

On Scalability of Fractionated Satellite Network Architectures

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Abstract— Fractionated Satellite Networks are a popular concept in space systems. On these networks, several satellites cooperate and collaborate by exchanging resources wirelessly in order to obtain an aggregated network capability higher than the sum of the individual capabilities of the different satellites that compose it. Fractionated Satellite Networks are a generalization of Fractionated Satellites.

Scalability is defined as the ability of a system to maintain its performance and function, and retain all its desired properties when its scale is increased greatly without having a corresponding increase in the systems complexity.

The whole concept of fractionation (both at spacecraft level and network level) is based on the use of multiple satellites that jointly perform a function that can be further expanded by adding new satellites to the system. Because of this expandable nature of Fractionated Satellite Networks, the concept of scalability is critical on these architectures, as systems that do not scale well present a very poor performance when adding new agents, increasing costs and harming quality of service and stakeholder satisfaction.

This paper presents a model and a framework for analyzing scalability of fractionated networks. Our model includes descriptions of the system at the resource, satellite, network and mission level. Connections and resource transfer among nodes are modelled using graphs whereas the study is approached from a resource allocation problem perspective.

Finally, the utility and applications of the developed methodology is demonstrated through the analysis of a case study of a potential fractionated network.

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1. INTRODUCTION

Fractionated Satellite Networks are a popular concept in space systems. On these networks, several satellites cooperate and collaborate by exchanging resources wirelessly in order to obtain an aggregated network capability higher than the sum of the individual capabilities of the different satellites that compose it. Fractionated Satellite Networks are a generalization of Fractionated Satellites (FracSats), where the functionalities of a single satellite are distributed within different physically independent wirelessly connected modules creating a virtual satellite with the same capabilities of its monolithic analogue satellite. This last concept was first introduced in 1984 [1], although it didn't capture much interest. In the last years fractionalization drew the attention of researchers and the space industry after DARPA started a program to prove the feasibility and advantages of such architectures compared to traditional monolithic ones [2]-[3]. Even though DARPA's F6 demonstration mission was cancelled in 2013, concepts such as Constellations of Distributed Spacecraft or Federated Satellite Systems (FSS), where satellites share resources in an opportunistic manner [4], are gaining popularity.

Different studies have shown the advantages of fractionalization in terms of flexibility [5], robustness and reduced risk [6], cost-benefit [7, 8] and development time. In addition, these new paradigms enable disruptive applications in the space domain, such as low frequency in-

space distributed synthetic aperture telescopes [9] or new business models where some companies will operate infrastructure fractions to provide basic services to other modules in the same system. In this sense, we envision Space Service Areas where basic infrastructure services such as power or communications down to Earth are guaranteed.

The whole concept of fractionation (both at spacecraft level and network level) is based on the use of multiple satellites that perform jointly a function by sharing resources. System capabilities can be further expanded by adding new satellites to the system. Because of this expandable nature of Fractionated Satellite Networks, scalability is one of the most desirable properties of these architectures, as poor scaling systems performance quickly degrades when new agents are added, increasing costs and harming quality of service and stakeholder satisfaction. [10]

In the systems domain, scalability is defined as the ability of the system to maintain its performance and function, and retain all its desired properties when its scale is increased greatly without having a corresponding increase in the systems complexity [11]. This topic has been extensively analysed on other fields where cooperation and interaction is essential, such as communication networks [12], distributed computing systems [13], smart grids [14], sensor networks [15] or software architecture [16]. Particularities on the fractionated satellite networks domain compared to the aforementioned fields include the coexistence of several shared resources (power, communications and computing power) which are actually tightly coupled and operate in a constrained environment.

This paper presents a general framework for analysing the scalability of fractionated networks, regardless of the specific degree of fractionalization of the nodes of the network (i.e: it is applicable to FSS as well as to FracSats). Section II describes the model used, whereas Section III describes the methodology of the analysis. Section IV validates the model by applying the methodology developed in Section III to a real scenario based on the TDRSS constellation and comparing the results with real data from a 15 day schedule of TDRSS. Section V shows and compares the results of applying this methodology to a potential fractionated network.

2. SYSTEM MODEL

The distinctive characteristic of a fractionated satellite network is the resource exchange among the different modules that compose the system. This cooperative behaviour might enable satellites to perform their mission at a lower cost or to get more valuable data (i.e., using the available computing capabilities of an idle satellite to pre-process the raw data obtained by another satellite will allow the later to perform more measures, as the data-volume to be downloaded to the Earth will be lower than for the non-

processed raw data).

Figure 1 shows a typical fractionated network. Satellite 1 (S1) acts as a resource supplier for the other smaller satellites. Satellite 4 (S4) is a relay satellite between S1 and S5. Finally, Ground Stations 1 and 2 (GS₁, GS₂) have a direct link with a particular satellite in the swarm, whereas GS₃ can communicate with all the satellites in the network, by establishing a link with satellite 1 and using its inter-satellite links (ISL) with the rest of the nodes in the network.

As cooperation and resource exchange is the base of fractionated networks, the developed system model is resource centric, meaning that all the characterization and analysis introduced by the framework refers to the amounts and characteristics of the resources exchanged among nodes. This applies both to the models of the entities at the satellite level and at the network level.

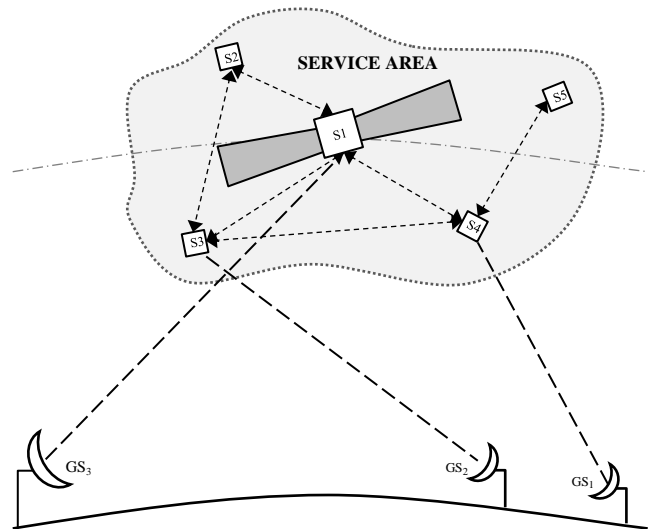


Fig. 1. Scheme of a general fractionated system architecture. Satellite 1 acts as an infrastructure node providing resources to the rest of the network. Satellites 3 and 4 communicate to dedicated ground stations 2 and 1 respectively whereas ground station 3 communicates with all the satellites in the network through the ISL of Satellite 1.

Resources

Three main shared resources have been identified in fractionated networks. First, energy could be distributed among the different fractions by using Wireless Power Transfer (WPT). Second, communications can be shared, so that some specialized satellites could provide downlink capabilities to the rest of the fractions in the system, similarly to how NASA's TDRSS or ESA's EDSS work nowadays. Finally, computing power can be shared between all the modules in the network, creating a distributed power, communications and computing system in space [17].

