Exploring Packaging Architectures for the Earth Science Decadal Survey

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Abstract—In this paper, we present an integrated tool to support the high level design decisions concerning the assignment of instruments to satellites in an Earth Observation Program.[12] This integrated tool features a rule-based expert system to model scientific synergies between measurements and engineering incompatibilities between instruments. We introduce two matrices: the science Design Structure Matrix (DSM) and the engineering DSM. Both matrices are calculated using the expert system, and provide insight into how to decompose the initial set of instruments into smaller tractable clusters. Then, each cluster of instruments is efficiently explored using metaheuristic algorithms (i.e. non-exact optimization algorithms that use heuristics to search the tradespace). We apply the methodology to the Earth Science Decadal Survey (DS) and identify a few architectures that are different from the baseline architecture and potentially better.

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1. INTRODUCTION

Motivation

In 2004, the National Aeronautics and Space Administration (NASA) Office of Earth Science, the National Oceanic and Atmospheric Administration (NOAA) National Environmental Satellite Data and Information Service (NESDIS), and the U.S. Geological Survey (USGS) Geography Division asked the National Research Council (NRC) Space Studies Board (SSB) to "conduct a decadal survey (DS) to generate consensus recommendations from the Earth and environmental science and applications communities regarding a systems approach to space-based and ancillary observations that encompasses the research programs of NASA; the related operational programs of NOAA; and associated programs such as Landsat, a joint initiative of USGS and NASA" [1].

In response to this request, an ad-hoc NRC committee consisting of experts from different disciplines of Earth sciences produced a report loosely known as the "Decadal Survey" (DS). The DS lays out a reference architecture for an integrated Earth Observation Program (EOP) for the next decade that will fulfill the needs of all the scientific communities in terms of space-based measurements, while also providing essential societal benefits [1].

This reference architecture consists of 15 missions for NASA and 2 missions for NOAA. A total of 39 instruments are assigned to these 17 missions on the basis of a variety of technical, scientific, and programmatic factors including amongst other synergies between instruments, data continuity, orbit compatibility, different instrument maturity levels, and expected yearly budget. For each mission, the report provides a description of the scientific objectives fulfilled by the mission, the physical parameters measured, the instruments used, the orbit required, a rough estimation of the lifecycle mission cost, and the expected mission launch date.

However, some of the assumptions used in the study concerning for example mission cost, yearly budget and precursor missions have now changed. First, mission cost estimates according to NASA have doubled on average. Second, yearly budget has decreased by about 50% with respect to the $750M/yr used in the Decadal Survey (although with the newest policy changes, it is likely to increase again). And finally, some of the precursor missions have failed or have been severely delayed (e.g. the Orbiting Carbon Observatory mission or OCO, and the National

[1] 978-1-4244-7351-9/11/$26.00 ©2011 IEEE.
[2] IEEEAC paper #1049, Version 3, updated January 11, 2011

Polar-orbiting Operational Environmental Satellite System, or NPOESS.) Therefore, the question arises whether this is still the best architecture possible given the current assumptions. The purpose of this paper is to lay out a methodology to explore alternative architectures in a systematic way.

Architecture of an Earth Observation Program (EOP)

We now describe a few terms from the system architecture jargon that will be used throughout this paper. A more thorough description of these terms can be found in [2]. System architecture essentially is system design at the highest level. The process of system architecting starts from stakeholder needs and goals, which respond to the question "Why do we want to build the system?". Function is "what the system does", i.e., the set of processes that the system needs to perform in order to fulfill stakeholder needs and goals. Form is the set of tangible elements from which the system is composed, or more loosely, "what the system is". The essence of an architecture lies in its concept, which relates the elements of function to the elements of form. Furthermore, key characteristics of elements of both function and form are provided by attributes.

In the case of an EOP, we can loosely associate measurements (e.g., soil moisture) to elements of function, and instruments (e.g., a radar altimeter) and missions to elements of form. Stakeholder needs usually map to one or more measurements, and thus, a list of the measurements required by the program can be made. In order to describe a measurement, attributes such as spatial, spectral and temporal resolution, and accuracy, are to be provided. Similarly, a list of the instruments can be made, where each instrument is described by a set of attributes, such as number of bands, spectral or angular resolution, and signal-to-noise ratio. Thus, at a certain level of fidelity, each architecture for an EOP can be uniquely identified with a table that assigns measurements (with their attributes) to instruments (with their attributes).

The System Architecting Process Is Hierarchical

System architecting of large complex systems such as EOPs is hierarchical. Figure 1 shows a hierarchical decomposition of a generic EOP.

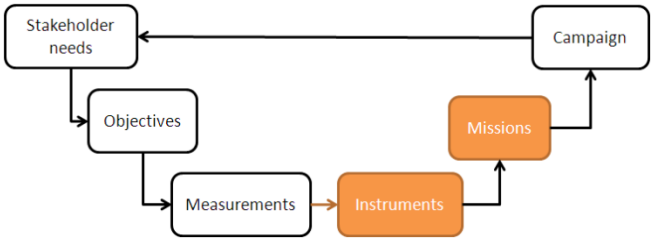


Figure 1: Hierarchical view of the system architecting problem for an EOP. The instruments-to-missions assignment, with which this paper deals, is highlighted.

Using the architectural jargon previously defined, the left wing of the "V" represents the function domain and the right wing defines the form domain. The interface between function and form is done at the instruments-measurements level. Following the hierarchy in the right wing of the "V", we define a mission as a set of instruments, and finally the campaign as a set of missions. Using this model, the architecture of an EOP is completely defined when: stakeholder needs and goals are mapped to measurements (with attributes); measurements (with attributes) are mapped to instruments (with attributes); instruments (with attributes) are mapped to missions (with attributes); missions (with attributes) are mapped to the program.

The left wing of Figure 1 essentially represents the downstream problem, which starts with a stakeholder analysis and ends with a list of measurement requirements. For a very comprehensive stakeholder analysis for the DS, see [3].

The upstream problem corresponds to the different levels of high-level system design. Indeed, the system architecting problem can be decomposed into several smaller problems. For instance, one can study the higher level problem of deciding when to launch each mission in the campaign. This problem - that we call mission scheduling problem – lies at the missions-to-campaign level on the diagram. For a discussion of the mission scheduling problem, see [4]. Our specific problem lies one level down in the hierarchy, and studies the assignment of instruments to satellites, which we call the instrument packaging problem. The instrument selection problem, in other words the assignment of measurements to instruments, lies another level down in the hierarchy. Finally, the campaign evaluation problem requires the direct traceability all the way from stakeholder needs to missions. A discussion on this topic can be found in [5].

Computational Tools to Support System Architecting

System architecting requires the comparison of different system architectures across technical and programmatic figures of merit, in order to select a small subset of architectures that deserve further attention and should be studied in more detail - at the design level. Some challenges appear when trying to perform this task in a systematic form: a) Experience of system architects in a particular type of architecture can lead them to ignore part of the trade space. b) Uncertainty and complexity make it difficult to be objective and rigorous when evaluating architectures.

Computational tools can help overcome some of these challenges by providing a rigorous and systematic way of exploring the architectural tradespace. They are certainly not a substitute for humans in the system architecting process, but rather a useful asset to support the parts of system architecting that humans don't do well. In particular, these tools can enumerate millions of different architectures and evaluate them across a set of technical and

programmatic figures of merit (e.g. affordability, scientific performance, schedule, and risk). They can also provide guidance for architecture selection, for example through tools such as fuzzy Pareto frontiers [6].

Research Question

This paper deals with the instrument packaging problem, i.e., the assignment of instruments to satellites. We consider henceforth a set of remote sensing instruments and their characteristics as an input to the problem, and try to create the best possible set of satellites to fly these instruments.

