalating. These challenges encompass not only the heightened complexity in system design, operation, and optimization but also multi-objective trade-offs in power consumption, bandwidth, coverage areas, and so on. Additionally, as satellites form a crucial nexus of global communication, the demand for efficient satellite network design and management is also growing exponentially. While conventional algorithms frequently struggle when dealing with high-dimensional, nonlinear, and multi-constraint problems, evolutionary computation becomes a feasible tool due to its robust global search capabilities, multi-objective optimization techniques, and adaptability to complex systems. This survey explores the various applications of evolutionary computation in the satellite domain, especially focusing on resource allocation, path optimization, signal processing, and network design and management.**

***Index Terms*—Evolutionary Computation, Satellite**

I. Introduction

Satellite technology has made significant strides in sectors like global communication, remote sensing, and navigation. As this technology evolves and diversifies its applications, satellite systems have become indispensable for daily operations. With such advancements come intricate challenges in the areas like trajectory optimization, interference management, payload configuration, and resource allocation [1]. Many of these challenges, marked by a multitude of parameters, diverse objectives, and constraints, often prove challenging for traditional optimization algorithms to navigate.

Evolutionary computation provides a vital adaptability suitable for confronting the intrinsic challenges of the satellite domain. Satellite signal and image processing, for example, involve a myriad of parameters that demand meticulous adjustments to enhance signal quality or image resolution [2], [3]. With its proficiency in handling nonlinear, multimodal, and high-dimensional problems, evolutionary computation promotes a thorough exploration of solution spaces, sidestepping the limitations of local optima.

In resource allocation scenarios, there is a persistent push to improve communication capacity and service quality [4], especially considering the limited bandwidth and energy. Conventional linear programming methods may not be able to support such multi-dimensional and nonlinear optimization tasks. In contrast, evolutionary computation, with its extensive search capabilities, can yield more competitive solutions.

The extensive search capability of evolutionary computation can play a important role when solving complex problems in the satellite domain. We can consider the satellite trajectory optimization, which aim to minimize fuel usage while evading space debris [5]. Traditional methodologies can at times be restricted to nearby solutions, inadvertently missing out on more optimal trajectories. However, evolutionary computation covers a wider range of exploration and can reveal efficient trajectories that might otherwise have been overlooked.

Furthermore, the inherent parallelism and scalability of evolutionary computation are especially relevant for addressing large-scale challenges in satellite domain. As these networks become more complex, the intricacies of managing inter-satellite links, optimizing throughput, and reducing latency become more pronounced. Thanks to their ability to simultaneously assess multiple solutions, evolutionary computation offers a more efficient approach to these challenges.

Overall, evolutionary computation stands as an effective and versatile strategy to address various challenges in the satellite domain. This survey aims to explore the applications of evolutionary computation in the satellite domain, highlighting its value and potential. The remainder of this paper is organized as follows: Section II provides a brief overview of commonly-used evolutionary computation algorithms, Section III discover different evolutionary algorithms from the perspective of satellite applications, and Section IV concludes the paper.

II. Evolutionary Computation

Evolutionary computation is a category of computational methods based on principles of biological evolution and collective intelligence. Its aim is to optimize and address various complex problems by simulating the natural evolutionary process. These methods mimic biological evolution mechanisms like inheritance, mutation, and selection to seek optimal or approximate solutions from candidate solution spaces. Evolutionary computation includes various algorithms, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), etc., each of which exhibits specific advantages in different problems and applications. With widespread applications in optimization, search, machine learning, and so on, evolutionary computation is employed to tackle intricate problems, optimize algorithm parameters, and perform multi-objective optimization tasks. Below are introductions to several common algorithms.

- **Genetic Algorithm** is one of the earliest and widely applied evolutionary computation algorithms. They simulate biological genetics and evolution mechanisms by representing solutions in the form of chromosomes. Through operations such as crossover, mutation, and selection, GAs search for optimal solutions within a population. GAs are suitable for various optimization problems, including parameter optimization, function maximization/minimization, and so on.