At this point, it is important to specify the units the resources are expressed in and how the values of these resources are derived from the satellite specifications.

Energy resources have energy units (J or kWh) and its value equals the amount of energy generated daily by the satellite. Communication resources are expressed using information units (bits) and its value equals the product of the available downlink access time and the downlink data-rate. Finally, computing power is dimensionless, and its value is calculated by multiplying the available computing time and the performance of the on-board microprocessor (expressed in MIPS).

As resource transfer implies some losses, we can define the exchange efficiency between a particular pair of satellites i and j as the ratio between the useful amount of resource received and the total amount of resource transferred. When energy is exchanged, losses might be due to free space losses and misalignment of nodes, whereas in communications or computing power exchange losses are mainly due to computation or protocol related overheads. The value of the transfer efficiency of resource R (Energy, Comms. or Computing Power) can be computed as,

$$\eta_{ij}^R = \frac{R_{UTIL}^R}{R_{TOTAL}^R} = \frac{R_{useful}}{R_{useful} + R_{losses}} \quad (1)$$

On the other hand, utilizing a resource might imply having a consumption of others. An obvious example of this situation in the space context occurs when transmitting a certain amount of data between two satellites, as this task requires a certain consumption of power. We model this interdependency among resources using the interdependency coefficient (κ^{R_1, R_2}) defined as,

$$\kappa^{R_1, R_2} = \frac{R_{TOTAL}^{R_1}}{R_{TOTAL}^{R_2}} \quad (2)$$

The efficiency of the aforementioned resources and interdependency coefficients depend on the technology limits and existing protocols. It's important to note that the framework we are describing is agnostic to these particular implementation parameters, and thus provides with a tool to compare how different protocols and technologies impact the scalability of different systems. A brief discussion that particularizes the value of η and κ for the three different resources and some current technologies is presented in Appendix A.

Satellites

Satellites are modelled according to their resource exchange and consumption. In a fractionated architecture, satellites can get resources in two ways: generating them themselves or through an exchange with other nodes in the system. Then, resources can either be consumed by the satellites in the execution of their tasks, stored for later use, transferred back to another node in the network or lost due to lack of storage capacity or the fleeting nature of the resource.

For any period of time and any resource R , the resource

balance equation must be satisfied:

$$R_{infr}^{R, in} + R_{own}^{R, in} = \Delta R_{stored}^{R, out} + R_{own}^{R, out} + R_{infr}^{R, out} + R_{lost}^{R, out} \quad (3)$$

where $R_{infr}^{R, in}$ and $R_{own}^{R, in}$ are the input resources from the infrastructure or produced by the satellite itself respectively, $\Delta R_{stored}^{R, out}$ is the variation of the amount of the resource stored in the satellite for that period of time, and $R_{own}^{R, out}$, $R_{infr}^{R, out}$ and $R_{lost}^{R, out}$ are the output resources spent executing the tasks of the satellite, given back to the infrastructure and lost respectively.

As stored resources will be used at certain point in time to execute a task, (no satellite has as an objective storing resources indefinitely) the expected value of $\Delta R_{stored}^{R, out}$ is 0, and equation (3) can be reformulated as:

$$R_{infr}^{R, in} + R_{own}^{R, in} = R_{own}^{R, out} + R_{infr}^{R, out} + R_{lost}^{R, out} \quad (4)$$

Based on the terms of equation (4), satellites can be classified according to the function that they perform in the network. In order to show how fractionated are our satellites, parameters α and β are defined for each of the resources R .

$$\alpha^R = \frac{R_{infr}^{R, in}}{R_{infr}^{R, in} + R_{own}^{R, in}} \quad \beta^R = \frac{R_{infr}^{R, out}}{R_{own}^{R, out} + R_{infr}^{R, out}} \quad (5)$$

Parameter α^R shows the percentage of the input resources of a satellite that come from the infrastructure and parameter β^R shows the percentage of the output resources that are given back to the network and not used for own purposes. Satellites with a high parameter β^R contribute to the network and thus we refer to them as infrastructure nodes (higher β^R means it is less self-dedicated). Satellites with a high value for parameter α^R need a lot of resources from the infrastructure and are considered clients of the network (higher α^R means it is less self-sufficient).

Based on the values of α^R and β^R a taxonomy to classify satellites involved in a fractionated network has been created, according to the satellite's function within the system. Table 1 shows this classification.

Note that one satellite could act as an infrastructure node for one resource and as a client node for another resource.

To conclude, we can model a satellite based on four main parameters; its input and output resources (R^{in} and R^{out}), and α^R and β^R parameters which show what type of node the satellite is. From now on, we will refer to a satellite S as,

$$S(R^{in}, R^{out}, \alpha, \beta) \quad (6)$$

TABLE I
TYPES OF NETWORK NODES

Type of Node	α^R	β^R	Source of R^{in}	Destination of R^{out}
<i>Infrastructure Node</i>	0 - 0,1	0,9 - 1	Own Production	Infrastructure
<i>Client Node</i>	0,3 - 1	0-0,1	Infrastructure	Own Consumption
<i>Relay Node</i>	1	1	Infrastructure	Infrastructure
<i>Buffer Node</i>	0 - 1	0	Infrastructure or Own Production	Storage
<i>Dedicated Node</i>	0,1 - 0,9	0,1 - 0,9	Infrastructure or Own Production	Own Consumption, Storage or Infrastructure
<i>Autonomous Node</i>	0 - 0,3	0 - 0,1	Own Production	Own Consumption or Storage

Network

The network model describes all the possible interconnections among satellites that enable resource exchange and its efficiencies. In this sense, the network comprehends the information related to the network topology (i.e: fully connected, partial mesh, star, ring) and to the limits of the resource transfer technologies used in the satellites.

In order to model the network, four parameters are needed. The connection matrix C_M^R is an adjacent matrix that shows all the possible links between any pair of satellites in the system ($c_{ij}^R = 1$ indicates that a link for resource R from satellite i to satellite j exists), whereas matrix η_M^R shows the efficiency of those links.

For each kind of shared resources a directed weighted graph is built, where each node represents a satellite in the network, the edges are the links as defined in C_M^R and the weights of each edge are the efficiencies of the resource exchange defined in η_M^R . As the swarm is in permanent motion, both the existing edges and the weights (efficiencies) of the graph are variable. In fact, the topology will change any time a new fraction is added to the swarm or a pair of satellites changes their relative position, as efficiencies are also a function of orientation and distance among satellites. Because of that, C_M^R and η_M^R are both time-dependent matrices. However given a set of satellites, their orbital parameters and their instruments characteristics, is easy to determine the graph that models their interconnections at any time.

