Mixed Integer Programming & Heuristic Scheduling for Space Communication Networks

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Abstract—**We introduce mixed integer programming and heuristic scheduling for space communication networks in this paper. The considered communication network consists of space and ground assets with the link dynamics between any two assets vary with respect to time, distance, and telecom configurations. One asset could be communicating with another at very high data rates at one time and at other times, communication is impossible, as the asset could be inaccessible from the network due to planetary occultation. Based on the network's geometric dynamics and link capabilities, the start time, end time, and link configuration of each view-period are optimized so that the resulting schedule meets the objectives and satisfies the operation constraints imposed by the missions. Mathematical framework for the constrained optimization along with the software, Mars Relay Network Planning Tool (MRNPT), was developed in 2003 at Jet Propulsion Laboratory. In this paper, we broaden the study to include communication networks whose nodal elements can simultaneously support multiple spacecrafts and vice versa. Sample scenarios include multiple combinations of ground stations at a DSN site can form an antennas array to track a spacecraft and conversely a single ground station can support multiple spacecrafts simultaneously. Such unique network capabilities make the schedule optimization problem more challenging. Namely, the number of passes between a spacecraft and a set of ground stations soars from linear to exponential. As a result, the search space for the network optimization using start times and end times grows intractably. The new framework, casted in this paper as a mixed integer problem, provides the means to keep the search space dimensions to the linear order. The difficulty is now in the court of the optimization process. Traditional methods such as the Sequential Quadratic Optimization (SQP), used in MRNPT, are time-consuming and do not guarantee a global solution. In this paper, we propose to solve the constrained optimization problem in two phases. The first phase uses heuristic methods such as the ant colony method, particle swarming optimization, and genetic algorithm to seek a near optimal solution among a list of feasible initial populations. The final optimal solution can be found by using the solution of the first phase as the initial condition to the SQP algorithm. We demonstrate the above problem formulation and optimization schemes with a large-scale network that includes the DSN ground stations and a number of spacecraft of deep space missions.**

TABLE OF CONTENTS

1. INTRODUCTION 1
2. NETWORK MISSION SUPPORT 2
3. NETWORK PLANNING APPROACH 4
4. NETWORK OPTIMIZATION PROBLEM SETUP...4
5. HEURISTIC OPTIMIZATION SCHEMES.....6
6. OPTIMAL COMMUNICATION SCENARIOS 7
7. SUMMARY 7
REFERENCES.....9
BIOGRAPHY 10

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1. INTRODUCTION

In this study, we consider a dynamic space communications network problem where links between any two nodes are constantly changing. One example of such network is a network that consists of the Mars surface assets, the Mars relay orbiters, and the ground stations within the Deep Space Network (DSN). The links can be momentarily unavailable due to planetary occultation and their communication performances can vary significantly due to the communication distances and the propagation losses caused by the atmospheres (both Earth and Mars). Based on the geometric information and the communication configurations, view-periods between two communication entities, and the time-dependent performances of the links can be computed in advance. A network scheduling function is required to optimize the start times and end times of the tracks between the communication entities so that certain network objectives are met, and without violating the given network and mission constraints. Examples of scheduling objectives include maximizing network data throughput and minimizing tracking times. In this paper, we cast the aforementioned network assets scheduling problem into a constrained optimization problem along the timeline. This type of problem is known to be very challenging, and many of the scheduling problems can be shown to be NP-complete with respect to the number of entities to be scheduled and the time span.

The considered communication network consists of spacecraft and ground stations with the link capabilities between any pairs of communication entities vary with respect to time, distance, and telecom configurations. A spacecraft could be communicating with a ground station at high data rate at one time and at other time, communication is impossible, as the spacecraft could be inaccessible from the network due to planetary occultation. The dynamic nature of space communication presents unique challenges

in efficient planning and scheduling of network resources to support multiple spacecraft in flight. The Mars Relay Network Planning Tool (MRNPT) was developed in 2003 at Jet Propulsion Laboratory with the goal of finding an optimal schedule for communication between different orbiters and surface assets at Mars and the DSN ground stations. Communication link resource predicts between any two assets within the network are generated by the operational Telecom Forecaster and Predictor tools developed at JPL. MRNPT uses Sequential Quadratic Optimization (SQP) to generate an optimal schedule that meets the objectives and constraint requirements as imposed by the DSN and the missions. The objectives for network optimization could range from maximizing network data throughput, minimizing tracking time, to minimizing end-to-end data deliver latency, and the constraints could include mission requirements, operation restrictions, and non-overlapping tasks, etc. A hypothetical scenario considered in a previous paper [3] consists of a pair of Mars Exploration Rovers (Spirit and Opportunity), the relay orbiters (Mars Odyssey and Mars Reconnaissance Orbiter) and the designated ground stations, one at each DSN site. In this paper, we broaden the study to include spacecraft that require support from multiple network elements, and network elements that can simultaneously support multiple spacecraft. For example, a DSN site with multiple ground stations that can be allocated to track a spacecraft using antenna arraying. Similarly, a ground station with Multiple Spacecraft Per Antenna (MSPA) capability can be used to support multiple spacecraft simultaneously. These unique network capabilities make the schedule optimization problem more challenging. Its solutions no longer depend on start times and end times, but also the particularly assigned network assets. As a result, the problem formulation belongs to a class of mixed integer optimization problems. In this paper we derive the mathematical formulations for the constrained mixed integer optimization problem, and we develop efficient analytical and numerical techniques to find the optimal solution. Since solving the constrained optimization using the SQP method is time-consuming with no guaranty that the solution is a global minimum, we propose to solve the constrained optimization problem in two phases. The first phase uses heuristic methods to seek a near optimal solution among a list of feasible initial populations. The final optimal solution is then found by using the solution of the first phase as the initial condition to the SQP algorithm. We demonstrate the above problem formulation and optimization schemes with a large-scale network that includes the DSN ground stations and a number of spacecraft of deep space missions.

