

An Optimization-Based Approach for Small Satellite Download Scheduling, With Real-World Applications

Brian Lemay^{*}, Jeremy Castaing[†], Robert A. E. Zidek[‡], Amy Cohn[§], James Cutler[¶]
University of Michigan, Ann Arbor, Michigan, 48109

In this paper, we introduce a deterministic optimization model for scheduling downloads from satellites to Earth and then use our scheduling approach to analyze the QB-50 mission (50 satellites and 50 ground stations). Given the large numbers of small satellites being launched into space, demand for downloading the large quantities of data acquired by each satellite has increased significantly. For a capacity-constrained ground station network, efficient scheduling can greatly improve the overall performance of satellite missions. Our approach maximizes the total amount of data downloaded from a satellite constellation while accounting for each satellite's dynamics of collecting, storing, using, and spilling both data and energy. We test our model on simulated QB-50 data and report the results. We also use our model to evaluate various satellite capabilities and deployment options for the QB-50 mission. We find that each satellite could either reserve less of its energy for downloading data or collect and download approximately 25 times more data than what is currently planned. When the satellites do collect more data than what is currently planned, our scheduling approach enables up to 61% more of this data to be downloaded than a scheduling heuristic that reasonably approximates a current scheduling method.

^{*} PhD Candidate, Department of Industrial and Operations Engineering, blemay@umich.edu

[†] PhD Candidate, Department of Industrial and Operations Engineering, jctg@umich.edu

[‡] PhD Candidate, Department of Aerospace Engineering, robzidek@umich.edu

[§] Associate Professor, Department of Industrial and Operations Engineering, amycohn@umich.edu

[¶] Associate Professor, Department of Aerospace Engineering, AIAA Member, jwcutler@umich.edu

Nomenclature

s	= index of satellite number
i	= index of time interval number
g	= index of ground station number
e_{si}	= energy available to satellite, J
e_{min}	= energy storage minimum, J
e_{max}	= energy storage maximum, J
e_{start}	= initial amount of energy available, J
d_{si}	= data stored on satellite, bits
d_{min}	= data storage minimum, bits
d_{max}	= data storage maximum, bits
d_{start}	= initial amount of data available, bits
δ_i^{e+}	= energy gained during interval, J
δ_i^{e-}	= energy lost during interval, J
δ_i^{d+}	= data gained during interval, bits
δ_i^{d-}	= data lost during interval, bits
η_{ig}	= percent of transmitted data received
γ_{sig}	= indicator for download opportunity
t_i	= duration of interval, sec
ϕ_{ig}	= data rate, bits/sec
α_{ig}	= energy cost of download, J/bit
q_{sig}	= amount of data transmitted, bits
x_{sig}	= percent of interval used for data transmission
h_{si}^e	= energy spilled, J
h_{si}^d	= data spilled, bits
\vec{r}	= satellite position vector, m
μ	= Earth's gravitational parameter, m ³ /sec ²
\vec{f}_g	= Earth's gravitational field, m/sec ²
\vec{f}_d	= atmospheric drag, m/sec ²
\vec{f}_{moon}	= gravitational influence of Moon, m/sec ²
\vec{f}_{sun}	= gravitational influence of Sun, m/sec ²
\vec{v}	= satellite velocity vector, m/sec
BC	= ballistic coefficient, kg/m ²
ρ	= atmospheric density, kg/m ³

I. Introduction

Historically, space missions have focused on using a small number of large, traditional satellites. Today, the use of many miniaturized satellites, such as CubeSats, is much more common due to their fewer barriers to launch. During 2001-2005, approximately 10 satellites in the 1-50 kg range were launched annually and during 2006-2012, the average number of annual launches rose to approximately 25 satellites. In 2013, the number of launches jumped to 92 and larger numbers are expected in the near future [1]. These small, far less expensive satellites provide many benefits over traditional satellites and have become a popular choice for many universities and commercial companies [2], especially given their wide variety of uses, a few of which are described in [3], [4], [5], [6], [7], [8] and [9].

With an increase in the number of orbiting satellites that are collecting data comes an increase in the amount of data that must be downloaded to Earth. In order for satellites to download data to Earth, three things must happen:

1. They must have data available to download.
2. They must have enough energy to transmit the data.
3. They must have an available ground station in view to receive the data.

Satellites gain both energy and data as they orbit Earth, but can only store a limited amount of each. Satellites use energy for both downloads and routine operations. They can typically only download data to one ground station at a time and ground stations can typically only receive data from one satellite at a time. Given that each satellite is in a unique orbit and therefore has a unique set of download opportunities, determining a download schedule that effectively uses the limited resources of the system is not only challenging, but can have a major impact on the overall performance of a mission.

In this paper we present an optimization-based scheduling approach that maximizes the total amount of data downloaded from a constellation of satellites to a network of ground stations while satisfying energy and data dynamics of the system. We call this the deterministic *Multiple-Satellite, Multiple-Ground Station Scheduling Problem (MMSP)*. For the sake of comparison, we also develop

a scheduling heuristic that mimics a more traditional, “by-hand” scheduling process. We apply our scheduling approach to QB-50, a real-world space mission consisting of 50 satellites and 50 ground stations in order to demonstrate the approach’s ability to effectively schedule and analyze the mission.

We make a number of contributions to the space community through our work. First, we create an optimization-based approach that schedules data downloads from satellites to ground stations in order to maximize the total amount of data downloaded. Second, we apply our approach to the QB-50 [10] mission data and show the benefits of optimization as compared to a simpler scheduling method. Third, we conduct sensitivity analysis on the QB-50 mission and provide insights into various mission parameters. Lastly, we lay the foundation for future work using different objectives and incorporating other real-world problem specifics.

The remainder of the paper is organized as follows. Section 2 describes the details of the scheduling problem and lists our assumptions. In Section 3, we review current literature related to the acquisition and downloading of data from space. Section 4 includes the formulation of our optimization model and a description of a scheduling heuristic that is used for computational comparison purposes. In Section 5, we introduce the QB-50 mission and describe the data that is used in our analysis. In Section 6, we present our analysis results, and we conclude and propose future research topics in Section 7.