For some types of fractionated architectures where satellites fly in closed formation (such as clusters or trains of satellites), this time dependency can be omitted and the values of C_M^R and η_M^R can be considered constant. This assumption, when valid, largely simplifies the analysis and

reduces the computation time needed to run it. For clarity purposes and without loss of generalization, all the examples and analysis conducted in this paper assume that the resource exchange graph is static in time.

Fig. 2 shows the network model for a generic 8-satellite architecture (where the weights of the edges have been explicitly omitted in order to make the diagram clean).

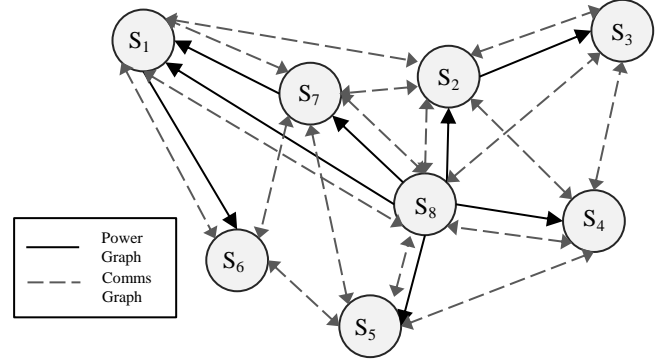


Fig. 2. Graph with the power and communication connections available in the network.

Analogously to parameters α and β when modelling a satellite, we can define parameters α_A and β_A to model the type of network we have.

$$\alpha_A = \frac{\sum_{i|n(T^i)>0} \alpha_i R_i^{in}}{\sum_{i|n(T^i)>0} R_i^{in}} \quad \beta_A = \frac{\sum_i \beta_i R_i^{out}}{\sum_i R_i^{out}} \quad (7)$$

where R_i^{in} and R_i^{out} are the input and output resources of satellite i respectively, and $n(T^i)$ is the number of tasks executed in satellite i . Note that when calculating α_A only resources from satellites that actually perform a task are considered, as otherwise pure infrastructure satellites distorts the real value of α_A , by lowering it.

High values of α_A show that most of the resources used to execute tasks come from the infrastructure (most of the nodes are clients and there is a high exchange of resources). High values of β_A show that most of the resources produced are given back to the infrastructure. If $\beta_A \ll 1$ most of the resources are used by client nodes. At some extent, we could say that α_A determines the degree of self-sufficiency and autonomy of the system, whereas parameter β_A indicates the degree of cooperation (to satisfy the purpose of its mission) among the elements of the architecture.

Based on the values of α_A and β_A different types of architectures can be described. Table II shows an architecture classification.

TABLE II
TYPES OF ARCHITECTURES

Type of Architecture	α_A	β_A	Observations
<i>Constellation</i>	0 - 0,1	0 - 0,1	Satellites are autonomous, resource exchange is almost not present
<i>Fractionated Network</i>	0,4 - 1	0,2 - 1	Resource sharing is essential for the network to execute its tasks
<i>Space Service Areas</i>	0,1 - 0,4	0,1 - 0,7	Some satellites receive some resources from the infrastructure. However, most of the resources come from own sources
<i>Oversized Network</i>	0,4 - 1	0 - 0,2	Resources needed to perform tasks come from the infrastructure, but resources delivered to the infrastructure are very little compared to the amount produced.
<i>Inefficient Network</i>	0,1 - 0,4	0,7 - 1	Most of the resources are given to the network but they are not used as input resources (losses in the resource exchange are too high)

Parameters C_M^R , α_A^R and β_A are architectural parameters whereas η_M is dependent both on the configuration and the technology used to implement the links. Thus, the model of the network is given by:

$$N(C_M^R, \eta_M^R, \alpha_A, \beta_A) \quad (8)$$

Tasks and missions

The objective of using a satellite network is to perform a series of tasks that will fulfil the mission requirements they were designed for. In that sense, a mission is the task or the set of tasks that are executed in one or more nodes of the network in order to satisfy a functional requirement. Associated to each mission we have:

- Some resource consumption in each of the satellites involved in that mission. ($R_{ned}^{t,x}$)
- A utility or value related to the satisfaction of the stakeholder requirements for that mission. (U^t)
- A list of the satellites where the mission has to be executed in. If a mission has to be executed in more than one satellite, one or more subtasks (with its own resources consumption) will be defined for each of the satellites involved.

Utility Function

Studying the scalability of the network means to determine how a set of metrics that measure the performance of the system evolve when its operational range is varied. In this study we define the aggregated quality of service (QoS_A) as a utility function that transform the different requirements and preferences of the stakeholder in a single comparable value. In other words, QoS_A provides a common interface among stakeholders to express how well a configuration satisfies their personal preferences related to system qualities (i.e: a stakeholder might prioritize latency over data volume, whereas others might prioritize task

completion over partial execution).

The value of QoS_A depends on the satellites in the system, the architectural parameters and the how resources are assigned to the different satellites involved in the network.

$$QoS_A = f(N_s, S_i(R_i^{in}, R_i^{out}, \alpha_i, \beta_i), N(C_M^R, \eta_M^R, \alpha_A, \beta_A), U^t, h(R)) \quad (9)$$

where N_s is the number of satellites (the scaling variable in the scalability analysis), $S_i(R_i^{in}, R_i^{out}, \alpha, \beta)$ are the satellite dependent parameters (the values of the resources needed and given to the network, and the type of satellites), $N(C_M, \eta)$ are the network parameters (C_M^R is the connection matrix between nodes and defines the topology of the network whereas η_M^R is the efficiency matrix which depends on technological parameters), U^t is the utility of the tasks executed in the system and $h(R)$ is the resource allocation algorithm used in the system.

Different algorithms exist to solve the resource allocation problem, which in this case is a non-linear problem due to the coupling between the different resources. Looking for the optimal solution, the one that maximizes the value of QoS_A, would be the preferred option. However, algorithms used to solve this problems (generally based in Karush-Kuhn-Tucker (KKT) conditions or Sequential Quadratic Programming (SQP)) are computationally intensive, which makes them inappropriate to implement in real systems that work on real time.

Because of that, heuristic algorithms are the most popular choice to solve real time resource allocation problems. A lot of work has been done in this area in the last years, due to the popularity of wireless communication networks [18] and grid-based systems [19]. Most of the approaches include game theory based algorithms and auction-based algorithms, which in the last years have become a popular topic.

For this analysis in particular, we have decided to formulate the aggregated quality of service as:

$$QoS_A = \frac{U}{U^*} = \frac{\sum_t U_m^t p_t}{\sum_t U_m^t} \quad (10)$$

where U_m^t is the utility achieved by executing mission task t and p_t is the probability of executing task t . Note that the election of this utility function is particular to the scenarios we will describe in sections 4 and 5, but (10) is not a universal formulation of a utility function. In another context, for example, the utility function might contain references to other performance metrics such as latency or returned data volume instead of percentage of task completion.