The main tension that arises is the trade-off between multi-instrument satellites and single-instrument satellites. From the systems point of view, there exist two main forces pushing the design towards monolithic satellites: cost reductions and scientific synergies between instruments. On the other hand, schedule, risk, flexibility and other "–ilities" (non-traditional figures of merit such as flexibility, adaptability, or scalability, that are typically represented using words that end with the suffix –ility) push the design towards smaller dedicated satellites. The instrument packaging problem tries to identify architectures with the right balance of large multi-instrument, observatory-class monolithic satellites, smaller, usually single instrument dedicated satellites, and intermediate architectures, such as dedicated satellites flying in loose formations or trains (e.g., NASA A-train).

The specific research goal is to create a tool that can automatically enumerate millions of different packaging architectures and evaluate them in terms of affordability, scientific performance and programmatic considerations. The main challenges to create such a tool are the following: a) the tradespace is extremely large; b) the figures of merit required to perform a fair comparison between architectures (e.g. scientific synergies between instruments, instrument maturity levels, engineering factors) are hard to assess and require the capture of expert knowledge. In this paper, we present an integrated solution to this problem that incorporates optimization and artificial intelligence tools to try to overcome the two aforementioned problems.

Literature Review

Concerning the specific instrument packaging problem for EOPs, the literature that is publicly available is rather scarce. Part of the reason is that although much related work has been done in space agencies, almost none has been published. The interest in the academic community has also been limited: Matossian applied a mixed-integer linear programming algorithm to the Earth Observing System [7]. Since very efficient algorithms exist to solve integer linear programs (branch and bound, cutting planes), Matossian compared millions of architectures in a very efficient way. However, modeling fidelity was limited due to the linearity of the objective function.

From industry, we highlight the work of Rasmussen, who published two related studies [8], [9]. Rasmussen compared architectures using both small and large satellites for EOPs with certain depth. In this case though, the number of different architectures considered was very small (i.e., 2-4).

Fortunately, even though the literature concerning this specific problem is scarce, much can be found on similar problems in the operations research, optimization and artificial intelligence communities. The instrument packaging problem is a constrained, multi-objective, non-linear, non-convex, mixed-integer optimization problem that can be naturally formulated, amongst others, as a set partitioning problem [10] or as a generalized assignment problem [11]. Both are well-known NP-hard problems[3] and much has been written on methods to approach them. Meta-heuristic algorithms such as genetic algorithms have been successfully applied to set partitioning problems [12]. Other approaches include graph algorithms (e.g. breadth-first, depth-first), heuristic search algorithms such as A* or solutions based on constraint-satisfaction formulations and sat-solvers [13]. See [14] for a comprehensive review of multi-objective constrained optimization problems.

2. APPROACH

Qualitative analysis

Before developing a quantitative model, it is necessary to perform a qualitative analysis of the problem. We presented a comprehensive qualitative analysis of the instrument packaging problem in our paper last year [15]. The main conclusions of this study are summarized in the next paragraph; a more detailed discussion can be found in the paper. A pictorial summary is also provided in Figure 2.

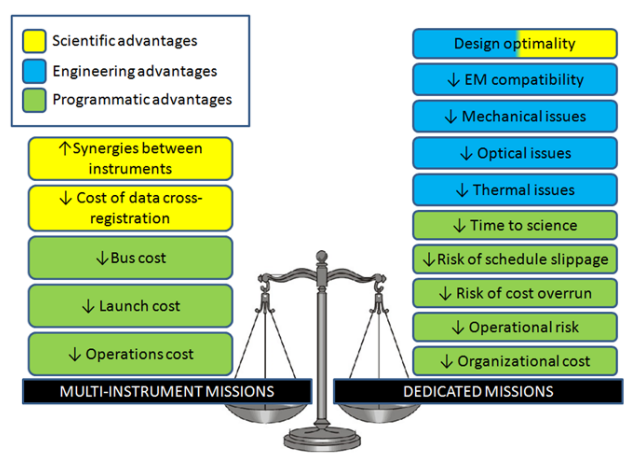


Figure 2: Scientific, technical and programmatic advantages of multi-instrument and dedicated missions.

[3] P is the class of problems for which we can find a solution in polynomial time. NP is the class of problems for which we can check a solution in polynomial time. NP-complete problems are the hardest problems in NP. NP-hard problems are at least as hard as NP-complete problems, but do not necessarily belong to NP.

Multi-instrument platforms have important scientific benefits and tend to be better in terms of lifecycle cost per instrument. On the other hand, dedicated missions are easier to design, build, and test, and are seen as more desirable options in terms of schedule and risk. Naturally, these are very general statements, and the optimal choice for each program will depend on its nature (scientific versus operational program), and more particularly, on how decision makers value these issues.

A 3-stage Quantitative Model

As explained in [14], the current trend for multi-objective optimization problems is to develop problem-specific models that are usually hybrids of some kind of meta-heuristic algorithm (e.g., genetic algorithms) and some kind of local search algorithm (e.g. gradient-based algorithms). Typically, instead of tackling the whole problem, the problem is decomposed into smaller sub-problems using heuristics, and then optimization algorithms are applied to each sub-problem. Finally, local-search algorithms take the solutions found by the meta-heuristic optimizer – which are not necessarily optimal because the tradespace is not exhaustively explored- and try to improve them by doing small changes to the architecture (hence local search). A good discussion on this decomposition approach can be found in [16].

Our integrated tool also follows these guidelines, but adds a rule-based expert system to inform different phases of the optimization process. The expert system provides a transparent and traceable way to account for the most subtle complexities of the problem, such as scientific synergies or engineering compatibility between instruments.

The approach consists in three steps. First, heuristics or rules embedding expert knowledge are used to evaluate the scientific synergies and engineering compatibility of pairs of instruments, so that a science synergy design structure matrices (S-DSM) and an engineering DSM (E-DSM) can be generated. Second, a clustering algorithm is used to find the optimal partitioning of the trade space, i.e., one that maximizes synergies between instruments within the subsets, and minimizes synergies across subsets. The clustering algorithm is tuned to find relatively few clusters. Third, since the size of each cluster is not greater than 9-10 instruments, each cluster can now be exhaustively explored, either using full factorial enumeration if the cluster is small enough, or a genetic algorithm for moderately large clusters. In the next paragraphs, each of these steps is described in further detail.

Rule-Based System for Architecture Screening

An expert system is an artificial intelligence program designed to: a) provide expert-level solutions to complex problems, b) to be understandable, and c) to be flexible enough to accommodate new knowledge easily [17]. When knowledge is represented as conditional statements of rules such as "if A and B then C", the expert system is called rule-based. In order to develop an expert system the following steps are necessary: 1) gather expert knowledge by means of formal interviews; 2) create a set of abstractions to represent expert knowledge as rules; 3) create an inference engine that uses the rules to reach a conclusion (in our case, an assessment of the extent of the synergies between two instruments), and present it to the user (either the system architect or the optimization algorithm.)

We followed these steps and implemented an expert system to assess the scientific synergies and the engineering and programmatic compatibility for a set of instruments. As of October 2010, our knowledge database contains 70+ rules concerning scientific synergies between instruments. These rules were obtained in the course of 12 interviews with experts in different disciplines of the Earth Sciences, mostly from the Massachusetts Institute of Technology (MIT) Earth and Planetary Science Department.

During these interviews, expert knowledge rules were captured in natural language, such as "if an atmospheric sounder shares a platform with a radar altimeter, then the quality of the altimetry measurement is improved". In order to be able to use this knowledge, the rules need to be expressed in a way such that a computer model can understand them. This goal is achieved using an ad-hoc set of abstractions, created so that a maximum number of rules in natural language can be easily expressed. Scientific synergies occur at the measurement level: e.g., a cloud measurement is synergistic with an aerosol measurement. However, it was clear during the course of the interviews and extensive literature review that, for some applications, scientists reason better in terms of instruments, as opposed to measurements. There are at least two situations when this happens: 1) the synergy is between two sets of measurements that are commonly identified with the name of the instrument that performs them, just for simplicity (e.g., radar altimeter and microwave radiometer); 2) The instruments perform the same measurement with different attributes that are complementary (e.g., a radar and a radiometer measuring soil moisture). Thus, oceanographers usually talk about radar altimeters and scatterometers as opposed to altimetry and ocean surface wind measurements. Hence, in the most general case, a rule concerns two instruments, two measurements, or one instrument and one measurement, and each of those can have attributes, which leads to the following rule structure:

Rule={'Instrument/Measurement1','Attributes1','Instrument/Measurement2','Attributes2', 'Strength', 'Justification'}

The strength field provides a qualitative assessment of the marginal synergy that one gets when Measurement1 and Measurement2 can easily be cross-correlated (because instruments are either on the same platform or on a train configuration). Strength can have four possible values: low, medium, high and highest. The justification is required for

traceability purposes, and it is shown to the user by the graphical user interface to explicitly show the reasoning behind decisions made by the tool.

