Integrated Assessment of Packaging Architectures in Earth Observing Programs

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Abstract—When designing Earth observation missions, it is essential to take into account the programmatic context. Considering individual missions as part of a whole enables overall program optimization, which may bring important cost reductions and scientific and societal benefits.[1][2]

Several implementation trade-offs arise in the architecting process of an Earth Observation program such as NASA's National Polar-orbiting Operational Environmental Satellite System (NPOESS) or ESA's Earth Explorers. Such trade-offs include choosing between large satellites and small satellites, standard buses and tailored buses, or centralized architectures versus clusters or trains of satellites. This work focuses on packaging problems, i.e. the assignment of instruments to satellites. More precisely, we study the trade-off between multi-instrument platforms – satellites that carry more than one instrument - versus dedicated satellites carrying a single instrument.

Our approach to the problem takes a systems engineering perspective and consists of three steps: first, a historical review of past Earth observation programs was done in order to gain insight into how decision makers have solved this trade-off in the past; second, we performed a qualitative analysis in which the most important issues of the trade-off were identified; third, a quantitative analysis was done based on an architecting model. The architecting model is multi-disciplinary because it takes a holistic view of the problem by considering at the same time scientific, engineering and programmatic issues. This exhaustive and multi-disciplinary exploration of the architectural tradespace can be very useful in the early steps of program architecting and could be a valuable tool to support decision making. The model is applied to ESA's Envisat satellite as an example. Finally, some general insights on the architecture of an Earth Observation Program that we gained by developing and applying this methodology are provided.

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1. INTRODUCTION

It has been almost 50 years since the launch of the first Earth observation satellite, TIROS-1 (Television Infrared Observation Satellite) in 1960. Since then, several other missions and programs have been architected and designed in Europe, the US and around the world. One could argue that the fundamental needs behind these programs have not changed (to get a better understanding of Earth science, to provide data for weather forecast and imagery for operational applications.) However, their architecture has greatly evolved over time: there have been programs with small missions costing less than $100M and programs with very large missions beyond $2 billion; programs based on large multi-instrument platforms and programs based on dedicated satellites; programs based on single satellites and programs based on constellations or clusters of satellites flying in formation; programs using standard commercially available buses and program using ad-hoc designed buses. Mission size, number of instruments per satellite or use of standard versus dedicated buses are some of the trade-offs that appear when architecting an Earth observation program. This paper focuses on one particular trade-off, namely the assignment of instruments to satellites.

The decisions that were made in the past concerning this and other trade-offs were different depending on the specific needs and context of the program. This work looks at how

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these decisions were made in the past, infers the main categories of issues behind the decisions and provides insight into how a systematic approach using system architecting techniques can be used for improved architecting of future programs.

This is not the first attempt to study packaging problems. As we mentioned before, NASA, ESA and other agencies have already faced this problem in the past. Unfortunately most of the relevant work by industry remains in the form of internal reports because industry is reluctant to release sensitive data. The work by Rasmussen is one of the few traces of this kind of work by industry. Rasmussen analyzes the trade-off between small and large Earth observing satellites in [1] and [2]. Some work also exists from academia. Matossian used a mixed integer programming algorithm to optimize NASA's Earth Observing System (EOS) using several metrics including cost and performance [3], [4]. In addition, the National Research Council (NRC) and the independent RAND Corporation have also contributed with reports on related studies such as references [5], [6], [7] and [8].

Sadly most of these references date from the late nineties. No relevant reference concerning the formal analysis of packaging problems in Earth observation programs was found that dates from the last five years. Furthermore, these previous attempts to analyze this complex multi-disciplinary suffer from either of these two main limitations: they explore a reduced number of architectures (typically 3 or 4); they consider only part of the problem (scientific or engineering issues are not treated). [3] and [4] took a similar approach to ours to analyze the particular case of NASA's Earth Observing System, but they did not explicitly consider engineering issues that we believe are a key factor in the trade-off. Schedule is also not taken into account.

2. APPROACH

Perhaps the most important contribution of this paper is that the problem is approached from a holistic, multi-disciplinary systems engineering perspective.

The methodology used to approach this problem has three steps:

(1) Historical study: We looked at past Earth observation missions and programs with focus in particular in how instruments were assigned to satellites. Understanding the reasons behind these decisions provides valuable insight into the main issues to take into account in the analysis.

(2) Qualitative analysis: Based on the findings of the historical study and on interviews with expert systems engineers, we identified the main advantages and disadvantages of multi-instrument satellites and dedicated satellites.

(3) Quantitative analysis: We built a quantitative and executable model that for a given set of instruments can explore millions of different architectures and identify the most promising ones taking into account all the issues identified in the qualitative analysis. An essential task in this step is to perform a sensitivity analysis to study the influence of the results to the inputs and parameters of the model. This provides indeed valuable insight into how sensitive is the system to the different issues.

This methodology could be extended to the study of other single axis architectural trade-offs. For instance, the trade-off between standard buses and ad-hoc designed buses could be approached in a similar fashion. There are several examples in the past where standard buses were used and many others were the decision makers selected an ad-hoc design for the bus. A historical study of the reasons behind these decisions could provide some initial insight into the main issues behind the trade-off. Then, on the basis of these findings and with the help of experts, the major advantages and disadvantages of the two strategies could be identified. Finally, a quantitative model that is sensitive to those issues could be built and run in order to analyze the trade-off from a multi-disciplinary perspective.

3. HISTORICAL NOTES

A comprehensive review of the history of Earth observation missions and instruments can be found in reference [9]. References [10] and [11] are also rich in useful information on missions and payloads. These three documents were used to perform a comprehensive historical review of American and European Earth observation missions and programs. For the sake of brevity, only a few notes concerning selected programs are presented in this paper.

The first coordinated series of civil Earth observation missions appeared in the early 60's with the US meteorological program, TIROS. In these early years, Earth observing programs were mostly based on small dedicated satellites mainly due to risk and technological considerations: only three years had passed since the launch of Sputnik I in 1957; space technology was still incipient and in particular launch capability was still very limited. Furthermore, almost every satellite in the TIROS series brought a major technological advance: TIROS-6 was first used for snow cover analysis in 1962; TIROS-8 was the first satellite to be equipped with an automatic picture transmission system.

No major architectural changes appeared with the follow-on of TIROS: the TOS/ESSA series (1966-69) and the ITOS/NOAA series (1970-76). In 1978, the advanced TIROS-N was launched with a completely different approach based on heavier satellites (700kg at the beginning, 1400-1700kg after) launched at a slower tempo (11 satellites in 16 years). With the advanced TIROS-N, the paradigm of larger multi-instrument platforms for operational meteorology was established. This architectural change is explained in part by increased payload capabilities and more demanding requirements. As more and more powerful instruments were built, scientists were able to do better science which led them to have more stringent requirements, thus asking for even more massive and powerful instruments. On the other hand, advances in space technology and launch capability permitted to design, build and launch more massive and long lasting satellites into space. Furthermore, a new element was introduced into the system, namely downward budget pressures after the end of the Cold War which brought about the idea of sharing the bus between several instruments to reduce bus and launch cost. And last but not least, more complex scientific models made scientists become conscious of the technical problems related to data cross-registration.

The trend of larger multi-instrument platforms became an architectural paradigm in the late 80's and 90s not only for operational Earth observation but also for scientific programs. Envisat (10 instruments, 8 mt) and Metop (12 instruments, 4 mt) are the best examples of large observatories in Europe. UARS, TRMM and EOS Terra/Aqua/Aura are the best examples in the US. Note that both Envisat/Metop and EOS are downgraded versions of their initial architectures. The initial EOS program with 38 instruments was conceived to be launched in very large 15mt platforms aboard the Space Shuttle. Envisat and Metop were first designed to be part of a single spacecraft, the Polar Orbiting Earth Mission (POEM [12]).