Next we outline the 2-step approach that we develop to solve the constrained optimization problem. As discussed earlier, that the MRNPT developed in [2][3] uses the SQP, which is a deterministic optimization process that requires updating the Hessian of the Lagrangian at every iteration. Like all gradient schemes, depending on the objective function of the problem and the initial guess, the iterative solution could converge to a locally optimal solution (a sub-optimal solution). Moreover, the SQP process is time-consuming; therefore, it is important that the initial guess is selected cautiously. In this paper, we propose to use the Particle Swarming Optimization (PSO) method to construct the best possible initial guess before feeding it to the FMINCON algorithm. The PSO method starts by using the Monte Carlo method to generate randomly a set of n feasible solutions (called particles) with uniform distribution between the upper and lower bounds. Each particle in the PSO scheme is regarded as a bird soaring over the feasible domain. As it flies, each bird keeps track of its personal best (local) solution as well as the flock"s best (global) solution, and tends to gear towards those directions. Thus the next iterative solution is constructed by perturbing its current location and velocity plus two small, but random (uniform distribution) pushes, one towards its personal best and the other towards the flock"s best. The PSO method provides an efficient and yet easy-to-use approach that heuristically constructs a feasible starting guess (the best among the locations the flock have been through).

PSO shares many commonalities with the Genetic Algorithm (GA), such as generating random initial guesses, and searching for the optimal solution by computing and comparing the values of the objective function. While all chromosomes in the GA share the search information with each other (with $O(n^2)$ complexity), each PSO particle shares only its personal best and the flock"s best (with $O(n)$ complexity).

In most cases, the schedule attained by the PSO algorithm is very close to the global optimal and thus the SQP process converges effortlessly. The PSO method is extremely fast because it requires only the evaluation of the objective function (no gradient approximation); however, it spends most of its time on constructing the initial flock of feasible solutions. Our immediate tasks include expediting this process by breaking the problem into smaller independent sub-problems, and by taking advantage of the structure of the constraints to generate the feasible solutions more effectively. The Ant Colony algorithm will also be studied.

The rest of the paper is organized as follows: Section 2 provides an overview of the mission usage of a space communication network, using the DSN as an example. Section 3 outlines the link-capability-driven network planning approach. Section 4 describes the setup of the network optimization problem. Section 5 discusses the heuristic optimization schemes that generate a near optimal solution. In Section 6, we demonstrate the problem formulation scheme and the network optimization approach using the DSN and a number of spacecraft of deep space missions. We provide concluding remarks in Section 7.

2. NETWORK MISSION SUPPORT

In this section, we use the DSN as an example to illustrate how a space communication network supports flight

missions. The DSN consists of large aperture and high-sensitivity tracking stations located in three longitudinally separated sites around the Earth, and they provide continuous coverage to flight missions from the Earth"s Geostationary Orbit (GEO) outward to the planets and other targets in the Solar System. The flight missions include flyby spacecraft, planetary surface assets, and orbiting spacecraft. Figure 1 shows a sample of flight missions supported by the DSN.

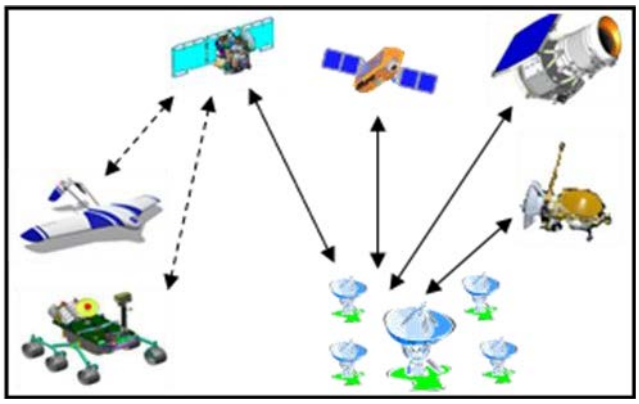

Figure 1 – A sample communication-link model support by the Deep Space Network.

To illustrate the flight project utilization of the DSN, we extract from the Space Communication Mission Model (SCMM) the set of existing, planned, and potential flight projects supported by the DSN during the period 2016-2021. The missions range from the Voyagers, to Cassini, to the James Weber Telescope, to the Solar Probes. The timeline for the deep space missions for the period of interest is displayed in Figure 2. For the duration of 5 years, there are 38 spacecraft that would require regular communication with the DSN. They include flyby spacecraft, orbiting satellites, and landing probes. Note that there are many overlaps among the missions, and they also spread out over the period. Some missions have shorter lives while others occupy much of the entire duration.