The scientific synergy rule database is completely generic, and does not depend on the instrument set. As a matter of fact, the set of possible instruments and measurements was adapted from the Committee on Earth Observation Satellites (CEOS) public online database[4]. An extract of our science database is provided in Figure 3. Note that rule 11 expresses a synergy between two measurements, rule 14 expresses a synergy between two instruments and rules 15 and 18 are expressed at the attribute level. The engineering rules database was obtained in a very similar fashion. As of October 2010, it contains about 30 rules that come mainly from interviews with senior system engineers from the European Space Research and Technology Centre (ESTEC). An extract of the engineering database is provided in figure 4.

Id#	Rule description	Priority	Justification
11	Wind mesaurement is synergistic with ocean color measurement	Low	Correction of whitecaps
12	O3 measurement is synergistic with ocean color	Low	1) Same band 2) Absorption by ozone must be corrected for in ocean color measurements
13	NO2 measurement is synergistic with ocean color	Low	Absorption by NO2 must be corrected for in ocean color measurements
14	All chemistry instruments are very synergistic	High	Global atmospheric chemistry models incorporate all relevant chemical species
15	A Nadir spectrometer is synergistic with a limb sounder	Medium	For independent profile and column retrievals
16	An O2 measurement is synergistic with a CO2 measurement	Low	To provide independent measurements of mixing ratios.
17	In aerosol missions, a MW instrument complements an optical instrument	High	MW see better larger particles such as cloud droplets and raindrops

Figure 3: Extract of the database containing the scientific synergy rules

Id#	Rule description	Priority	Justification
8	A SAR is not compatible with another SAR	High	Data rate requirements would be too high
9	An imaging hyperspectral instrument is not compatible with another imaging hyperspectral instrument	High	Data rate requirements would be too high
10	A SAR is not compatible with an imaging hyperspectral instrument	Medium	Data rate requirements would be too high
11	A MW active instrument is not compatible with a MW passive instrument in the same band	High	Electromagnetic compatibility issues
12	A large scanning instrument is not compatible with a limb sounder	Low	Scanning induces vibrations on the platform that may hinder the capability of a sensitive sounder
13	An instrument requiring cryocooling is not compatible with a limb sounder	Low	Cryocoolers induce vibrations on the platform that may hinder the capability of a sensitive sounder
14	A GEO instrument is not compatible with a LEO instrument	Highest	Completely different sensor designs
15	A lidar is not compatible with a passive optical imager	Medium	Lidars require low orbits whereas passive optical imagers require high orbits

Figure 4: Extract of the database containing engineering compatibility rules

It is important to note that the quality of the results of an expert system is determined by the number and quality of its rules.

[4] http://www.eohandbook.com

Science Synergy and Engineering Compatibility DSMs

Design Structure Matrices (DSMs) are matrices that describe the relationships between components of a system in a compact, visual, and analytically advantageous format [18]. Cell *(i,j)* represents the intensity of the connection between elements *i* and *j*. The cells along the diagonal are either unused or represent interactions within each element. Mathematically, DSMs are adjacency matrices of a network where each element is a node, and the arc between two nodes represents their connectivity.

Using the rule-based expert system, the scientific synergies between each pair of instruments can be assessed by counting the number of low, medium, high and highest priority rules that are satisfied or broken. The next step is to transform these data (four numbers) into a single number, in order to populate a DSM where cell *(i,j)* represents the synergy existing between instruments *i* and *j*. A pair of instruments satisfying a few high priority synergy rules, or many medium or lower priority synergy rules, is considered to be highly synergistic. Conversely, a pair of instruments satisfying very few or no synergy rules, is considered to have low synergy.

More precisely, let *s* be a 1x4 array containing the number of rules satisfied from each priority (low, medium, high, highest). Several strategies can be used to transform this array into a single number representing overall synergy between the pair of instruments. One of the simplest consists in performing a weighted average where weights are assigned according to priority. Exponentially increasing weights (e.g., 1, 3, 9, 27) were used instead of linearly increasing weights (e.g., 1, 2, 3, 4), in order to better capture the non linear nature of the problem. A similar reasoning is applied for example in Saaty's Analytic Hierarchy Process for each pairwise comparison of system attributes [19].

A Clustering Algorithm to Divide the Trade Space

Once we have obtained the bilateral relationships between instruments, the next step is to divide the set of instruments into smaller clusters that we can analyze exhaustively and efficiently. This is generally called clustering or cluster analysis, and is a very well known problem, useful in many applications including not only design, but also biology, psychology and marketing, amongst others. Several types of clustering algorithms exist for different kinds of applications: hierarchical versus partitional, exclusive versus overlapping versus fuzzy, and complete versus partial [20]. Without entering into the details, our model uses a simple implementation of the K-means clustering algorithm. A description of this algorithm, as well as a survey of current clustering algorithms, can be found in [21]. Note that in this process, global optimality is lost. Indeed, it will generally not be the case that the global optimum of the problem is also optimal for each of the sub-problems. However, as mentioned before, some kind of decomposition is absolutely needed to tackle such large

optimization problems. A proper sensitivity analysis will analyze a posteriori the effects of the clustering process in the choice of optimal architectures.

Exhaustive Cluster Exploration

Once the instrument set is partitioned in clusters, each cluster can be analyzed individually and exhaustively. If their size allows it, full factorial enumeration and evaluation may be possible. Conversely, if the number of instruments in the set is larger than 5 or 6, full factorial enumeration becomes impossible, but the tradespace is still small enough so that it can be effectively explored by metaheuristic optimization algorithms, such as a genetic algorithm, without long and complicated tuning processes.

For example, let us say that from an original set of 50 instruments, the clustering algorithm identifies a cluster of highly synergistic instruments all related to atmospheric science, namely: an infrared spectrometer, a limb sounder, a polarimeter, a differential absorption lidar, a cloud radar, a precipitation radar, a visible-ultraviolet hyperspectral sensor, and a water vapor imager. This allows a much more efficient exploration of the architectural tradespace related to this subset of instruments, and avoids looking at architectures mixing these instruments with instruments from other clusters, with which synergies are relatively small.

Figures of Merit

Several technical and programmatic metrics are considered for the evaluation of architectures. Since the instrument set is fixed, a large portion of the scientific performance is constant throughout the tradespace and is thus not considered. Hence, the scientific performance of an architecture is measured against two criteria that vary considerably across architectures: overall scientific synergies, and instrument performance with respect to an ideal design, in which the requirements needed for every instrument to perform at the maximum of its capabilities would all be fully satisfied, without compromises between instruments. Note that this condition is met by a design consisting of exclusively dedicated satellites, for which the bus design is tailored to the needs of one particular instrument.

Scientific synergies are evaluated using the rule-based system previously described. Instrument performance with respect to the ideal design represents the loss in instrument performance due to compromises made in the design of multi-instrument platforms. Compromises are necessary because instrument requirements are generally conflicting. For instance, in a multi-instrument mission flying a lidar and a passive optical imager, there will be a tension in the orbit altitude selection. Ideally, the lidar would fly in a low orbit around 400km to minimize power requirements for a given signal-to-noise ration, while the passive optical imager would fly in a higher orbit to maximize swath. If these instruments flew on separate platforms, each on its corresponding optimal orbit, their individual performance would be higher than the performance they can achieve if they share a platform. Indeed, because they are forced to share a platform in order to make the most of their synergies, at least one of them will have a suboptimal altitude.