This was the culmination of the architectural paradigm of large observatories. However both ESA and NASA experienced a number of problems during the development of these missions that would make them reconsider this architectural choice in the future. ESA Engineers for instance recognize that several engineering issues (e.g. mechanical or EMC problems between instruments) appeared in the development of Envisat. Designing, building and testing such complex systems proved indeed to be a very challenging endeavor.

Thus little after, and perhaps partially reacting to the aforementioned problems, the concept of small dedicated missions was re-born with programs such as NASA's Small Explorers (SMEX). The idea behind such programs was that a variety of scientific objectives can be achieved by small missions with usually a single instrument with lower costs and shorter development times than larger missions.

In the last years, both NASA and ESA seem to have adopted a strategy mainly based on small (1mt) dedicated missions for Earth science (ESA Earth Explorers, NASA Earth Science System Pathfinder). Mid-size platforms remain used for operational applications which have lower risk and require longer lifetimes (future NASA/NOAA's NPOESS and ESA/Eumetsat's EPS).

Although very succinct, these historical notes allow the identification of some of the most important categories of issues behind the decision of assigning instruments to satellites:

(1) Scientific issues: there are benefits to the scientific community in flying synergistic instruments on the same platform. Scientific issues were an important factor on the decision to build large observatories such as EOS, Envisat and Metop.

(2) Engineering issues: a variety of engineering issues such as mechanical and EMC problems appear when designing, building and testing multi-instrument satellites. These issues probably played an important role in the paradigm change that led to the creation of small missions programs such as NASA's SMEX or ESA's EE.

(3) Programmatic issues: cost, schedule and risk issues continuously appeared as important drivers for almost all the decisions made in the past. For instance, the potential savings in bus and launch cost were important factors supporting the decision to build large observatories, and reductions in development time and cost drove the decision of creating NASA's SMEX or ESA's EE.

4. QUALITATIVE ANALYSIS

The goal of the second step of the methodology was to identify and describe the driving issues behind the trade-off between multi-instrument satellites and dedicated satellites. Some insight into what these main architectural drivers are was already provided by the historical analysis, in which three main categories of issues were identified: scientific issues, engineering issues and programmatic issues. In this section, we present a more detailed description of these issues. The discussion provided here is mainly qualitative and is based on several interviews held with senior systems engineers at the European Space Research and Technology Center (ESTEC) during the summer of 2009.

Scientific issues

As pointed out previously, most people currently concur that the quality of the science that comes from a set of remote sensing instruments can be improved if several instruments share a common platform. This is due to various reasons:

(1) Most modern scientific models (e.g. climate models) require more than one measurement to be taken simultaneously on the same geographical zone. For instance, carbon cycle models require not only the measurement of CO_2 atmospheric concentration, but also atmospheric concentration of O_2, CO or other trace gases, atmospheric pressure and temperature.

(2) Secondary measurements can improve the quality of primary measurements by providing for example

atmospheric correction or precise geolocation. The typical example are altimetry missions in which the main instrument (a radar or laser altimeter) is usually accompanied by a broadband microwave radiometer for atmospheric correction and some kind of navigating instrument (e.g. a DORIS , GPS or laser retro-reflector) to provide high precision geolocation.

(3) Certain instruments are complementary in the sense that they provide the same measurements under different conditions such as daytime or weather. For instance, an instrument with spectral bands on the visible region may capture well a phenomenon on the Earth during day and sunny weather but it will not work on a cloudy day or during night; thus an equivalent passive instrument with bands on the infrared or an active instrument may provide measurements during night and may see through clouds.

(4) The reliability of a given measurement can be increased by observing it using two different instruments, regardless of the nature of the instrument.

All these factors generally translate more or less directly into strong coregistration requirements that are naturally met on a multi-instrument platform. Therefore, it can be considered that multi-instrument satellites are generally preferable in terms of these scientific issues.

However, it should be noted that current advances in distributed systems, formation flying and miniaturization are diminishing the cost of data cross-registration in clusters of small satellites commonly called "trains" of satellites flying in almost identical orbits with only a few minutes difference in local time (e.g. the A-train). Trains of satellites provide near simultaneous measurements of the same geographical zones with minimum coregistration effort and are generally seen as a good alternative to multi-instrument platforms.

Trains of satellites have not been explicitly considered in this study. As will be shown later, dedicated satellites are assumed to be worse than multi-instrument platforms in terms of data-cross registration. As these technologies continue to advance, this assumption will lose force and it will become necessary to incorporate trains of small satellites into the architectural trade-off. However, this is let for future work.

Engineering issues

A variety of engineering issues appear whenever one tries to design a common bus for several instruments:

(1) Mechanical problems: a common source of engineering problems in multi-instrument platforms are micro-vibrations induced on the platform by one or multiple instruments that are propagated by the structure to the rest of the instruments. The problem arises when on the same platform there are other instruments which are very sensitive to vibrations. For instance, in one of the interviews, a senior engineer at ESA mentioned problems with the IASI instrument on the Metop satellite due to the microvibrations induced by the rest of the instruments on the platform. In that particular case the problem was solved by adding dampers on the instrument to isolate it from its environment, but this obviously had a penalty in development cost during the testing phase.

(2) Electromagnetic Compatibility (EMC) problems: most remote sensing instruments send and/or receive radiation on a certain region of the electromagnetic spectrum. When an active instrument and a passive instrument that use similar spectral bands share a common platform, one may jam the other and EMC problems may arise. Note that it is not necessary that the instruments use the same band in order to see problems appear: harmonics an intermodulation products extend the dangerous zone to regions relatively close but not necessarily identical in the spectrum. EMC problems are extremely difficult to characterize analytically. Hence the most reasonable way to avoid them is by carefully studying the configuration of the satellite and performing extensive testing. Long booms have actually been used in the past to isolate sensitive passive instruments from active instruments (e.g. magnetometers on ESA's Swarm mission, or those on the 3rd generation of GOES spacecraft).

(3) Thermal problems: instruments and bus components all have more or less stringent thermal requirements which may bring forth incompatibilities. For instance, sensors on the mid and thermal infrared (e.g. ADEOS/GLI, MIPAS and AATSR from Envisat and ASTER, MOPITT, AIRS and HIRDLS from NASA's Earth Observing System) usually require active cryocooling that cool down the focal plane to 70 or 80K in order to achieve acceptable signal to noise ratios. These very cold points on the platform need to be sufficiently away from other pieces of equipment requiring ambient temperature (typically secondary batteries). Furthermore, Stirling engines or other cryocoolers induce additional vibrations on the platform. Finally, even in the case of purely passive thermal control, problems appear when multiple instruments "fight" to get a clear view of cold space.

(4) Optical problems: the configuration of the satellite needs to be carefully designed so that the dynamic fields of view of all the instruments are compatible, including calibration sequences. Since most of the instruments on Earth observing satellites share the same observable (the Earth), instruments tend to be all on the nadir face of the spacecraft, further increasing the complexity of the problem.

Most of these problems can be solved using a good dose of engineering skills and creativity. However, this has a price in the mission development process, which can be very expensive in platforms with large numbers of instruments (e.g. ESA's Envisat). Obviously, all these problems are naturally avoided when instruments are flown on dedicated satellites. Therefore, we may say that from the perspective of engineering issues, dedicated satellites are preferable as they usually are easier to design, build and test.