II. Problem Description

In this paper, we address a scheduling problem that was first presented by Castaing in [11], “Maximize the total amount of data downloaded from a constellation of satellites to a network of ground stations over a fixed planning horizon while satisfying all energy and data dynamics,” which in turn is an extension of the single satellite scheduling problem addressed in [12].

As satellites orbit Earth, they collect and use both energy and data. Collected data or energy that exceeds the maximum storage capacity of a given satellite must be spilled and is therefore lost. Energy is not only necessary for routine satellite operations such as altitude adjustments or telemetry collection, but also to download data to ground stations. Each ground station has a data

transfer rate, energy cost, and efficiency rate associated with it. These ground station attributes determine the speed (bits/second), amount of energy required (joules/bit), and percent of data successfully received for data transmitted to the ground station, respectively. Typically, ground stations can only receive data from one satellite at a time and satellites can only transmit data to one ground station at a time.

When scheduling downloads for a single satellite, decisions must be made to determine when and to which ground station data will be downloaded. Since some ground stations are more efficient than others, it may be beneficial to forgo current download opportunities for future opportunities involving different ground stations. For a multi-satellite constellation, these download decisions become more complicated since it is common to have numerous satellites simultaneously in view of a single ground station. We define this situation as a *conflict*. During conflicts, decisions must be made to determine which satellites download to which ground stations. For the problem of maximizing the total amount of downloaded data, we generate a schedule that indicates, for specific intervals of time, the optimal amount of data for each satellite to download and to which ground station it downloads.

A. Intervals

To model this problem, we first discretize the planning horizon into smaller intervals of time based on the view of each ground station. Any time a satellite enters or exits the view of a ground station, we define a new interval. The view of every ground station and satellite is therefore constant throughout each individual interval. A visual representation of intervals is provided in Figure 1. In this representation, each line segment represents a window of time when a satellite can communicate with a ground station. As an example of how intervals are determined, consider Ground Station 3. During the first interval, both Satellite 1 and Satellite 3 are in its view. At time t_1 , Satellite 3 exits the view of Ground Station 3, so the first interval ends the second interval begins.

B. Energy and Data Dynamics

Most satellites have the ability to gain energy when they are in view of the Sun and use this energy to perform both routine operations and downloads. Data is collected as a satellite orbits

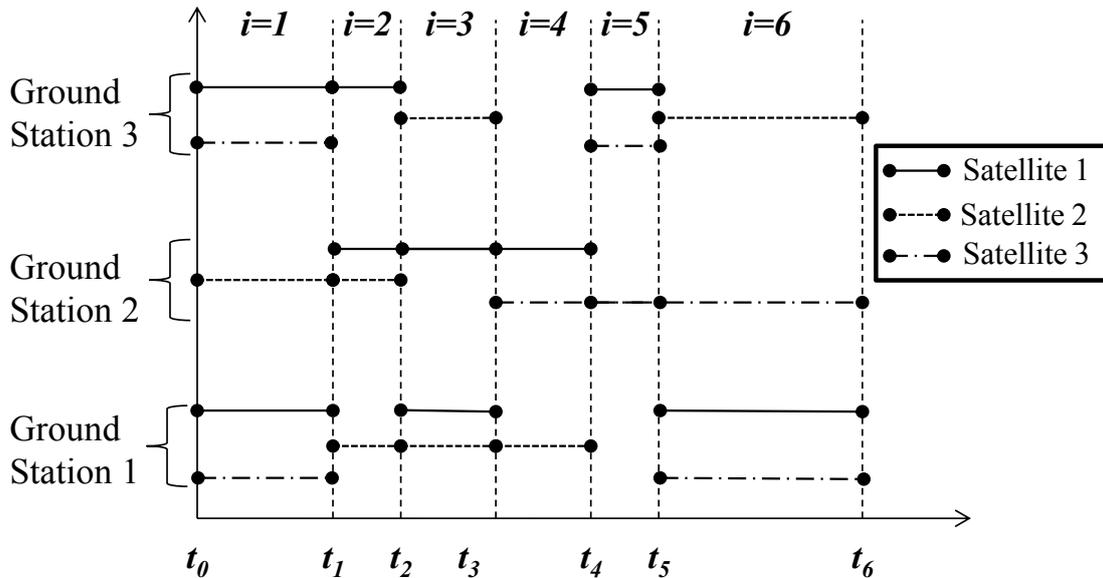


Fig. 1 Defining Time Intervals

Earth and is downloaded to Earth via a ground station as determined by the schedule. We assume that all data is equally valuable and therefore treat data as a single commodity when scheduling downloads.

Given the initial amount of energy stored on a satellite, we can calculate the amount of energy available at the start of interval $i + 1$ using the following recursive equation:

$$e_{(i+1)} = \min\{e_{max}, e_i + \delta_i^{e+} - \delta_i^{e-} - \sum_g \alpha_{ig} q_{ig}\}$$

This equation states that the amount of available energy at the start of interval $i + 1$ (e_{i+1}) is equal to the minimum of two terms: 1) The maximum amount of energy that can be stored (e_{max}) and 2) The amount of energy available at the start of the current interval (e_i), plus the amount of energy gained during the current interval (δ_i^{e+}), minus the amount of energy used for non-download operations (δ_i^{e-}), minus the amount of energy used for downloading data during the current interval ($\sum_g \alpha_{ig} q_{ig}$). Here, α_{ig} is the energy cost (joules/bit) for downloading to ground station g , and q_{ig} is the amount of data (bits) transmitted to ground station g . Note that any energy collected that exceeds the maximum storage capacity is spilled.

Similarly, we can calculate the amount of data available during interval $i + 1$ using the following

equation:

$$d_{(i+1)} = \min\{d_{max}, d_i + \delta_i^{d+} - \delta_i^{d-} - \sum_g \eta_{ig} q_{ig}\}$$

Here, the amount of data available at the start of interval $i + 1$ (d_{i+1}) is equal to the minimum of: 1) The maximum amount of data that can be stored (d_{max}) and 2) The amount of data available at the start of interval i (d_i), plus any data acquired during interval i (δ_i^{d+}), minus any data lost that is unrelated to downloads (δ_i^{d-}), such as corrupt data, minus any data that is downloaded ($\sum_g \eta_{ig} q_{ig}$). Here, η_{ig} is the percentage of data that is successfully received by ground station g and q_{ig} is the amount of data that is transmitted. We assume that any data that is not successfully transmitted is kept on the satellite for a later download opportunity, but that the energy used attempting to transmit the data is lost. As with the energy dynamics, any data collected that exceeds the storage capacity is spilled.

