

# AN OPTIMIZATION FRAMEWORK FOR GLOBAL PLANETARY SURFACE EXPLORATION CAMPAIGNS

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As the scale of space exploration increases, planning of planetary surface exploration becomes more complex and campaign-level optimization becomes necessary. This is a challenging profit maximization problem whose decisions encompass selection of bases, technological options, routes, and excursion methods under constraints on a route, a mission, and a whole campaign. This paper introduces the Generalized Location Routing Problem with Profits (GLRPP), which is a framework to deal with this campaign optimization problem. A mathematical formulation for the GLRPP is developed and solution methods to solve the GLRPP are presented. A case study for a global Mars surface exploration campaign optimization has been carried out. Problem instances with 100 potential bases and 1000 potential exploration sites are solved with consideration of realistic future technologies and constraints.

**Keywords:** Surface exploration, campaign optimization, Mars, ISRU, orbiting depot

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## 1. INTRODUCTION

As the scale of space exploration increases, planning of planetary surface exploration becomes more complex. Various stakeholder groups are interested in scientific exploration of a planetary body and each group wants to obtain information from distinct regions of the body. To satisfy these diversified groups, exploration for these multiple locations distributed over the surface of the whole planet is required. In other words, optimization of global planetary surface exploration is highly desirable.

The amount of on-surface activities for historical missions was limited for several reasons. First, a much higher priority was given to successful in-space transportation, which was far more challenging for early missions than it is now. Second, capabilities of the surface mobility systems for early missions were limited. Last, especially for the case of the human lunar missions, surface stay times were relatively short. Figure 1 shows a superimposed view of the surface exploration paths for a set of historical missions.

The situation will be different for future planetary surface exploration missions. Accumulated experiences from past missions will make in-space transportation more reliable and easier to carry out; benefits from exploration will be considered more important than they used to be. In addition, improved capabilities of planetary surface mobility systems will be available and surface stay times for future human missions will be much longer than those for previous missions. These factors make it very important to carefully design surface activities of the missions. Stakeholder groups will identify globally-distributed locations which they are interested in [1]. The amount of resources that can be used for the missions however will remain limited, which prohibits visiting all the identified locations. Therefore, the design of the surface exploration missions should be carried out such that total benefits from the missions can be maximized.

This paper discusses a framework to optimize a campaign for global planetary surface exploration. A routing problem referred to as the Generalized Location Routing Problem with Profits (GLRPP) is used for the framework. Mathematical formulation and solution methods for the GLRPP are developed. A global Mars surface exploration campaign optimization problem is provided as a case study to demonstrate the framework.

## 2. PROBLEM DESCRIPTION

### 2.1 Concepts used for Problem Description

#### 2.1.1 Agent, Site and Profit

An *agent* (human or robotic) visits locations and collects profits, which are a surrogate for expected scientific value. A *site* is a location at which the agent can obtain *profit*. The profit for each site is expressed as a scalar number. The amount of time to collect the profit is also assigned to each site. Candidate sites and profits/required time associated with the sites are estimated and provided as an input to the problem. Multiple stakeholder groups are interested in Mars surface exploration. For a specific exploration site, different stakeholder groups can show different degrees of interest. It is assumed that a scalar profit value for a site should be determined. Ideally, it would be the best situation to reach an “agreement” on the profit value for the site through discussion. The Delphi Method could be used to determine the value of a site [2]. Figure 2 shows candidate exploration sites on Mars compiled from mission studies and individual contributions from scientists in fields like Geochemistry, Geology, Seismology, Meteorology, and Exobiology [3].

#### 2.1.2 Base, Route, Routing Tactic and Single-Route Constraint

A *base* is a location at which an agent starts and ends a *route*.

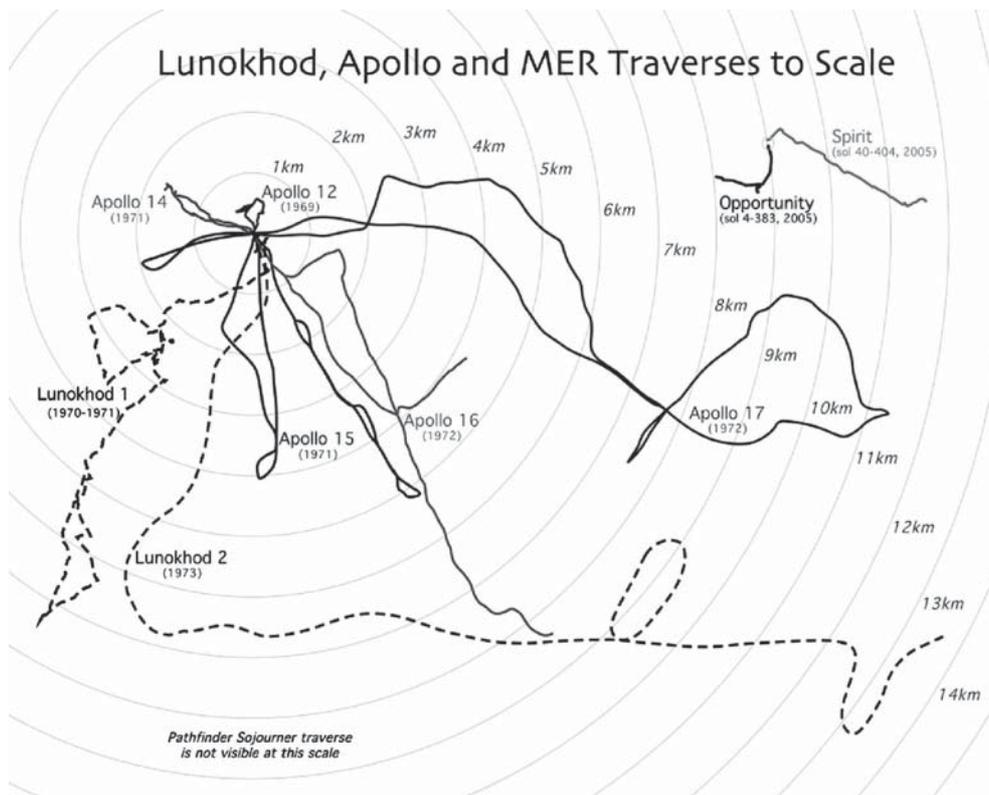
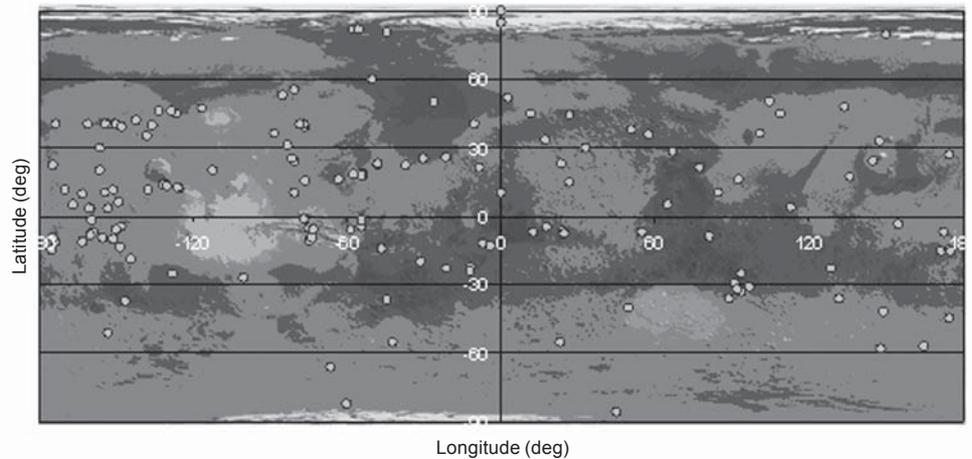


Fig. 1 Superimposed plot for historical planetary surface exploration [11].