Programmatic issues

Programmatic issues include cost, schedule and risk. It is commonly believed that a very strong programmatic argument that favors multi-instrument satellites is cost. Indeed, both bus and launch cost per instrument tend to be lower in multi-instrument platforms because instruments share a common bus and launch vehicle, and it is usually the case that one large platform is cheaper than two small platforms. However, there are two caveats to this statement: first, because of all the aforementioned engineering issues, the economic advantage of very large platforms may be reduced; and second, a more adequate study of the cost issue must be comprehensive and include all aspects of lifecycle cost as opposed to only bus and launch cost.

Rasmussen performs a cost comparison in [2] which takes into account estimations for operations cost, overhead cost and insurance cost based on historical data. Operations cost per instrument may be higher when instruments are on different satellites. The same seems to be true for the other aspects of lifecycle cost with some exceptions. For instance, one could argue that there is a penalty in “organizational” cost that grows more than linearly with the number of instruments on a platform, because the number of bilateral conflicts which can arise between instruments are proportional to the combinations of all the instruments taken 2 by 2 (i.e. proportional to $n*(n-1)/2$ where n is the number of instruments). This captures facts such as meetings being more difficult to organize when a larger number of different teams are involved, and so forth. All in all, it may be that multi-instrument platforms are cheaper in terms of lifecycle cost per instrument, although the comparison is not as straightforward as one may think.

The situation is reversed when we look at the problem from the point of view of schedule. If we accept that minimizing mission development time, or total time to deploy a set of instruments, are reasonable figures of merit for program schedule, then it seems intuitive that a program based on dedicated missions has more chances of meeting schedule requirements than a program based on a few large multi-instrument platforms. The main reason for this is that when several instruments share a satellite and a launch vehicle, the mission development time and the launch date are driven by the slowest component of the system, which can be the instrument with the longest development time, or the bus, or even in some cases the launch vehicle itself. In other words, if an instrument is simple (e.g. it is a reflight from a previous instrument) and has a very short development time, it will have to wait for all the other instruments to be ready in order to be launched. The same instrument could have been launched before on a dedicated satellite. That way the system would deliver some value to the stakeholders before.

As we mentioned earlier, risk is omnipresent and affects not only performance but also schedule and cost. In other words, there is not only technical risk, but also risk of schedule slippage and risk of cost overrun. It seems intuitive that risk of schedule slippage is higher for missions with long development times. Increasing the number of instruments is also a penalizing factor because the more instruments the higher the chances that one instrument suffers delays. As for risk of cost overrun it is well known in project management that schedule slippage and cost overrun are far from being independent. Indeed, delays in the development process systematically result in cost penalties which may not have been forecasted, leading to cost overruns.

If dedicated missions appear to be a better option in general in terms of risk of schedule slippage and risk of cost overrun, the issue of technical risk is more controversial. Technical risk, or risk of program failure, is associated to the probability of failure of the instruments, satellites or launch vehicles of the program. The relevant question in the context of this study is whether the architectural decision of putting N instruments on the same satellite or on different satellites affects the probability of failure of each individual instrument. One could argue that the probability of instrument failure increases when flown with other instruments due to interferences between instruments, etc. However, this argument is similar to the one presented in the engineering issues. If engineering issues are adequately solved in the development phase, there is no reason to believe that the reliability of the instrument will decrease when flown on a multi-instrument platform. In other words, this phenomenon has already been taken into account and we must be careful not to account for it twice in a quantitative model.

However, there is an important factor related to risk that affects the preferences of decision makers: risk aversion. Indeed, risk averse decision makers will naturally tend to prefer that critical instruments fly on different satellites in order to minimize the probability of losing everything if the large satellite is lost, say, at launch. On the other hand, risk takers might prefer gathering the critical instruments on a single platform in order to maximize the probability of a complete success, i.e. a scenario in which all the critical instruments are successfully put into orbit. It can be shown that a risk neutral decision maker would be indifferent between the two alternatives provided that no distinctions are made in terms of reliabilities of big and small launch vehicles.

To illustrate this, consider the following very simple example. We have a small set of N=4 identical instruments and we wish to study two different architectures in terms of risk of instrument failure. One consists in a single satellite with the 4 instruments and the other consists of 4 dedicated satellites, launched individually. To simplify, we only consider the risk of failure at launch, although the same discussion could easily be extended to other phases of the spacecraft lifetime. Each launch can be modeled as a Bernoulli trial with only two possible outcomes: success or failure. If the launch vehicle fails, all the instruments are loss; if it succeeds, all the instruments are correctly injected into orbit. Since each launch is modeled as a Bernoulli trial, the number of instruments successfully put into orbit follows a binomial distribution with parameters N = 4 instruments and p = R_{LV} = reliability of launch vehicle. Assuming that the two types of launch vehicle have the same reliability (e.g. R_{LV} =95%), the probability mass functions given in Figure 1 can be obtained.

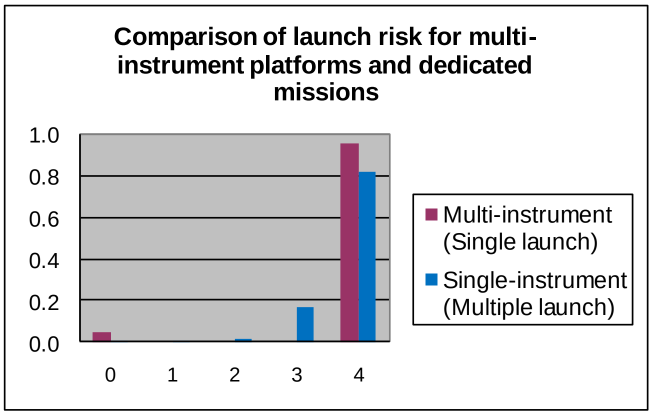


Figure 1: Example of comparison of launch risk for multi-instrument platforms and dedicated missions for a simple program with N=4 instruments, R_{LV}=95%. The calculations assume a binomial distribution for the number of instruments successfully put into orbit.

As shown in Figure 1, in the multi-instrument case, only two outcomes are possible (either all the instruments make it or they all fail) whereas in the dedicated satellites option, any number between 0 and 4 successful instruments is possible. The multi-instrument satellite maximizes the probability of having all the instruments successfully launched, but has a non negligible probability of losing all the instruments. On the other hand, the dedicated satellites option minimizes the risk of losing all the instruments, but has a smaller probability of total success. It is important to note that both architectures are exactly equivalent in terms of average number of instruments. In both cases, the average number of instruments successfully put into orbit is identical and equals the average of a binomial distribution, i.e. N*p=4* R_{LV} = 3.6 instruments. The difference is in the shape of the curve. The dedicated satellites option has a more spread risk profile. Therefore, whether one option is better than the other in terms of risk, eventually depends on the risk preferences of the decision maker. Should the decision maker have risk averse preferences, he or she would most probably pick the dedicated satellites option in order to minimize the probability of having very strong failures. We assume that in most space projects, decision makers will exhibit risk aversion, which makes dedicated satellites a slightly better option than multi-instrument platforms in terms of technical risk. However decision makers in certain types of programs such as technology-driven programs may actually be risk takers and prefer the multi-instrument alternative.