Utility weight values U_m^t are input parameters that can be obtained from a stakeholder analysis. The value of p_t depends on the satellites, the network architecture, the amount of resources available and required for each

satellite, the resource allocation algorithm and the efficiency of the resource exchange. Total probability of executing task t , p_t , is calculated as:

$$p_t = \min(f_t^E, f_t^C, f_t^P) \quad (11)$$

where f_t^R is the fraction of the needed amount of resource R (Energy (E), Comms (C) or computing power (P)) to execute task t which can be calculated as indicated in (12). Note that p_t can be understood as the QoS associated to task t (QoS_t), as it shows its probability of succeeding when trying to execute.

$$f_t^E = \frac{R_{N_t,obt}^E}{R_{N_t,need}^E} \quad f_t^C = \frac{R_{N_t,obt}^C}{R_{N_t,need}^C} \quad f_t^P = \frac{R_{N_t,obt}^P}{R_{N_t,need}^P} \quad (12)$$

3. METHODOLOGY

A scalability analysis of a system consists on studying how the performance of the system evolves as its operational range is varied. In our model the performance of the system (QoS_A) depends on a series of variables that determine its value, as shown in Eq. (9). These variables, however, have different natures. Some of them can scale in the scalability analysis, whereas other either are fixed or vary in a nominal scale.

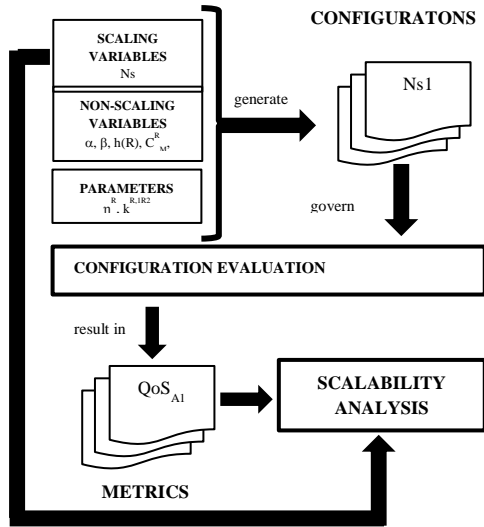


Fig. 3. Scheme of the methodology for assessing the QoS for a certain fractionated satellite network configuration.

N_s , the number of satellites, plays a special role in our analysis as it is the scaling variable and determines the range of operation of the system. The rest of the variables can be classified as non-scaling variables or parameters. Non scaling variables are fixed during the analysis, but its value is established by the system designer when architecting the network. These include α and β . or the resource allocation policy $h(R)$. Finally, parameters are characteristics of the system that cannot be manipulated by the system architect as they obey to technological and

physical limitations. Variables η^R and $\kappa^{R1,R2}$ as described in the Section 2 are parameters of the system.

In order to assess the scalability of an architecture, first we fix the parameters that define the network characteristics (α_A, β_A, C_M), the properties of the satellites and the resource transfer efficiencies (η^R) and the resource interdependencies parameters ($\kappa^{R1,R2}$). Then, different configurations are evaluated (varying the number of nodes and its characteristics) and the evolution of the QoS_A over the range of users is studied. Figure 3 shows the workflow within the framework.

Configuration Evaluation

As a first step to assess the scalability of a fractionated network, a way to evaluate the QoS_A of a certain configuration is needed. (We refer to a particular realization of an architecture with a certain number of satellites as a configuration). The methodology followed for that purpose in this analysis is shown in Fig. 4. Input data includes information from satellites, network topology and stakeholder mission and services analysis.

Satellite data includes information about the satellites, their orbits, technological parameters of the payloads they carry, etc. Technological data together with network topology are used to calculate efficiency values for communications, power and distributed computing links by using the models detailed in Appendix A. Stakeholder information contains the resource consumption of each of the tasks satellites have to execute and its utility value.

This information is used to create the connection graphs and thus, to build the complete model for that configuration. Once the network model is created, the highest efficiency path between any two nodes is calculated using a modified shortest path algorithm that takes as inputs matrices C^R and η^R and. This information is captured in a third matrix η^R_{CM} .

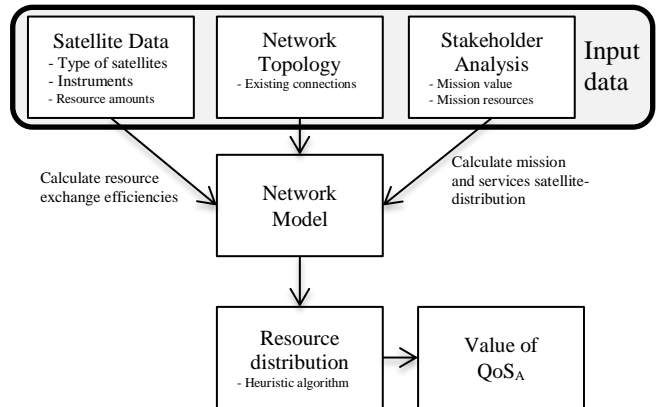


Fig. 4. Scheme of the methodology for assessing the QoS for a certain fractionated satellite network configuration.

Next, resources are allocated to the different satellites in the system. The following discussion shows the approach adopted in this study and formulates the resource allocation

problem as a mathematical problem. If time is a critical variable or the orbit-dynamics of the system play a crucial role in the resource allocation process, the complexity and number of variables of the problem might render it unsolvable by using classic optimization techniques, thus being necessary the use of simulation. All the formulation presented in the following lines assumes the system to be static and omits the time dependency of variables $\boldsymbol{\eta}_{CM}^R$ and \mathbf{x}^R for the sake of clarity. Nevertheless, the reader can trivially derive the time dependent expressions.

The input variables for the resource allocation problem are: U_t , the utility of each task, $R_{need}^{R,t}$, the needed resources of type R from task t , R_i^R , the amount of resources of type R available in satellite i , and η_{ij}^R , the efficiency of the highest efficiency path to exchange the resource R from node i to node j . The variables that the allocation algorithm must determine are $x_{ij}^{R,t}$, which is the fraction of the available resources of type R in node i that will be assigned to node j to execute task t .

This information is stored in the following matrices; \mathbf{x}^R is a $N_s \times N_s$ matrix whose elements are $x_{ij}^{R,t}$; $\boldsymbol{\eta}^R$ is a $N_s \times N_s$ matrix whose elements are η_{ij}^R ; \mathbf{T} , is a $N_t \times N_s$ matrix where $t_{ii} = 1$ if the task t is executed in satellite i and 0 otherwise.

The objective of the resource allocation is to determine what fraction of resources is assigned to each task in order to maximize the value of QoS_A . That is, to maximize equation (10). This implies knowing the probability of executing a certain task, which is calculated using equation (11).