Potential Exploration Sites on Mars Surface

Fig. 2 Mars candidate exploration sites.



Potential landing locations are determined by campaign planners and are used as candidate bases [4]. A *route* is a sequence of locations (sites or bases) that represents movement of an agent over time. Only one base is included in a route, and the base is both a starting and an end point of the route. An agent collects profits by visiting sites along the route. A site cannot be visited twice. A *routing tactic* characterizes a route by specifying single-route constraints and the maximum number of routes. A *single-route constraint* is expressed by a constraining resource type, consumption coefficients (per route, on-arc, and on-site), and a consumption limit. A route is feasible if the route satisfies single-route constraints defined by the routing tactic selected by the route. The maximum number of routes limits the number of routes that can use a specific routing tactic in a mission.

Figure 3 shows examples of routing tactics for surface exploration. *Walking*, *rover*, and *depot-assisted rover* are tactics

presented here. Figure 4 shows how resource consumption is calculated for a feasibility check of a route with respect to a single-route constraint. The upper figure shows an infeasible route using the walking tactic. Time consumed on the route is larger than the consumption limit (10 [hr] > 8 [hr]). The lower figure shows a feasible route using the rover tactic, where fuel consumption on the route does not exceed the consumption limit (460 [kg] < 600 [kg]).

2.1.3 Mission and Mission Strategy

A *mission* is a collection of feasible routes sharing a base. There exist multiple technologies for surface exploration, each of which represents a *mission strategy*. A *mission strategy* characterizes the mission by specifying collective constraints, available routing tactics for the mission, and mission cost. Similar to a single-route constraint, a collective constraint is expressed by a constraining resource type, consumption coeffi-

agents, and a consumption limit. Routes belonging to the mission should use available routing tactics specified by the mission strategy. Mission cost is used to calculate the total cost of a campaign, on which a budget constraint is imposed.

A mission for planetary surface exploration is a set of routes associated with a common base. Figure 5 shows examples of mission strategies which use routing tactics pre-

sented in Fig. 3. Figure 6 shows how resource consumption constraints for a mission are calculated. The standard rover strategy presented in Fig. 4 is considered. Resource (time) consumption for all routes included in each mission is aggregated and compared with a limit value as a feasibility check. For the mission in Fig. 6(a), the sum of time consumed over all routes is less than the consumption limit and the mission is therefore feasible. It is assumed that the

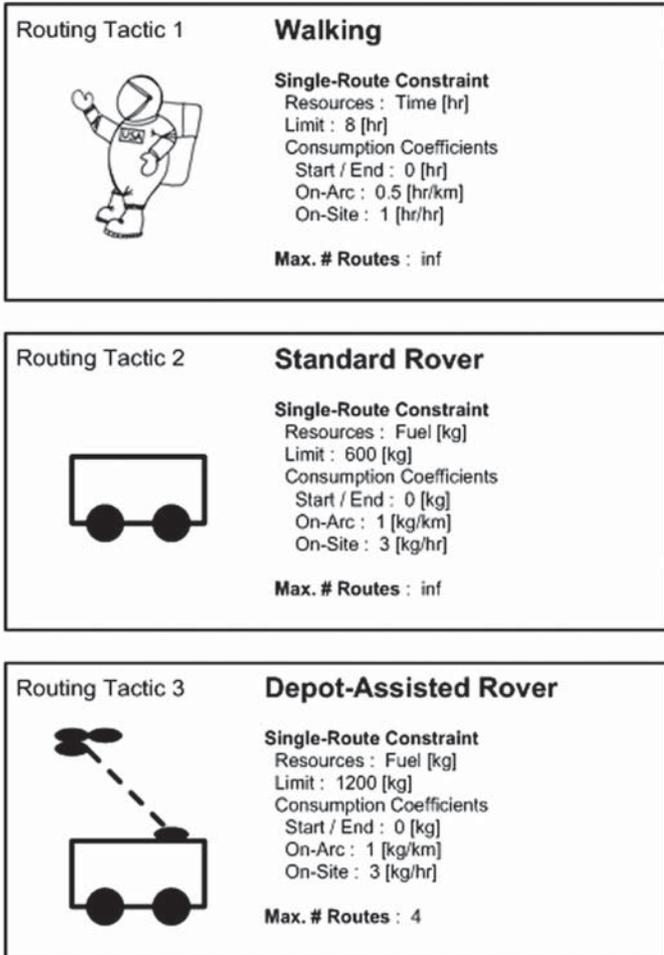


Fig. 3 Examples of routing tactics.

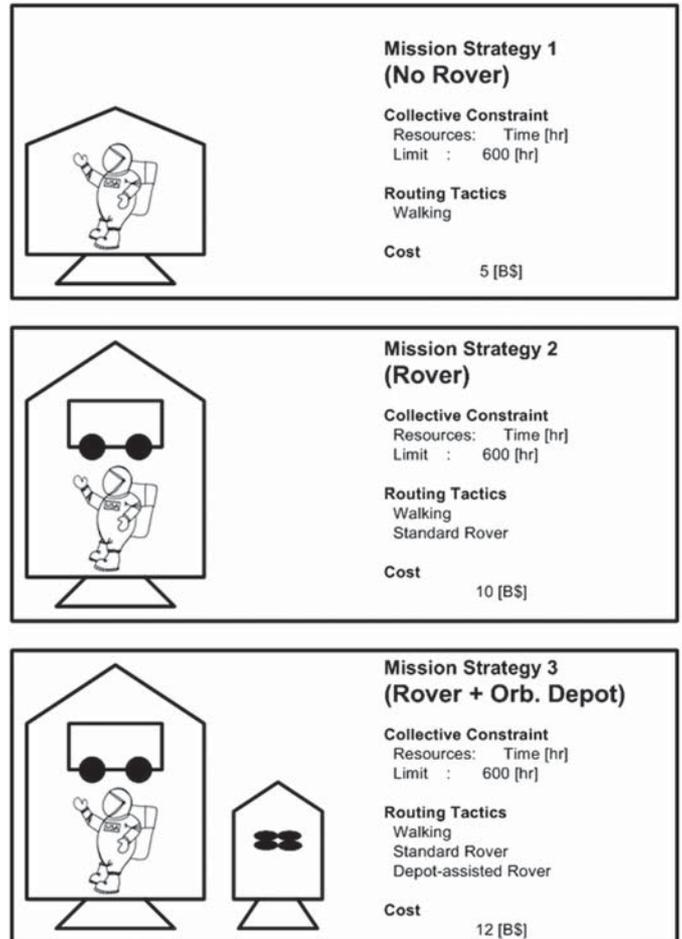
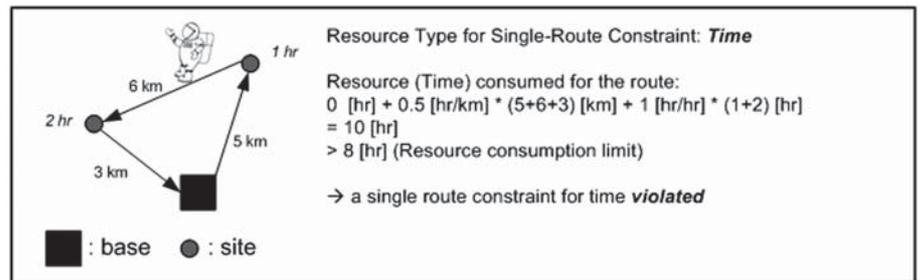
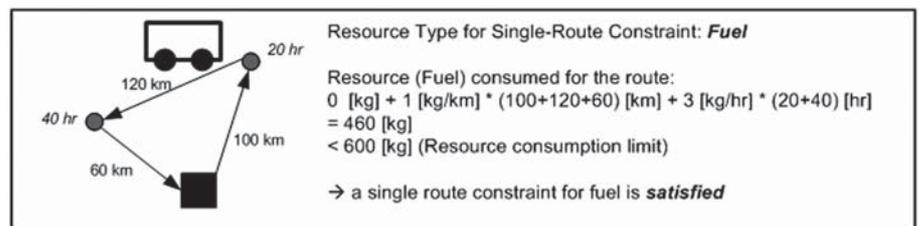