- **Particle Swarm Optimization** is inspired by the behavior of bird flocks and fish schools, simulating the process of particles searching for optimal solutions in the solution space. Each particle represents a solution and updates its position and velocity based on individual experience and group information to find the global optimal solution. PSO performs well in optimization problems and continuous space search.
- **Differential Evolution** is a widely used evolutionary computation method in the field of numerical optimization. It involves generating random differential vectors and performing crossover and mutation operations on the objective function values in the population to search for optimal solutions. DE outperforms in parameter optimization, function fitting, and global search tasks, effectively exploring problem spaces and discovering improved solutions.
- **Ant Colony Optimization** is inspired by the observed behavior of ants searching for food, simulating the process of ants searching for optimal solutions in solution spaces. Ants communicate by releasing pheromones, and more ants tend to choose paths with higher concentrations of pheromones. ACO finds wide applications in areas such as graph optimization and the traveling salesman problem.

Each of these evolutionary computation algorithms exhibits distinct advantages in various problem domains and applications, simulating biological evolution mechanisms to search for optimal or near-optimal solutions within solution spaces, thus playing a significant role in addressing practical problems.

III. Applications in the Satellite Communications

The satellite domain encompasses various aspects of satellite system design, launch, operation, and optimization. These systems cover a range of applications such as communication, Earth observation, navigation, and scientific research. Satellites are deployed into orbit to provide essential services including global communication coverage, weather monitoring, disaster management, and navigation assistance. The complexity of satellite operations requires addressing challenges related to orbit design, communication protocols, data processing, resource allocation, signal transmission, and network management.

Given the intricacy of satellite systems and the need for efficient solutions, various advanced technologies, including evolutionary computation methods, have found widespread applications in this field. These methods aim to enhance performance, optimize operations, and overcome complexities associated with satellite activities. The following sections will outline the role of evolutionary computation in addressing key challenges within various satellite domains.

A. Resource Allocation and Scheduling

In recent years, the field of satellite communication faces significant transformation. On one hand, expansive constellations launched by companies like SpaceX, SES, and Amazon, encompassing dozens to thousands of satellites, are redefining the conventional industries [6], [7]. Simultaneously, emerging, highly flexible payload technologies [8], such as tunable phased-array antennas and adaptive modulation techniques, coupled with surging demands [9] (like amplifying internet-based services and streaming facilities for air and sea vessels) are prompting a move from static approaches to dynamic, high-dimensional settings. Moreover, the advent of non-geostationary orbits (NGSO) introduces a temporal dependency, which was non-existent in the early era of satellite communication. Consequently, in this complex high-dimensional environment, traditional manual operations are becoming outdated. Considering the above, both the academics and industries are actively searching for innovative solutions to tackle dynamic resource allocation and its associated challenges.

Resource allocation within the satellite communication domain covers a range of sub-problems [10]. One key aspect is the scheduling of beam-to-satellite [11], which mainly revolves around deciding the appropriate times to activate or deactivate specific beams to achieve balanced loads and minimal interference. In the next generation of satellite constellations, most locations on Earth will be continuously visible to multiple satellites, as shown in Fig. 1. Consequently, beam-to-satellite scheduling must decide which satellite will serve each user and manage transitions between satellites. In addition to introducing temporal dependency, these technological advancements allow operators to deploy hundreds or even thousands of beams, further enhancing resource utilization efficiency. However, this also pushes the challenge of beam-to-satellite scheduling into a highly challenging high-dimensional domain.

For high-throughput, multi-beam, and single-plane satellite constellations, the beam-to-satellite scheduling problem can be formalized as an integer problem [12], where the number of involved variables grows quadratically with the number of beams. Traditional integer programming methods can efficiently pinpoint optimal solutions in low-dimensional situations. However, as the dimensionality increases, these methods become inefficient over escalating complexities. In such complex situations, evolutionary computation, with its ability to effectively handle high-dimensional problems, offers strong support for tackling this increased complexity. Pachler *et al.* used the PSO algorithm as a viable solution [12], benchmarking it against other Artificial Intelligence (AI) and conventional methodologies. The results proved that, in high-dimensional scenarios (i.e., when the number of beams exceeds 200), the PSO method exhibits noticeable advantages.