Using this notation, the amount of resources obtained by each task can be calculated as:

$$\begin{pmatrix} R_{1,obt}^R \\ \vdots \\ R_{t,obt}^R \end{pmatrix} = \begin{pmatrix} \eta_{1,d(t_1)} x_{1,d(t_1)}^{R,t_1} & \cdots & \eta_{N_s,d(t_1)} x_{N_s,d(t_1)}^{R,t_1} \\ \vdots & \ddots & \vdots \\ \eta_{1,d(t_{N_t})} x_{1,d(t_{N_t})}^{R,t_{N_t}} & \cdots & \eta_{N_s,d(t_{N_t})} x_{N_s,d(t_{N_t})}^{R,t_{N_t}} \end{pmatrix} \begin{pmatrix} R_{1,ava}^R \\ \vdots \\ R_{N_s,ava}^R \end{pmatrix} \quad (13)$$

or more compact as $\mathbf{R}_{obt}^R = \left((\mathbf{T} \cdot \boldsymbol{\eta}_{CM}^R) \circ \mathbf{x}^R \right) \mathbf{R}_{s,ava}^R = \mathbf{H}^R \mathbf{R}_{s,ava}^R$ where \mathbf{T} is the matrix that indicates in which satellite a task is executed, \circ represents the Hadamard product ($\mathbf{C} = \mathbf{A} \circ \mathbf{B}$ means that $c_{ij} = a_{ij} \cdot b_{ij}$) and $d(t_i)$ indicates the destination node of t_i (the node where t_i is executed).

Equation (13) applies to each of the three resources identified in Section II.A. On the other hand, the available resources equal the initial resources minus the amount of interdependency resources. This can be formulated as shown in equation 14. Note that the general expression of the resources obtained by each task is the result of substituting Eq. (14) in Eq. (13).

$$\begin{pmatrix} R_{ava}^E \\ R_{ava}^C \\ R_{ava}^P \end{pmatrix} = \begin{pmatrix} R_s^E \\ R_s^C \\ R_s^P \end{pmatrix} - \begin{pmatrix} \mathbf{0} & \kappa^{E,C} \mathbf{I}_{N_s} & \kappa^{E,P} \mathbf{I}_{N_s} \\ \kappa^{C,E} \mathbf{I}_{N_s} & \mathbf{0} & \kappa^{C,P} \mathbf{I}_{N_s} \\ \kappa^{P,E} \mathbf{I}_{N_s} & \kappa^{P,C} \mathbf{I}_{N_s} & \mathbf{0} \end{pmatrix} \text{diag} \left(\begin{pmatrix} R_s^E \\ R_s^C \\ R_s^P \end{pmatrix} \right) \mathbf{x}' \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \quad (14)$$

where \mathbf{I}_{N_s} is a $N_s \times N_s$ identity matrix, \mathbf{R}_s^R is a vector of size N_s that contains the initial resources of type R on each

satellite, and \mathbf{R}_{obt}^R is a vector of size N_t that contains the resources of type R obtained by each task. Note that expression (14) contains both the efficiencies of the resource exchange as well as the interdependencies among resources.

Finally, the mathematical problem that describes the resource allocation problem that we are trying to solve is described by the following equations:

$$[MAX] QoS_A = \sum U_t p_t = \sum U_t \min(\mathbf{f}_t^R) = \sum U_t \min \left(\frac{R_{t,obt}}{R_{t,need}} \right) \quad (15)$$

s.t:

$$\begin{pmatrix} R_{need}^E \\ R_{need}^C \\ R_{need}^P \end{pmatrix} \geq \begin{pmatrix} H^E & 0 & 0 \\ 0 & H^C & 0 \\ 0 & 0 & H^P \end{pmatrix} \begin{pmatrix} R_{ava}^E \\ R_{ava}^C \\ R_{ava}^P \end{pmatrix}$$

$$\begin{aligned} \mathbf{1} &\geq (\mathbf{x}^R)^T \mathbf{1} \\ 1 - \alpha_i &\geq x_{ii}^{R,t} \geq 0 \end{aligned}$$

$$\begin{pmatrix} R_{interdep}^E \\ R_{interdep}^C \\ R_{interdep}^P \end{pmatrix} \geq \mathbf{0} \quad \begin{pmatrix} R_{ava}^E \\ R_{ava}^C \\ R_{ava}^P \end{pmatrix} \geq \mathbf{0}$$

$$\alpha_i \geq \sum_{i \neq j} x_{ij}^{R,t}$$

$$\beta_{d(t_j)} \geq x_{ij}^{R,t} \geq 0, \quad i \neq j$$

Once the resources are assigned, calculating the value of QoS_A is immediate, as values of p^t can be obtained by using equations (11) and (12) and plugging them in equation (10) we get the value of QoS_A .

4. RESOURCE ALLOCATION VALIDATION

As several-resource fractionated satellite networks are a novel concept still under theoretical development, there are no examples of space architectures that have such a complex and coupled resource exchange that can be used to validate the resource allocation methodology presented in section III. The closest on-orbit system that could be used to assess, verify and validate this methodology is NASA's Tracking and Data Relay Satellite System (TDRSS).

TDRSS is a space communication network composed of eleven geosynchronous satellites (6 remain operative, 1 is in service testing, 2 were decommissioned, 1 was lost in the Challenger accident and 1 is in storage) and two ground stations (WSGT and GRGT) whose goal is to provide operational tracking and communications support to Low Earth Orbit (LEO) satellites [20].

In this architecture, TDRSS' satellites are infrastructure nodes that make available their communication resources to the rest of the nodes in the network, namely NASA's science missions that rely on TDRSS to download their science data and telemetry. Contacts happen as determined by a schedule created in the Network Control Centre Data System (NCCDS). Most of the time TDRSS satellites support single access contacts.

To validate the resource allocation methodology, an input-file with the technological parameters of the operative TDRSS satellites was created. The mission’s satellites that are currently supported by TDRSS were also added as client satellites. Appendix B shows the characteristics of TDRS Satellites (TDRSS) used to perform the analysis. Also, two metrics are defined to assess the validity of the methodology. These are the percentage of utilization of each of the antennas (calculated as the percentage of time that the antenna was used) and the percentage of utilization of each of the TDRSS. These metrics were then compared with real data from a dataset of the scheduling activities of TDRS during 15 days [21].

Absolute values used on this analysis are not presented due to non-disclosure agreement (NDA) restrictions. Instead, the percentage of error between the value of the metrics when calculated using real data and the values obtained when using our methodology are showed.

TABLE III
RESULTS OF THE VALIDATION TEST

Metric	Band	Difference (%)	
<i>Antenna Utilization</i>	S (SA)	6,48 %	
	Ku (SA)	3,46 %	
	S (MA)	42,74 %	
	Satellite	S-Band Difference (%)	Ku-Band Difference (%)
<i>Satellite Utilization</i>	TDRS-3	2,28 %	29,75 %
	TDRS-5	10,79 %	31,13 %
	TDRS-7	57,40 %	81,02 %
	TDRS-9	55,06 %	0,24 %
	TDRS-10	31,01 %	102,3 %

Table III shows the results of the comparison between both data obtained applying our methodology and data from TDRSS dataset. Differences between values are lower than 10 % for both S and Ku single access antennas, and more than 40 % for multiple access antennas. This can be explained by the following two reasons. First, the methodology does not capture the multi-access nature of the resource exchange. Second, most missions use this MA interface to send housekeeping data and other non-science data, and thus, the resources needed for this tasks are unknown and difficult to include into the model, as opposed to science data, that can be easily estimated or inferred from the mission specifications such as instrument data rate, instrument duty cycle or orbital coverage.

