5.6 Summary

Robust MOO often comes at the price of a large computational cost. This is due to the fact that the average performance needs to be computed, therefore many more simulations than a standard optimization technique are needed in the process. In this chapter, we introduced a repository-based approach that allows to reduce the computational effort to obtain optimal-robust solutions. In the test cases presented here we demonstrated that the number of simulations can be reduced by 70%, providing accurate results. At the same time, it allows to keep the joint PDF of the uncertain factors intact even when sample points are re-used from the repository. This approach to maintain a repository and use it efficiently was used for the study of unmanned re-entry vehicles. The study demonstrates that indeed robust optimization can help in identifying already optimal solutions that are also robust to uncertainties in the environment, and uncertainties in the design variables themselves. Further, we demonstrated that robust-optimization can also be used to take model uncertainties into account. This is especially useful for preliminary design, where the models used for the analysis may be at infant stage and still unknown dynamics and unknown parameters (coefficients) may be considered for the analysis.

For the atmospheric entry vehicle test case we show that small, fully reusable capsules for unmanned entry from low Earth orbits perform as well as capsules with ablative materials, also under uncertainties. This is also true for large optimal capsules that show, nevertheless, less efficient behavior in the presence of these uncertainties. This indicates that the robust optimization has a selection pressure that works towards heavier capsules, with larger mass due to larger thickness of the skin to withstand possibly larger heat fluxes if compared to the non-robust solutions.

Chapter 6

The Design Methods in Real Concurrent Environments

The natural test-bed for the analysis methods presented in this thesis are the concurrent design infrastructures currently in use by the space industry, and other organizations also in sectors that are different from space. These infrastructures, or concurrent environments, are used to implement concurrent engineering to the maximum extent, from the very beginning of the system life-cycle. In this respect, we proposed our design methods as an applicative layer to be used on top of the concurrent design infrastructures of two organizations, namely the ESA Concurrent Design Facility (CDF), and JAQAR-Concurrent Design Services B.V. (J-CDS). In Section 6.1 we briefly introduce the notion of conceptual design in a concurrent environment, summarizing the improvement we propose in the design process of these organizations. In Section 6.2 we present the experience of the utilization of the design methods in the CDF for the mass-budget management of Ops-Sat, a cubesat mission. In Section 6.3, instead, we describe the experience of the utilization of the design methods in the concurrent design environment developed by J-CDS, the Concurrent Design Platform, CDP^{TM}, for both a space and a non-space test-case.

6.1 Conceptual design in a concurrent environment

The experience of the Jet Propulsion Laboratory (JPL) first, immediately followed by the European Space Agency in mid 90s, introduced a revolution in the field of conceptual design. Up to that period the most widely adopted method for the design of a space system in all phases, thus also during conceptual design, was the *sequential* approach. The design process was performed with domain experts working one after the other, in a sequential way, with a substantial lack of communication and collaboration between each other.

The revolution introduced by adopting concurrent design was that all the aspects of a system and the mission it will perform are studied at the same time. This approach has demonstrated to allow for the project consistency to improve rapidly, thus providing also advantages in terms of development time and cost reduction, while at the same time providing high-quality design solutions (Fortescue *et al.*, 2011). Concurrent design is particularly suited for being implemented at conceptual phases. A relatively small amount of experts are involved in the process, resulting in the fact that design sessions with everybody working at the same time are still manageable. The space community is actually pushing for the utilization of concurrent design also for more advanced phases, to obtain the same benefits also later in the design process. However, no general consensus has been reached yet, at least in a European context, regarding the software/hardware infrastructure to serve concurrent design in this case.