The assessment of affordability for each architecture is based on an estimation of cumulative lifecycle cost for all the missions in the program. For each mission, the lifecycle cost estimate includes instrument development, bus development, integration, assembly and testing, launch, 5 or 10 years of operations (5 for LEO satellites, 10 for GEO satellites) and overhead cost. The bus cost model is top-down, with subsystem mass as the main parameter for the cost estimating relationships (CER). CERs are taken from [22]. The mass budget is based on a standard top-down mass budget calculated from payload mass, power and data rate requirements [23]. However, this standard mass budget is modified with mass penalties to account for the engineering issues highlighted in Figure 2. For example, if an active microwave instrument and a passive microwave instrument in the same spectral band are put on the same platform, a penalty of 5% is applied to the structure mass. This penalty can either be interpreted as a real mass penalty (to account for additional structures such as long booms needed to separate the instruments from each other), or as a development cost penalty, capturing the extra engineering required to come up with a configuration that ensures that both instruments will work correctly. Additional details on this mass budget and on the cost model can be found in [15].

Other important programmatic figures of merit are related to schedule and risk. The schedule metric takes into account the fact that in the development of multi-instrument satellites, schedule slippage in less mature instruments affects all the instruments in the platform, thus leading to suboptimal value delivery. From the schedule standpoint, architectures with small dedicated satellites are better than architectures consisting of several monolithic satellites or trains. The risk metric takes into account the risk aversion of most decision makers to put all their assets (instruments) on the same platform. Hence, from the risk standpoint, architectures consisting of either dedicated satellites or trains are preferred over architectures with several monolithic satellites. The schedule and risk metrics are described in further detail in [15].

Modeling Trains of Satellites

In addition to the two main building blocks for EOPs, namely multi-instrument missions and dedicated satellites, a new approach has gained acceptance in the last few years: the use of "trains" of satellites, such as NASA's A-train [24]. A train can be defined as a set of satellites carrying synergistic instruments, which fly in almost identical orbits, with small offsets in true anomaly, local time of the

ascending node (LTAN), or other orbital parameters, so that the satellites appear to "follow" each other.

Since a train consists of independently developed and launched satellites, it does not suffer from most of the engineering and programmatic disadvantages of multi-instrument satellites, while still capturing some of the scientific synergies Note however that satellites in a train are forced to share an orbit, and therefore as explained before, some individual instrument performance might be lost.

Following our previous discussion, multi-instrument missions are preferred when instruments are both highly synergistic and have high engineering compatibility (see Figure 5). Conversely, dedicated satellites are preferred when instruments have little scientific synergies and low engineering compatibility. Opportunities for using trains essentially arise in cases where highly synergistic instruments have low compatibility from either the engineering or programmatic standpoints, and this incompatibility is not related to orbit selection. We labeled the remaining region, for instruments that have low scientific synergies but high engineering compatibility, as opportunity payloads.

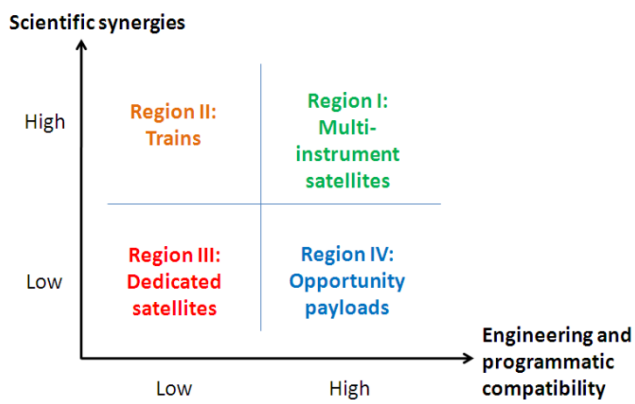


Figure 5: Science synergies vs Engineering compatibility.

As an example, in the A-train, the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) satellite follows Cloudsat at only 15 seconds of difference [24]. While this small difference may be enough to lose some of the fastest events in the atmospheric chemistry of short-lived species [25], many important processes related to, for instance, cloud formation can be considered as constant in the ~10s time scale [26]. Therefore, cross-registration of the data from the lidar in CALIPSO with the data from the radar in Cloudsat is relatively easy, and both data sets can be used in the same models with relatively high confidence.

Although trains can capture some of these scientific synergies, their performance cannot always be compared to that of multi-instrument missions where instruments actually share a platform. As a first approximation, we chose to model this fact using weights for the science synergy rules in trains (1, 2, 3, 4) that are lower than those used for multi-instrument missions (1, 3, 9, 27). Results obtained with this model will thus be dependent on the choice of these weights, and must be complemented with a sensitivity analysis study.

3. APPLICATION TO THE DECADAL SURVEY

Instrument Set

We now apply our tool to the DS instrument set. The original mission set in the DS consists of 17 missions, from which some are multi-instrument satellites, and some are dedicated satellites. No trains were considered in the original DS architecture. As of October 2010, to the best of our knowledge, 39 instruments are considered for the DS including highly uncertain secondary and support instruments (e.g., the laser altimeter in ASCENDS considered to enhance the differential absorption lidar measurement). A major difficulty in this analysis is the high degree of uncertainty existing in the design parameters of most of the instruments in the DS. Except for the five Tier I missions (SMAP, ICESAT-II, DESDYNI, ACE, GPSRO), most of the missions and instruments are still in the early conceptual phases, and it is thus difficult to estimate required instrument characteristics such as mass, power, data rate and dimensions. Parameters used in the analysis come mostly from available on-line sources when possible (NASA website), and from best educated guesses in the other cases.

Instrument Clustering

We first applied our rule-based expert system to the instruments in the DS, and obtained a DSM for scientific synergy (S-DSM) and a DSM for engineering-programmatic compatibility (E-DSM). These matrices are provided in Figure 6 and Figure 7.

In these matrices, both rows and columns represent the same set of 39 instruments from the original DS mission set. For the S-DSM, the value of element *(i,j)* is an assessment of how synergistic instruments *i* and *j* are, with larger values indicating higher synergies. In the case of the E-DSM, the value of element *(i,j)* is an assessment of how incompatible instruments *i* and *j* are from both the engineering and programmatic standpoints. Accordingly, lower values are better. Note that since interactions between instruments *i* and *j* are identical to those between instruments *j* and *i*, the matrix is symmetric. Elements in the main diagonal of both matrices are not used and are arbitrarily set to 1 in the S-DSM and to 0 in the E-DSM.

These matrices contain very large amounts of data and may be difficult to interpret. To facilitate the reading process, cells of similar values are colored. In the S-DSM, any pair of instruments for which there is some synergy is

highlighted in green. Hence, according to these results, the polarimeter in ACE (named ACE_POL in Figure 6 and Figure 7) and the cloud profiling radar in ACE (ACE_CPR in Figure 6 and Figure 7) are synergistic (value of 0.3, green cell) while the ocean altimeter from the SWOT mission and the instruments from the ACE mission are not. Concerning the E-DSM, the color code is as follows: green indicates highly compatible pairs of instruments; yellow and red indicate mild and severe incompatibilities. For instance, we observe two large red zones in the E-DSM corresponding to the separation between GEO and LEO instruments. Conversely, the instruments in the GEO-CAPE mission are found to be highly compatible (green cells).

For completeness, the reference DS architecture is indicated using black lines. Note that in general, the missions in the DS are relatively good matches both in terms of science and engineering, with very few exceptions. This does not imply that there are not good alternative architectures. In fact, we observe that there are other opportunities in terms of synergistic instruments, such as the scatterometers in XOVWM and the radar altimeter in SWOT, or the ocean color instrument in ACE.