On the other hand, the absolute difference between satellite utilization when applying our methodology and real data varies a lot, and in average its value is higher than 30%, being more than 100 % in some cases. Two clarifications must be made at this point: First, the allocation algorithm doesn’t try to mimic the behaviour of the real schedule, and thus, elements such as load balance, latency minimization or specific policies to priority of some contacts are not taken into account when assigning resources. Second, as the

network offers more resources than the required by the missions it supports, there are multiple solutions for the resource allocation problem and all of them lead to a maximum QoS_A score. The resource allocation optimization process stops once an optimal solution is found, and in general, this solution will differ from the real one.

Based on the previous results, we can conclude that the resource allocation methodology reproduces the behaviour of the network at the system level (as the results of the antenna utilization through the system are precise enough) but is not valid to evaluate particular behaviours at the node level. As we are studying scalability as a system-level property, the methodology is well suited to perform this kind of analysis.

Finally, the resource allocation methodology does not take into account the temporal dependency of resource exchange, and instead uses mean values (this time-dependency is eliminated by averaging distances between satellites, data-rates and contact times). This could lead to overestimations on the capacity of the network, as peak situations where the resource demand exceeds the resource offer cannot be captured.

5. RESULTS

This section contains an analysis that exemplifies the field of application of this framework. We assess the scalability of a small-satellite based architecture depending on the values of the parameters α_A and β_A , that is, depending on its degree of fractionalization.

We would like to remark that this example is based on a hypothetical future architecture that might be implemented using Fractionalization. As there are still a lot of unknowns on how these type of systems will be implemented, some technological values might render incorrect in the future. Nevertheless, this does not preclude the theoretical and conceptual validity of the methodology presented in this paper, as a useful tool to identify scaling trends during the design phase of these systems.

The architecture that we will study is a cluster of satellites flying in close flight formation, which rely on a central node (a resource producer) to obtain the resources they need to execute its mission. We will assume that the capabilities of the central node in terms of communication availability, power generation and computing power are similar to the ones offered by a 702HP satellite bus manufactured by Boeing Space Systems, and the communication capabilities of a third generation TDRSS satellite. This information can be found in Table IV.

On the other hand, client satellites will have a similar bus to the bus in the 5 satellites that compose NASA’s THEMIS mission, an A100 bus commercialized by ATK. Furthermore, we will assume that all the satellites have to download their data through the central node as suggested in

[22]. It's assumed that the network is uniform in terms of the characteristics of the client satellites and their missions. Also, we assume that all the clients will be flying evenly spaced in the region of coverage of the central node and with a separation of no more than 100 m. between them. The characteristics and tasks to be performed can be found in tables IV and V respectively.

TABLE IV
SATELLITES' CHARACTERISTICS

Satellite	Resource	Value	Description
<i>Mother (702HP)</i>	Power Generation	15 kW	2x 33.8m Triple-Junction AsGa
	Comms Data rate	610 Mbps	Ku-band 2 x 300 Mbps S-band 2 x 5 Mbps
<i>Client (A200)</i>	Power Generation	41 W	Body Mounted SmallSat
	Comms Data rate	-	No capabilities for direct downlink to Earth

The resources available to the infrastructure and the number of client satellites are swept during the analysis, and then results are grouped depending on values of α_A and β_A . Let's recall that α_A expresses how much do nodes need the resources from the architecture to operate whereas β_A expresses how much of the produced resources are given back to the infrastructure.

TABLE V
TASKS' CHARACTERISTICS

Task Name	Satellite	Utility	Resource	Consumption
<i>Housekeeping Operations</i>	<i>Mother</i>	100	Power	3 kW
			Data Volume	5Mbps
			Duty-cycle	100%
<i>Housekeeping Operations</i>	<i>Daughter</i>	100	Power	35 W
			Data Volume	1 Mbps
			Duty-Cycle	100%
<i>Mission Data Download</i>	<i>Daughter</i>	50	Power	40 W
			Data Volume	150 Mbps
			Duty-Cycle	40%

In our first result, we present the scalability of the system as a function of parameter α_A . As explained in section 2, this parameter shows how dependent on the infrastructure resources are the nodes in order to complete their missions. Figure 5.- shows the evolution of QoS_A for different values of α_A over different ranges of customer satellites.

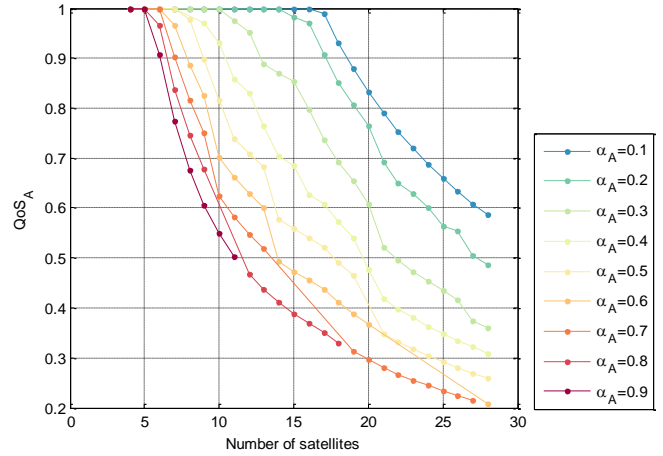


Fig. 5. Performance of the network (QoS_A) as function of the number of satellites and values of α_A .

The figure shows how the number of satellites that the network can support decreases with the value of α_A . This occurs as the higher the value of α_A , the more dependent the satellites are on the network, and although the resources of the system grow due to the addition of satellites, the losses associated with the resource exchange devalue the utility that the network can achieve. Besides, it can also be observed that the distance between the lines decreases as α_A increases. This shows an exponential degradation of the performance of the network as more dependent are the satellites on the infrastructure resources. This finding aligns perfectly with the fact that there are high losses in the resource exchange among the nodes of the network, and thus the more dependent the satellites are of the infrastructure resources, the more the utility the network can achieve degrades.

Secondly, the results of the analysis as a function of parameter β_A under the same conditions are presented in Figure 6.

