Towards Optimization for Large-scale Earth Observation Missions from a Global Perspective

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CCS CONCEPTS

• **Networks** → **Network dynamics**; Network design principles.

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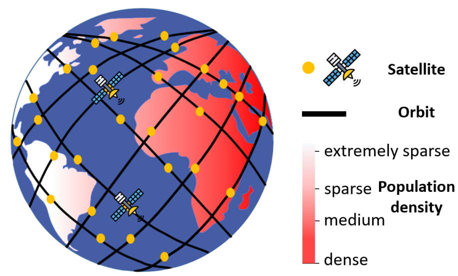

Figure 1: Imbalance between satellites and missions

1 INTRODUCTION

Earth observation is crucial for many real-world applications. With recent advances in nanosatellite technologies that reduce the manufacturing and launching cost of monolithic satellites by ~10,000× [2], industrial giants are launching *thousands* of low-Earth orbit (LEO) nanosatellites to form mega-constellations over the past years. These mega-constellations have great potential in stimulating advances in Earth observation because low orbits can take high-resolution images and the large constellation scale enables the satellites to travel above an observation spot at a higher frequency [5].

Yet, it is challenging to deliver the large volume (i.e., multi-Gbps [1]) of data with the limited downlink bandwidth. Therefore, many recent efforts [1, 2] try to offload some computation to satellites and pre-process the observed data to save bandwidth by transmitting a smaller amount of data. Such a concept is also known as orbital edge computing.

However, with the increasing need for Earth observation, naively matching the local nearby satellites to missions could lead to sub-optimal resource utilization and mission incompletion. The main reason is the imbalance of the geographical matching relationship between satellites and the observation spots of missions. Most existing constellations [4] are deployed in a grid pattern with fixed orbital parameters (as marked by black lines for orbits and yellow dots for satellites in Figure 1). But observation spots are usually set up unevenly according to population density (e.g., the darkness of red shades in Figure 1). Therefore, in populated regions, limited satellites and numerous missions lead to mission incompletion, whereas in some rural regions, satellite bandwidth resources are wasted. Moreover, new missions from different spots are continuously submitted, which might also follow a similar distribution of existing missions, making bandwidth resources even scarcer. These circumstances prevent us from fully leveraging satellite resources to complete more missions. Furthermore, because many applications are planned to be deployed on satellites to occupy bandwidth [1], the performance will be further exacerbated.

Our observation is that we need to optimize Earth observation from a global perspective. In global optimization, resources are allocated to the most needed missions. Moreover, global optimization also enables the collaboration among multiple satellites to coordinate the resources and complete more missions.

Therefore, we build a model to optimize the transmission globally to serve more observation missions (i.e., maximize mission completion rate). However, the optimization meets several challenges. First, it is challenging to coordinate the optimization with the existing mechanisms of visual tasks. For example, DDS [3] propose to send low-resolution images

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first for localization and high-resolution in those region-of-interest for further analysis. Therefore, we model the bandwidth consumption for different types of requirements (low resolution or high-resolution). Second, because visual tasks are usually completed with heavy-weight neural networks, it is hard to ensure the inference accuracy. In response, we approximate accuracy with the linear regression of bandwidth based on [3]. Finally, with the increasing scale of observation missions, reducing the complexity of the model is necessary. Hence, we would always check the correspondence between satellites and missions to prune unnecessary variables.

Our preliminary simulation demonstrates a performance improvement of up to 61.5% over the local optimization.

2 DESIGN: LP FORMULATION

We establish a model for global transmission and apply linear programming (LP) to find the optimal solution.

Inputs:

- h: average area of the target in a low-quality image
- W_i^*: bandwidth constraint for communication.

Outputs:

- X_{ij}: binary variable indicating whether to transmit the image taken by satellite i for observation spot j. Here, we actively trim the output variables and filter out the non-corresponding combination of i and j.
- lr_{ij}: low resolution, continuous variable from 0 to 1.

Constraints:

- `Bandwidth:` To prevent a large amount of imaging data exceeding the limited bandwidth, DDS [3] first sends low-quality images and uses high quality only to resend feedback regions. We model the bandwidth consumption in this way. $hr = 1$ means high-resolution, $size$ is for one raw image, T is the transmission time between one satellite and the ground, M is the number of observation spots.

$$\sum_j^M X_{ij}\left(lr_{ij} \times size + hr \times h \times size\right) \le W_i^* T, \forall \text{satellite i} \quad (1)$$

- `Latency:` There are low-latency requirements in military or emergency rescue. We mainly control the neural network completion time. t_{dds} is the time for DNN network to process a raw image and t is the time limit less than T.

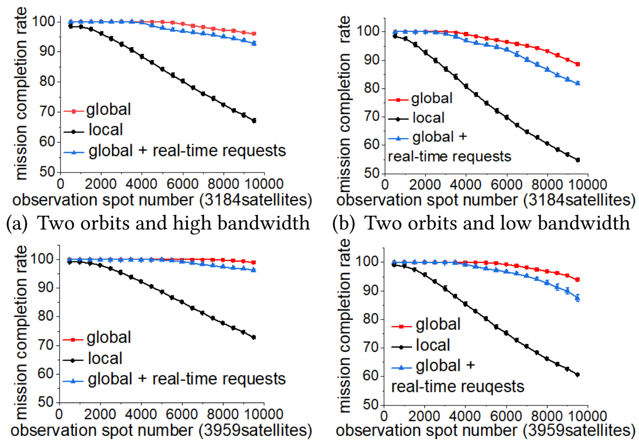
$$\sum_j^M X_{ij} t_{dds} \times \left(lr_{ij} + hr \times h\right) \le t, \forall \text{satellite i} \quad (2)$$

- `Accuracy:` We must ensure the inference accuracy of the DNN network for each observation spot. According to [3], we use bandwidth to approximately express accuracy. y_j indicates whether the mission is completed.

$$y_j = \begin{cases} 0 & \sum_i^{satenum} bandwidth_{ij} < A^* \\ 1 & \sum_i^{satenum} bandwidth_{ij} \ge A^* \end{cases} \quad (3)$$

Note that we use the DDS framework here but our method could comply with other visual methods.

Optimization goal: max $\sum_i^M y_j$, maximize the sum of completed missions means achieve as many missions as possible.



(a) Two orbits and high bandwidth (b) Two orbits and low bandwidth (c) Four orbits and high bandwidth (d) Four orbits and low bandwidth

Figure 2: Mission completion rate performance

Real-time setup:

To cope with real-time requests from different spots, W_i^* will be updated after each round of optimization. All parameters are continuously updated to adjust the model.

3 PRELIMINARY EVALUATION

We use Starlink parameters to simulate Earth observation and compare global (our method) and local optimization on the mission completion rate. We also evaluate the ability of our method to handle real-time missions and denote this scheme as `global + real-time requests` in Figure 2.

As shown in Figure 2, our method (denoted as `global`) has obvious advantages (i.e., up to 61.5% improvement in mission completion rate) compared with local baseline (denoted as `local`), verifying the importance of resource coordination. As the number of observation spots increases, `local` baseline's performance declines rapidly while `global` has minor degradation, showing stronger scalability. If real-time missions are considered, our method has a small reduction in the performance compared to the original situation. Moreover, both `global` and `local` show improvement with more satellites (more affluent resources), but our method still has up to 55.5% improvement. It indicates that blindly launching more satellites is inefficient because the utilization of resources is the real bottleneck. In the future, we will complete our theory and complexity analysis for our method.

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