In addition to the PSO algorithm, other evolutionary computation algorithms also have widespread applications in the

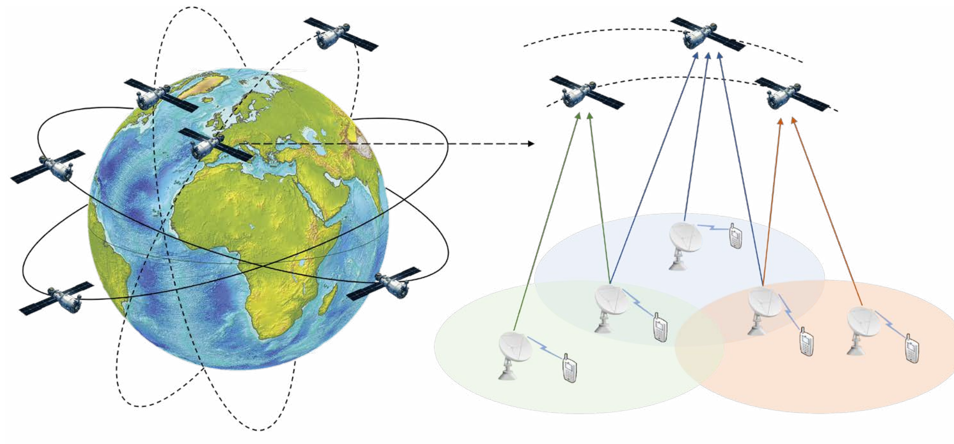

Fig. 1. Ultra-dense low earth orbit based terrestrial-satellite network.

field of satellite resource allocation. To address the co-channel interference issue of neighboring satellites through frequency allocation, Sanz *et al.* separately combined the simulated annealing algorithm [13] and the GA [14] with the Hopfield neural network, proposing two hybrid algorithms. Salman *et al.* proposed several algorithms based on DE, including adaptive DE, standard DE with appropriate mapping, and hybrid algorithms that combine greedy heuristics with adaptive or standard DE [15].

Due to the high adaptability, outstanding robustness, rapid convergence, and ability to find approximate global optimal solutions to complex problems, evolutionary computation has become a key technology in addressing resource allocation and scheduling challenges in satellite communications.

B. Orbit Design and Planning

Satellite orbit design plays a crucial role in ensuring that satellite missions, whether for communication, observation, or scientific purposes, are executed effectively. Common challenges in this domain include optimizing coverage areas, minimizing fuel consumption, ensuring efficient maneuvers, and adjusting to unforeseen events like natural disasters. Moreover, ensuring that satellites avoid debris and other space objects requires dynamic orbit adjustments [16]. Evolutionary computation has emerged as a potent tool in addressing these challenges, providing flexible, efficient, and adaptive solutions that traditional deterministic methods might struggle with. The adaptability of evolutionary algorithms allows them to find near-optimal solutions in complex, high-dimensional design spaces, making them particularly well-suited for the intricacies of satellite orbit design.

One of the major concerns in the field of satellite orbit design is the design and optimization of Earth observation satellite (EOS) systems. Earth observation satellites are instrumental in capturing images of Earth's surface, especially for disaster monitoring like earthquakes and floods [17], [18]. Their widespread use is attributed to their extensive observation capacity and high frequency. However, as shown in Figure 2, when a rapid response is required, their effectiveness

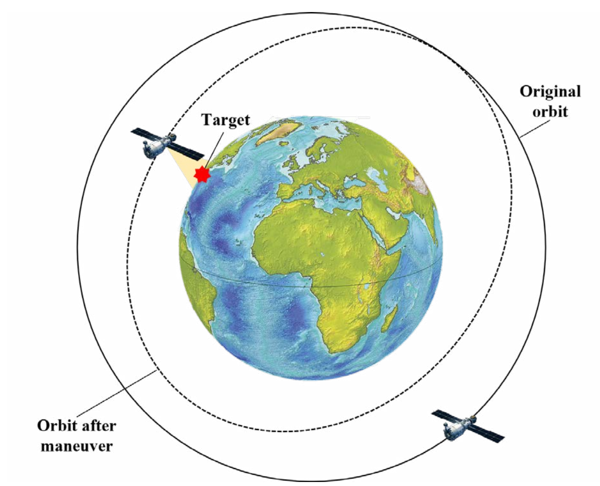

Fig. 2. Orbit maneuver scheduling for EOS disaster observation.

can sometimes be constrained. Their regular orbits might not promptly or adequately cover the affected area, thus requiring the adjustment of satellites to more optimized orbits.