Cluster Exploration

We now consider one of the clusters of instruments, namely the four instruments in the ASCENDS mission: the CO_2/O_2 differential absorption lidar (DIAL), the CO gas correlation radiometer (GCR), the six-channel infrared radiometer (IRR), and the laser altimeter (LALT). The number of possible architectures for a set of four instruments is 35 (or 15 if we do not take into account architectures with trains), and therefore full factorial evaluation is possible. We chose this relatively small cluster as an example for ease of illustration. The charts presented in the next figures get more difficult to read for larger clusters.

Visualizing several dozens of architectures in five dimensions (cost, schedule, risk, science synergy and science performance) is a very difficult task and the subject of research itself [27]. A typical approach is to combine several metrics into a single one to reduce dimensionality and allow the use of standard 2D or 3D visualization tools. In this case, we chose to use the average of the two science metrics as a combined science metric, and the average of the schedule and risk metrics as a combined robustness metric. We plot in Figure 8 science versus robustness for all 35 architectures. Lifecycle cost is also indicated for each architecture through the use of color. The values of lifecycle cost obtained for the 35 architectures are classified in five bins from least costly ones (orange points) to the most costly ones (black points).

We now define two terms to be used in the rest of the section. An architecture is non-dominated in the Pareto sense if there exists no other architecture that is better than the former in all metrics simultaneously. Hence, the set of non-dominated solutions for a multi-objective optimization problem is the equivalent of the optimal solution for a single-objective optimization problem. The utopia point is defined as the point on the objective space that has the highest possible score for all metrics. Note that this point does not correspond to a real design, since in real life figures of merit are usually conflicting and compromises are necessary.

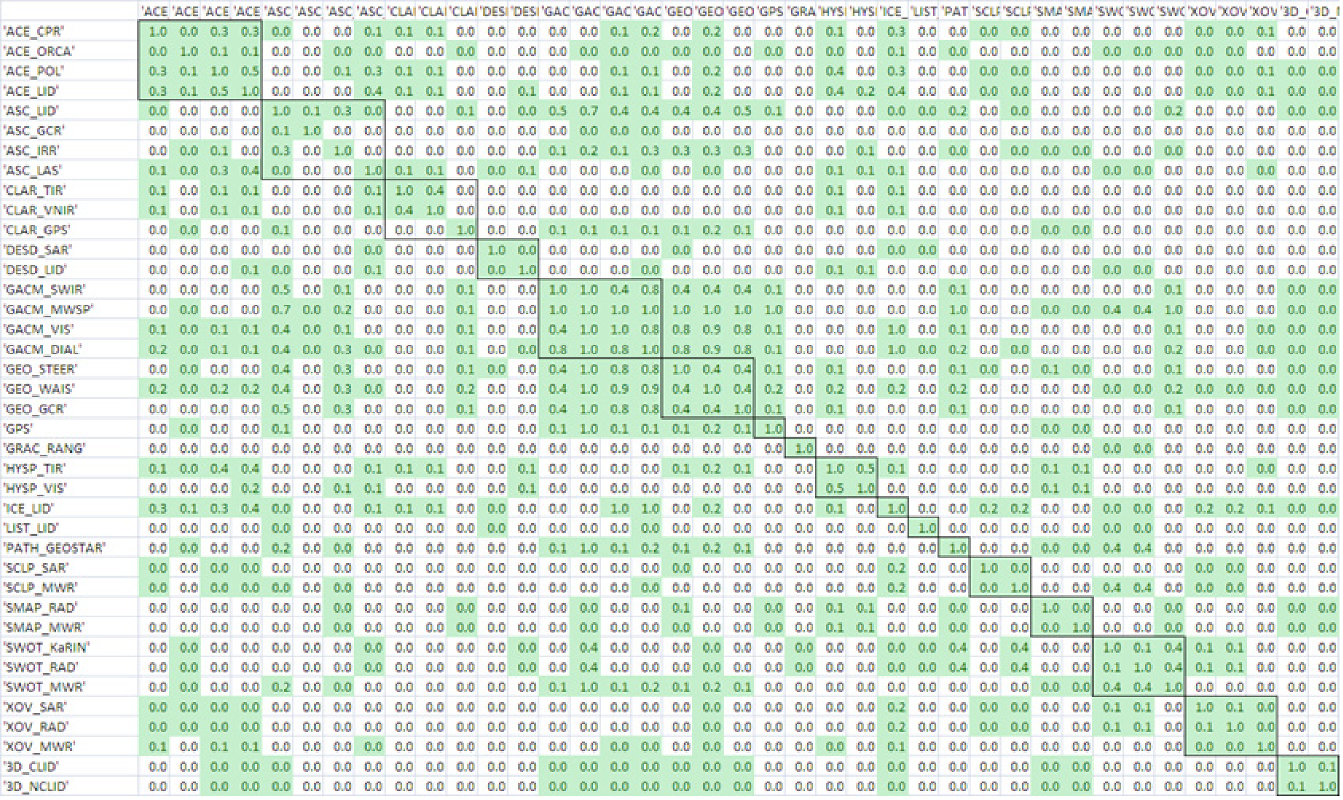
Non-dominated architectures with respect to the three metrics are circled in green in Figure 8. The utopia point and the reference architecture, i.e. a monolithic satellite carrying the 4 instruments, are also included in the plot for comparison. Note that all metrics are normalized and Large-Is-Better (LIB) metrics, which implies that the utopia point is an orange circle (least costly) on the top right corner (maximum robustness and maximum science).

Architecture selection

The next step is the selection of a subset of architectures for further studies. Several strategies can be used to select a subset of optimal architectures in a multi-objective optimization problem. One strategy is to pick the subset of non-dominated architectures a.k.a. Pareto front, or more loosely, a fuzzy Pareto frontier as defined in [6]. In a fuzzy Pareto frontier, designs that are "close" to the real Pareto frontier are also retained even though they are dominated. This is justified for at least two reasons: 1) there is modeling uncertainty that makes it difficult to discriminate similar designs; 2) there is uncertainty in all the other processes of the system development process, and designs on the real Pareto frontier are usually the least robust to these uncertainties [6]. Another strategy is to select the architectures that are closest to the utopia point using, for example, Euclidean distance. A third strategy is to rank the architectures based on a weighted average of all the metrics, as done in Figure 9.This approach comes from multi-attribute utility theory [28] and has been widely used in system design [29].