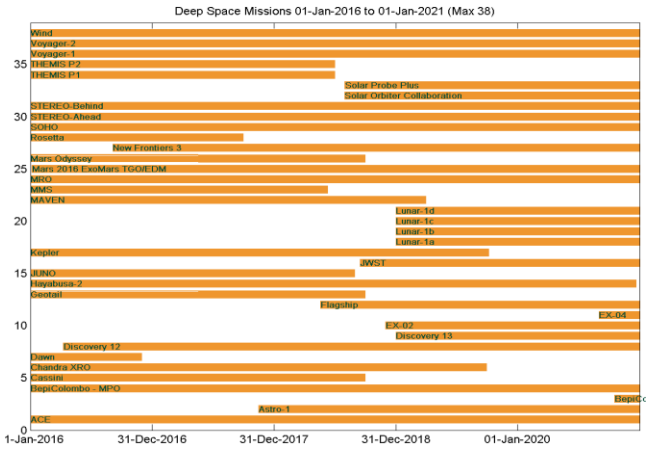

Figure 2 – Timeline of Deep Space missions between 2016 and 2021

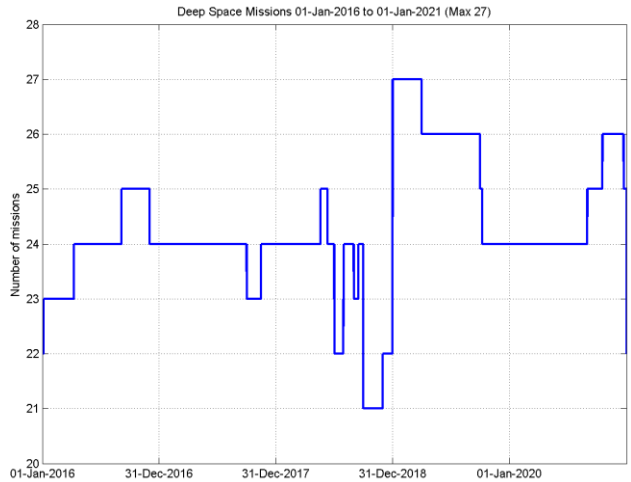

Figure 3 – Timeline of the number of links within the Deep Space Network between 2016 and 2021

Figure 3 shows the total number of links simultaneously supported by the DSN as a function of time between 2016 and 2021. It ranges from the lightest period of 21 spacecraft in the middle of 2018, to the busiest period of 27 spacecraft at the beginning of 2019.

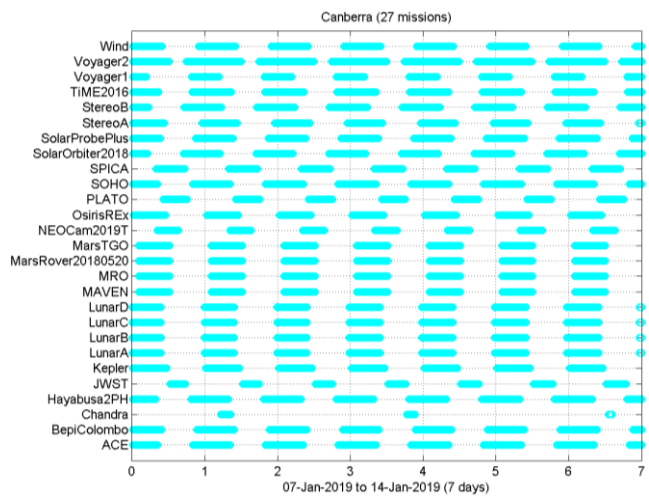

Figure 4 – Timeline of the mission links for a week in 2019 at Canberra.

To understand the network loading of the DSN during its busiest period with 27 missions, we look into the detailed mission support schedule of Canberra during the week of January 7, 2019. The line-of-sight view periods between the Canberra stations and the spacecraft are computed, and they are shown in the timeline plot in Figure 4.

Since the missions are scattered in space, it is unlikely that all 27 spacecraft are in view with a DSN site. To further understand the loading at the DSN sites, we sum up the timelines for the DSN-supported spacecraft at Canberra, Goldstone, and Madrid, and we display the results in Figure 5. At any time, a DSN site could support simultaneously from 3 to 21 deep space spacecraft.

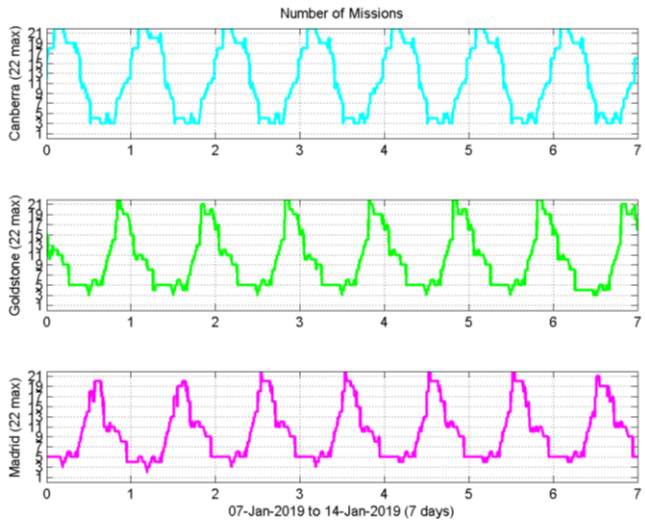

Figure 5 – Timelines of the number of links for a week in 2019 at Canberra, Goldstone, and Madrid.