Fig. 5 Examples of mission strategies.



(a) single-route constraint for **Walking** tactic (Infeasible Route)



(b) single-route constraint for **Rover** tactic (Feasible Route)

Fig. 4 Feasibility check for a route.

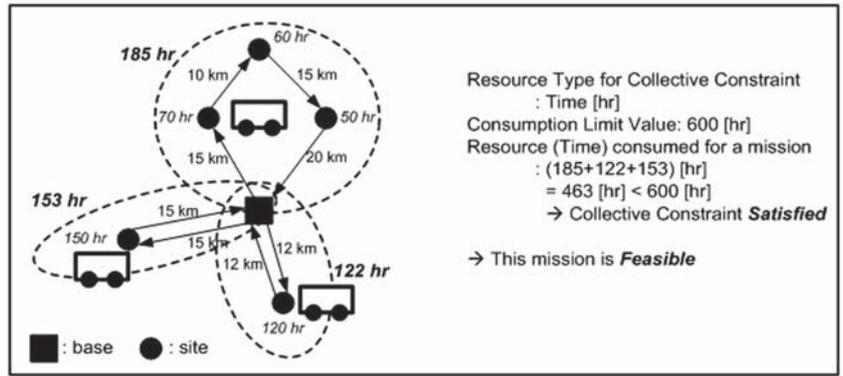
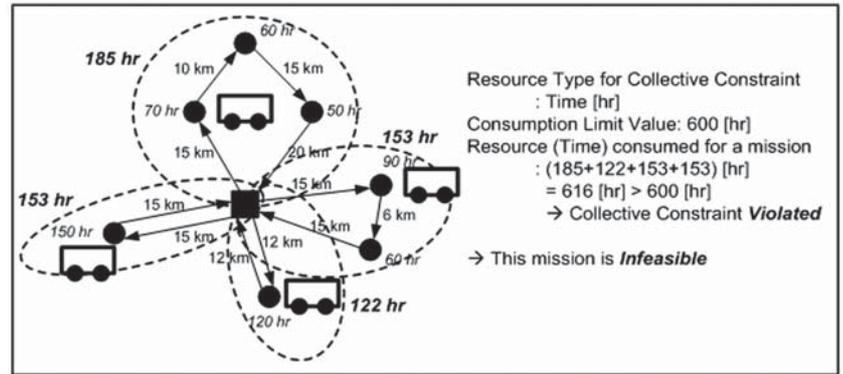


Fig. 6 Feasibility of a mission.



(b) Infeasible Mission: Violates Collective Constraint

routes are executed sequentially. The total time for the mission in Fig. 6(b) is, however, larger than the consumption limit and the mission is infeasible.

2.1.4 Campaign and Budget Constraint

A *campaign* is composed of missions sharing an objective and budget. A subset of potential bases is selected for missions included in the campaign. A *budget constraint* is imposed on a campaign such that the total cost for missions comprising the campaign cannot exceed the budget. Figure 7 illustrates an example of a planetary surface exploration campaign. Three out of five potential landing locations are used as bases. Mission strategies presented in Fig. 5 are used for missions comprising the campaign.

2.2 Optimization of a Global Planetary Surface Exploration Campaign

Consider a surface exploration campaign for a planet. Geographical information on candidate landing locations and exploration sites is given and distance between any two positions can be generated out of this information. A profit value assigned for each exploration site and the amount of time required to obtain the profit at the site is also determined as an input to the problem.

The amount of budget and the mission strategies that can be used for the campaign are pre-determined. Each mission strategy characterizes a mission by specifying a mission cost, collective constraints, and available routing tactics. A routing tactic characterizes a route by specifying single-route constraints and the maximum number of routes.

The overall objective is to maximize the sum of profits ob-

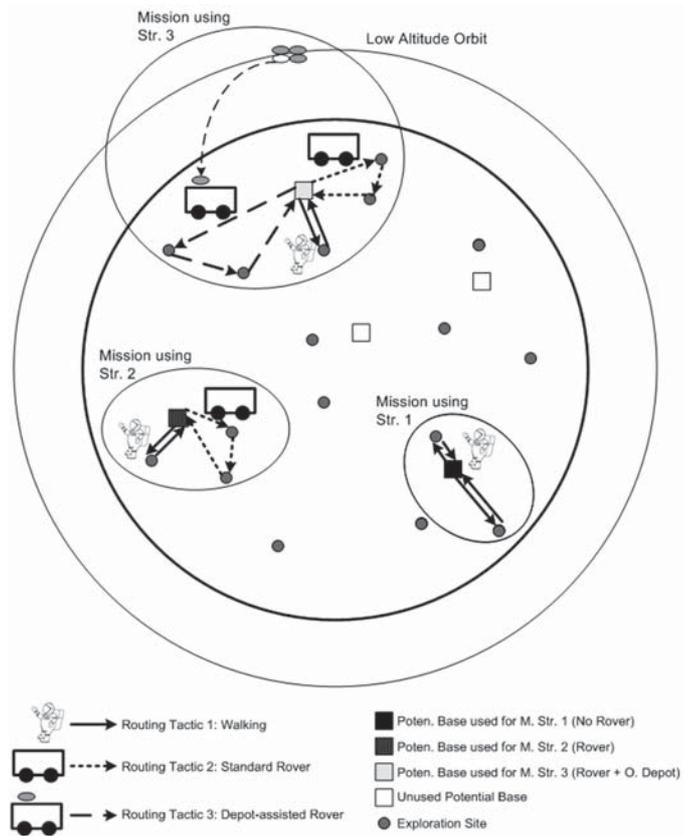


Fig. 7 Example of a planetary surface exploration campaign.

tained from all visited exploration sites. Decisions for this problem are: (1) landing locations (bases) used for exploration missions, (2) mission strategies chosen by the missions, (3) routes corresponding to each base, and (4) routing tactics for selected routes.