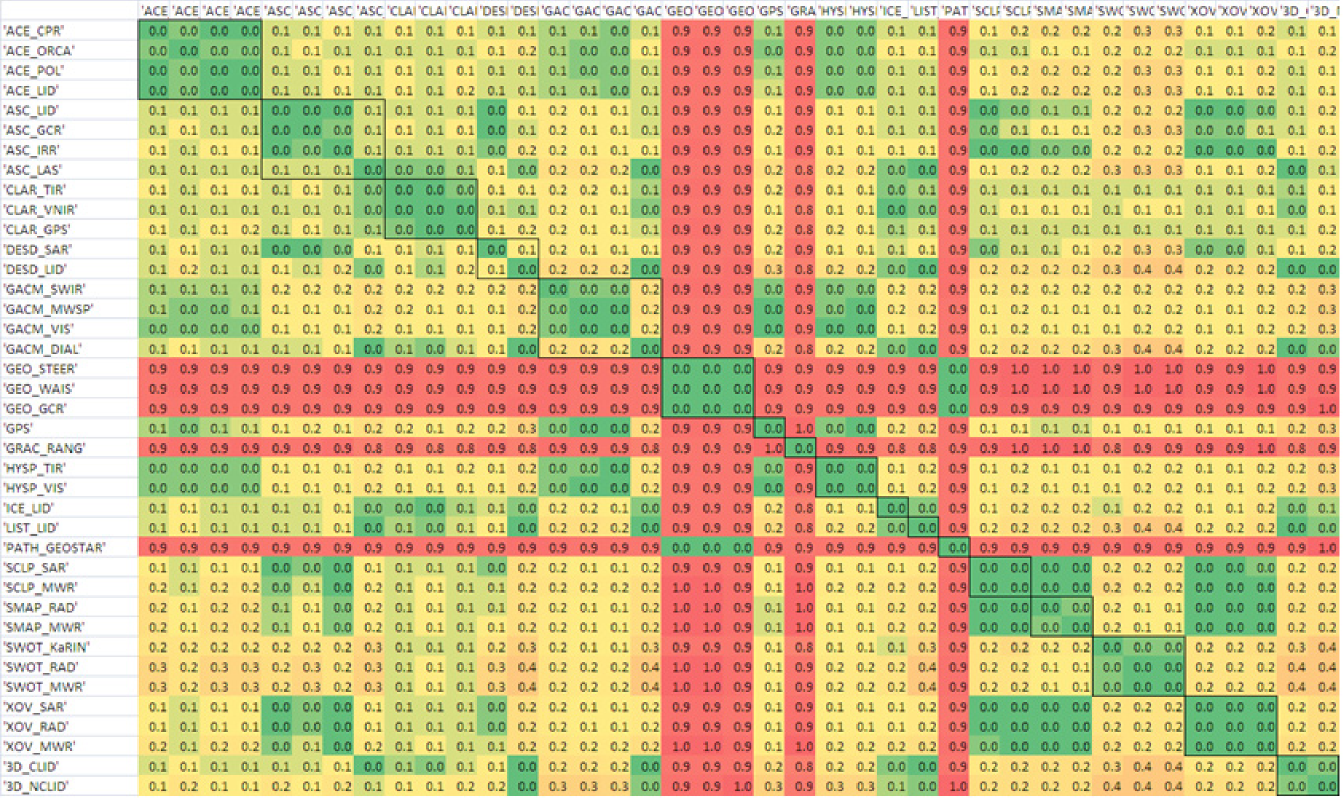
Note that the reference architecture, consisting of only one satellite, is non-dominated because it is the most affordable, and is ranked second in overall utility when science, affordability, schedule and risk are equally weighted. On the other side of the spectrum, we highlight that the architecture consisting of a single train, with the four instruments flying in dedicated satellites, is also non-dominated. A few good architectures between these extremes are shown, consisting of either two or three satellites. Regardless of the architecture selection method, some of the top ranked and non-dominated architectures include a train of two or more dedicated satellites.

The methodology illustrated in this section can be repeated for all remaining clusters. The result of this process will be a selection of a subset of good architectures for each individual cluster. These architectures need to be studied in more detail at the mission level, as opposed to the program level.



	'ACE	'ACE	'ACE	'ACE	'ASC	'ASC	'ASC	'ASC	'CLAI	'CLAI	'CLAI	'DESI	'DESI	'GAC	'GAC	'GAC	'GAC	'GEO	'GEO	'GEO	'GPS	'GRA	'HYSI	'HYSI	'ICE_	'LIST	'PAT	'SCLI	'SCLI	'SMA	'SMA	'SWC	'SWC	'SWC	'XOV	'XOV	'XOV	'3D_	'3D_I
'ACE_CPR'	1.0	0.0	0.3	0.3	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.2	0.0	0.0	0.0	0.1	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0
'ACE_ORCA'	0.0	1.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'ACE_POL'	0.3	0.1	1.0	0.5	0.0	0.0	0.1	0.3	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.2	0.0	0.0	0.0	0.4	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0
'ACE_LID'	0.3	0.1	0.5	1.0	0.0	0.0	0.0	0.4	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.0	0.2	0.0	0.0	0.0	0.4	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0
'ASC_LID'	0.0	0.0	0.0	0.0	1.0	0.1	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.5	0.7	0.4	0.4	0.4	0.4	0.5	0.1	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0
'ASC_GCR'	0.0	0.0	0.0	0.0	0.1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'ASC_IRR'	0.0	0.0	0.1	0.0	0.3	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.1	0.3	0.3	0.3	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'ASC_LAS'	0.1	0.0	0.3	0.4	0.0	0.0	0.0	1.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'CLAR_TIR'	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.1	1.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'CLAR_VNIR'	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.4	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'CLAR_GPS'	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'DESD_SAR'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'DESD_LID'	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'GACM_SWIR'	0.0	0.0	0.0	0.0	0.5	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	1.0	1.0	0.4	0.8	0.4	0.4	0.4	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
'GACM_MWSP'	0.0	0.0	0.0	0.0	0.7	0.0	0.2	0.0	0.0	0.0	0.1	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.4	0.4	1.0	0.0	0.0	0.0	0.0	0.0
'GACM_VIS'	0.1	0.0	0.1	0.1	0.4	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.4	1.0	1.0	0.8	0.8	0.9	0.8	0.1	0.0	0.0	0.0	1.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
'GACM_DIAL'	0.2	0.0	0.1	0.1	0.4	0.0	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.8	1.0	0.8	1.0	0.8	0.9	0.8	0.1	0.0	0.0	0.0	1.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0
'GEO_STEER'	0.0	0.0	0.0	0.0	0.4	0.0	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.4	1.0	0.8	0.8	1.0	0.4	0.4	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
'GEO_WAIS'	0.2	0.0	0.2	0.2	0.4	0.0	0.3	0.0	0.0	0.0	0.2	0.0	0.0	0.4	1.0	0.9	0.9	0.4	1.0	0.4	0.2	0.0	0.2	0.0	0.2	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0
'GEO_GCR'	0.0	0.0	0.0	0.0	0.5	0.0	0.3	0.0	0.0	0.0	0.1	0.0	0.0	0.4	1.0	0.8	0.8	0.4	0.4	1.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
'GPS'	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.1	0.1	0.1	0.2	0.1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'GRAC_RANG'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'HYSP_TIR'	0.1	0.0	0.4	0.4	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.2	0.1	0.0	0.0	1.0	0.5	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'HYSP_VIS'	0.0	0.0	0.0	0.2	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'ICE_LID'	0.3	0.1	0.3	0.4	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.2	0.0	0.0	0.0	0.1	0.0	1.0	0.0	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.1	0.0	0.0
'LIST_LID'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'PATH_GEOSTAR'	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.1	0.2	0.1	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.4	0.4	0.0	0.0	0.0	0.0	0.0	0.0
'SCLP_SAR'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'SCLP_MWR'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	1.0	0.0	0.0	0.4	0.4	0.0	0.0	0.0	0.0	0.0	0.0
'SMAP_RAD'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'SMAP_MWR'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
'SWOT_KaRIN'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.4	0.0	0.0	1.0	0.1	0.4	0.1	0.1	0.0	0.0	0.0
'SWOT_RAD'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.4	0.0	0.0	0.1	1.0	0.4	0.1	0.1	0.0	0.0	0.0
'SWOT_MWR'	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.1	0.2	0.1	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.4	1.0	0.0	0.0	0.0	0.0	0.0
'XOV_SAR'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	1.0	0.1	0.0	0.0	0.0
'XOV_RAD'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	1.0	0.0	0.0	0.0
'XOV_MWR'	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
'3D_CLID'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.1
'3D_NCLID'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0

Figure 6: S-DSM for the DS. Rows and columns represent the same set of instruments. Black lines represent the reference architecture presented in the DS. Green highlights synergistic instruments.