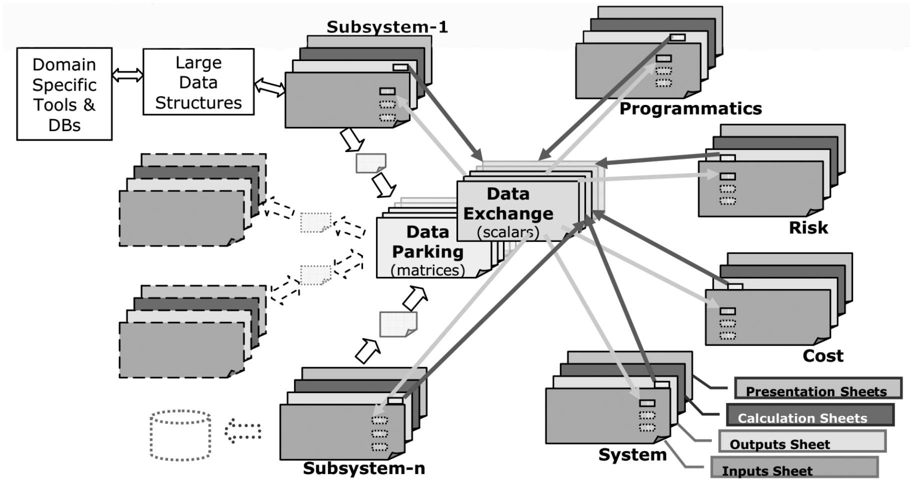


Figure 6.1 The CDF Integrated Design Model, adapted from Fortescue *et al.* (2011).

Following the experience of the ESA Concurrent Design Facility, many other concurrent design infrastructures were built in Europe in the following years by industry and other organizations. Integrated design environments enable excellent data exchange amongst the discipline domain experts, and allow for creating a productive atmosphere where emerging solutions and innovative ideas can be obtained concurrently, also at the coffee corner.

After more than 15 years of experience in the space and recently also in the non-space industry, we believe that time is mature enough for integrated applications to be used on top of the concurrent-design infrastructures. The scope is to provide the discipline-domain experts with standard analysis tools and results-visualization techniques enabling an efficient exploitation of the models during the concurrent design sessions, enhancing the exchange of information and promoting discussions even more.

The schematic representation of the Collaborative Bi-Level (COBiL) formulation for complex system models presented in Figure 2.8, Chapter 2, indicates the typical flow of information that takes place in a concurrent environment. This flow of information amongst the discipline-domain experts is made possible by the integrated design model and a central *data exchange* block. In Figure 6.1 we present the architecture of the Integrated Design Model adopted in the ESA CDF.

In the space industry, many years of experience with the concurrent approach to conceptual design have given the opportunity to develop domain-specific mathematical models for the various disciplines involved: communication, power, thermal, *etc.* When necessary, discipline-domain experts are invited to concurrent-design sessions. They bring their models and link them in the concurrent-design infrastructure. Besides models, there are also tools available for designing purposes. For instance *Satellite Tool Kit*© (Analytical Graphics, 2012), for orbit, mission, and communication is widely adopted, and *Matlab-Simulink*© (The MathWorks, 2012), for Guidance Navigation and Control amongst others, *ESARAD*© (ESA, 2012), for thermal analyses, and so on. These are all domain-specific tools that were not developed for being implemented in a concurrent environment. The result is that they hardly integrate in any concurrent design infrastructure leading to the tangible risk that domain experts may use their models outside the concurrent infrastructure. It can push the discipline domain-experts to work on their own, only providing the interfaces, thus leaving the actual mathematical models not linked to each other. The process would still be concurrent but the concurrent infrastructure would not be used to the full extent.

In the non-space industry, concurrent design is being increasingly adopted: it represents a growing trend at the moment. This means that models for conceptual design may not be directly available. Discipline domain-experts may be called to develop discipline-domain models from case to case, also because the disciplines involved may be different from one product to the other. This is the case, for instance, for the J-CDS customers. Also domain-specific tools for conceptual design may not be available, for the same reasons. Therefore, there may be the risk that the concurrent-design infrastructure is left without any specific analysis tool to be used by the discipline domain-experts, thus limiting their design possibilities.