Under the assumption that all data and energy rates are linear across each interval, by restricting each satellite's available energy and data at the beginning of each interval to their allowable ranges, each satellite maintains an allowable amount of energy and data within each interval for the entire planning horizon. A detailed discussion and proof of this property is included in [12].

C. Assumptions

- Each satellite's orbit is deterministic and known a priori. Therefore, all download opportunities between satellites and ground stations are also known in advance. We describe how we use simulation software to generate orbit information in Section 5.
- The data and energy collection rates are linear with respect to time across each time interval and are known in advance. Energy is only collected during intervals when a satellite is in view of the Sun, as determined by its orbit.
- There is a maximum amount of energy and data that each satellite can store.
- Satellites can only transmit data to one ground station at a time.
- Ground stations can only receive data from one single satellite at time.

- The efficiency rate (percent of sent data that is successfully received by the ground station), the data transfer rate (bits/second), and the energy transmission cost (joules/bit) of each ground station are constant over the planning horizon and are known in advance.
- There is no time or energy cost incurred when a satellite starts or stops downloading to a ground station. Likewise there is no cost incurred when a ground station starts or stops receiving data from a satellite.
- Data not successfully received by a ground station due to inefficiencies in transmission is detected and the data is stored on the satellite for a later download opportunity. However, the energy used attempting to download the data is lost.

III. Literature Review

Although we are unaware of any research that directly addresses the topics of this paper, a number of articles related to spacecraft operations and scheduling have been published in both Operations Research and Aerospace journals.

A significant amount of related research has focused on the *Satellite Range Scheduling* (SRS) problem. This problem involves scheduling time-dependent communication requests between satellites and ground stations. Energy dynamics are not considered in the problem. The objective is to maximize the number of communication requests that are scheduled. Communication requests cannot be split up and once a particular request is started, it must complete while the satellite and ground station are in view of one another, a difference from MMSP in which all data is treated as a single commodity and can be split up.

Early research in [13] and [14] formulated the SRS problem using binary decision variables to represent whether or not each communication task is scheduled using a specific ground station and continuous, non-negative decision variables for indicating when the communication task will start. The authors also proposed algorithms for solving the combinatorial problem for a single day. A genetic algorithm for solving the same formulation is presented in [15] and a tool to evaluate the total capacity of the Air Force network is developed in [16]. The previous work is revisited in [17] using modern hardware and software and an exact hybrid approach that combines column

generation and logic-based benders decomposition to solve the problem is proposed.

The SRS is studied further in [18] and it is proven that the single ground station version is equivalent to the well-studied single machine scheduling problem with the objective of minimizing the number of tardy jobs, an NP-complete problem. Known machine scheduling algorithms are shown to work well for the single ground station version but they do not generalize to the multi-ground station situation. Of a variety of algorithms that are evaluated for the multi-ground station version, a genetic algorithm is found to provide the best results. A generalization of the multi-resource range scheduling problem is studied in [19] and a heuristic to solve it using Lagrangian relaxation is presented.

The Deep Space Network (DSN) Scheduling problem involves scheduling more complicated communication tasks on the DSN antennas and is described fully in [20] and [21]. This problem typically requires lengthy negotiations between numerous users in order to schedule the DSN resources. It is shown that complementing a local search technique with a systematic search algorithm to solve the problem generates promising results. Mixed integer programming and heuristic scheduling for DSN resources is introduced in [22] and the situation where ground stations simultaneously communicate with multiple satellites is considered.

Another scheduling problem that is frequently addressed in the literature is the *Earth Observing Satellite* (EOS) problem. This problem involves deciding if and when satellites collect data on specific targets on Earth and typically does not address downloading the collected data back to Earth. EOS is studied in [23], [24], [25], and [26], but on board data capacity limits are only addressed in [27]. A nonlinear mathematical formulation that addresses both observations and downloads with data capacity and transition time constraints is presented in [28] and a heuristic is developed for solving a small instance of the problem. However, energy dynamics are not considered in its formulation.

Although some of the above literature addresses both the acquisition and downloading of data, to our knowledge, [12] is the first research to also consider the acquisition and expenditure of energy, a crucial piece of spacecraft operations. The authors formulate a *Single Satellite, Multiple Ground Station Scheduling Problem* (SMSP). We use energy and data dynamics similar to their

MIP formulation, but extend their model and consider multiple satellites in MMSP.

IV. Methodology

In this section, we first present and describe our mathematical model for solving the MMSP. We then describe a greedy scheduling heuristic that we use as a benchmark and alternative approach for solving the MMSP.

A. MMSP Optimization Formulation

The following formulation enforces the data and energy dynamics described in Section 2.2 and optimally schedules satellite downloads to ground stations over the planning horizon.

Sets and Subsets

- S is the set of satellites.
- G is the set of ground stations.
- I is the set of time intervals.

Parameters

- γ_{sig} is 1 if satellite s is in view of ground station g during interval i , 0 otherwise.
- η_{ig} is the efficiency (fraction of downloaded data successfully received by the ground station) during interval i when downloading to ground station g .
- t_i is the duration of interval i , measured in seconds.
- ϕ_{ig} is the data rate associated with downloading data to ground station g during interval i , measured in bits/second.
- α_{ig} is the energy cost associated with downloading data to ground station g during interval i , measured in joules/bit.
- e_{min} , e_{max} , d_{min} and d_{max} are the minimum and maximum allowable amounts of energy and data to be stored in the buffer, measured in joules and bits, respectively. We assume that all satellites are homogeneous, but this assumption can easily be relaxed.

- e_{start} and d_{start} are the amounts of energy and data stored in the buffers at the beginning of the planning horizon, measured in joules and bits, respectively. This again assumes that all satellites are homogeneous, but this assumption can also easily be relaxed.
- δ_{si}^{e+} and δ_{si}^{d+} are the amounts of energy and data that are acquired by satellite s during interval i , measured in joules and bits, respectively.
- δ_{si}^{e-} and δ_{si}^{d-} are the amounts of energy and data that are used or lost, unrelated to downloads, by satellite s during interval i , measured in joules and bits, respectively.