3. Network Planning Approach

We consider the network planning and scheduling as a resource optimization problem. A key resource of a space communication network is the mission data throughput generated by the network. Currently the DSN planning approach emphasizes fulfilling the mission-by-mission tracking time requirements agreeable between DSN and individual missions (based on their own network coverage and communication link analyses). As the link performance between a ground station and a spacecraft changes according to the elevation angle and weather condition, it is possible that a ground station would see multiple spacecraft during a period of time, and the link during that time would favor one mission over the others in terms of the supportable data return and the tracking time required to downlink a planned volume of science data. Also when a conservative mission overestimates its tracking time for a given pass, the unused network resource cannot be easily and timely passed on to another mission in need[1]. There is a lack of flexibility and there is inherit inefficiency in the current planning process. In this paper, we propose to perform network planning and scheduling not just based on individual mission requirements on antenna tracking-time, but also on the pair-wise communication link performances between the ground stations of the network and the spacecraft. A similar approach was described in [1]. As we will demonstrate in later sections, this approach enables global optimization of network resource, both in terms of maximizing mission data throughput and minimizing network tracking time. This approach, though promising, is a major departure from the current network planning process, and imposes additional programmatic and logistical requirements to the flight projects as well as the DSN. More analysis is needed to determine its feasibility.

[1] This is analogous to a telephone service that requires the callers to specify the call durations before each call.

Next we describe the key aspects of the above link-capability-driven network planning approach. Assuming that the spacecraft communication system design and trajectory information is known, the pair-wise coverage and link capability between the DSN ground stations and the spacecraft in flight can be computed a priori. We can predictively construct a timeline of the supportable data rates between a spacecraft and a receiving ground station. Such a link prediction can be highly dynamic; it could be momentarily unavailable due to planetary occultation; and when the spacecraft and the ground station is in view, the supportable data rate could vary significantly due to slant paths, spacecraft activities and orientations, and the propagation losses caused by the atmosphere. Figure 6 shows an example of an aggregate of link capability timelines, one for each mission, as viewed by one DSN ground station. Note that due to the Earth rotation, each mission has at most one pass per day with a DSN site. The communication performance, when computed with respect to another ground station within the same DSN site, could be altered due to different antenna sizes. In addition, due to the DSN operation capability of Multi Spacecraft Per Aperture (MSPA), when Mars is in view, a DSN ground station can support up to 3 spacecraft at Mars"s vicinity. Also the DSN antenna arraying capability allows arraying up to 4 34-m ground antennas to support a spacecraft. The link-capability-driven network planning takes into account all the pair-wise timelines of link capabilities and the unique network operation models (e.g. arraying and MSPA) to generate an optimal network support plan that maximize mission data throughput and minimize network tracking time.

4. Network Optimization Problem Setup

In this section, we describe the problem formulation of optimal scheduling for a communication network and using the DSN as an example. Let us build the mathematical formulations for optimization process. Suppose within the communication network, there are N_{sc} spacecraft. Note that within each DSN site, there are several ground stations. One can consider optimizing the communication network based on the passes to the individual DSN site or on the entire DSN. However, there are scenarios that require planning over the entire DSN. For instance, a mission may require a certain amount of data volume per day and may be flexible and may not care from which ground station the data are received. Let N_{gs} be the number of ground stations within the communication network. For the finite duration that we consider, we can search for all view-periods between the N_{sc} spacecraft and the DSN sites, and we denote this number to be N_p. For a particular k^{th} view-period, $1 \le k \le N_p$, which is planned to support the ith spacecraft, $1 \le i \le N_{sc}$, we can compute the earliest start time $T_o^{(k)}$ and the latest end time $T_f^{(k)}$ from the spacecraft trajectory, the

topocentric position of the DSN site, and the corresponding local horizon mask. The supportable data rate to the jth ground station, denoted by $R_{i,j}^{(k)}(t)$, $1 \le j \le N_{gs}$, can be evaluated. If the entire view-period is use to support the ith spacecraft using the jth ground station, the data volume is computed as

$$DV(j, T_o^{(k)}, T_f^{(k)}) = \int_{T_o^{(k)}}^{T_f^{(k)}} R_{i,j}^{(k)}(t)\,dt \qquad (1)$$

The example of an aggregate of view-periods as seen by a DSN station in 24 hours is displayed in Figure 6, where they are highlighted in red and the data rate curves are plotted in blue and the supportable data volumes for the view-period are also given.