The following constraints are imposed: (1) Every route should satisfy single-route constraints (single route feasibility); (2) Routes which belong to a mission should satisfy collective constraints and maximum route constraints specified by the strategy selected by the mission and routing tactics chosen by the routes, respectively (mission feasibility); and (3) The total cost of missions comprising a campaign should not exceed the campaign budget (campaign feasibility). Table 1 summarizes the objectives, decisions, constraints, and parameters of the global planetary surface exploration campaign optimization problem.

An abstraction of the problem is required for mathematical formulation. Consider a complete graph  $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ .  $\mathcal{N} = (\mathbf{B} \cup \mathbf{E})$  is an index set for nodes and  $\mathcal{A} = \{(i, j) \mid i, j, \in \mathcal{N}\}$  is an index pair set for arcs.  $\mathbf{B} = \{1, \dots, n_B\}$  is an index set for potential bases ( $n_B$ : number of potential bases) and  $\mathbf{E} = \{n_B + 1, \dots, n_B + n_E\}$  is an index set for exploration sites ( $n_E$ : number of the exploration sites). For each potential site  $i \in \mathbf{E}$ , two real values  $v_i$  and  $t_i$  are assigned.  $v_i$  represents the profit that can be obtained by visiting site  $i$ , and  $t_i$  is the time required to collect the profit. Cost (distance) associated with each arc is expressed as a matrix

$$\mathbf{C} = [c_{i_1 i_2}]$$

where  $c_{i_1 i_2}$  represents the length of an arc from  $i_1$  to  $i_2$  ( $i_1, i_2 \in \mathcal{N}$ ).

A *route* related to a potential base  $b \in \mathbf{B}$  is a sequence of nodes representing the transportation between nodes. Potential base  $b$  starts the route, is followed by sites belonging to  $\mathbf{E}$ , and ends the route. A *mission* associated with base  $b$  is a set of routes related to  $b$ . A *campaign* is a set of all missions which are defined over graph  $\mathcal{G}$  and are collectively pursuing an objective - profit sum maximization.

Resource consumption occurs in order to carry out a campaign; hence the resource consumption is required to carry out a mission and all associated routes. The resource consumption is expressed using three consumption classes: per-route, on-arc, and on-site consumption classes. A per-route class is a routing tactic specific constant representing the resource consumed when the route starts and/or ends. An on-arc class represents the resource consumed during transportation between nodes, and is proportional to the total distance of the route. An

on-site class represents the resource consumed during activities to obtain profits, and is proportional to the sum of time spent on sites included in the route.

Given a base and a set of sites, only a minimum distance path that can be obtained from solving the Traveling Salesman Problem (TSP) is considered as a viable route for the problem; inefficient routes are not considered [5]. Thus the total number of routes related to a base, regardless of the feasibility of routes, equals the total number of subsets of the site set  $\mathbf{E}$  ( $2^{n_E}$ ). An index set of subsets of  $\mathbf{E}$  is defined as  $\mathbf{J} = \{0, \dots, 2^{n_E} - 1\}$ .

Routing tactic  $k \in \mathbf{T}^s$ , where  $\mathbf{T}^s$  is a set of routing tactics available for mission strategy  $s$ , characterizes a route by specifying single-route constraints and a maximum number of routes. Single-route constraints are expressed using constraining resource types, resource consumption coefficient vectors ( $\mathbf{c}_0^{s,k}, \mathbf{c}_d^{s,k}, \mathbf{c}_\tau^{s,k}$ ) and a resource consumption limit vector for the constraining resources ( $\mathbf{I}_r^{s,k}$ ). The maximum number of routes  $n^{s,k}$  limits the number of routes using the tactic  $k \in \mathbf{T}^s$  included in a mission.

$\mathbf{J}_f^{b,s,k} \subset \mathbf{J}$  is an index set of feasible routes related to the base  $b$  with respect to a routing tactic  $k$  of a mission strategy  $s$  and is defined as follows:

$$\mathbf{J}_f^{b,s,k} = \{j \in \mathbf{J} \mid \mathbf{c}_0^{s,k} + \text{TSP}_j^b \cdot \mathbf{c}_d^{s,k} + (\sum_{i \in \mathbf{R}_j} t_i) \cdot \mathbf{c}_\tau^{s,k} \leq \mathbf{I}_r^{s,k}\}$$

where  $\mathbf{R}_j$  is the exploration site subset with an index  $j$  and  $\text{TSP}_j^b$  is travel distance of the TSP solution for the nodes  $(\{b\} \cup \mathbf{R}_j)$ .

Mission strategy  $s \in \mathbf{S}$ , where  $\mathbf{S}$  is a set of available strategies for the campaign, characterizes a mission by specifying a set of available routing tactics ( $\mathbf{T}^s$ ), collective constraints, and a mission cost ( $C^s$ ). Collective constraints are expressed using constraining resource types, resource consumption coefficient vectors ( $\mathbf{d}_0^s, \mathbf{d}_d^s, \mathbf{d}_\tau^s$ ), and a resource consumption limit vector for the constraining resources ( $\mathbf{I}_c^s$ ).

All missions in a single campaign are funded under the same budget source. There is a budget constraint on the cost sum for all missions in a campaign; the cost sum cannot exceed a pre-determined budget  $M$ .

**TABLE 1:** Parameters, Decisions, Constraints, and Objective for the Problem.

Objective	Maximization of the profit sum obtained from explored sites
<b>Decisions</b>	<ol style="list-style-type: none"> <li>1. Selection of landing locations (bases)</li> <li>2. A mission strategy for each base used in 1</li> <li>3. Routes for each of the bases used in 1</li> <li>4. Routing tactics for the routes in 3</li> </ol>
<b>Constraints</b>	<ol style="list-style-type: none"> <li>1. Feasibility of routes (single route constraints)</li> <li>2. Feasibility of missions (collective constraints)</li> <li>3. Feasibility of campaign (budget constraint)</li> <li>4. Each site cannot be explored more than once</li> </ol>
<b>Parameters</b>	<ol style="list-style-type: none"> <li>1. Geographical information on destination body</li> <li>2. Potential landing locations</li> <li>3. Potential exploration sites and associated profit</li> <li>4. Set of possible mission strategies</li> <li>5. Set of possible routing tactics for each mission strategy</li> <li>6. Budget</li> </ol>

Selection of routes and landing locations out of a candidate set are decisions included in the problem hence it can be classified as a Location Routing Problem (LRP) [6, 7]. There are two unique features of the problem compared with the conventional LRP. The first is consideration of *profit* [8] and the second is generalization of base selection from whether to use or not to use each base (*binary choice*) to how to use each base (*multiple choice*). This is a new routing problem class referred to as the *Generalized Location Routing Problem with Profits* (GLRPP). Figure 8 shows the hierarchical structure of decisions and parameters for the GLRPP.