Variables

- $q_{sig} \geq 0$ is the amount of data transmitted by satellite s during interval i to ground station g , measured in bits.
- $x_{sig} \in [0, 1]$ is a continuous variable that represents the proportion of interval i during which satellite s downloads data to ground station g .
- $e_{si} \geq 0$ and $d_{si} \geq 0$ are the amounts of energy and data available for satellite s at the beginning of interval i , measured in joules and bits, respectively.
- $h_{si}^e \geq 0$ and $h_{si}^d \geq 0$ are the amounts of excess energy and data spilled by satellite s throughout interval i , measured in joules and bits, respectively.

Linear Programming Formulation

$$\text{maximize } \sum_{s \in S} \sum_{i \in I} \sum_{g \in G} \eta_{ig} q_{sig} \quad (1)$$

Subject to:

$$x_{sig} \leq \gamma_{sig} \quad \forall s \in S, i \in I, g \in G \quad (2)$$

$$\sum_{s \in S} x_{sig} \leq 1 \quad \forall i \in I, g \in G \quad (3)$$

$$\sum_{g \in G} x_{sig} \leq 1 \quad \forall s \in S, i \in I \quad (4)$$

$$q_{sig} = t_i \phi_{ig} x_{sig} \quad \forall s \in S, i \in I, g \in G \quad (5)$$

$$e_{s0} = e_{start} \quad \forall s \in S \quad (6)$$

$$e_{min} \leq e_{si} \leq e_{max} \quad \forall s \in S, i \in I \quad (7)$$

$$e_{s,i+1} = e_{si} + \delta_{si}^{e+} - \delta_{si}^{e-} - \sum_{g \in G} \alpha_{ig} q_{sig} - h_{si}^e \quad \forall s \in S, i \in I \quad (8)$$

$$d_{s0} = d_{start} \quad \forall s \in S \quad (9)$$

$$d_{min} \leq d_{si} \leq d_{max} \quad \forall s \in S, i \in I \quad (10)$$

$$d_{s,i+1} = d_{si} + \delta_{si}^{d+} - \delta_{si}^{d-} - \sum_{g \in G} \eta_{ig} q_{sig} - h_{si}^d \quad \forall s \in S, i \in I \quad (11)$$

$$x_{sig} \leq 1 \quad \forall s \in S, i \in I, g \in G \quad (12)$$

$$q_{sig}, e_{si}, d_{si}, h_{si}^e, h_{si}^d \in \mathbb{R}^+ \quad \forall s \in S, i \in I, g \in G \quad (13)$$

Formulation Description:

- (1) The objective maximizes the total amount of data that is successfully downloaded across all satellites during the planning horizon.
- (2) Downloads are only allowed if the satellite is in range of the ground station.
- (3) The proportion of an interval that a ground station spends receiving data cannot exceed 1.
- (4) The proportion of an interval that a satellite spends transmitting data cannot exceed 1.

Note: (3) and (4) ensure that we generate a schedule where satellites only download to one ground station at a time and ground stations only receive data from one satellite at a time.

- (5) The amount of data downloaded from a satellite to a ground station is determined by the time length of the download and the download rate.
- (6) Each satellite starts with an initial amount of energy.

- (7) The amount of energy stored on each satellite during each interval is bounded.
- (8) Energy dynamics (see Section 2.1).
- (9) Each satellite starts with an initial amount of data.
- (10) The amount of data stored on each satellite during each interval is bounded.
- (11) Data dynamics (see Section 2.1).
- (12-13) Variable restrictions.

B. Greedy Heuristic Description

As a benchmark for the computational performance of our optimization-based scheduling approach, we develop and implement a greedy scheduling heuristic. The greedy heuristic represents a realistic, “by-hand” scheduling method. The greedy heuristic schedules downloads for one interval at a time in sequential order. Thus, future download opportunities are not considered.

The following algorithm describes the greedy scheduling heuristic:

1. Initialize the interval counter: set $i = 1$.
2. Generate $D(i)$, which we define as the set of the maximum possible download amounts for each satellite and ground station pair that are in range of each other during interval i . The maximum possible download amount from a satellite to a ground station is dependent on the length of the interval, the satellite’s available energy and data, and the ground station’s data rate, energy cost, and efficiency.
3. Select the maximum value in $D(i)$, schedule the corresponding download from satellite s to ground station g , and remove any download involving satellite s or ground station g from $D(i)$. Repeat step 3 while $D(i)$ is not empty.
4. Update the amount of energy and data available on each satellite for interval $i + 1$ according to the energy and data dynamics in Section 2.1.

5. End if the last interval of the planning horizon is reached. Otherwise, set $i = i + 1$ and return to step 2.

Since this heuristic does not consider future intervals, in scenarios when it is possible to use or lose energy or data unrelated to download activities (meaning δ_i^{e-} and δ_i^{d-} can take on positive values) it is possible to generate infeasible schedules. For example, if a satellite uses all of its energy in interval i and does not gain any additional energy, it will have zero energy available in interval $i + 1$, but may be required to use energy for non-download operations during interval $i + 1$. To avoid this situation and allow for a better comparison with our optimization approach, we assume $\delta_i^{e-} = 0$ and $\delta_i^{d-} = 0$ in our computational experiments. For the energy losses, it is reasonable to assume that a portion of each satellite’s energy is dedicated specifically to downloads and is therefore not used for other operations. Since data losses are often unexpected, it is also reasonable to assume that any data losses will not be known in advance. Under these assumptions, the greedy heuristic generates feasible schedules for the MMSP.

V. Real-World Satellite Constellation

In this section we describe the QB-50 space mission which we use for computational testing and analysis. The mission is planned to consist of 50 ground stations and 50 CubeSats to be built by universities from around the world, and is currently expected to launch in January of 2016 [10].

In addition to demonstrating the possibility of launching such a collaborative, low-cost network of satellites and providing educational value to each participating university, the mission plans to gather multi-point, in-situ measurements from the lower thermosphere [10].

The satellites will be deployed from a single launch vehicle in a “string-of-pearls” configuration and will carry identical payloads for data collection. To date, only a limited number of in-situ measurements have been recorded from the lower thermosphere.