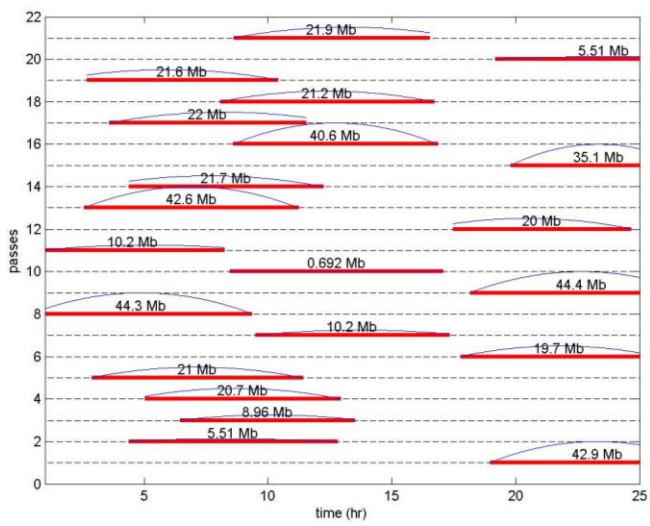

Figure 6 – Example of the view-periods along with the data rate performance and the corresponding data volume for one ground station within a DSN site

In this paper the planning objective is to maximize the network data throughput, and at the same time to satisfy the requirements and constraints as imposed by the missions and the DSN. This translates into the problem of, for a given view-period, finding the communication start time and end time between the spacecraft and the ground station such that there is no conflict in scheduling between spacecraft and ground stations along the timeline. Once the start time and end time are determined, we call the time period within the view-period a pass. In the original MRNPT approach, the focus is to support a set of Mars orbiters and Mars surface assets with a pre-designated ground station at each DSN site, so that the optimization is based on the start time and end time within each view-period. If we follow the MRNPT approach to explore the more challenging problem of multiple ground stations per DSN site, we need to consider the link capability from a spacecraft to each and every ground station of the DSN site within the view-period, and optimize the start times and end times of all the ground stations. In this case, the dimension for the search space for a single view-period would be $2N_{gs}$, which is already large and could be as large as $2(2^{N_{gs}}-1)$ if all possible antenna arraying combinations are considered. On the other hand, if mixed integer optimization (MIP) is considered, the dimension for the search space for each pass would be 3; namely, the variable set involves an integer and two real numbers. The integer would correspond to which ground station or combination of ground stations is being used, and the real numbers are the respective start time and end time. If there are N_p passes within the considered time span, the search space is decreased by at least $2(N_{gs}-3)N_p$ for single antenna case, and up to $2(2^{N_{gs}}-4)N_p$ for the arraying case, a substantial reduction.

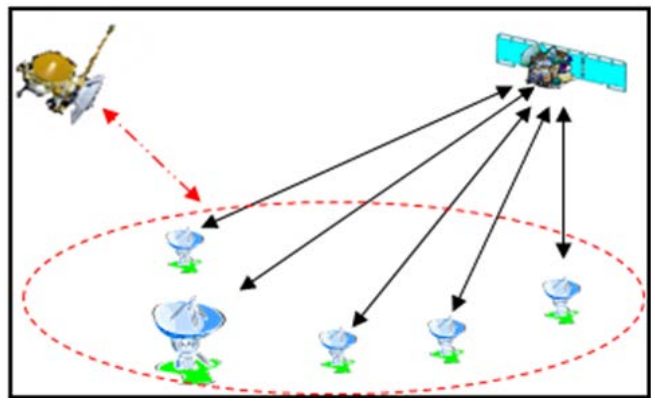

Figure 7 –Complexity of the optimization schemes for a pass using continuous variables (solid black) versus the mixed integer programming (broken red)

Let us build the mathematical formulations for optimization process. We denote the variable for each pass to be

$$x^{(k)} = \begin{bmatrix} gs^{(k)}, & t_o^{(k)}, & t_f^{(k)} \end{bmatrix}^T, \qquad (2)$$

where $gs^{(k)} \in \{1, 2, \ldots, N_{gs}\}$ and $T_o^{(k)} \le t_o^{(k)} \le t_f^{(k)} \le T_f^{(k)}$ for $1 \le k \le N_p$. Our goal is to find the best set of $\vec{x} = [\vec{x}^{(k)}]_{k=1}^{N_p}$ so that the data volume throughputs from all spacecrafts to the DSN are maximally possible. In this case, the cost function for which we want to minimize is

$$J(\vec{x}) = -\sum_{k=1}^{N_p} DV(\vec{x}^{(k)}). \qquad (3)$$

As mentioned earlier, formulating the optimization formulation using MIP reduces the dimension of the search space down tremendously. But then problems with MIP types are very challenging to solve. In this paper, we use the penalty function to handle the integer variables. Particularly, the following penalty function is used

$$P(gs^{(k)}) = \prod_{j=1}^{N_{gs}} \frac{\left(gs^{(k)} - j\right)^2}{\left(gs^{(k)} - j\right)^2 + 1}. \qquad (4)$$

and an example of its shape is shown in Figure 8. With the penalty function, the integer variable $gs^{(k)}$ can now be continuous and bounded by $1 \le gs^{(k)} \le N_{gs}$. The size of the penalty is an input parameter, denoted by σ, and the cost function is expressed as

$$J_\sigma(\vec{x}) = J(\vec{x}) + \sigma \sum_{k=1}^{N_{gs}} P(gs^{(k)}) . \tag{5}$$