	'ACE	'ACE	'ACE	'ACE	'ASC	'ASC	'ASC	'ASC	'CLAI	'CLAI	'CLAI	'DESI	'DESI	'GAC	'GAC	'GAC	'GAC	'GEO	'GEO	'GEO	'GPS	'GRA	'HYSI	'HYSI	'ICE_	'LIST	'PAT	'SCLI	'SCLI	'SMA	'SMA	'SWC	'SWC	'SWC	'XOV	'XOV	'XOV	'3D_	'3D_I
'ACE_CPR'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.9	0.9	0.9	0.1	0.9	0.0	0.0	0.1	0.1	0.9	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.1	0.1	0.2	0.1	0.1
'ACE_ORCA'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.0	0.0	0.1	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.1	0.1	0.9	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.2
'ACE_POL'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.1	0.9	0.9	0.9	0.1	0.9	0.0	0.0	0.1	0.1	0.9	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.1	0.1	0.2	0.1	0.1
'ACE_LID'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.0	0.1	0.9	0.9	0.9	0.1	0.9	0.0	0.0	0.1	0.1	0.9	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.1	0.1	0.2	0.1	0.1
'ASC_LID'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.1	0.9	0.9	0.9	0.1	0.9	0.1	0.1	0.1	0.1	0.9	0.0	0.0	0.1	0.1	0.2	0.2	0.2	0.0	0.0	0.0	0.1	0.2
'ASC_GCR'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.1	0.9	0.9	0.9	0.2	0.9	0.1	0.1	0.1	0.1	0.9	0.0	0.1	0.1	0.1	0.2	0.3	0.3	0.0	0.0	0.1	0.1	0.1
'ASC_IRR'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.2	0.2	0.1	0.1	0.1	0.9	0.9	0.9	0.1	0.9	0.1	0.1	0.1	0.1	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.1	0.2
'ASC_LAS'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.0	0.9	0.9	0.9	0.2	0.8	0.2	0.2	0.0	0.0	0.9	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.1	0.1	0.2	0.0	0.1
'CLAR_TIR'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.2	0.2	0.1	0.1	0.9	0.9	0.9	0.2	0.9	0.1	0.1	0.0	0.1	0.9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
'CLAR_VNIR'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.2	0.1	0.1	0.0	0.9	0.9	0.9	0.1	0.8	0.1	0.1	0.0	0.0	0.9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1
'CLAR_GPS'	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.2	0.2	0.1	0.1	0.1	0.9	0.9	0.9	0.2	0.8	0.2	0.1	0.1	0.1	0.9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2
'DESD_SAR'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.1	0.9	0.9	0.9	0.2	0.9	0.1	0.1	0.1	0.1	0.9	0.0	0.1	0.1	0.1	0.2	0.3	0.3	0.0	0.0	0.1	0.1	0.2
'DESD_LID'	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.0	0.1	0.1	0.2	0.1	0.0	0.2	0.2	0.2	0.0	0.9	0.9	0.9	0.3	0.8	0.2	0.2	0.0	0.0	0.9	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.2	0.2	0.2	0.0	0.0
'GACM_SWIR'	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.2	0.2	0.9	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
'GACM_MWSP'	0.1	0.0	0.0	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.2	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.2	0.2	0.9	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.2	0.3
'GACM_VIS'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.1	0.2	0.9	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.2	0.3
'GACM_DIAL'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.0	0.9	0.9	0.9	0.2	0.8	0.2	0.2	0.0	0.0	0.9	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.2	0.2	0.2	0.0	0.0
'GEO_STEER'	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.0	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.9	1.0	1.0	1.0	0.9	1.0	1.0	0.9	0.9	1.0	0.9	0.9
'GEO_WAIS'	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.0	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.9	1.0	1.0	1.0	0.9	1.0	1.0	0.9	0.9	1.0	0.9	0.9
'GEO_GCR'	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.0	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0
'GPS'	0.1	0.0	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.1	0.2	0.2	0.3	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	1.0	0.0	0.0	0.2	0.2	0.9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3
'GRAC_RANG'	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.8	0.8	0.9	0.8	0.9	0.9	0.9	0.8	0.9	0.9	0.9	1.0	0.0	0.9	0.9	0.8	0.8	0.9	0.9	1.0	1.0	1.0	0.8	0.9	0.9	0.9	0.9	1.0	0.8	0.9
'HYSP_TIR'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.2	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.1	0.2	0.9	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.2	0.3
'HYSP_VIS'	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.0	0.0	0.0	0.2	0.9	0.9	0.9	0.0	0.9	0.0	0.0	0.1	0.2	0.9	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.2	0.3
'ICE_LID'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.2	0.2	0.1	0.0	0.9	0.9	0.9	0.2	0.8	0.1	0.1	0.0	0.0	0.9	0.1	0.2	0.2	0.2	0.1	0.2	0.2	0.1	0.1	0.2	0.0	0.1
'LIST_LID'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.0	0.9	0.9	0.9	0.2	0.8	0.2	0.2	0.0	0.0	0.9	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.2	0.2	0.2	0.0	0.0
'PATH_GEOSTAR'	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.0	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0
'SCLP_SAR'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.2	0.2	0.1	0.1	0.2	0.9	0.9	0.9	0.1	0.9	0.1	0.1	0.1	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2
'SCLP_MWR'	0.2	0.1	0.2	0.2	0.0	0.1	0.0	0.2	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	1.0	1.0	0.9	0.1	1.0	0.2	0.2	0.2	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2
'SMAP_RAD'	0.2	0.1	0.2	0.2	0.1	0.1	0.0	0.2	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	1.0	1.0	0.9	0.1	1.0	0.1	0.1	0.2	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2
'SMAP_MWR'	0.2	0.1	0.2	0.2	0.1	0.1	0.0	0.2	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	1.0	1.0	0.9	0.1	1.0	0.1	0.1	0.2	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2
'SWOT_KaRIN'	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.1	0.1	0.1	0.2	0.3	0.2	0.1	0.1	0.3	0.9	0.9	0.9	0.1	0.8	0.1	0.1	0.1	0.3	0.9	0.2	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2	0.2	0.3	0.4
'SWOT_RAD'	0.3	0.2	0.3	0.3	0.2	0.3	0.2	0.3	0.1	0.1	0.1	0.3	0.4	0.2	0.2	0.2	0.4	1.0	1.0	0.9	0.1	0.9	0.2	0.2	0.2	0.4	0.9	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2	0.2	0.4	0.4
'SWOT_MWR'	0.3	0.2	0.3	0.3	0.2	0.3	0.2	0.3	0.1	0.1	0.1	0.3	0.4	0.2	0.2	0.2	0.4	1.0	1.0	0.9	0.1	0.9	0.2	0.2	0.2	0.4	0.9	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2	0.2	0.4	0.4
'XOV_SAR'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.2	0.2	0.1	0.1	0.2	0.9	0.9	0.9	0.1	0.9	0.1	0.1	0.1	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2
'XOV_RAD'	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.2	0.2	0.1	0.1	0.2	0.9	0.9	0.9	0.1	0.9	0.1	0.1	0.1	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2
'XOV_MWR'	0.2	0.1	0.2	0.2	0.0	0.1	0.0	0.2	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	1.0	1.0	0.9	0.1	1.0	0.2	0.2	0.2	0.2	0.9	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.2	0.2
'3D_CLID'	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.0	0.9	0.9	0.9	0.2	0.8	0.2	0.2	0.0	0.0	0.9	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.2	0.2	0.2	0.0	0.0
'3D_NCLID'	0.1	0.2	0.1	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.0	0.3	0.3	0.3	0.0	0.9	0.9	1.0	0.3	0.9	0.3	0.3	0.1	0.0	1.0	0.2	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.2	0.2	0.0	0.0

Figure 7: E-DSM for the DS. Rows and columns represent the same set of instruments. Black lines represent the reference architecture presented in the DS. Green (red) indicates highly compatible (incompatible) instruments.