Design issues

During the interviews with experts, an additional category of relevant issues appeared that was not identified during the historical study. This category can be loosely named design issues and it can be summarized in one sentence: the design of multi-instrument platforms is necessarily suboptimal because each design decision is a compromise amongst antagonist requirements of different instruments. No matter what the final decision is, the final design cannot be optimized for all the instruments. This kind of situation arises for instance when high energy instruments such as lidars or radars share a common platform with passive optical instruments. Lidars and radars prefer to fly on low orbits to limit the power requirements which increase heavily with altitude. That is why most spacecraft dedicated to laser payloads fly between 450 and 600km. On the other hand, passive optical instruments do not have the same constraints and usually seek large swaths, which are more easily achieved from higher altitudes. Hence passive optical instruments usually fly at 700 or 800km. A similar argument can be given for the right ascension of the ascending node of sun synchronous orbits, which fixes the local time of observation for most latitudes. In this case passive instruments are limited by sunlight constraints. They need to fly on min-morning or mid-afternoon orbits in order to optimize sunlight conditions. On the other hand, active instruments are not constrained by sunlight issues and can hence fly on dawn-dusk orbits which are more favorable in terms of power and thermal control. The two examples particularly concern orbit design, but the same reasoning could be extended to many other design decisions such as the allocation of limited resources of the spacecraft. Spacecraft resources such as mass, volume, power, data rate, or surface with a good view of cold space to name a few are scarce and limited by state-of-the-art technology. For instance, state-of-the-art downlinks achieve data rates of a few hundreds of Mbps, and available launchers fix the maximum satellite volume to approximately 10m x 4.5m x 4.5m.

Certainly, there are sometimes smart ways to partially overcome these limitations. For instance, volume and power limitations can be overcome to a certain degree by using mechanisms (e.g. the James Webb Space Telescope). However these solutions are not universal and at a certain point they may become too expensive and/or decrease the overall reliability of the mission in an unacceptable way.

Conclusions of qualitative analysis

This section has provided a relatively in-depth qualitative analysis of the trade-off between multi-instrument platforms and dedicated missions. A summary of this analysis is presented in Figure 2.

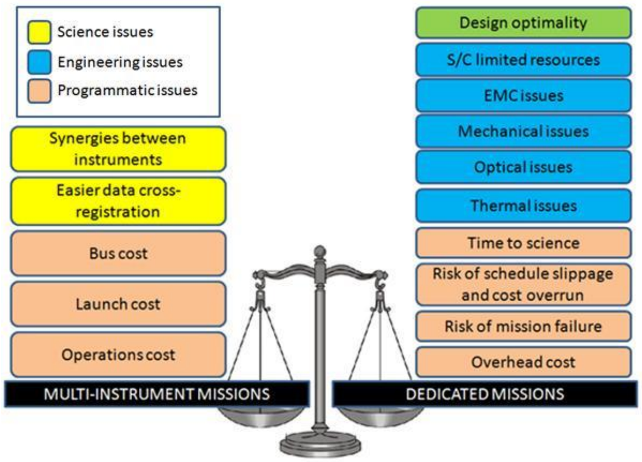


Figure 2: Qualitative analysis of the trade-off between multi-instrument platforms and dedicated missions. Each box is a category of advantages of one of the strategies. The color of the box represents the nature of the issue (science, engineering, programmatic, and design issues).

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 a more desirable option 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.

5. QUANTITATIVE ANALYSIS

Quantitative models support early concept exploration by providing a means for automatic enumeration and evaluation of thousands of different architectures. They capture part of the knowledge that is used by expert system architects and allow reproducing simplified architecting processes under changing conditions.

However, users of such models need to be careful about their results. Architectural models are usually breadth oriented as opposed to depth oriented. This means that their level of fidelity is medium to low. In other words, they are very good to identify promising architectures or rather to discard dominated architectures, but they should not be used as a unique means to select the final architecture of the system. Furthermore, building and using an architectural model provides valuable insights on trade-offs such as the one being studied in detail in this paper. Last but not least, architectural models provide a formal metacognitive framework for the otherwise ambiguous system architecting process.

Architectural tradespace exploration framework

Several frameworks exist that perform tradespace exploration for large design spaces. Multi-attribute tradespace exploration (MATE) for instance has been used to analyze different architecting problems concerning complex space systems (see for example [13]). Algebra of Systems [14] is another framework, based on architectural decisions as opposed to design variables.

In general all these frameworks consist in three major cognitive steps that carry different names: encoding, enumeration and evaluation. In the encoding phase the architectural or design vector containing the selected set of architectural variables or decisions is defined, together with the range of feasible values for each variable. In the enumeration phase, the architectural tradespace is generated by enumerating all the possible combinations of architecting variables. Additional constraints can be added to discard impossible combinations of variables. Finally, in the evaluation step, each feasible architecture is evaluated in terms of a set of metrics or objectives.

These metrics are calculated from the architectural variables and the parameters of the model using objective functions or value functions. In the case of a single metric, an absolute ranking of architectures can be computed. This is not possible when two or more metrics are considered. Instead, there are two options: the simplest one is to assign weights to the metrics and build a single metric as a weighted average of the set of metrics; then an absolute ranking can again be calculated. Instead of reducing the problem to one dimension, the set of “non dominated” architectures can be identified and used as a set of potentially good architectures.

Here the term “dominance” is defined in the Pareto sense, i.e. an architecture *Ai* is dominated if and only if we can find another architecture *Aj* in the tradespace that is better than *Ai* in all four metrics. In some cases however the set of non dominated architectures may still be too large and further downselection will be required. These two options are not necessarily mutually exclusive and can actually be used together.

Encoding

Encoding is the phase where an ambiguous architecting problem is transformed into an unambiguous mathematical model. This is a very important step because different encodings will lead to different – although not necessarily contradicting – results. It is essential to encode the problem with a purpose in mind.

We wish to study an Earth observation program and in particular we are interested in the trade-off between multi-instrument platforms and dedicated missions. Hence, our model will be instrument-centered as opposed to mission-centered for instance. We define a program as a set of N_{ins} instruments that need to be flown. For simplicity we assume that all the instruments are flown exactly once. One possible architecture is then to fly them all on the same satellite. Another one is to fly them all on separate satellites. And there are naturally many other combinations. Hence the architectural vector can be defined as follows:

$$
\begin{aligned}
A_{I\to S} &= \begin{bmatrix} S_1 & S_2 & \dots & S_{N_{ins}} \end{bmatrix} \\
S_i &\in [1, N_{ins}] \; \forall i = 1..N_{ins}
\end{aligned}
\tag{1}
$$

Where S_i is an integer representing the satellite to which instrument i is assigned. This single array contains all the information that we need in order to identify one architecture. For instance, for a program with $N_{ins} = 4$ instruments we can define the following architectures:

$$
\begin{aligned}
A_1 &= \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} \\
A_2 &= \begin{bmatrix} 1 & 2 & 3 & 4 \end{bmatrix} \\
A_3 &= \begin{bmatrix} 1 & 2 & 1 & 3 \end{bmatrix}
\end{aligned}
\tag{2}
$$

A_1 is a purely multi-instrument platform with only one satellite. A_2 is a purely dedicated satellites approach with all the four instruments flying on different satellites. A_3 is an intermediate architecture with 3 satellites, where instruments 1 and 3 share a common platform.

Enumeration

Once the architectural variables and their range have been selected, the architectural tradespace is generated. In our case, the tradespace consists of all the possible values of $A_{I\to S}$ that satisfy the constraints given in Equation (1).

Note that our definition of the problem assumes that each instrument is flown exactly once. Hence the problem is equivalent to finding all the possible partitions of instruments in satellites. Two such partitions are shown in Figure 3 for an example with seven instruments.