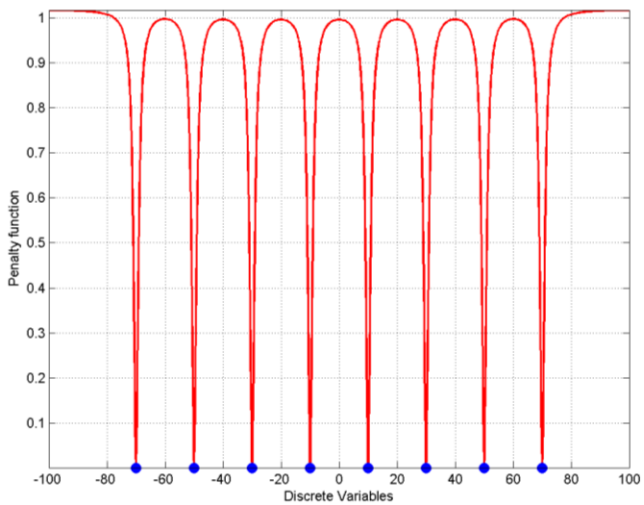

Figure 8 –Profile of a penalty function applied to the cost function to handle the integer variables as continuous variables.

Next we discuss the incorporation of mission and operational constraints into the optimization problem:

I. Communication in a view-period must happen within the view-period itself:

$$T_0^{(k)} \le t_0^{(k)} \le t_f^{(k)} \le T_f^{(k)} . \tag{6}$$

II. The ground station number is bounded by

$$1 \le gs^{(k)} \le N_{gs} . \tag{7}$$

III. Each pass must be longer than a minimum pass length $T_{\min}$

$$t_f^{(k)} - t_0^{(k)} \ge T_{\min} . \tag{8}$$

IV. If $gs^{(k_1)} = gs^{(k_2)}$ (ground stations are identical), then transmission time cannot overlap :

$$[t_0^{(k_1)}\ t_f^{(k_1)}] \cap [t_0^{(k_2)}\ t_f^{(k_2)}] = \varphi . \tag{9}$$

V. Each mission is required to achieve certain value of throughput:

$$\sum_{\substack{k=1 \\ sc^{(k)}=i}}^{N_p} DV(\vec{x}^{(k)}) \ge DV_{req}^{(i)} . \tag{10}$$

It should be pointed out that these are a few missions and operational constraints that we consider. Additional ones can be incorporated in a similar fashion. The constraints (6)-(8) can be translated into linear and bounded constraints:

$$A\vec{x} \le B , \tag{11}$$

$$L_B \le \vec{x} \le U_B , \tag{12}$$

where

$$A = \begin{bmatrix} 0 & 1 & -1 & & & \\ & & & \ddots & & \\ & & & 0 & 1 & -1 \end{bmatrix}_{N_p \times 3N_p} , \quad B = \begin{bmatrix} -T_{\min} \\ \vdots \\ -T_{\min} \end{bmatrix}_{N_p \times 1} \tag{13}$$

and

$$L_B = \begin{bmatrix} 1 \\ T_o^1 \\ T_o^1 \\ \vdots \\ 1 \\ T_o^K \\ T_o^K \end{bmatrix}_{3N_p \times 1} ; \quad U_B = \begin{bmatrix} N_{gs} \\ T_f^1 \\ T_f^1 \\ \vdots \\ N_{gs} \\ T_f^K \\ T_f^K \end{bmatrix}_{3N_p \times 1} . \tag{14}$$

The constraints (9) and (10) are employed as a nonlinear constraint

$$g(\vec{x}) = \begin{bmatrix} g_1(\vec{x})_{N_{gs} \times 1} \\ g_2(\vec{x})_{N_{sc} \times 1} \end{bmatrix} \le 0 , \tag{15}$$

where

$$g_1^{(j)}(\vec{x}) = \begin{cases} [t_0^{(k_1)}\ t_f^{(k_1)}] \cap [t_0^{(k_2)}\ t_f^{(k_2)}] & gs^{(k_1)} = gs^{(k_2)} = j \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

$$g_2^{(i)}(\vec{x}) = DV_{req}^{(i)} - \sum_{\substack{k=1 \\ sc^{(k)}=i}}^{N_p} DV(\vec{x}^{(k)}) \tag{17}$$

5. Heuristic Optimization Schemes

The resulting scheduling formulations turn into a constrained optimization problem, whose solution procedure is NP-complete. In other words, as the number of communication nodes or time span increases, the optimal solution cannot be solved in polynomial time and becomes intractable. Classical mathematical programming techniques such as gradient-descent methods, conjugate direction methods, and nonlinear programming can provide a solution, but often may yield a sub-optimal one depending on its initial guess. To ensure that we start with a good initial solution, in this paper, we propose to find an initial

solution that is „reasonably good" using heuristics optimization techniques, then we feed the result into a traditional optimization method to attain the final solution. Such hybrid scheme is a good approach in two aspects; first heuristics schemes are flexible and computationally efficient to allow sampling of a sufficiently large portion of the search space in reasonable time, and second many classical mathematical methods guarantee convergence to the optimal solution if the initial solution is reasonably close to the optimal solution.