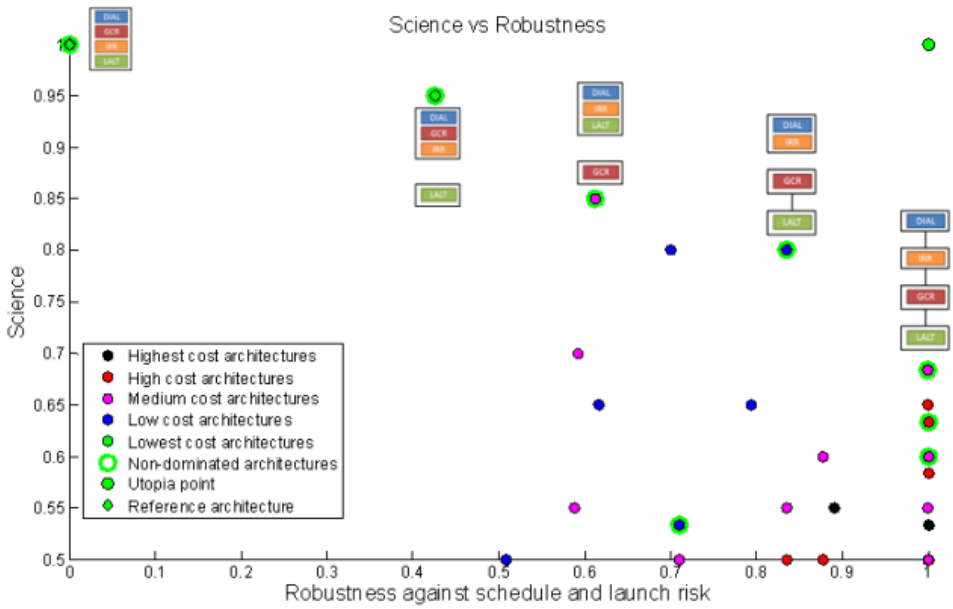


Figure 8: Combined science versus robustness and affordability for 35 architectures for the ASCENDS mission. Each point represents an architecture. Non-dominated architectures are highlighted in green. The reference architecture and the utopia point are included for completeness. Five of the best architectures are explicitly shown with colored rectangles and black lines. Each colored rectangle represents an instrument. Black rectangles represent satellites. Satellites united by a black line represent trains.

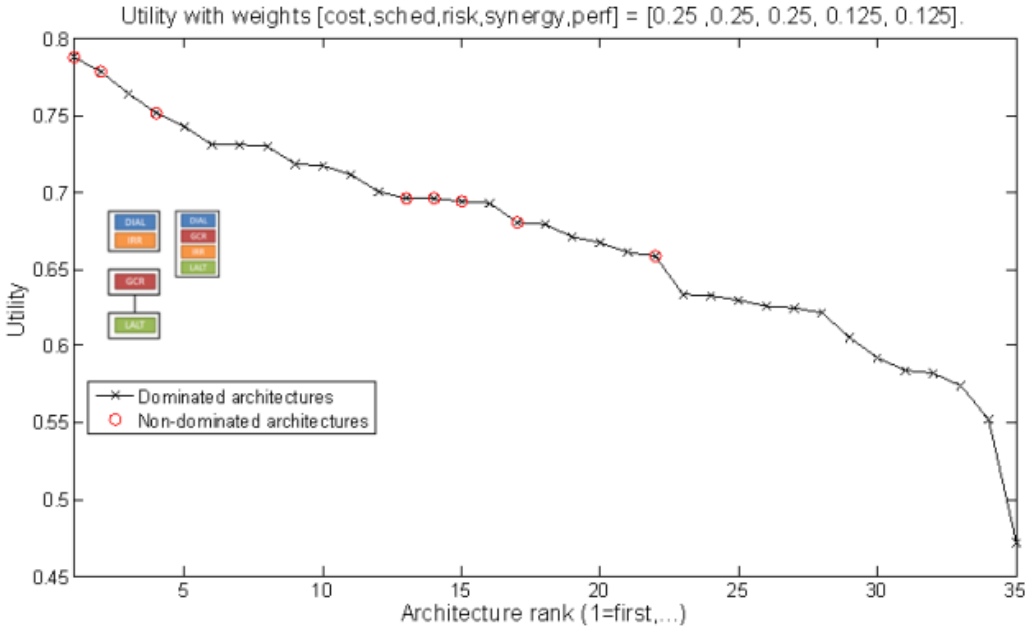


Figure 9: Ranking of the 35 packaging architectures for the ASCENDS mission in terms of overall utility. Each cross represents an architecture. Non dominated architectures are circled in red. Top two architectures are explicitly shown using colored rectangles and lines.

4. CONCLUSION

Accomplishments

We presented an integrated tool to support the systems architecting process of an Earth Observation Program and applied it to the Decadal Survey.

Such a tool is not meant to replace system architects, but rather to enhance the architecting process by assisting the system architects in the tasks in which they are less proficient: exhaustiveness in the search of the tradespace, and systematic computation and visualization of several figures of merit for a large number of architectures.

We identified scientific synergies between measurements and engineering (in)compatibility between instruments as key modeling issues, and designed a rule-based expert system to account for them. Expert knowledge was acquired through interviews, and expressed as logical rules understandable by the computational tool.

We devised a 3-step architecting methodology for EOPs: 1) create the science DSM (S-DSM) and the engineering DSM (E-DSM) of the set of instruments using the rule-based expert system; 2) use the S-DSM, the E-DSM and a clustering algorithm to decompose the set of instruments in clusters of highly synergistic instruments; 3) exhaustively explore the architectural tradespace of each individual cluster using either full factorial enumeration or a meta-heuristic algorithm. A sensitivity analysis is necessary at the end to assess the dependence of the results on the modeling assumptions, in particular the clustering in step 1.

We applied the first step of the methodology to the DS instrument set and concluded that, with few exceptions, the original mission set makes sense from both the science and engineering standpoints. However, some opportunities for improvement were identified, in particular concerning the ASCENDS mission or a potential oceanography instrument cluster including instruments from SWOT, XOVWM and ACE.

We took one of the clusters from step 1, namely the ASCENDS cluster, and performed a comprehensive exploration of the tradespace using full factorial enumeration (step 3). We concluded that although the current baseline architecture is non-dominated and well-ranked, alternative architectures including trains are also non-dominated and potentially preferable to the baseline, if the decision makers put a high value on the robustness metrics.

Limitations and Future Work

Scientific synergies are one of the key issues in the instrument packaging problem. We used a rule-based expert system as the cornerstone of our scientific synergy model. The performance of rule-based expert systems depends highly on the number and quality of the rules in the database. Hence, we will continue to expand our database by doing more expert interviews.

In order to have a more complete set of results, an exhaustive sensitivity analysis is needed. Since the number of parameters in the model is very high, this is a long process that is currently being performed.

Much potential exists to add man-in-the-loop capabilities to computational tools supporting the system architecting process. For instance, a user can guide the search of the tradespace, add or remove architectures from the tradespace, or provide initial populations for optimization algorithms to name a few options. The challenge remains in efficiently allocating functions to the system architect and to the computational tool. This is certainly a direction to be explored in further research.

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ACRONYMS

ACE: Aerosol-Clouds-Ecosystems
ASCENDS: Active Sensing of CO2 Emissions over Nights, Days, and Seasons
CALIPSO: The Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation
CEOS: Committee on Earth Observation Satellites
CER: Cost Estimating Relationship
CO: Carbon monoxide
CO_2: Carbon dioxide
DESDYNI: Deformation, Ecosystem Structure and Dynamics of Ice
DIAL: Differential Absorption Lidar
DS: Decadal Survey
DSM: Design Structure Matrix
E-DSM: Engineering Design Structure Matrix
EOP: Earth Observation Program
ESTEC: European Space Research and Technology Centre
GCR: Gas filter Correlation Radiometer
GEO: Geostationary Earth Orbit
GPSRO: Global Positioning System Radio Occultation
ICESAT: Ice, Cloud, and land Elevation Satellite
IRR: InfraRed Radiometer
LALT: Laser ALTimeter
LEO: Low Earth Orbit
LIB: Large-Is-Better
LTAN: Local time of the Ascending Node
MIT: Massachusetts Institute of Technology
NASA: National Aeronautics and Space Administration
NESDIS: National Environmental Satellite Data and Information Service
NOAA: National Oceanic and Atmospheric Administration
NRC: National Research Council
O_2: Molecular oxygen

S-DSM: Science Design Structure Matrix
SMAP: Soil Moisture Active-Passive
SSB: Space Studies Board
SWOT: Surface Water and Ocean Topography
USGS: United States Geological Survey
XOVWM: Extended Ocean Vector Wind Measurement

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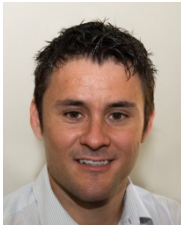
BIOGRAPHIES



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