Although there is some research relating to the QB-50 mission, we are unaware of any work that addresses scheduling data downloads. In [29], various satellite deployment options are considered in order to reduce the risks of collision while maximizing the distribution of the satellites around the Earth. Other QB-50 literature includes an analysis of the opportunities and challenges of

formulation flying in [30], available communication technologies and inter-satellite links in [31], and orbital dynamics of atmospheric re-entry in [32].

A. QB-50 Data and Parameters

In order to test our model on the QB-50 mission, we need the orbital information for each satellite in order to determine when each satellite is in view of each ground station and the Sun. We also need satellite and ground station specific parameters as described in Section 4. In this subsection we describe how we generate the data for our computational testing.

1. Orbit Data

The orbit data for each satellite is generated in Matlab[®] using the following model

$$\ddot{\vec{r}} = -\frac{\mu}{r^3}\vec{r} + \vec{f}_g + \vec{f}_d + \vec{f}_{\text{moon}} + \vec{f}_{\text{sun}}, \quad (2)$$

where \vec{r} is the position vector of the satellite relative to the Earth's center resolved in the Earth-centered inertial (ECI) frame, $r = |\vec{r}|$, and μ is the gravitational parameter of the Earth. We account for perturbing accelerations due to the nonuniform gravitational field of the Earth (\vec{f}_g), atmospheric drag (\vec{f}_d), and the gravitational influence of the Moon (\vec{f}_{moon}) and Sun (\vec{f}_{sun}). According to [33], these are the main perturbations for small satellites in low Earth orbit.

We model \vec{f}_g according to the the Joint Gravity Model 3 (JGM-3) [34] up to degree and order four. The drag perturbation is

$$\vec{f}_d = -\frac{1}{2BC}\rho|\vec{v}|\vec{v}, \quad (3)$$

where \vec{v} is the ECI velocity vector of the satellite relative to the Earth's atmosphere. This includes the rotational speed of the upper atmosphere which we assume to be 1.3 times the rotational speed of the Earth as suggested in [35]. The ballistic coefficient (BC) varies among the satellites. Similarly to [29], values for the ballistic coefficient are random according to a normal distribution with a mean of 74.32 kg/m² and a standard deviation of 2.0 kg/m². The density (ρ) is obtained using the NRLMSISE-00 atmospheric model [36]. Furthermore, we assume that the trajectories of the Moon around the Earth and of the Earth around the Sun are constant ellipses. Under this assumption, \vec{f}_{moon} and \vec{f}_{sun} follow from Newton's law of universal gravitation.

The launch date and launch profile of the QB-50 mission has not yet been decided. For our analysis we assume that the satellites are launched on April 15th 2015 at 10 pm (GMT) into a 370 kilometer near-circular parking orbit. The parking orbit has an inclination of 98.2 degrees and a right ascension of the ascending node of 324 degrees. This is in accordance with the specification of the Cyclone 4 rocket which is the proposed launch vehicle for the QB-50 mission. Furthermore, we assume that the deployment of the satellites starts at a true anomaly of 45 degrees (measured from the line of nodes of the parking orbit) at approximately 100 minutes after launch.

The time span for our analysis is three months. The orbital data is generated with a time resolution of one minute.

2. Satellite Deployment Scenario

An element of the QB-50 mission that has not yet been decided is the satellite deployment scenario. We assume that the 50 satellites are deployed from the initial parking orbit in groups of four. The respective deployment directions are assumed to be orthogonal to the orbital track of the parking orbit. In particular, two satellites are deployed in the orbital plane of the parking orbit in opposing directions (away from and towards Earth). The other two satellites are deployed orthogonal to the orbital plane of the parking orbit in opposing directions (left and right from the orbital track of the parking orbit). A deployment velocity relative to the parking orbit of 1.5 meters per second is used for each direction.

The spacing time indicates the time between the deployment of each group of four satellites and directly affects the specific orbit of each of the satellites. Moreover, it determines the initial relative distances among the satellites, thus affecting the download opportunities for each satellite. To assess the respective effects on data download, we consider orbital data for three separate deployment options: 1 minute, 5 minutes, and 10 minutes spacing between each group of four satellites.

3. Ground Station Contact Detection

The ground station network in our analysis consists of 50 ground stations that belong to the participating institutes of the QB-50 mission. We assume that the location of each ground station corresponds to the location of the respective institute and obtain geographical coordinates of the

ground stations from Google Maps. These coordinates are transformed into positions in the ECI frame for our analysis.

A satellite contact with a ground station (communication link) is detected based on the straight line between the satellite and the ground station. If the straight line intersects with the Earth, then there is no contact. On the other hand, if the straight line does not intersect with the Earth, then the satellite can contact the ground station. Note that the communication link between a satellite and a ground station is generally a function of the elevation angle of the satellite. We take this into account by using an average download efficiency for each ground station.

4. Satellite Parameters

Each satellite in the QB-50 mission will acquire 0.3 MB of data per day. We assume the data is collected uniformly across each day. Therefore, we use a data acquisition rate of 27.8 bits/second as the base case for all satellites in our computational tests. Given the small amount of data storage required for the mission, data storage will not be a limiting factor, so we use an arbitrary maximum data storage capacity of 1,000 MB. We assume that each satellite starts the planning horizon with an empty data buffer.

For energy gained strictly for download purposes, we assume each satellite gains 0.5 joules/second when it is illuminated by the Sun, and 0 joules when it is in eclipse. We conduct sensitivity analysis on this energy acquisition rate in Section 6. We also assume that each satellite can store up to 8,000 joules of energy that is dedicated to download purposes and that each satellite starts with zero energy for downloads. Each of the satellite parameters we use are included in Table 1.

5. Ground Station Parameters

Each ground station has three parameters associated with it: efficiency, data rate, and energy cost. For computational simplicity we assume that all ground stations have an efficiency of 100%, thus all transmitted data is successfully received. For data rate, we categorize each ground station as either “poor,” “average,” or “good.” The data rate for each category is included in Table 2. For energy cost, we also categorize each ground station as either “poor,” “average,” or “good” and list the

Table 1 Satellite Parameters

Satellite Data Descriptions	Value
Data Gain (δ_{si}^{d+}) (bits per second)	27.8
Data Loss (δ_{si}^{d-}) (bits per second)	0
Starting data level (d_0) (bits)	0
Minimum data level (d_{min}) (bits)	0
Maximum data level (d_{max}) (MB)	1000
Energy Gain (δ_{si}^{e+}) (joules per second)	0.5
Energy Loss (δ_{si}^{e-}) (joules per second)	0
Starting energy level (e_0) (joules)	0
Minimum energy level (e_{min}) (joules)	0
Maximum energy level (e_{max}) (joules)	8000

energy cost for each category in Table 2. This categorization creates nine potential types of ground stations. We use the distribution indicated in Table 3 to arbitrarily assign each of a ground stations as one of the nine types. For example, we arbitrarily choose two (of the 50) ground stations and assign them a “poor” data rate and “poor” energy cost. The specific geographic locations of each type of ground station may impact the overall download performance of the system, but we leave that analysis for future work.