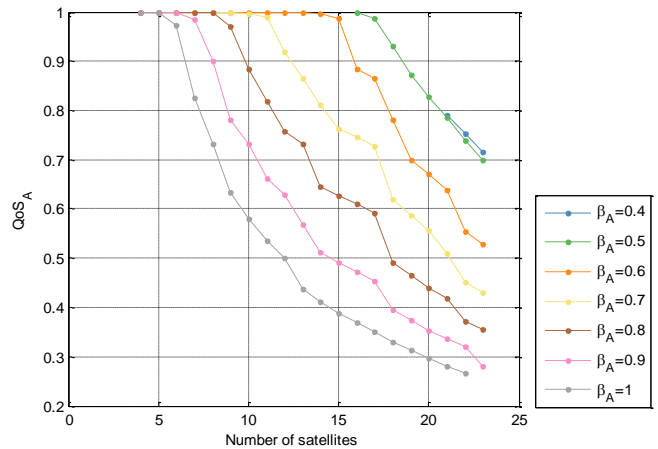


Fig. 6. Performance of the network (QoS_A) as function of the number of satellites and values of β_A .

In this case, the value of the QoS_A that the network can achieve also decreases as β_A increases. However compared to the evolution of the network as a function of α_A , the dependence with β_A is weaker, as the system can support more satellites for the same values of β_A and α_A . Besides, the degradation rate shows a linear degradation with the value of β_A . (The distance between same β_A lines remains constant for same increments of the value of β_A).

It's interesting to look at the evolution of the number of satellites that the network can provide service effectively as a function of β_A and α_A . We define the threshold to "provide service effectively" as achieving an aggregated quality of service (QoS_A) above 0.9. Figure 7 shows this evolution. It can be observed that the maximum number of satellites decreases exponentially as α_A increases, whereas it decreases linearly as β_A increases. This is due to the nature of the losses involved in the energy exchange.

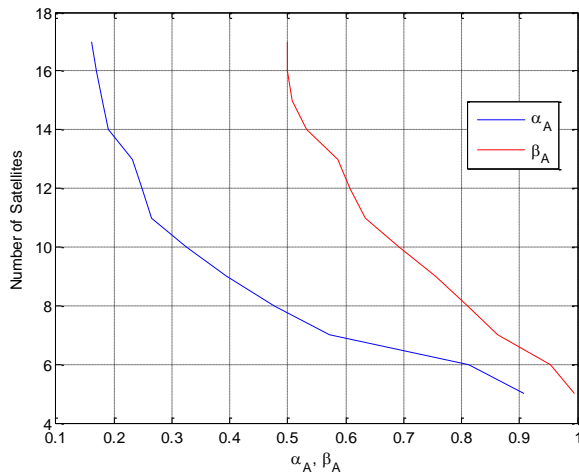


Fig. 7. Evolution of the maximum number of satellites that achieve vales of QoS_A over 0.9 as a function of α_A and β_A .

6. CONCLUSIONS

In this work a methodology to assess the scalability of fractionated space networks where multiple and highly coupled resources are involved has been presented. A vertical model that includes all the different levels in the system (resource, satellite, network, tasks and utility) has been developed. Finally, a taxonomy of the different types of satellites and the different types of networks based on the amount of resources taken from other nodes and given back to the infrastructure has been introduced and the mathematical problem of resource allocation, coupling between resources and utility calculation has been formulated.

The resource allocation methodology has been validated using the closest real scenario to a fractionated satellite network where capabilities of certain members of the system (in this case communication capabilities) are shared across all the nodes of the network. The TDRSS analysis used real scheduling data, and the results show that the

methodology mimics the real performance of the network at a system level with errors lower than 10 %.

Finally a scalability analysis over a hypothetical system composed of a mother satellite that provides communications and power resources to the rest of the satellites in the swarm has been conducted as an example to show the usefulness of the framework.

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BIOGRAPHY



Iñigo del Portillo is a visiting student in the department of Aeronautics and Astronautics at MIT. His research interests include dynamics of fractionated satellite system and small satellites communications. Iñigo received his degrees in Industrial Engineering, Electronics Engineering and Telecommunications Engineering in 2014 from Universitat Politècnica de Catalunya, Barcelona.



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Marc Sanchez Net is currently a second year M.S. student in the department of Aeronautics and Astronautics at MIT. His research interests include machine learning algorithms and rule-based expert systems, and their suitability to the fields of system engineering and space communication networks. Prior to his work at MIT, Marc interned at Sener Ingenieria y Sistemas as a part of the team that develops and maintains

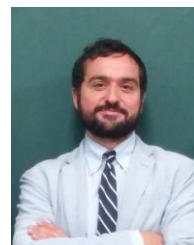
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Dr. Daniel Selva received a PhD in Space Systems from MIT in 2012, and he is Assistant Professor at the Sibley School of Mechanical and Aerospace Engineering at Cornell University, where he directs the Systems Engineering, Architecture, and Knowledge (SEAK) Lab. His research interests focus on the application of knowledge engineering, global optimization and machine learning techniques to space systems engineering and architecture, with a strong focus on space systems. Prior to MIT, Daniel worked for four years in Kourou (French Guiana) as a member of the Ariane 5 Launch team. Daniel has a dual background in electrical engineering and aeronautical engineering, with degrees from Universitat Politècnica de Catalunya in Barcelona, Spain, and Supaero in Toulouse, France. He is also a Faculty Fellow at the Mario Einaudi Center for International Studies.



Ángel Álvaro Sanchez is Head of R&D and Digital Design Authority in Thales Alenia Space España, has a long background as a designer and technical responsible for satellite equipment since Rosseta and Mars Express to the first AmerHis units. Telecommunications Engineer (1997) by UPM in Madrid has 15 years of experience, starting Alcatel Space as a designer of digital equipment, has been responsible for the digital engineering group and director of operations. In 2009 returns to the technical activity and occupies a position within R&D Management Area at Thales Alenia Space Spain, where he coordinates the European R&D projects and has also been responsible for several projects in the area of Telecommunication Systems.



Eduard Alarcon received the M.Sc. (National award) and Ph.D. degrees (honors) in Electrical Engineering from the Technical University of Catalunya (UPC BarcelonaTech), Spain, in 1995 and 2000, respectively. Since 1995 he has been with the Department of Electronic Engineering at UPC, where he became Associate Professor in 2000. He has co-authored more than 250 scientific publications, 4 books, 4 book chapters and 4 patents, and has been involve in different National, European and US (DARPA, NSF) R&D project within his research interests including the areas of on-chip energy management, circuits, energy harvesting and wireless energy transfer, and nanotechnology-enabled wireless communications.

APPENDIX A

This section discuss values of parameters η^R and $\kappa^{R1,R2}$ for different state of the art technologies.

Efficiency parameters

Efficiency of energy transmission depends mainly on the technology used. In [23] and [24] a deep analysis on different wireless power transfer methodologies is presented. For example microwave power transfer uses RF signals to transmit power between different nodes. Other alternatives are LASER., and witrlicity (or resonant inductive coupling - RIC). Apart from energy transfer efficiency, these different methods also have strong implications on mass and pointing requirements. As an example, RIC works well at distances lower than 10 meters, but efficiency decreases very quickly for longer distances. In contrast, LASER works well for long distances, but its strict pointing requirements makes it a heavy system to implement.