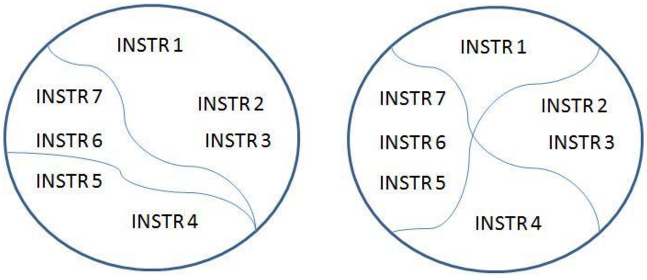


Figure 3: Two possible architectures for a set of 7 instruments.

This problem is commonly called "set partitioning", "set covering" or "bin-packing" problem in combinatorics and has been thoroughly studied. The number of partitions in a set of N elements is given by the Bell number, which is defined by the recursivity below:

$$
\begin{aligned}
B_{n+1} &= \sum_{k=0}^{n} \binom{n}{k} B_k \; \forall n > 1 \\
B_0 &= 1, B_1 = 1
\end{aligned}
\tag{3}
$$

The Bell number grows worse than exponentially with N. Hence for practical purposes, exhaustive unconstrained tradespace exploration is unfeasible unless N_{ins} is small ($N_{ins} < 12$). Beyond this threshold, it is necessary to incorporate as many constraints as possible into the problem in order to reduce the size of the tradespace.

Adding constraints is not only necessary but also desirable because we do not wish to lose computational time exploring architectures that we know in advance are poor architectures. The more constraints or heuristics we add to the model in order to identify these bad architectures, the more efficient the algorithm will be in screening the rest of architectures. The following constraints are used in the model:

(1) Maximum number of instruments per satellite (MAXINSPERSAT): a satellite carrying more than MAXINSPERSAT instruments is considered unfeasible.

(2) Maximum payload mass or volume per satellite: limitations on payload mass and volume are given based on current launch vehicle capabilities.

(3) Scientific constraints: The model allows forcing some instruments to be flown on the same platform in order to meet very strong cross-registration requirements.

Evaluation

Once the feasible tradespace has been found, the architectures are evaluated in terms of the set of selected metrics. Selecting the metrics is important because much of the sensitivity of the model to the particular trade-off that we want to study depends on the metrics that are considered. For instance, if we only consider cost and science as metrics, multi-instrument platforms will come up as a better option according to Figure 2. Conversely, if we only consider schedule and risk, architectures based on dedicated missions are likely to dominate the others. We selected four metrics for this study: lifecycle cost, schedule, risk and performance. The cost metrics captures both engineering and programmatic issues. The schedule and risk metric are mainly programmatic issues. Design issues are captured in the performance metric. Engineering issues are translated into cost penalties in the development process. The risk metric considers only technical risk since risk of schedule slippage and risk of cost overrun are taken into account by the schedule and cost metrics respectively. Finally, scientific issues are expressed as constraints as opposed to metrics. In the next paragraphs the four metrics are described in more detail.

Schedule—The schedule model estimates the development time of each mission in order to calculate when each instrument will start delivering data (i.e. value) to the stakeholders. There are two main assumptions behind the schedule model:

(1) The development time of each mission is driven by the worst case development time of each instrument. In other words, instruments have to wait for each other. This concept is illustrated in Figure 4 which shows the probability density function (PDF) of the development time of a single instrument mission compared to the PDF of the development time of a multi-instrument mission with four instruments.

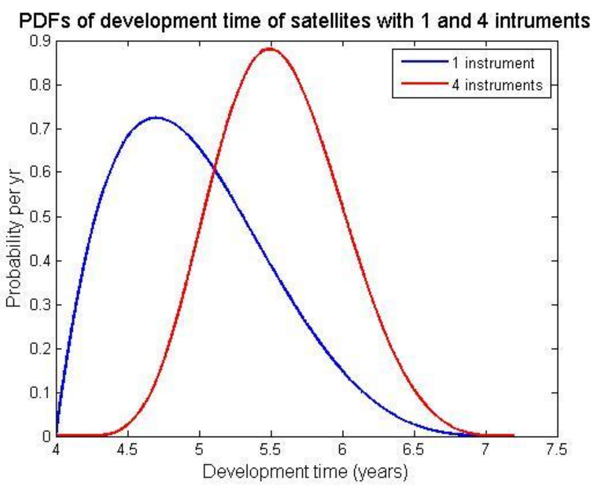


Figure 4: PDF of the development time of two missions: one with a single instrument (blue) and another one carrying four instruments. All instruments are considered equivalent in terms of TRL, complexity, etc.

Notice how the red line is shifted towards the right because instruments have to "wait for each other". In this case, the platform with 4 identical instruments takes approximately one year longer to develop than the single-instrument satellite even if the instruments are assumed to have identical expected development times. This is so due to the aleatory nature of instrument development time.

(2) The development time of each mission is driven by the Technology Readiness Level (TRL) of the instrument at the beginning of the development. In other words, instruments with low TRL are assumed to take longer to develop than instruments with high TRL.

More precisely, the schedule model is a stochastic model based on Monte Carlo simulations of the development process of each mission. The uncertain parameter is the development time of each instrument, which is assumed to follow a Beta distribution, typically used in project management. The parameters of the Beta distribution are inferred from the Technology Readiness Level (TRL) of the instrument, in part using the exponential relationship between schedule slippage and TRL derived in [15].

At each iteration, the model estimates a set of instrument development times using the Beta distributions and then computes mission development times as the maximum of the instrument development times.

The metric used for schedule borrows the concept of net present value from economics to discount the value of the data produced by each instrument according to its development time. Hence short missions that are able to provide the data faster are considered better in terms of schedule. Weights are optionally used to capture the criticity of the instruments for the program. The metric is calculated as follows:

$$Sched = \sum_{i=1}^{N_{ins}} V_i e^{-rT_i} \qquad \sum_{i=1}^{N_{ins}} V_i = 1 \tag{4}$$

where *sched* is the schedule metric; V_i are the relative weights capturing the criticity of the instruments; T_i are the development times of the instruments taking into account their delay due to other instruments on the same missions; r is a discount rate that similar to the one used in engineering economics to take into account the time value of money, only in this case it is the time value of data.

Cost—The metric used for cost is lifecycle cost. Lifecycle cost includes not only instrument and bus development and implementation cost, but also launch cost, operations cost, ground segment cost, overhead cost and an estimation of cost overrun. The cost model based is largely based on the parametric Cost Estimating Relationships (CER) provided in reference [16]. In order to use these CERs it is necessary to have a rough mass and power budget for each satellite. The mass budget is adapted from [17]. However, since this mass budget does not explicitly take into account many of the issues that were discussed in the previous section, mass penalties were introduced in the mass budget to account for all types of engineering issues, as shown in Table 1.

This table reads as follows. In the absence of penalties, the mass budget is given by the second column. Mass penalties are added to subsystem mass for each of the engineering issues highlighted in the qualitative analysis. For instance, if an active microwave instrument shares a bus with a passive microwave instrument, a penalty of 2% is added to the structure subsystem. Notice that this penalty does not model an actual increase in the structure mass, but rather an increase in the complexity of the spacecraft that translates into a penalty in development cost.

Table 1: Mass budget and mass penalties.

Subsytem	Allocated mass	Penalties
Payload	m	
Power	(power budget)	
Structure (includes configuration and mechanisms)	0.81m + penalties	+5% if mechanical coolers +5% if scanning instruments +10% if mechanisms +2% if EMC issues
TT&C	0.22m if simple 0.44m if complex	Complex if instruments have high data rates
ADCS	0.22m if simple 0.44m if complex	Complex if high point reqs. (e.g. HR sounders)
Thermal	0.04m if simple 0.22m if complex	Complex if instruments with cryocoolers
Propulsion	0.14m	

This is an example of how a classic architecting tool (top down mass budgets) is modified to fit our particular purpose, i.e. in this case to rank packaging architectures in terms of lifecycle cost taking into account engineering issues.