Table 2 Ground Station Parameters

	Poor	Average	Good
Data Rate (bits/sec)	1200	9600	57600
Energy Cost (joules/bit)	0.002	0.001	0.0005

VI. Computational Results

In this section we conduct computational testing in order to answer the following questions about our optimization-based scheduling approach:

- **Tractability:** Can it solve real-world problems in a reasonable amount of time?
- **Quality:** How much value does it add over a simpler scheduling approach?

Table 3 Ground Station Type Distribution

Ground Station Type	Percentage	Quantity (of 50)
Poor Data Rate, Poor Energy Cost	4%	2
Poor Data Rate, Average Energy Cost	12%	6
Poor Data Rate, Good Energy Cost	4%	2
Average Data Rate, Poor Energy Cost	12%	6
Average Data Rate, Average Energy Cost	36%	18
Average Data Rate, Good Energy Cost	12%	6
Good Data Rate, Poor Energy Cost	4%	2
Good Data Rate, Average Energy Cost	12%	6
Good Data Rate, Good Energy Cost	4%	2

- **Applications:** How can it be used as a mechanism for conducting analysis on a mission?

To answer these questions, we apply our scheduling approach to the QB-50 mission. For our computational tests, unless otherwise noted, we use the base case parameter values described in Section 5 and the 5-minute satellite deployment data.

A. Run-times

To test our optimization-based approach’s ability to solve real-world problems in a reasonable amount of time, we test it on planning horizons of various lengths. For each test we solve the model using an Intel Xeon E3-1230 quad-core running at 3.20 GHz with hyper-threading and 32 GB of RAM. We use IBM ILOG Optimization Studio (*CPLEX*) 12.6 C++ API software package. In Figure 2 we plot the times required by *CPLEX* to find an optimal solution for a variety of planning horizon lengths. For readability, we only plot solve times for the 5-minute deployment option, but the 1-minute and 10-minute deployment options can be solved in approximately the same amount of time.

With 50 satellites, 50 ground stations, and the large number of intervals contained in each day of the planning horizon for QB-50 (up to 1,440 and usually not less than 1,400), each day involves millions of variables and constraints. Despite the large problem size, it takes just over five minutes

to generate a schedule for 35 days. In reality, shorter mission planning horizons are likely to be used so that unexpected changes to the system, such as orbital perturbations, can be accounted for. Given that schedules are generated in advance, these solve times are acceptable for practical use.

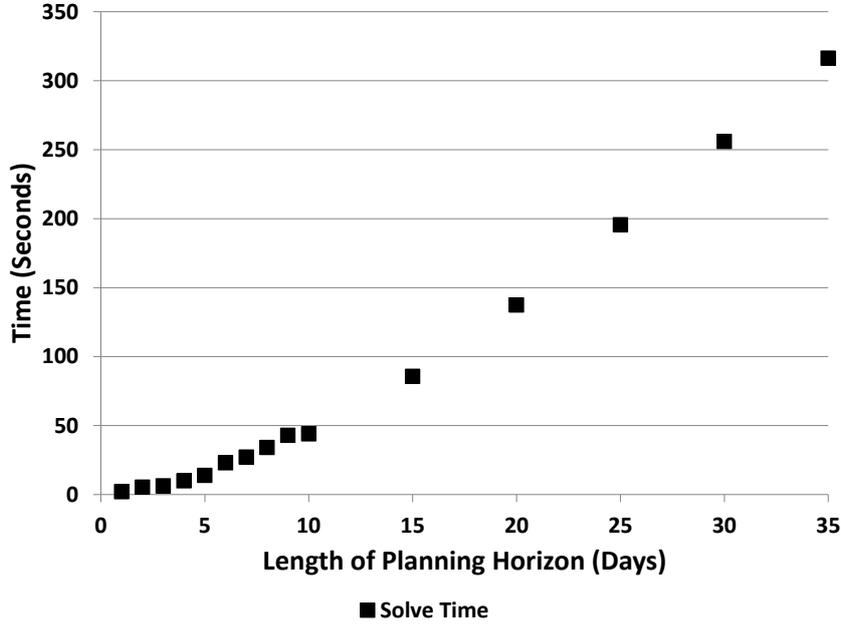


Fig. 2 MMSP Solve Times

B. Value of Optimization

When we compare the total amount of data downloaded under the base case parameters by an optimal schedule to the data downloaded by the greedy heuristic schedule described in Subsection 4.2, we find that the optimization based approach is generally only 0.1% better than the greedy heuristic. Upon further inspection, we recognize that there is significantly more energy available on the satellites to download data than what is needed, so there is no need for optimization. This fact may be by mission design since it ensures that all satellites will easily be able to download all of their data. However, this highlights that each satellite could likely either dedicate less energy to data downloads or collect and download more data. We test the effects of lower energy acquisition rates and higher data collection rates in the following subsections and compare results from the two scheduling approaches.

1. Energy Acquisition

To assess the effects of dedicating less energy to downloads and determine whether or not our optimization-based approach is valuable in scenarios where energy is scarce, we solve the MMSP with both our optimization-based approach and the greedy heuristic under various energy acquisition rates and compare the results. When solving scenarios where energy is scarce, solve times increase, therefore we use a planning horizon of 7 days to reduce the time required to solve each problem instance.

In Table 4, we see that for the default QB-50 energy acquisition rate of 0.5 joules/second (when illuminated by the Sun), optimization does not produce significant gains over the greedy heuristic. However, as the rate decreases, optimization becomes significantly better than the greedy heuristic. Interestingly, we can see that decreasing the energy gain from 0.5 to 0.01 does not have an effect on the the total amount of data downloaded when using the optimization-based approach. This means that satellites could reduce their energy acquisition abilities, which may reduce their cost, without reducing the total amount of data downloaded. Alternatively, each satellite could plan to use more energy for collecting and downloading additional data, which is what we study next.