We envision an evolution of Concurrent Design, where concurrent design borne analysis tools are concurrently exploited and fully integrated in the concurrent-design infrastructures.

It is for these reasons that in the course of the research that lead to the production of this thesis, we proposed the implementation of some of the design methods presented here to the ESA Concurrent Design Facility, and to J-CDS. These two organizations gave us the possibility to experiment with their facilities and software infrastructures, giving us the benefit of the doubt. The design methods presented in this thesis were used to facilitate two main interfaces of a concurrent environment. They allow for an easier utilization of the mathematical models at discipline-domain level and system-domain level, thus interfacing between the multidisciplinary team and the integrated design model (the human-machine interface). Further, the objective of this chapter is to also demonstrate how a structured design approach with structured analysis tools (as these proposed in this thesis) in a concurrent environment can enhance also the human interactions. The human resources and their interactions are a corner stone for successful concurrent design. Finally, we demonstrate that standard analysis techniques and standard approaches for the visualization and sharing of the results may bring benefits to the whole process.

6.2 Cubesat mass-budget management in the ESA CDF

6.2.1 Introduction

Ops-Sat was a recent study in the ESA CDF aimed at the design of an in-orbit demonstrator to test innovative mission-control and operations concepts by using a *3U* cubesat. A 3U cubesat is a satellite with the dimensions of approximately $10 \times 10 \times 30$ cm. It is called 3U, because its volume is three times larger than the 1U cubesat, which measures $10 \times 10 \times 10$ cm. Ops-Sat is a small satellite which will carry in-orbit demonstration experiments designed to answer the operation needs of future missions, CDF (2012). In particular, Ops-Sat will carry a number of experiments that will require a combination of changes to on-board and ground-software and will test methods for handling satellite data and operational processes that may be of use on future ESA missions. The focus of the mission design will be to implement software on off-the-shelf hardware. The preliminary design of Ops-Sat was carried out in the ESA Concurrent Design Facility. The design was mainly driven by the requirement of having a very low-cost mission, that lead to the adoption of commercial off-the-shelf (COTS) components. This includes the cubesat structure, a 3-axis attitude control system, deployable solar arrays, a low-rate data bus, a GPS receiver, a high-resolution optical camera, and a low-rate communication system. However, some radio equipment (especially in the S-Band Tx/Rx chain) had to be selected from ESA's standard equipment to provide realistic (in terms of procedures and functional chains) back-end for the software experiments. A CAD model of the spacecraft is shown in Figure 6.2. The cubesat standards specify a maximum mass of 4 kg allocated for a 3U cubesat. This is mainly due to the structural properties of the standard Picosatellite Orbital Dispenser (POD), that is the standard interface of the cubesat to the launcher. The volume is fixed to a $10 \times 10 \times 30$ cm form factor. Given those strict requirements, the usual ESA space hardware was not found suitable in most of the cases. Mass and volume became *de-facto* design drivers, dictating the use of more compact and sometimes not space-qualified COTS

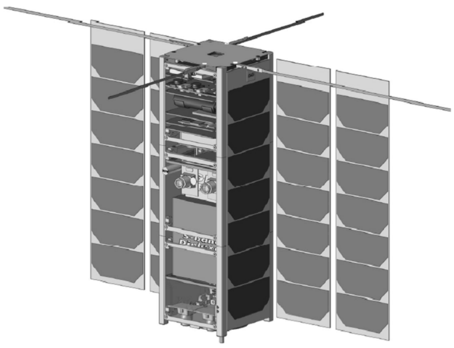


Figure 6.2 CAD model of Ops-Sat, adapted from CDF (2012).

hardware. Later in the process, the mass limitation of 4 kg was relaxed due to the existence of a POD from Innovative Solutions In Space B.V. (ISIS) capable of launching cubesats with a mass up to 6 kg. Changes had to be made to the CDF's Integrated Design Model (IDM) and to the design process as a whole to adapt to this specific study and the increased level of detail covered during the sessions.