It is important to understand that these mass penalties do not represent increases in the dry mass of the satellite; they represent instead an increased complexity of the satellite that has a penalty in terms of lifecycle cost. However, these penalties were modeled as mass penalties in order to avoid modifying the cost model. Mass penalties are directly translated into cost penalties by the CERs in the cost model.

The NASA Instrument Cost Model was used to estimate the cost of instruments and the NASA Mission Operations Cost Model to estimate mission operations cost. Further information on these models can be found for instance in [18] and [19].

Although the CERs provided in [16] were left as they are, the cost model includes two additional modifications that make it explicitly sensitive to programmatic issues that were pointed out during the qualitative discussion:

(1) Organizational cost penalty: this penalty accounts for the fact that increasing the number of instruments has a negative effect on overhead cost, and that this effect is not linear but combinatorial in nature. We used a very simple model for this in which a minimum overhead cost for the case of a dedicated satellite is computed using the CERs in [16] and then this number is multiplied by a factor of $C(N_{ins},2)= N_{ins}\ (N_{ins}\ -1)/2$ in order to account for this negative effect. This modification artificially increases the cost of multi-instrument platforms in order to increase the sensitivity of the model to this particular issue in the trade-off. In consequence, the absolute magnitude of lifecycle cost will be artificially higher, but it does not matter since this the goal of the model is not to provide accurate cost estimations, but rather to compare architectures with each other. Indeed, models have to focus on a purpose, capture only the issues that are relevant to this purpose and make sure the model is sensitive to these issues. As noted by the authors of [20], a good model is like a caricature: it exaggerates some aspects of our system and leaves out the others.

(2) Cost overrun: an estimation of cost overrun is added to each mission's lifecycle cost. The main assumption is that cost overrun depends exclusively on schedule slippage, which depends on the architecture of the program but also on the TRL of the instruments as we have already seen. A constant value of 11% of overrun for each year of schedule slippage is assumed. This number comes from data concerning both ESA and NASA missions [21], [22].

Risk—The risk model is also a stochastic model that simulates the operational lifetime of each instrument and satellite, from launch to disposal. The lifetime is modeled as the combination of one discrete event (launch) followed by three continuous phases: early operations or commissioning, maturity and aging. At each iteration of the Monte Carlo analysis, the model simulates the launch as a Bernoulli process with two possible outcomes (success or failure). If the launch is successful, the times to failure of each instrument and the bus are simulated using a 3-stage Weibull probability distribution, commonly used in reliability theory because it allows modeling the three stages of the bathtub curve. Previous attemps to quantify spacecraft reliability used Weibull single stage distributions, with a shape parameter that was either greater than 1 (Dezelan uses 1.6 in [23]) to account for wear-out or smaller than 1 (Saleh et al use 0.4 in [24]) to account for infant mortality. Our approach contains both an infant mortality phase that lasts roughly for 6 months and wear-out that starts past the spacecraft design lifetime.

The model assumes that a failure on the launch vehicle or the bus results in an immediate failure of all the instruments carried by that bus. Furthermore, the parameters of the Weibull distributions depend exclusively on the expected lifetime (an input to the model). They are thus independent of the architecture but also of mass, cost, TRL or any other instrument parameter. However, the risk metric is not independent of the architecture because of the inclusion of the utility functions and the weightings for the instruments. These weights allow accounting for the existence of critical and non critical instruments. The risk metric is more precisely defined as a weighted average of the probability of instrument success:

$$risk = \sum_{i=1}^{N_{ins}} v_i u\left(prob_{succ,i}\right) \qquad \sum_{i=1}^{N_{ins}} v_i = 1 \tag{5}$$

where risk is the risk metric; V_i are the relative criticities of the instruments; u(x) is the utility function of the decision maker for the probability of instrument success. Instrument success can be arbitrarily defined. One possibility is to define instrument success as time to failure of the instrument being larger than expected lifetime. Risk preferences for a unique decision maker are then entered in order to favor architectures with more or less spread risk profiles. For example, for a risk averse decision maker, one possibility is to use a logarithmic function:

$$u\left(prob_{succ,i}\right) = \log\left(1 + prob_{succ,i}\right) \tag{6}$$

The marginal contribution of the first successful instruments is thus greater than the marginal contribution of the last instruments. This corresponds to the preferences of a risk averse decision maker who values more avoiding the risk of losing all the instruments than seizing the opportunity of having a total success.

Performance—The performance metric is based on penalties that capture the sub-optimal design decisions that are necessarily made in the presence of contradicting requirements in multi-instrument platforms. Numerically, the metric is defined as follows:

$$perf = \sum_{i=1}^{N_{ins}} V_i prf_i \qquad prf_i = 1 - \sum penalties \qquad \sum_{i=1}^{N_{ins}} V_i = 1 \tag{7}$$

where *perf* is the performance metric; V_i are the relative criticities of the instruments; prf_i are the instrument design performances; *penalties* are the performance penalties which account for situations in which conflicting requirements between instruments sharing a platform result in suboptimal design decisions from the standpoint of the instruments. At this point, only two performance penalties have been implemented: orbit altitude and orbit RAAN. Instruments that fly at their preferred altitude and RAAN score 1 in their individual prf_i. If they fly higher or lower they have a certain penalty and if they fly at a different local time they have an additional penalty. Hence there are only four possible values for the performance metric of a given instrument. Additional granularity is obtained by the introduction of the criticities of the instruments, which favor the architectures in which the critical instruments are flown at their preferred orbits. The aforementioned metrics are calculated from the architecture and the model parameters using value functions. Note that the goal of these functions is not to provide accurate absolute estimations of the metrics, but rather to provide a relative comparison of the architectures. The individual models for cost, schedule, risk and performance are succinctly described in the next paragraphs.

Normalized metrics and utility

The four metrics that have been defined are not necessarily normalized. Lifecycle cost is a number in $M; schedule and risk metrics are bounded between 0 and 1 but high values are very unlikely. This problem is solved in a post-processing phase by introducing normalized metrics that are always Larger-Is-Better (LIB) metrics - some transformation is needed for lifecycle cost – and bounded between 0 and 1. At this point, utility curves can also be applied in order to account for the risk preferences of the decision maker. For instance, for lifecycle cost, an exponential utility function is used so that the least costly architecture receives a score of 1, and an architecture costing 50% more receives a score of 0.25. The overall utility of the architecture is a single metric that captures the information of the four metrics using a simple weighted average, as suggested in classic multi-attribute utility theory.

Selection of best architectures

The next step is the selection of the potentially optimal architecture or set of architectures. This occurs in two steps: first, dominated architectures are filtered out of the tradespace; second, the set of efficient or non dominated architectures is ranked using a single value – utility – that combines the four metrics into a single one using a set of weights that capture the preferences of the decision maker. Table 3 summarizes the main features of the architectural model following the framework previously defined. A schematic representation of the model is also provided in Figure 5.