Table 4 Energy Acquisition Comparison

Energy Gain (joules/sec)	Optimization Total Download (MB)	Greedy Total Download (MB)	Download Improvement Over Greedy
0.5	104.97	104.91	0.1%
0.05	104.97	104.91	0.1%
0.04	104.97	104.91	0.1%
0.03	104.97	104.91	0.1%
0.025	104.97	102.73	2.2%
0.02	104.97	86.27	21.7%
0.01	104.97	69.36	51.3%
0.005	54.94	35.08	56.6%
0.004	27.47	17.55	56.5%
0.003	21.98	14.04	56.5%
0.002	16.48	10.53	56.6%
0.001	10.99	7.02	56.5%

2. Data Collection

To assess the effects of collecting more data and determine whether or not our optimization-based approach is valuable in such scenarios, we solve the MMSP with the optimization-based approach and the greedy heuristic under various data collection rates and compare the results.

In Table 5, we see that for the base case QB-50 data collection rate of 0.3 MB/day, the optimization-based approach is only slightly better than the greedy heuristic. However, as we increase the data collection rate, our optimization-based approach generates schedules that download significantly more data than those generated by the greedy heuristic. With the additional data, energy becomes a limiting factor and it is therefore beneficial for satellites to save their data for download opportunities that require less energy. Our optimization-based approach identifies these opportunities and is able to provide a significant improvement in the total amount of data downloaded.

With this analysis, we're also able to identify the point at which there is no benefit from collecting additional data. This point occurs at 25 times the base case value, or 7.5 MB/day. At this point, although the satellites have capacity to store additional data and opportunities to download the additional data, they do not have enough energy to download any additional data.

Table 5 Data Collection Comparison

Data Collection Multiplier	Total Download Improvement Over Greedy
Base Case	0.2%
x5	0.2%
x10	0.2%
x15	4.5%
x20	32.8%
x25	61.0%
x30	61.0%
x35	61.0%

C. QB-50 Deployment Option Analysis

In this section we demonstrate our optimization-based approach’s ability to help analyze a mission by comparing different QB-50 satellite deployment options. To do so, we solve the MMSP with our optimization-based approach for the 1-minute, 5-minute, and 10-minute deployment options. Recall that the deployment options determine the initial spacing between the satellites which may have a significant impact on the total amount of downloaded data. When satellites are spread out, there are less conflicts between satellites which may enable more data to be downloaded.

First, to help visualize the impact of the deployment options on download opportunities, we calculate what we call the “ground station opportunity score.” This score is the percentage of a day that a specific ground station has at least one satellite in its view. Thus, it represents the maximum utilization, as a percentage of the day, for each ground station. By averaging the ground station opportunity scores across all ground stations for each day in the planning horizon, we can see how the download capacity of the system changes over time. For example, an average ground station opportunity score of 20% means that the average ground station spends 20% of the day with at least one satellite in it’s view. In Figure 3 we plot the ground station opportunity score for each deployment option for each of the first 80 days of the planning horizon.

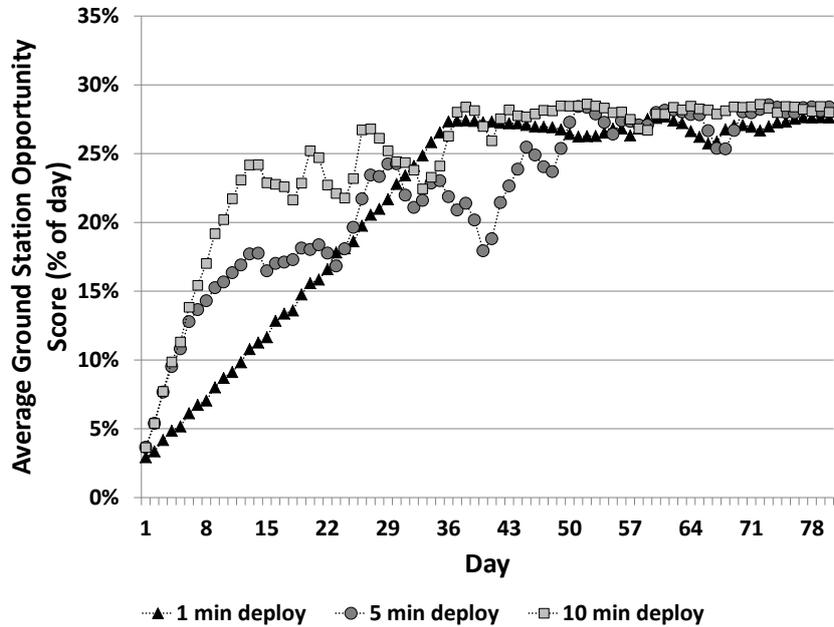


Fig. 3 Ground Station Opportunity Score

When the satellites first deploy, they will be very close to one another and will therefore pass over each of the ground stations in near unison. As a result, the ground stations spend most of the day without any satellites in view. As the satellites spread into a “string-of-pearls” configuration around the Earth, the ground stations spend a larger portion of each day with at least one satellite in view as can be seen in Figure 3. In Figure 3 we can also see that the spreading of satellites occurs quicker when they are spaced out more at deployment. After approximately one month, the system reaches a point when the average ground station opportunity score remains relatively constant.

With the small amount of data collection that is planned to occur for QB-50, we find that the deployment options make no difference in the total amount of data downloaded since in each scenario all satellites are able to download all of their data with their available energy. To analyze the effects of the deployment options on data downloads when resources are scarce, we reduce the amount of energy that each satellite has available for downloads by using an energy acquisition rate of .0005 joules/second. As seen in Figure 4, when energy is scarce, both the 5-minute and 10-minute deployment options result in a greater amount of data being downloaded each week, especially during the first month of the mission. This result is due to the fact that when the satellites are bunched together, there is not enough time for all of them to download their data to the most efficient ground stations. Consequently, some satellites are forced to download data to less efficient ground stations and are therefore unable to download all of their data. When satellites are more spread out, satellites are able to schedule more of their downloads with the most efficient ground stations.