The objective of the campaign is to maximize the sum of profits that can be obtained during the campaign while not exceeding the campaign budget. Decision variables for this problem are selection of bases that are used, mission strategies for the used bases, selection of routes to visit sites from each of the selected bases, and routing tactics for the selected routes. The solution of the problem should satisfy single-route constraints, maximum route number constraints, collective constraints, and the campaign budget constraint. A constraint that a single site cannot be visited multiple times should also be satisfied.

### 3. MATHEMATICAL FORMULATION AND SOLUTION PROCEDURES

#### 3.1 Mathematical Formulation of the GLRPP

Mathematical formulation of the GLRPP is developed and solution procedures to solve the problem are presented. An Integer Program (IP) formulation of the GRLPP is provided as follows:

(GLRPP)

$$\max_{x_j^{b,s,k}, y^{b,s}} \sum_{b \in \mathbf{B}} \sum_{s \in \mathbf{S}} \sum_{k \in \mathbf{T}^s} \sum_{j \in \mathbf{J}_j^{b,s,k}} (r_j \cdot x_j^{b,s,k}) \quad (1)$$

subject to

$$\sum_{b \in \mathbf{B}} \sum_{s \in \mathbf{S}} \sum_{k \in \mathbf{T}^s} \sum_{j \in \mathbf{J}_j^{b,s,k}} (\mathbf{A}_j \cdot x_j^{b,s,k}) \leq \mathbf{1}_{n_E} \quad (2)$$

$$\sum_{k \in \mathbf{T}^s} \sum_{j \in \mathbf{J}_j^{b,s,k}} (h_j^{b,s} \cdot x_j^{b,s,k}) \leq \mathbf{1}_c^s \cdot y^{b,s} \quad (3)$$

$$\sum_{j \in \mathbf{J}_j^{b,s,k}} x_j^{b,s,k} \leq n^{s,k} \cdot y^{b,s} \quad (\forall b \in \mathbf{B}, \forall s \in \mathbf{S}) \quad (4)$$

$$\sum_{s \in \mathbf{S}} y^{b,s} \leq 1 \quad (\forall b \in \mathbf{B}) \quad (5)$$

$$\sum_{b \in \mathbf{B}} \sum_{s \in \mathbf{S}} C^s y^{b,s} \leq M \quad (6)$$

$$x_j^{b,s,k} \in \{0,1\} \quad (\forall b \in \mathbf{B}, \forall s \in \mathbf{S}, \forall k \in \mathbf{T}^s) \quad (7)$$

$$y^{b,s} \in \{0,1\} \quad (\forall b \in \mathbf{B}, \forall s \in \mathbf{S}) \quad (8)$$

$x_j^{b,s,k}$  and  $y^{b,s}$  are binary decision variables for this problem.  $x_j^{b,s,k}$  takes value 1 if a route determined by base  $b$  and site subset  $\mathbf{R}_j$  using routing tactic  $k$  and mission strategy  $s$  is included in the solution and takes value 0 otherwise.  $y^{b,s}$  takes value 1 if mission strategy  $s$  is selected by base  $b$  and takes value 0 otherwise.  $r_j$  is the sum of profits for all sites belonging to site subset  $\mathbf{R}_j$  and equals

$$\sum_{i \in \mathbf{R}_j} v_i$$

Constraint (2) requires that each site be visited no more than once. Collective constraint (3) imposes that the resource sum for routes in a mission be bounded. Vector  $\mathbf{h}_j^{b,s}$  represents consumption of constraining resource types for collective constraints specified by mission strategy  $s$  on the routes determined by base  $b$  and site subset  $\mathbf{R}_j$  and is defined as follows:

$$\mathbf{h}_j^{b,s} = \mathbf{d}_0^s + \text{TSP}_j^b \cdot \mathbf{d}_d^s + \left( \sum_{i \in \mathbf{R}_j} t_i \right) \cdot \mathbf{d}_r^s \quad (9)$$

Constraint (4) requires that the total number of routes using a routing tactic (routing tactic  $k$  of mission strategy  $s$ ) in a

Fig. 8 Decision hierarchy for the problem.

## ● Campaign

### ● Mission Strategy: $s \in \mathbf{S}$

#### ● Collective Constraints

- Resource Consumption Coefficients:  $\mathbf{d}_0^s, \mathbf{d}_d^s, \mathbf{d}_r^s$
- Resource Consumption Limits:  $\mathbf{1}_c^s$

#### ● Routing Tactics: $k \in \mathbf{T}^s$

##### - Single Route Constraints

- Resource Consumption Coefficients:  $\mathbf{c}_0^{s,k}, \mathbf{c}_d^{s,k}, \mathbf{c}_r^{s,k}$
- Resource Consumption Limits:  $\mathbf{1}_r^{s,k}$

- Maximum Number of Routes:  $n^{s,k}$

#### ● Mission Cost Associated with the Strategy: $C^s$

### ● Campaign Budget: $M$

mission be at most a certain value ( $n^{s,k}$ ). Constraint (5) imposes that no more than one strategy be selected by a base. Constraint (6) imposes that the sum of costs for all missions in a campaign not exceed budget  $M$ .

### 3.2 Solution Methods

The GLRPP formulated as Equations (1-8) is an integer program (IP) with a large number of columns. The *three-phase method* developed by Ahn [9] has been used to solve the GLRPP. The whole procedure of this method is composed of three phases, which are referred to as the *Divide Phase*, the *Conquer Phase*, and the *Synthesize Phase*, respectively.

In the *Divide Phase*, the whole node set is divided into multiple groups, each of which is referred to as a Cluster. For each cluster all base/mission strategy combinations are considered, and each combination is referred to as a Cluster Strategy. In the *Conquer Phase*, the Multi-Depot Vehicle Routing Problem with Profits (MDVRPP), which is a special case of the GLRPP in which decisions  $y^{b,s}$  are given, is solved for every cluster strategy. Finally the *Synthesize Phase* collects the MDVRPP results (near-optimal solution, near-optimal profit sum, and upper-bound profit sum) for all cluster strategies and solves an IP that selects one cluster strategy for each cluster, maximizing the total profit sum for the campaign subject to the budget constraint.

## 4. CASE STUDY: GLOBAL MARS SURFACE EXPLORATION CAMPAIGN OPTIMIZATION

As a case study, a *Global Mars Surface Exploration Campaign Optimization* is formulated and solved as a GLRPP and solved. Recent results for the Mars surface exploration vehicle study are used to make the case up to date and realistic. An orbiting depot technology and an In-Situ Resource Utilization (ISRU) [10] technology are introduced as mission strategies. A methodology to evaluate a technology by comparing the solutions of the GLRPP with and without the technology is demonstrated.

### 4.1 Problem Characteristics

#### 4.1.1 Potential Bases and Sites

Potential landing locations and exploration sites on Mars surface are pre-determined and given to the problem (**B**: potential bases, **E**: sites). Profit value that can be obtained by exploring each site and the amount of time required to obtain the profit are also assigned to each site as real scalars ( $v_i$ : profit,  $t_i$ : time). For historical Mars surface exploration missions with very limited mobility, practically a landing location is not different from an exploration site. Any selected landing location should be safe for descent and ascent and be scientifically interesting [1]. The surface exploration system that is used for this case study has a range of 500 [km] [11, 12]. This advanced capability enables agents to carry out exploration far from the landing location, which makes it possible to select landing locations and exploration sites separately.