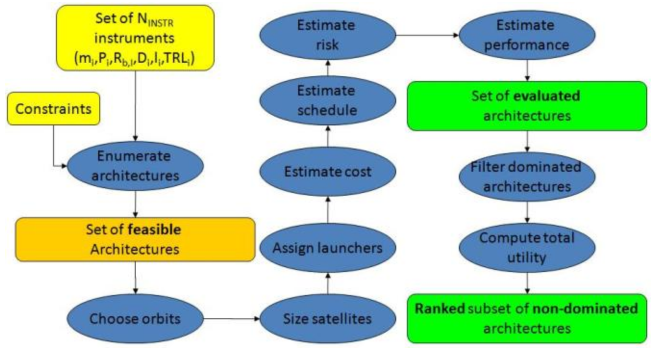


Figure 5: Flow diagram representation of the model

6. APPLICATION

In this section, the quantitative model is applied to an example, namely ESA's Envisat program in its final configuration. We have chosen this example because data is readily available for Envisat instruments and because the relatively small size of the program (ten instruments) is convenient to run the model using different sets of parameters. The mass, power and data rate of the ten Envisat instruments as well as other inputs to the model are provided in Table 4. The actual Envisat program consisted in a single satellite weighing 8211 kg and measuring 10.5m x 4.5m. Envisat is by far the largest Earth observation satellite ever built so in this case ESA clearly adopted a multi-instrument approach.

Using our model, we enumerated and evaluated all the possible architectures for the set of ten instruments as defined in Table 2 and Table 3.

Table 2: Parameters used for the Envisat test case.

Name	Value	TRL	Pref. Altitude	Pref. LTAN
AATSR	1	8	800km	1030
ASAR	2	7	600km	0600
GOMOS	1	7	800km	1030
MERIS	1	7	800km	1030
MIPAS	1	7	800km	1030
MWR	0.5	9	600km	0600
RA-2	0.7	9	600km	0600
SCIAMACHY	1	7	800km	1030
DORIS	0.2	9	600km	0600
LRR	0.1	9	600km	0600

The "Value" column captures the criticity of the instrument. Preferred orbits are all SSO; altitude is given in the 4th column and local time of the ascending node (LTAN) in the 5th column.

It was further assumed that the radar altimeter, the DORIS receiver, the laser retroreflector (LRR) and the microwave radiometer (MWR) need to fly together as a unique altimetry payload. This is consistent with what was presented in the qualitative analysis section. Under these constraints, the tradespace of feasible architectures contains 877 different combinations of instruments into satellites. Possible solutions range from the original architecture using only one extremely large satellite to a solution with seven dedicated small satellites.

In a first stage, the model identified 61 non dominated architectures taking into account the four metrics. Hence the remaining 816 architectures were dismissed as they were strongly dominated. Since there are four objectives, it is not possible to graphically show the 4D Pareto frontier with the 61 non dominated architectures. However, one bi-objective Pareto frontier (cost-schedule) is explicitly shown in Figure 6.

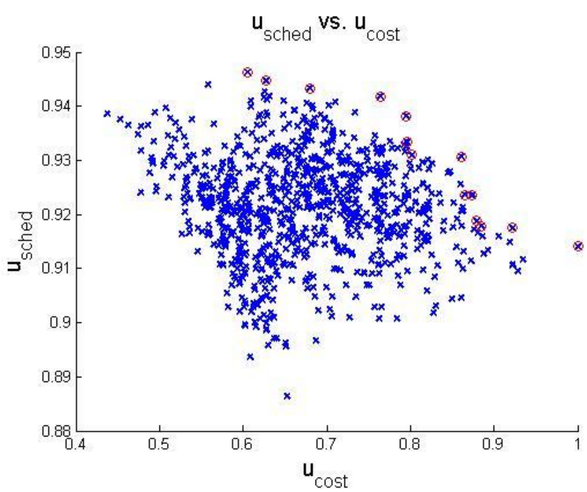


Figure 6: Architectural tradespace for the Envisat case in the cost-schedule space. Each blue cross represents an architecture. Pareto efficient architectures when only cost and schedule are considered are marked with a red circle.

Note that these architectures are not necessarily efficient when the four metrics are considered.

The set of 61 architectures is still rather large to enter a more detailed analysis phase, thus further downselection is necessary. The methodology performs this second level of selection under the basis of a single metric, namely utility, combining the four previous metrics with different weights.

Table 3: List of the main exogeneous and endogenous parameters of the model. Endogeneous parameters vary to form the architectural tradespace; exogeneous parameters do not vary across architectures.

Architectural variables (endogenous)	A_{I2S}: array containing the satellite to which is assigned each instrument
Inputs (exogeneous)	For each instrument: mass, power, data rate, dimensions, TRL, criticity.
Model Parameters (exogenous)	Weights for overall utility Mass penalties Performance penalties Launch vehicle data Risk utility functions Discount rate for schedule
Constraints	Instruments that need to fly together (science) Instruments that cannot fly together (engineering) Instruments that need to fly alone (engineering)
Metrics	Program Lifecycle cost Program discounted value (schedule) Weighted Average Probability of Instrument Success (risk) Program Performance
Major Assumptions	Instruments are only flown once. Mission development time is driven by worst case development time. Instrument development time follows a Beta distribution that depends only on TRL. Instrument and bus time to failure follow a three-segment Weibull distribution that depends only on design lifetime.

Table 4: Mass, power and data rate of the Envisat instruments. Data comes mainly from [9]**. Some of the information concerning in particular the dimensions and the viewing strategy of the instruments was not found in any public source. "Best guesses" were used as inputs in these cases.**

Name	Mass (kg)	Power (W)	Duty cycle	Data rate (Mbps)	illum	d_x (m)	d_y (m)	d_z (m)	freq	thermal	Viewing strategy	Point reqs.
AATSR	101	100	1	0.61	P	1	1	0.2	O	Stirling	Mechanical scanning	L
ASAR	832	1395	1	100	A	4.2	1.3	1	MW	none	Electrical Scanning	L
GOMOS	175	200	1	0.217	P	0.3	0.2	0.1	O	passive	Mechanical Scanning	H
MERIS	200	175	0.43	24	P	1.8	0.9	1	O	Peltier	Fix pushbroom	L
MIPAS	327	210	1	8	P	0.75	0.17	0.17	O	Stirling	Mechanical Scanning	H
MWR	24	18	1	0.016	P	0.6	0.6	0.1	MW	none	Fix nadir	L
RA-2	110	161	1	0.098	A	1.5	1.5	0.2	MW	none	Fix nadir	L
SCIAMACHY	198	122	1	1.781	P	0.15	0.11	0.01	O	passive	Mechanical scanning	L
DORIS	17	20	1	0	P	0.38	0.28	0.21	MW	none	Fix nadir	L
LRR	2	0	1	0	P	0.2	0.2	0.2	N/A	none	N/A	N/A

For the purpose of this example we chose a set of weights that emphasizes cost (50%) and puts little importance to the performance metric (10%) which at this stage was still too simple to provide a good basis for comparison. Schedule and risk were equally valued (20%).

Figure 7 plots the overall utility using these weights as a function of the number of satellites. Note that the choice of the weights by the decision maker highly depends on the nature of the program. For instance, an operational program is likely to put more emphasis on low recurring cost and low risk, whereas a technological program may emphasize performance and schedule and a scientific program cost and schedule.

The model finds that with the current parameters, the original Envisat architecture consisting in a single large satellite, although it is non dominated, is less desirable than other architectures. This is explained in part because a single satellite architecture scores very low in the schedule metric and in part because the cost of this multi-instrument platform is increased by the engineering penalties.