Table 6 presents a comparison of the three deployment options in terms of total download after 12 weeks. By plotting the ground station opportunity score against the amount of data downloaded in Figure 5, we can see that there appears to be relationship between the amount of data downloaded each week and the ground station opportunity score for each week. The plot shows that when satellites are spread out and the ground stations spend more of the day with at least one satellite in view, more data is downloaded.

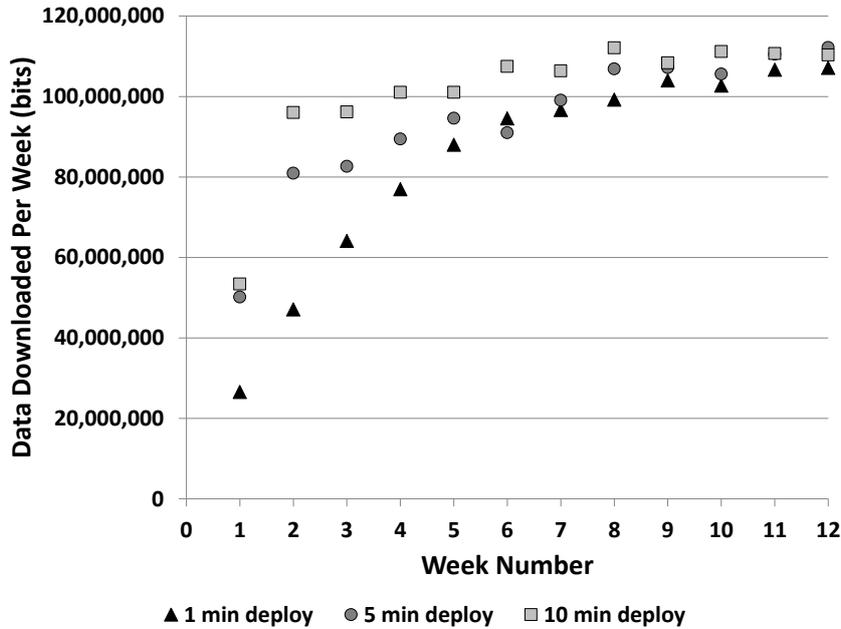


Fig. 4 Satellite Deployment Options

Table 6 Total (12-Week) Download by Deployment Strategy

Deployment Spacing:	1 minute	5 minutes	10 minutes
Total Download (MB):	126.7	141.3	151.8
Improvement:	-	11.5%	19.8%

VII. Conclusions and Future Research

With the growing amount of data being collected that needs to be downloaded from space, scheduling for the efficient use of both satellites and ground station resources can have a major impact on overall mission performance. In this paper, we have presented the Multiple-Satellite Multiple-Ground Station Scheduling Problem and an optimization based approach for solving it. We conducted computational experiments on the real-world QB-50 mission, which consists of 50 satellites and 50 ground stations with a mission length of three months. We have demonstrated how our optimization-based approach can be used to quickly analyze a variety of mission design parameters, such as energy acquisition rates, data collection rates, and satellite deployment options. We have also identified the types of situations where optimization adds the most value relative to a simpler scheduling approach.

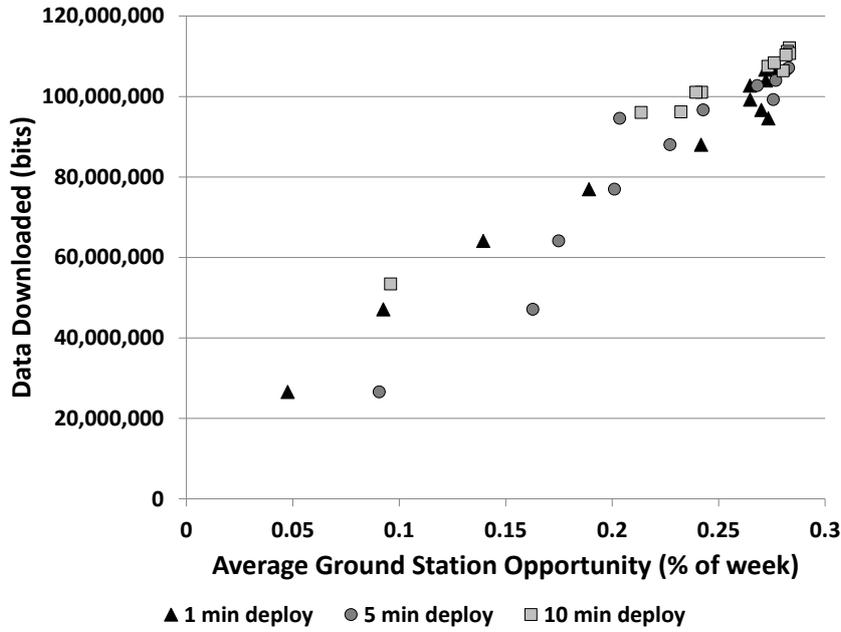


Fig. 5 Relationship Between Data Downloaded and Opportunity Score

We found that for the QB-50 mission under our model assumptions, each satellite could either collect and download 25 times more data, or dedicate significantly less of their energy to download operations, relative to what is currently planned. Due to the conservative nature of the current QB-50 mission specifications, each satellite has plenty of energy to successfully complete data collection and download tasks. However, when energy is a limiting resource, optimization provides significant value over a greedy scheduling heuristic by identifying and scheduling future download opportunities that most effectively use the scarce resources. Additionally, we showed that deployment options that increase the initial spacing of the satellites increases the maximum possible ground station utilization which allows for approximately 20% more data to be downloaded over the 12-week planning horizon.

For future research, the stochastic nature of the system could be modeled. For example, during a mission, a receiving ground station may be unavailable due to a variety of reasons, such as an equipment failure. These situations might not be predictable before the start of the mission and might conflict with the scheduling decisions that have already been made. Accounting for these unknowns could improve the robustness of the schedule. Incorporating fairness into the download schedule is another issue worth addressing. Many space missions involve multiple, independent users, each desiring to maximize their own downloads. One way of handling fairness is to guarantee each

satellite some minimum amount of downloaded data based on its total download capacity. Lastly, incorporating prioritized downloads where specific downloads are more important than others, and are possibly time sensitive, provides an area for future work.

Acknowledgments

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