Motivated by social behavior of organisms such as bird flocking and fish schooling, the Particle Swarm Optimization (PSO) algorithm is introduced by J. Kennedy and R. Eberhart in 1995 as a tool for optimization. In principle, the PSO starts out with a swarm of N_{sw} particles $[X_n(0)]_{n=1}^{N_{sw}}$ in a hyper-dimensional search space and a metric that can measure the fitness of its members. The PSO algorithm stochastically mimics the social behaviors and psychology of birds and fish when they are out to hunt for food. At any time, the individual particle $X_n(t)$ tries to improve itself by migrating to a better ground based on the knowledge of its personal best $P_n(t)$ position (its own experience) as well as the group"s best $G_n(t)$ position (social interaction). During its flight, each particle adjusts its position as follow,

$$X_n(t+1) = X_n(t) + V_n(t+1), \tag{18}$$

$$V_n(t+1) = c_o V_n(t) + c_1[P_n(t) - X_n(t)] + c_2[G_n(t) - X_n(t)]. \tag{19}$$

The term $V_n(t)$ in equations (18)-(19) is referred as the current velocity of the particle. The terms on the right hand side of equation (19) are known as the particle"s momentum (to prevent excessive oscillations), cognitive component (environment familiarity), and the social component (successes of others). c_o is fixed constant while c_1 and c_2 are random numbers between 0 and 1 at each instant.

Once a good initial solution is found from the PSO algorithm, we will use a mathematical optimization method to find the final solution. There are many commercial-off-the-shelf software tools that are capable of solving such a problem. Specific software, which we have used, includes MATLAB"s optimization toolbox and the ILOG Optimization Suite. In this paper, we implement with MATLAB"s FMINCON, which uses Sequential Quadratic Programming (SQP).

6. Optimal Communication Scenarios

For the proof of concept, we consider in this scenario a network of 20 spacecraft that is in view with a DSN site. We assume that the DSN site has three pre-allocated ground stations to handle these spacecraft. As shown in Figure 9, the ground stations typically see multiple spacecraft at any one time. The supportable data rate profiles of the spacecraft-ground station pairs can vary greatly due to the different link configuration, range, and weather condition as seen by each pair. The dotted vertical lines over any view-periods signify the regions where overlapping view-periods occur. Our objective in this simulation is to optimally assign for each view-period the optimal start time and end time so that (i) the achieved network data throughput is maximized, (ii) the individual mission data volume requirements are met, (iii) each ground station supports one spacecraft at any one time (non-overlapping pass), (iv) each pass must be sufficiently long to ensure efficient usage of a ground station, and (v) each pass must start and end within its bounds. The dimension for the search space is 60 in this scenario. There are 20 linear bounds, 60 upper bounds, 60 low bounds, and 23 nonlinear constraints (3 non-overlapping and 20 mission data volume). In seeking for an optimal solution, the PSO algorithm is used with 200 randomly generated particle elements. The process for both PSO and FMINCON with 200 iterations takes about 2482 seconds. Note that the computation of the nonlinear constraints is time consuming. The results of the optimal schedule for the three ground stations are displayed in Figure 10. The blue lines indicate the view-periods and the red lines indicate assigned passes after the scheduling. The achieved data volume for each scheduled pass is also shown. The optimal results contain passes that includes the entire view-period with respect to a single spacecraft, as well as passes generated by the constrained optimization scheme that de-conflicts and splits the overlapping view-periods into disjointed time intervals, each assigns to a spacecraft.

7. Summary

In this article, we describe a framework and the mathematical formulation for optimizing communication network using mixed integer programming. The design in this paper yields a system that is much smaller, in search space size, when compared to the earlier approach [2][3]. Our constrained network optimization takes into account the dynamics of link performance within the network along with mission and operation requirements. We introduce a unique penalty function that transforms the hard problem of mixed integer programming into the more manageable problem of searching in a continuous space. We propose to solve the constrained optimization problem in two stages: first using the heuristic Particle Swarming Optimization algorithm to get a good initial starting point, and then feeding the result into the Sequential Quadratic Programming algorithm to achieve the final optimal schedule. We demonstrate the above planning and scheduling methodology using a tracking scenario of 20 spacecraft and 3 ground stations of a Deep Space Network site. Our approach and framework have been simple and flexible so that problems with larger number of constraints and network can be easily adapted and solved.