6.2.2 The Ops-Sat mass budget

The design of Ops-Sat was performed in three subsequent iterations in the CDF. The official mass budget related to the last iteration is shown in Figure 6.3. This mass budget is obtained using the classical margin-based approach. The margin-based approach foresees a baseline mass-increase that is divided into two steps. First, the mass of each subsystem is increased with a certain percentage by the subsystems' experts, mostly based on the *readiness* of the selected concept. Then, the sum of the subsystems' masses is further increased at system level with a margin of 20% to account for unknowns at the moment of the design due to the very preliminary nature of the design phase. The value of 20% is mainly chosen because, after many years of practice in the space industry, it demonstrated to be a good estimate for the mass increase faced during the remaining part of the design process of the system.

In this specific case, however, it was clear that there is very little experience in the space industry in designing and building cubesats. Thus a *blind* 20% of system-level mass margin would probably not represent a good estimate for mass increase anymore. Further, due to the reduced scale of the system, and possibly also reduced complexity if compared to other larger satellites, it was also clear that the analysis would be much more detailed than what is normally achieved in the CDF. The increased level of detail would leave less uncertainty for successive design phases, thus with a possibly reduced margin for mass increase.

For these reasons, it was decided to adopt an alternative approach for the mass-budget management in the case of Ops-Sat. We used the design methods presented in this thesis to perform a probabilistic-based mass-budget analysis in parallel to the classical one based on mass margins, to allow for a more informed baseline-mass estimation. Therefore, the purpose of the analysis is to provide a probabilistic description of the uncertainty related to the mass budget of Ops-Sat, so to allow for a more informed determination of the system margin for the final mass budget.

Probabilistic Approach

Each subsystem expert, taking part in the design in the CDF, was asked to associate an estimated probability distribution to the worst-case mass margins provided in the CDF integrated data model. Then, samples were taken from the joint probability distribution of all

Element 1 Ops-Sat

				Target Spacecraft Mass at Launch			6.00	kg
				Below Mass Target by:			0.75	kg
	Input Mass	Input Margin	Dry mass contributions	Without Margin	Margin %	Margin kg	Total kg	% of Total
EL			Structure	0.55 kg	7.18	0.04	0.59	13.47
EL			Thermal Control	0.00 kg	-	-	-	-
EL			Mechanisms	0.00 kg	-	-	-	-
EL			Communications	1.82 kg	9.95	0.18	2.00	45.73
EL			Data Handling	0.34 kg	19.89	0.07	0.41	9.36
EL			AOCS	0.36 kg	9.29	0.03	0.40	9.10
EL			Power	0.82 kg	7.65	0.06	0.88	20.13
EL			Instruments	0.09 kg	5.00	0.00	0.10	2.21
			Total Dry(excl.adapter)	3.99			4.38	kg
			System margin (excl.adapter)		20.00 %		0.88	kg
			Total Dry with margin (excl.adapter)				5.25	kg

Figure 6.3 Mass summary breakdown for iteration 3, adapted from CDF (2012).

the elements of all subsystems to compute the final probability distribution of the mass of the cubesat, as the sum of the mass of all the elements. One of the objectives of the analysis is to subdivide the uncertainty related to the final mass of the subsystems into the uncertainty related to each single component (or group of components) of every subsystem, where possible. Then, an estimated probability distribution is associated to each component by the experts to obtain a better description of the design uncertainties related to them. The scope is thus to gain more insight in the uncertainty described by the margins, which is related to an inherent uncertainty at subsystem level due to unknowns at the time of conceptual design. The results are obtained considering decoupled subsystem uncertainties. This is done, because it is common practice, during the design of each subsystem, to consider cautionary margins also with respect to values or estimated data coming from the other subsystems. Therefore, this source of uncertainty is already taken into account when the margins are estimated. Furthermore, a correlation structure between the mass uncertainties of all the subsystems would not be trivial to estimate in this phase of the design process. Besides, this kind of subsystem interrelations and modification of requirements is expected to be covered by the system margin.