#### 4.1.2 Mission Strategies and Routing Tactics

Two mission strategies are considered for this case ( $\mathbf{S} = \{1,2\}$ ). One is the standard strategy ( $s = 1$ ), and the other is the orbiting depot strategy ( $s = 2$ ). There is one collective resource constraint for total exploration time for the standard strategy. Table 2 exhibits the procedure to calculate the time consumption limit for the standard strategy ( $I_c^1$ ).

**TABLE 2:** Resource (Time) Consumption Limit for the Campaign.

Stay Time ( $T_{stay}$ ) [9]	600	[day]
Set-Up Time ( $T_{setup}$ )	150	[day]
Wrap-Up Time ( $T_{wrapup}$ )	100	[day]
Work Time ( $T_{work}$ )	350	[day]
Exploration Fraction ( $f_{exp}$ )	0.25	[-]
Exploration Time ( $T_{exp}$ )	87.5	[day]
Exploration Time Limit ( $I_c^1$ )	2100	[hr]

The resource consumption coefficients are calculated based on a planetary exploration reference scenario presented in Table 3 and operational characteristics of the surface exploration vehicle proposed by Hong [12]. Table 4 summarizes the characteristics of the collective constraint associated with the standard exploration strategy and Table 5 summarizes the single-route constraint characteristics.

Based on the assumption that it costs more to deliver a larger amount of mass to the planetary surface, the “Mass Delivered on Planetary Surface [MT]” is used as a proxy metric for the cost associated with a strategy. Zubrin’s *Mars Direct* mission plan is modified and used for cost calculation [10]. The *Mars Direct* mission plan is composed of two flights. Table 6 summarizes the mass allocation of each flight for this case study and the total mass delivered to Mars’ surface, which is  $C^1$ .

Now the orbiting depot strategy ( $s = 2$ ) is introduced. An orbiting depot is a cluster of supply units circling in low Mars orbit. Each supply unit in the depot is capable of landing at a predetermined location on Mars’ surface. Exploring agents can reach the landed supply unit and increase the exploration range using the additional fuel and consumables included in the supply unit.

The orbiting depot strategy has two routing tactics. The first routing tactic is the standard routing used for the standard strategy. The second routing tactic is the depot-assisted tactic. Both tactics have one single-route constraint imposed on the total amount of fuel consumption for each route. It is assumed that the surface exploration vehicle used for the standard strategy is also used for the orbiting depot strategy. Thus resource consumption coefficients for the two tactics of the orbiting depot strategy are identical to those for the standard strategy.

Now details of the Mars orbiting depot are presented to identify the cost associated with the orbiting depot strategy and the characteristics of the depot-assisted routing tactic.

#### 4.1.3 Orbiting Depot Strategy

An orbiting depot is a cluster of supply units deployed to a Martian orbit. Each pre-packaged supply unit contains supply items (propellant and food) that can extend the Mars surface exploration range. A conceptual diagram of the orbiting depot is presented in Fig. 9. Without the support of the orbiting depot, only the standard routing tactic is available. Suppose that there is an orbiting depot in Martian orbit and it is possible to command the depot to drop a supply unit filled with fuel and consumables. If the supply unit lands in such a location that the surface exploration vehicle can get the unit before it runs out of fuel or consumables, the vehicle can

**TABLE 3:** Reference Scenario for a 7-day Excursion.

<b>Day 1</b>	Inactivity, 8 [hr]	Driving, 8 [hr]	Inactivity, 8 [hr]
<b>Day 2</b>	Inactivity, 8 [hr]	Driving, 8 [hr]	Inactivity, 8 [hr]
<b>Day 3</b>	Inactivity, 8 [hr]	Exploration, 6 [hr]	Science, 2 [hr]
<b>Day 4</b>	Inactivity, 8 [hr]	Exploration, 6 [hr]	Science, 2 [hr]
<b>Day 5</b>	Inactivity, 8 [hr]	Exploration, 6 [hr]	Science, 2 [hr]
<b>Day 6</b>	Inactivity, 8 [hr]	Driving, 8 [hr]	Inactivity, 8 [hr]
<b>Day 7</b>	Inactivity, 8 [hr]	Driving, 8 [hr]	Inactivity, 8 [hr]

**TABLE 4:** Collective Constraint Characteristics (Standard Exploration Strategy).

Resource Type	Exploration Time	[hr]
<b>Coefficients</b>	$d_0^1$	0.0 [hr]
	$d_d^1$	$3/V_V = 2$ [hr/km]
	$d_\tau^1$	3.0 [hr/hr]
<b>Constraint</b>	$l_c$	2100 [hr]

**TABLE 5:** Single-Route Constraint Characteristics (Standard Tactic).

Constraining Resource	Fuel	[kg]
<b>Coefficients</b>	$c_0^{1,1}$	= 0.0 [kg]
	$c_d^{1,1}$	$\dot{m}_D / V_V + 2\dot{m}_I / V_V = 1.1$ [kg/km]
	$c_\tau^{1,1}$	$(\dot{m}_S + 3\dot{m}_E) / 4 + 2\dot{m}_I = 5.7$ [kg/hr]
<b>Limit</b>	$l_r^{1,1}$	= 677 [kg]

**Note:** 1. Power source for this case study is a NaBH<sub>4</sub>/H<sub>2</sub>O<sub>2</sub> fuel cell [13, 14], whose effective energy density equals 685 [Wh/kg]. 2. It is assumed that 85 [%] of the power requirement is provided by the fuel cell and the remaining 15 [%] is provided by the solar panel.

**TABLE 6:** Mass Delivered on Mars Surface (Standard Strategy).

	Flight 1	Flight 2	Total
<b>Contents</b>	ERV ISRU Facility	Habitat Crew Surface Exploration Vehicle	
<b>Mass Delivered</b>	28 [MT]	26 [MT]	54 [MT]

then travel from the supply unit’s landing location for almost the same distance as it has already gone through. In effect, the additional supply from the orbiting depot almost doubles the capability of the surface exploration vehicle.

The amount of fuel and consumables contained in an individual supply unit equals the capacity of the surface exploration vehicle. The mass of an individual supply unit is calculated to be 2.5 [MT] [9] and four individual supply units support one mission using the orbiting depot strategy ( $n^{2,2} = 4$ ). The cost of the orbiting depot

strategy is expressed as  $C^2 = (C^1 + 4 \cdot 2.5) = 64$  [MT]. Strategies and tactics used in the Mars exploration case study are summarized in Table 7.