In contexts that involve satellite orbit maneuvers, the current research largely concentrates on the reconfiguration of satellite constellations [19]. Evolutionary computation has shown great potential and application value in this field. A variety of evolutionary algorithms, such as PSO and GA, have been widely used in this research direction, effectively solving complex trajectory design and adjustment question. Numerous evolutionary algorithms, such as PSO and GAs, have been rigorously employed in this field, effectively addressing intricate orbit design and adjustment challenges.

For instance, He *et al.* [20] introduced a physical programming technique, paired with a GA, to address the multi-objective satellite constellation reconfiguration problem for disaster monitoring. Hu *et al.* [21] proposed a multi-objective optimization framework for satellite constellation optimization, aiming to meet the requirements of emergency observations during disasters. Luo *et al.* [22] presented an adaptive

TABLE I
RELATED APPLICATIONS OF EVOLUTIONARY COMPUTING IN THE FIELD OF SATELLITE ORBIT DESIGN

Author	Algorithm	Research Focus
Soleymani *et al.*	PSO & GAs [23]	Optimal mission planning of satellite constellation reconfiguration (best starting and ending points for satellites)
Wang *et al.*	Hybrid-resampling PSO [24]	Agile satellite constellation design (considering sensor types, attitude maneuvers, and coverage performance metrics)
Shirazi	GAs with simulated annealing [25]	Multi-objective orbit maneuver optimization
Pontani*et al.*	PSO [26]	Four impulsive orbit transfer problems (optimization between co-planar & non-co-planar, circular & elliptical orbits)
Yao *et al.*	Enhanced DE algorithm [27]	Orbit design (with adaptive and stochastic mechanisms)
Hitomi *et al.*	Evolutionary algorithm with variable-length chromosome [28]	Metrics optimization related to coverage, number of satellites, and semi-major axis in multiple constellations

DE algorithm combined with ACO to study the satellite orbit maneuver optimization problem for urgent observation tasks under sudden disasters.

Besides considering satellite orbital maneuvering, evolutionary computation also has extensive applications in other aspects of satellite orbit design. Table I lists some relevant studies in this area.

C. Data Processing and Analysis

A core focus of satellite communication is signal processing and data analysis, with satellite image processing playing a pivotal role. As satellite technology grows increasingly sophisticated and the generation of high-resolution images expands, the number of parameters in these images intensifies, posing significant challenges in processing and analysis. Evolutionary computation, with its capability of parameter optimization, feature selection, and model tuning, provides powerful tools for tackling these intricate, high-dimensional, and multimodal problems. Its nature-inspired search strategies and global optimization capabilities make it an ideal solution for tasks like image segmentation, denoising, and fusion.

1) Image Segmentation and Object Detection: Satellite image segmentation is among the most crucial techniques in image processing, dividing a given image into distinct, non-overlapping categories based on color, texture, edges, and other parameters [29], [30]. Over the past decades, numerous segmentation methodologies have been proposed, including clustering, edge detection, region growing, and threshold segmentation [31]–[33]. Among them, threshold segmentation has gained widespread acceptance due to its simplicity and efficiency [34]. However, in satellite images with multiple objects and intricate details, conventional bimodal thresholding often falls short, prompting researchers to develop multi-level thresholds to enhance its applicability.

Optimistic segmentation thresholds can be pinpointed more precisely by utilizing the parameter optimization and feature selection capabilities of evolutionary algorithms. This not only improves segmentation quality but also addresses high-dimensional issues efficiently. Recently, evolutionary computation techniques combined with Minimum Cross Entropy (MCE) have shown promise in satellite image segmentation, particularly in finding optimal segmentation thresholds [35]. For instance, an efficient satellite image segmentation method based on the Grasshopper Optimization Algorithm (GOA) and MCE combines GOA with adaptive DE to enhance search efficiency and retain population diversity in subsequent iterations [36].