On microwave systems, efficiency depends on the diameters of the transmitter antenna (D_t) and receiver rectenna (D_r), the distance between them and the efficiency of the electronics used to generate the radiated power [23].

$$\eta_{\mu W}^E = \eta_E G_t G_r \left(\frac{\lambda}{4\pi d} \right)^2 \quad (1)$$

where G_t and G_r are the gains of the transmitter and receiver antenna respectively, η_E is the efficiency of the electronics (and can be approximated by 0.4 [23]), d is the distance between transmitter and receiver and λ is the wavelength they operate.

LASER has a constant efficiency of $\eta_{LASER}^E = 0.37$ for a wide range of distances, ranging from 10 to 1000 meters, which makes them a good choice for long range power transmission systems. However, its strict pointing requirements make them not very suitable for fractionated systems [23].

Finally, systems based on RIC have a very high efficiency for short distances (as high as 60%), although its value degrades very quickly when the distance between the emitter and receiver coil increases. The following equation obtained from reference [6] shows the relation between the efficiency of the RIC link and the distance d (in meters) between the resonant coils.

$$\eta_{RIC}^E = 0.81 \frac{\left(1 - \operatorname{atan}\left(\frac{0.9(d-2)}{3.5}\right)\right)}{2} \quad (2)$$

On the other hand, wireless communications efficiency is defined as the quotient between the amount of useful data transmitted and the total amount of data transmitted. This

value is determined by the protocol. For the last years a TCP/IP-based protocol called Delay Tolerant Networking (DTN) has been proposed [25] and tested on space [26]. Because of that reason we will consider the efficiency (in terms of the losses due to the overhead involved in the data-formatting for the transmission) of a communications transmission using shared resources to be the same as the one over a common TCP protocol, which is $\eta^C = 0,95$.

Finally, distributed computing systems have not been tested in space yet. However, there are no reasons to think that its efficiency should be different to the one obtained on Earth. Thus, efficiency for sharing computing power capabilities is $\eta^P = 0,95$.

Interdependency coefficients

This section presents the values of the interdependency coefficients for state of the art technologies and some common components currently used in space applications. As a reminder, coefficient $\kappa^{R1,R2}$ indicates the consumption of resource R_1 derived of the consumption of resource R_2 .

Table VI shows the values of κ for Energy and Communications resources. This coefficient represents the extra energy that a supplier satellite needs in order to transmit a megabit of information from a client satellite. Values have been obtained from reference [27].

TABLE VI
INTERDEPENDANCY COEFFICIENT BETWEEN
ENERGY AND COMMS

Frequency Band	Data-rate	Amplifier Technology	RF Power	Efficiency	$\kappa^{E,C}$
S-band	1 Mbps	SSPA	15 W	40 %	37.5 J/Mb
		TWTA	30 W	60 %	50 J/Mb
X-Band	100 Mbps	SSPA	15 W	28 %	0.54 J/Mb
		TWTA	25 W	60 %	0.42 J/Mb
Ka-band	300 Mbps	SSPA	9 W	17 %	0.18 J/Mb
		TWTA	50 W	50 %	0.33 J/Mb

Table VII shows the values of the interdependency coefficient for Energy and Computing Power resources. Values have been obtained from the datasheets of the microprocessors they refer to.

TABLE VII
INTERDEPENDANCY COEFFICIENT BETWEEN
ENERGY AND COMPUTING POWER

Micro-processor	Performance	Consumption	$\kappa^{E,P}$
RAD750	400 MIPS	5 W	0.0125 J/MJ
ATMEL AT697F	86 MIPS	1 W	0.0116 J/MJ
TSC695FL	12 MIPS	0.3 W	0.025 J/MJ

Finally, the values of the rest of interdependency coefficients are negligible compared to the coefficients described before, so it's a reasonable assumption to consider that $\kappa^{C,E}$, $\kappa^{P,E}$, $\kappa^{P,C}$ and $\kappa^{C,P}$ equal 0. This is equivalent to say that energy transfer does not imply a consumption of communications.

APPENDIX B

The Tracking and Data Relay Satellite System (TDRSS) is a constellation of eleven geostationary satellites that provide communication capabilities and tracking support to other satellites. The program started in 1983 with the launch of TDRS-1 followed by another 6 satellites of the first generation. One of them (TDRS-2) was lost in the Challenger accident.

TDRS-8 to TDRS-10 formed the second generation of TDRSS satellites and were launched between the years 2000 and 2002 to replace the older nodes of the first generation, further expanding and upgrading the capabilities of the network. In the year 2013 the first satellite of the third generation (TDRS-11) was launched and at the beginning of 2014, TDRS-12. Actually both of them are in service

testing. TDRS-13 is planned to be launched on 2015, completing that way the third generation upgrade of TDRSS.

As today 5 satellites and two ground stations (White are active and provide communications capabilities to more than 10 NASA missions flying in Low Earth Orbit. The satellites are evenly spaced in a geostationary orbit, being their orbital positions the North-eastern coast of Brazil (providing service to the Atlantic Region), the Phoenix Islands (providing service to the Pacific Region) and the (providing access to the Indian Ocean). All of them are equipped with two single access antennas working in S and Ku bands and a multi-access antenna working on S band. Satellites of the second and third generation are also equipped with a Ka-band transceiver that enables higher communication data rates.

The complete list of characteristics of TDRSS's satellites used in the validation of our methodology is shown in Table VIII. Values for the interdependency coefficient between Energy and Comms are described in Appendix A.

TABLE VIII
TDRSS SATELLITES CHARACTERISTICS

Satellite	General Characteristics		Antenna Characteristics				
			Antenna	Number of antennas	Band	Polarization	FOV
TDRS-3	TDRSS Generation	First	Multiple Access Antenna	1	S	LHC	$\pm 13^\circ$
	Weight at lift-off	2224 kg	Single Access Antenna	2	S and Ku	LHC and RHC	$\pm 22^\circ$ E-W $\pm 28^\circ$ N-S
	Power generated	1700 Watts	Omni-Directional Antennas	1	S	LHC	-
TDRS-5 TDRS-7	TDRSS Generation	First	Multiple Access Antenna	1	S	LHC	$\pm 13^\circ$
	Weight at lift-off	2108 kg	Single Access Antenna	2	S, Ku and Ka	LHC and RHC	$\pm 22^\circ$ E-W $\pm 28^\circ$ N-S
	Power generated	1700 Watts	Omni-Directional Antennas	1	S	LHC	-
TDRS-8 TDRS-9 TDRS-10	TDRSS Generation	Second	Multiple Access Antenna	1	S	LHC	$\pm 13^\circ$
	Weight at lift-off	3197 kg	Single Access Antenna	2	S, Ku and Ka	LHC and RHC	$\pm 22^\circ$ E-W $\pm 28^\circ$ N-S
	Power generated	2300 Watts	Omni-Directional Antennas	1	S	LHC	-