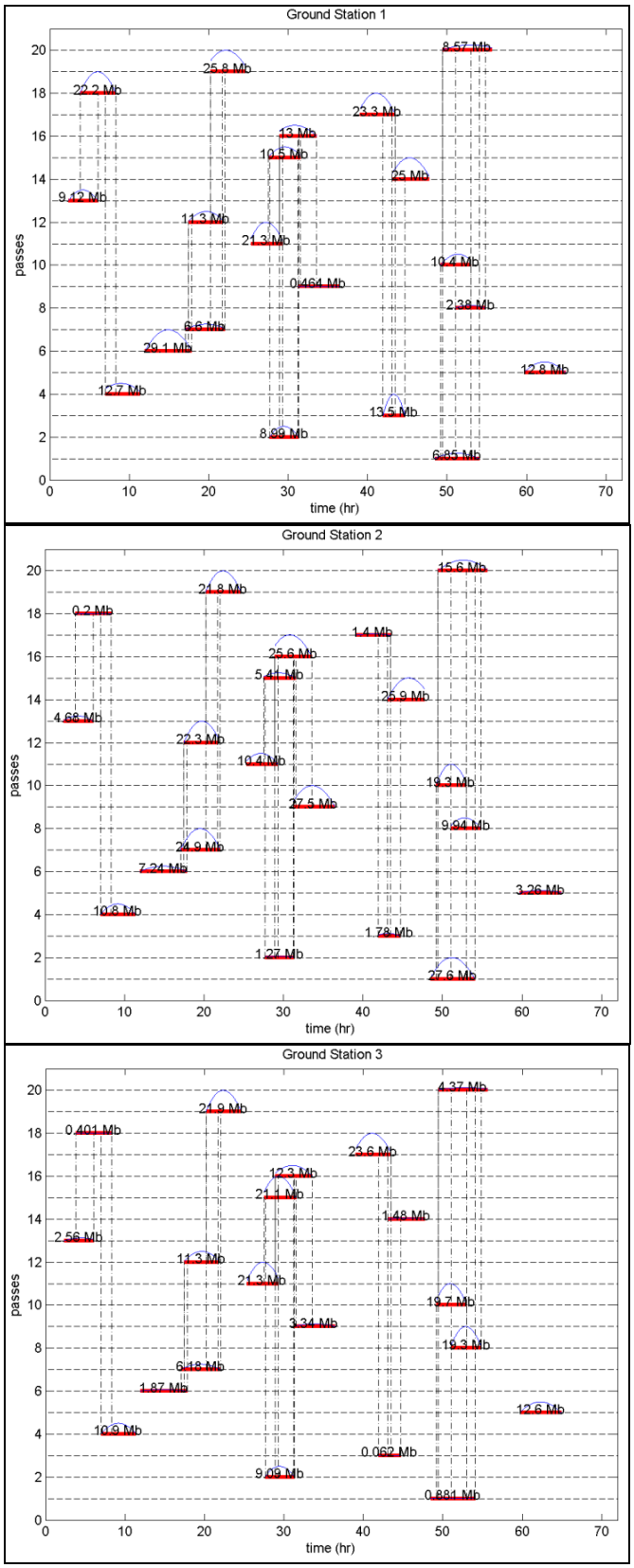

Figure 9 –Profiles of the link predicts of 20 missions to ground stations 1 (top), 2(middle), and 3(bottom).

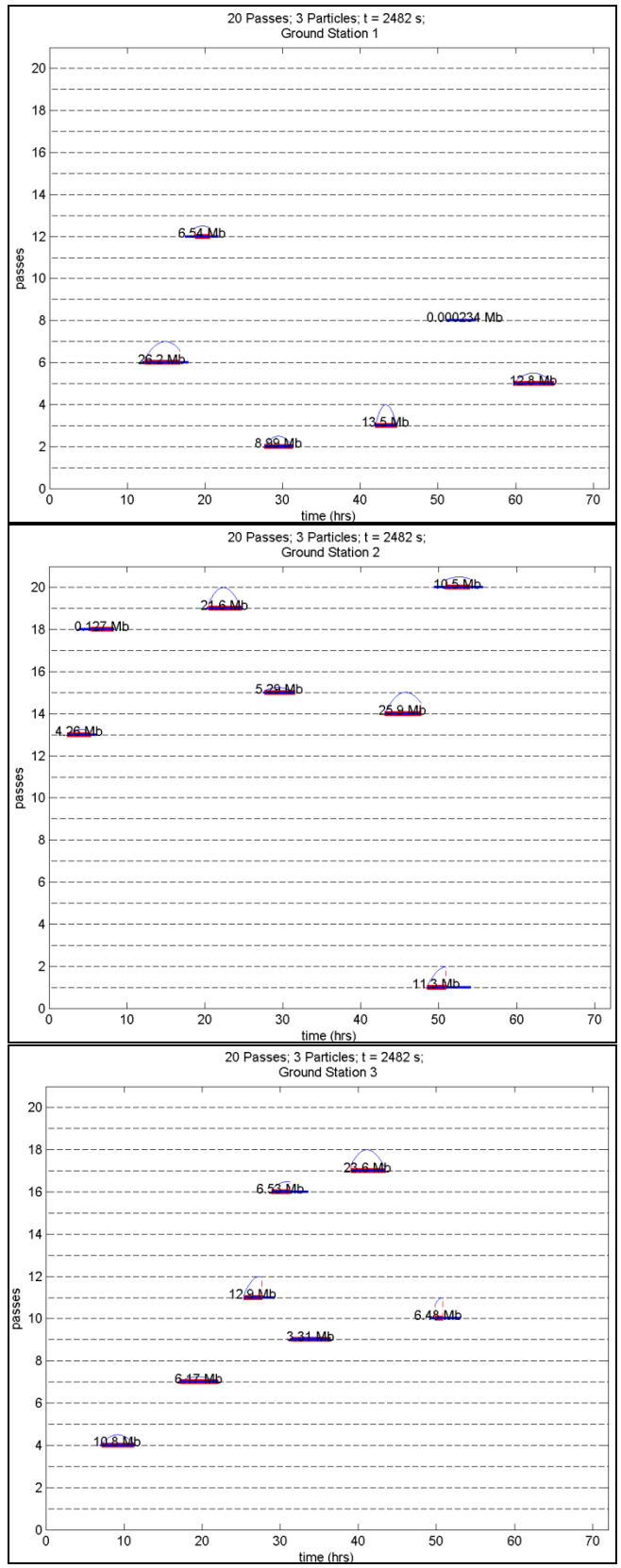

Figure 10 –Optimal schedule of 20 missions to 3 ground stations.

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