#### 4.2 Numerical Example

Ten GLRPP instances for the Mars surface exploration are created. For each instance 100 potential bases and 1000 sites are randomly generated on the surface of Mars. (154 actual Mars candidate exploration sites shown in Fig. 1 [3] are in-

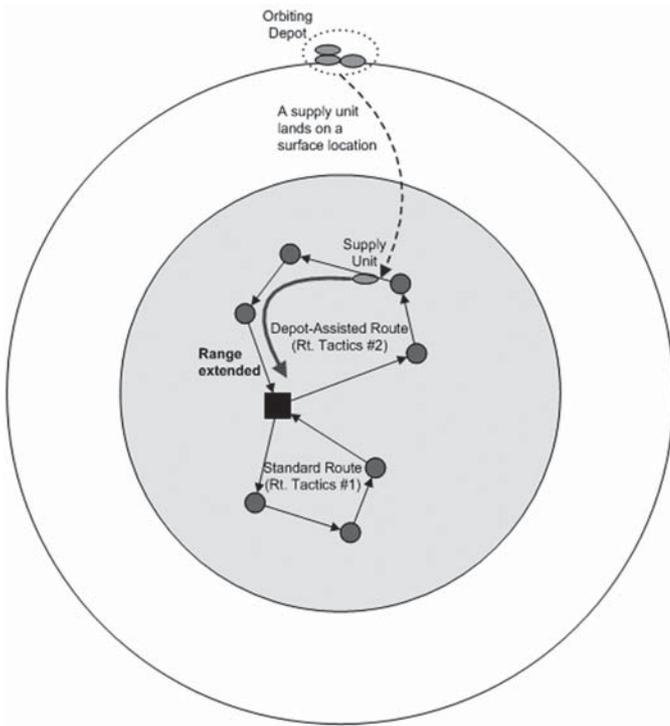


Fig. 9 Concept diagram for the orbiting depot and its functionality.

cluded in these sites.) The total campaign budget is set as 700 [MT] delivered to the surface. Table 8 summarizes the parameters used in the instance generation. The three-phase solution method is used to obtain the solutions.

Figure 10 shows the result of the “Divide” phase for one of the created instances. Four big clusters out of the total 38 clusters can be seen in the figure.

Table 9 summarizes the results of the numerical experiments (average of 10 instances). Each campaign in the ten problem instances is composed of eleven missions - ten out of them use the orbiting depot strategy and only one mission uses the standard strategy. Figure 11 shows the solution for the instance presented in Fig. 10.

### 4.3 Value of a Technology

A finite difference technique to calculate the value of a technology is proposed. In the Mars exploration case, it has been implicitly assumed that the orbiting depot technology – to manufacture the supply units and orbiting depot assembly, to send them to the Martian orbit, and to operate the depot for supporting the Mars surface exploration mission – is available. Suppose that the orbiting depot technology does not exist. In this case, only the standard strategy is available for the missions. The amount of profit from the global Mars surface exploration campaign in this case can be obtained by solving the GLRPP using only the standard strategy. Table 10 summarizes the result using only the standard strategy for the instances generated for the case study. The average profit sum for this case is 131.7 [-], which is 155.8 [-] less than the profit sum for the result presented in Table 9 (287.5 [-]). This difference (155.8 [-]) is the marginal profit that can be obtained by having the orbiting depot technology. It can be interpreted as the value of the orbiting depot technology expressed as exploration profits.

Similarly the value of the In-Situ Resource Utilization (ISRU) technology is also calculated. The standard strategy and the

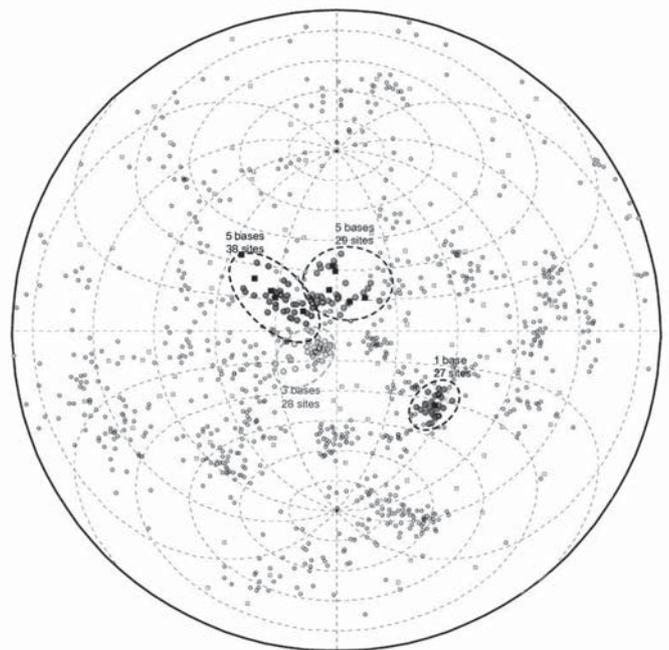


Fig. 10 Clustering result (Instance 4).

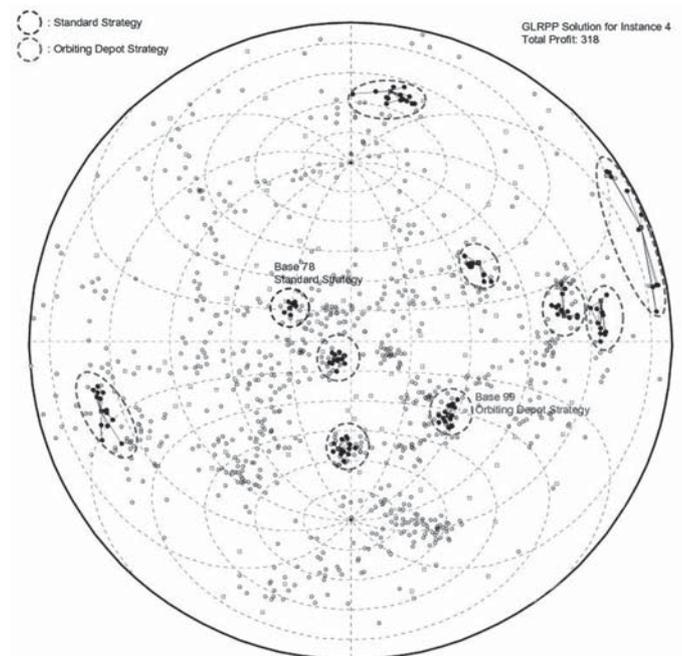


Fig. 11 Solution (Instance 4).

orbit-depot strategy assume that the propellant used for the Earth Return Vehicle (ERV) and the surface exploration vehicle is produced on Mars surface using the ISRU technology. Without the ISRU technology, more propellant should be brought from the Earth.

The amount of propellant used for ERV in the case study is 82 [MT] [10, 12]. The fuel capacity 677 [kg] is based on a 7-day exploration scenario. Total time allowed for the surface exploration is 2100 [hr] and the maximum amount of fuel for the surface transportation is  $0.677 \times 2100 / (24 \times 7) = 8$  [MT]. Assuming that the ISRU plant mass is relatively small, the increase in mass that has to be delivered from the Earth is 90 [MT]. This situation can be interpreted as an increase in mission cost. The mission cost of the standard strategy now be-