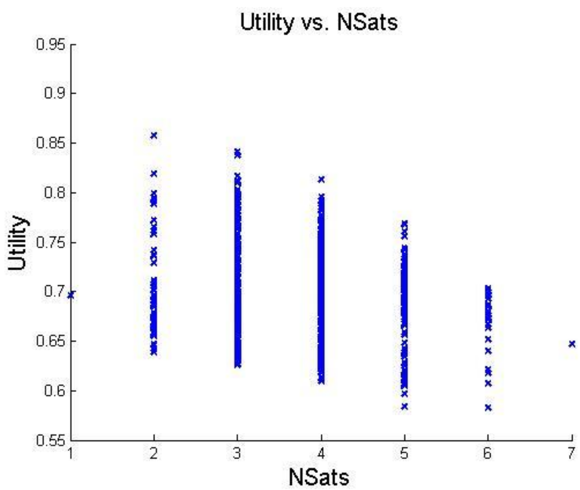
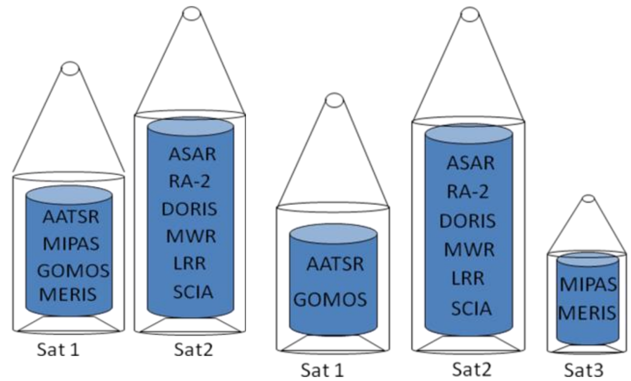


Figure 7: Overall utility of non dominated architectures as a function of number of satellites.

The top two architectures identified by the model are explicitly represented in Figure 8.

Notice how satellite two is the same in both architectures and contains the two active microwave instruments (radar altimeter and synthetic aperture radar) plus SCIAMACHY, which is a passive optical instrument. The selection of the best architecture is driven in this case by the large gain assigned to the cost metric. Indeed, the top two architectures identified are the least costly.

Varying the weights of the metrics or other model parameters would result in a different selection of architectures. For instance, we notice that the best architecture scores poorly in the performance/design optimality metric because it is flying the two active instruments at a higher orbit than their preferred orbit. Indeed, one of the heuristics in the model requires that whenever a conflict of preferred orbits appear, the higher orbit is always preferred. This soft constraint is not respected here because the presence of SCIAMACHY in satellite 2 is constraining the SAR and the RA to fly higher than they want, thus innecesasarily increasing their power requirements. However, the weight of this metric being only of 10%, this does not affect the final decision very much.



1st Architecture: utility = 0.88

2nd architecture: utility = 0.83

Figure 8: Top 2 architectures for the Envisat example.

The purpose of this paper is not to provide insights into the architecture of Envisat, but rather to illustrate the methodology and in particular the quantitative architectural model. Therefore the detailed sensitivity analysis is not shown. However, we were able to show by varying the inputs and parameters that the model correctly captures at least partially the main issues involved in the trade-off.

7. CONCLUSION

Accomplishments

This paper proposes a methodology to analyze single-axis trade-offs in systems architecting. The methodology relies on a historical study to identify drivers of the trade-off, which where the reasons behind the architectural decisions in the past. A qualitative study is then performed through interviews with expert systems engineers, customers and program managers to add a level of detail into the categories of issues highlighted in the historical study. Then, a quantitative model is built to perform a systematic exploration of the architectural tradespace. This model must capture the issues encountered during the qualitative analysis and only these issues. The model can then perform exhaustive concept exploration and provides a framework for concept selection based on the elimination of dominated architectures and multi-attribute utility theory for downselection of a handful of well balanced architectures.

The methodology was illustrated with an integrated assessment of the trade-off between multi-instrument satellites and dedicated satellites in Earth observation program architecting. In particular, the quantitative model was applied to a relatively small program containing only ten instruments, namely ESA's Envisat. Results show that the model provides reasonable answers and is able to reproduce part of the decision logic that is necessary to architect Earth observation programs.

Future work

There is much potential to improve the quantitative model. An improved version of the model is based on a multi-objective genetic algorithm. This evolutionary algorithm allows the exploration of extremely large tradespaces that result of programs with more than 11 instruments, for which full factorial enumeration is unfeasible. This version of the model is currently being developed.

Second, we have shown that the model captures part of the knowledge required to architect a program. However, more and better heuristics could improve the quality of the model. For instance, one factor that has not been taken into account concerns the payload to spacecraft mass ratio which is considered constant with spacecraft mass. The historical study shows that larger satellites tend to have higher payload to spacecraft mass ratios. It is important to take this into account because neglecting it can artificially bias the trade-off against multi-instrument platforms.

Another important aspect of Earth observation program architecting that has not been captured in this study is budgeting and robustness of different architectures to changes in budget. One could argue that smaller missions are more robust to political and economic instability because they are less costly, and that this should be taken into account in a comprehensive architecting analysis.

Finally, the quantitative model could also be improved to take into account uncertainty in the representation of the metrics. We captured some of the uncertainty in the problem by using Monte-Carlo simulations for the schedule and risk metrics and by systematically adding an expected cost overrun coming from the schedule model into the expected lifecycle cost. However, a more systematic approach to architecting under uncertainty should be entirely based on PDFs as opposed to average metrics as suggested for instance in [25].

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BIOGRAPHIES

***Daniel Selva** is a PhD student in the department of Aeronautics and Astronautics at the Massachusetts Institute of Technology (MIT). His research interests focus on the earliest phases of space systems engineering or systems architecture, in particular applied to Earth observation missions and programs. Prior to MIT, Daniel worked for four years in Kourou (French Guiana) as a member of the Ariane 5 Launch team where he worked as a specialist in operations concerning the guidance, navigation and control subsystem, the avionics and ground systems. Daniel has a dual background in electrical engineering and aeronautical engineering, with MS degrees from Universitat Politecnica de Catalunya in Barcelona, Spain, and Supaero in Toulouse, France. He is a 2007 la Caixa fellow, and received a Nortel Networks prize for academic excellence in 2002.*

***Dr. Ed Crawley** received an Sc.D. in Aerospace Structures from MIT in 1981. His early research interests centered on structural dynamics, aeroelasticity, and the development of actively controlled and intelligent structures. Recently, Dr. Crawley's research has focused on the domain of the architecture and design of complex systems. From 2003 to 2006 he served as the Executive Director of the Cambridge – MIT Institute. For the previous seven years, he served as the Department Head of Aeronautics and Astronautics at MIT, leading the strategic realignment of the department. Dr. Crawley is a Fellow of the AIAA and the Royal Aeronautical Society (UK), and is a member of three national academies of engineering: the Royal Swedish Academy of Engineering Science, the (UK) Royal Academy of Engineering, and the US National Academy of Engineering. He is the author of numerous journal publications in the AIAA Journal, the ASME Journal, the Journal of Composite Materials, and Acta Astronautica. In his outreach and public service, Dr. Crawley was chairman of the NASA Technology and Commercialization Advisory Committee, and was a member of the NASA Advisory Committee. He holds the NASA Public Service Medal. In 1993 was a member of the Presidential Advisory Committee on the Space Station Redesign. He is conversant in Russian, and has spent time as a visitor at the Moscow Aviation Institute, the Beijing University of Aeronautics and Astronautics, Stanford University and Cambridge University. He was a finalist in* *the NASA Astronaut selection in 1980, is an active pilot, and was the 1990, 1995 and 2005 Northeast Regional Soaring champion. In 2004 he received the Distinguished Eagle Scout Award of the Boy Scouts of America. Recently, Prof Crawley was one of the ten members of the presidential committee led by Norman Augustine to study the future of human spaceflight in the US.*