2) Image Enhancement and De-noising: The objectives of image enhancement and de-noising are to ameliorate or augment the visual effects of an image and to reduce unnecessary noise within it. Images may be tainted by various unwanted noises during acquisition and transmission, potentially compromising the image's resolution, quality, and accuracy. Hence, de-noising becomes an important task in satellite image processing. Image enhancement and de-noising often involve numerous parameters like thresholds, filter sizes, and weights [37]. Evolutionary algorithms can seek the optimal or near-optimal combinations of these parameters over a broad parameter space, ensuring peak image processing performance.

For instance, a novel approach employing the Clustering-Based Multi-Swarm Differential Evolution Aided Harris Hawk Optimization (CMDHHO) in the wavelet domain has been introduced for satellite image de-noising [38]. This method shows superior de-noising results, high computational efficiency, and reduced processing times, seamlessly integrating with the aforementioned objectives and strategies.

3) Image Fusion: To efficiently utilize energy resources and communication bandwidth, multi-spectral images captured by earth observation satellites typically have a lower spatial resolution compared to panchromatic images. Image fusion techniques can integrate images from multiple sources, capturing their geometric shapes and information content to produce a clearer and more detailed image [39]. This method finds applications in various domains, including land classification, spectral analysis, and change detection [40], [41]. Evolutionary computation can optimize parameters in the fusion process, yielding more authentic and higher-quality images. Among them, the weighted DE algorithm can be employed to optimize the parameters of the Contrast Stretching Based Pansharpening (CSP) method [42], ensuring the best image processing results.

D. Network Design and Management

The satellite communication consists of the complicated interactions of various components, from ground-based stations to satellites orbiting the Earth [43]. Central to this system is the challenge of designing and managing robust and efficient satellite networks. Such networks need to facilitate smooth data transmission, mitigate potential communication failures, and adapt to ever-changing environmental conditions.

One of the key issues in satellite network design and management is satellite routing. This crucial aspect needs toidentify the optimal communication pathways between satellites, and from satellites to ground stations. Effective routing is critical to ensure timely, reliable, and efficient data transfers. However, the dynamic nature of satellite networks, characterized by shifting topologies, bandwidth constraints, and transmission delays, often complicates this task [44]. The relative motion between satellites, coupled with Earth's rotation, can result in frequent disruptions and re-establishments of links.

Effective routing is vital [45], not just for the technical aspects but also for the practical implications of sub-optimal routing decisions: increased latencies, reduced data throughput, and potential communication breakdowns. Failure in this critical aspect can have cascading effects on dependent systems, emphasizing the urgency and precision required in routing decisions.

Evolutionary computation techniques offer unique capabilities to navigate the vast solution space associated with satellite routing problems. Their inherent capability to adapt and learn makes them well-suited to tackle the complexities presented by the dynamic nature of satellite networks. Using these algorithms, a near-optimal routing path can be derived, making efficient use of the capabilities of the satellites and ensuring seamless communications.

Long *et al.* explored the application of evolutionary algorithms in satellite network routing [46]. They integrated evolutionary computing techniques, such as ACO and GAs, with improved virtual topology strategies to provide an effective solution for routing challenges in Double-Layered Satellite Networks (DLSNs). Compared to traditional methods like Shortest Path First (SPF), this evolutionary approach demonstrates significant superiority, especially in tackling issues of link congestion and packet loss probability.

As the satellite industry continues to grow, with more satellites being launched into orbit and newer applications being explored, the importance of efficient satellite network design and management will only amplify. Evolutionary computation methods, with their adaptability and optimization capability, will undoubtedly play a pivotal role in this process.

IV. Conclusion

Satellite technology is an indispensable part of modern society, with its scope and intricacy constantly on the rise. To address these challenges, evolutionary computation offers a potent approach. This survey predominantly showcases the application of evolutionary computation in satellite orbit design, resource allocation, signal processing, and network design and management. The highlighted applications demonstrate the competitive performance of evolutionary computation, rendering global optimum or near-optimum solutions and displaying real-time adaptability in dynamic satellite communication settings.

In other areas of satellite applications, such as fault detection, navigation and positioning, satellite cluster management, and task scheduling, evolutionary computation also holds huge potential. As technology further evolves, we anticipate that evolutionary computation will play a critical role in numerous sub-domains of satellites, steering us towards a more efficient and intelligent space era.

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