**TABLE 7:** Strategies and Corresponding Tactics for the Mars Exploration.

	Standard Strategy	Orbiting Depot Strategy
<b>Collective Constraint</b>		
<i>Resource</i>	Exploration Time	Exploration Time
<i>Coefficients</i>	$d_0^1 = 0$ [hr]	$d_0^2 = 0$ [hr]
	$d_d^1 = 0.2$ [hr/km]	$d_d^2 = 0.2$ [hr/km]
	$d_\tau^1 = 3$ [hr/hr]	$d_\tau^2 = 3$ [hr/hr]
<i>Limit</i>	$l_c^1 = 2100$ [hr]	$l_c^2 = 2100$ [hr]
<b>Routing Tactics</b>		
<b>Tactic I</b>	Standard	Standard
<b>Single-Route Constraint</b>		
<i>Resource</i>	Fuel	Fuel
<i>Coefficients</i>	$c_0^{1,1} = 0$ [kg]	$c_0^{2,1} = 0$ [kg]
	$c_d^{1,1} = 1.1$ [kg/km]	$c_d^{2,1} = 1.1$ [kg/km]
	$c_\tau^{1,1} = 5.7$ [kg/hr]	$c_\tau^{2,1} = 5.7$ [kg/hr]
<i>Limit</i>	$l_r^{1,1} = 677$ [kg]	$l_r^{2,1} = 677$ [kg]
<b>Max. Number of Routes</b>	$n^{1,1} = \infty$ [-]	$n^{2,1} = \infty$ [-]
<b>Tactic II</b>		Depot-Assisted
<b>Single-Route Constraint</b>		
<i>Resource</i>		Fuel
<i>Coefficients</i>		$c_0^{2,2} = 0$ [kg]
		$c_d^{2,2} = 1.1$ [kg/km]
		$c_\tau^{2,2} = 5.7$ [kg/hr]
<i>Limit</i>		$l_r^{2,2} = 1286$ [kg]
<b>Max. Number of Routes</b>		$n^{2,2} = 4$ [-]
<b>Cost</b>	$C^1 = 54$ [MT]	$C^2 = 64$ [MT]

**Note:** 10 % margin that agents may need to travel more due to the landing position error of the individual supply unit is considered for calculation of depot-assisted tactic consumption limit.

**TABLE 8:** GLRPP Instance Generation for Mars Surface Exploration Case.

<b>Potential Bases and Sites</b>	
Region of Mars Surface	Global
Number of Potential Bases ( $n_B$ )	100 [-]
Number of Potential Sites ( $n_E$ )	1000 [-]
Aerial Distribution of Locations	Uniform over all region
<b>Budget Constraint</b>	
Budget (M)	700 [MT]
<b>Experiment Size</b>	
Number of Instances (N)	10 [-]

**TABLE 9:** Result Summary for Mars Surface Exploration Case.

	Profits [-]	Number of Missions [-]	Profit per Mission [-/-]	Profit per Cost [-/MT]
<b>Standard Strategy</b>	11.3	1	11.3	0.21
<b>O. Depot Strategy</b>	276.2	10	27.6	0.43
<b>Overall Campaign</b>	287.5	11	26.1	0.41

**TABLE 10:** Result Summary for Mars Surface Exploration – Without Orbiting Depot.

	Profits [-]	Number of Missions [-]	Profit per Mission [-/-]	Profit per Cost [-/MT]
<b>Standard Strategy</b>	131.7	12	11.0	0.20
<b>Overall Campaign</b>	131.7	12	11.0	0.20
<b>With Orbiting Depot</b>	287.5			
<b>Value of O. Depot</b>	155.8			

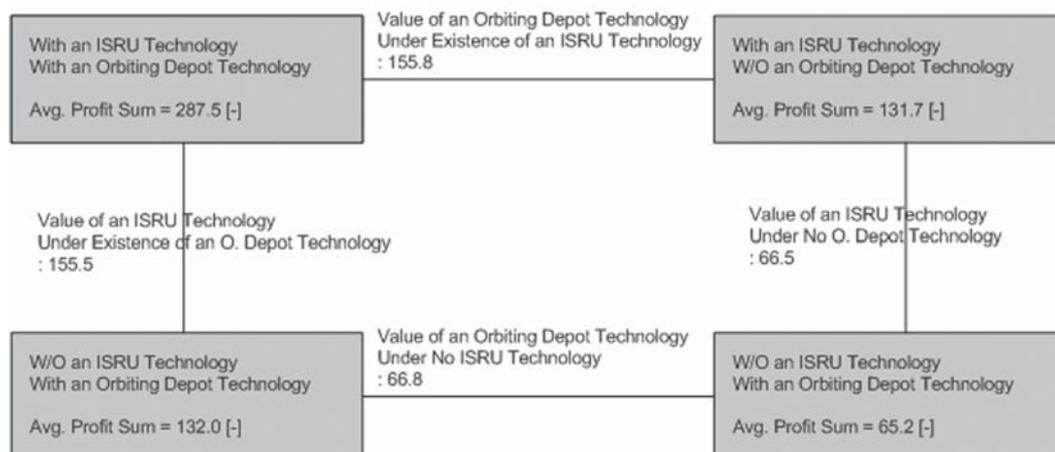
comes  $(54 + 90) = 144$  [MT] and that for the orbiting depot strategy becomes  $(64 + 90) = 154$  [MT]. The average profit sum for the instances without the ISRU technology is 132 [-]. This value is less than the average profit sum with the ISRU technology by 155.5 [-], which is the value of the ISRU technology. The value of the ISRU technology when it is used without the orbiting depot technology can be also calculated in a similar way. Figure 12 summarizes the profit sums for the instances with/without orbiting depot and ISRU and associated values of the two technologies.

### 5. CONCLUSIONS AND FUTURE WORK

This paper formulates global planetary surface exploration as a campaign optimization problem. Given locations of potential landing locations and exploration sites, profit values for visiting exploration sites, time durations required to obtain the profits, surface exploration technologies, and amount of budget that can be dedicated to the exploration campaign, the problem maximizes the sum of profit obtained over the whole campaign by making decisions on selection of bases to use, selection of strategies for the missions using the bases, selection of routes to

visit sites, and selection of routing tactics the routes use, with constraints imposed on each route, each mission, and the overall campaign. It is referred to as the Generalized Location Routing Problem with Profits (GLRPP), a new routing problem class. The GLRPP is formulated as an Integer Program (IP) and results are obtained with the three-phase method. A global Mars surface exploration campaign optimization problem is presented as a case study. A realistic design of a planetary surface exploration vehicle is used and an orbiting depot is considered as a technology option for exploring Mars. Problem instances with 100 potential bases and 1000 exploration sites are generated and successfully solved using the three-phase method. A methodology to calculate the value of a technology is proposed and used for valuation of an orbiting depot technology and an In-Situ Resource Utilization technology used in the case study.

Consideration of multiple stakeholder groups is suggested as future work. Under the current framework, profit value to visit a site is set as a scalar value. When there are more than one stakeholder groups interested in visiting sites, however, valuations of a site from different stakeholder groups will likely



**Fig. 12** Value of technology – orbiting depot and ISRU.

be different. Currently these different values are aggregated and represented as a scalar. In this case even when the overall profit sum obtained by visiting sites is maximized, if the original evaluation of sites by different groups is tracked back, there may be some groups which could not obtain much value in terms of their own interests and are not satisfied about the optimization result. We could extend current framework so that

it can deal with valuations of a site obtained from different stakeholders. One possible approach is the balanced optimization scheme in which the profit sum of the least satisfied group is maximized [9]. In this approach, optimization of the degree of satisfaction of the “least” satisfied group is proposed. This problem can be formulated as a max-mini problem by modifying the GLRPP framework presented in this paper.

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