Communication Subsystem The communication subsystem is divided into 7 units. For each unit a mass distribution was estimated, between a minimum and a maximum value, as presented in Table 6.1.

In this case, and in all the other cases the *nominal* value is the value used to fill in the CDF mass model. For certain items, like the UHF board and the UHF antenna, a uniform distribution was considered between the nominal value (off the shelf) and a margin estimated by the subsystem expert. For other items, such as the S-band Transmitter and the S-band Diplexer, a more elaborated reasoning was performed. In these cases the subsystem expert estimated a probable mass reduction achievable with a minimum reworking-effort, and a less probable mass reduction with a more sustained reworking-effort. The description of these uncertainties is shown in Figure 6.4 (a) and (b), respectively. The S-band transmitter's mass as reported on the datasheet is 0.820 kg. This mass was estimated by the subsystem expert as the maximum mass achievable by this item. Then, a probability of 75% of the mass being between 0.820 kg and 0.620 kg (minimum rework effort) was estimated, and a reduced probability of the mass of the item of being between 0.620 kg and 0.40 kg (more consistent rework effort). The same reasoning applies to the S-band diplexer, see Figure 6.4(b).

Power Subsystem The mass uncertainty estimation for the power subsystem is presented in Table 6.2.

In Figure 6.5 the estimated probability density function for the battery board only is presented. In this case the subsystem expert estimated the probability of the mass being between 0.241 kg and 0.246 kg as 75%, the probability of being between 0.240 kg and 0.235 kg as 10%,

		Min	Nominal	Max	
UHF Board	kg	0.200	0.200	0.210	Uniform Distribution (5% margin)
UHF Antenna	kg	0.100	0.100	0.105	Uniform Distribution (5% margin)
X-band Transmitter	kg	0.400	0.500	0.550	Uniform Distribution (Min and MAx provided by the supplier + 10% margin)
X-band Antenna	kg	0.100	0.100	0.105	Uniform Distribution (5% margin)
S-band Transponder	kg	0.400	0.620	0.820	Max: Component as it is. Nominal: Component with a likely achievable reworking. Min: Component with a less likely achievable reworking. Estimated distribution in Figure
S-band Diplexer	kg	0.100	0.200	0.280	Max: Component as it is. Nominal: Component with a likely achievable reworking. Min: Component with a less likely achievable reworking. Estimated distribution in Figure
S-band Antenna	kg	0.100	0.100	0.110	Uniform Distribution (10% margin)
TOTAL	kg		1.820		

Table 6.1 Communication subsystem mass uncertainty estimation

		Min	Nominal	Max	
PDM, PCDU, SA Deployable, SA Body	kg	0.522	0.577	0.638	Uniform Distribution (10% margin w.r.t. nominal)
Battery Board	kg	0.235	0.240	0.252	Max: Nominal + 5%. Min: Nominal -5grams. Estimated Distribution in FIGURE
TOTAL	kg		0.820		

Table 6.2 Power subsystem mass uncertainty estimation

and the probability of being between 0.246 kg and the nominal mass plus 5% margin as 15% probability.

Command and Data Handling Subsystem The command and data-handling subsystem mass is divided into 4 contributions, see Table 6.3.

In this case there is a large uncertainty on the masses of the Application Specific Integrated Circuit, ASIC, and Field-Programmable Gate Array, FPGA, (however, it has a low impact on the overall mass) and large uncertainties in the masses of the boards and components (including connectors and wires). The subsystem experts estimated the probability of the mass of ASIC and FPGA being between 0.002 kg and 0.003 kg as 75%, and the probability of being between 0.003 kg and 0.006 kg as 25%, see Figure 6.6(a). The probability of the mass of the Printed Circuit Boards, PCBs, was estimated to be between 0.150 kg and 0.200 kg as 75%, and the probability of being between 0.200 kg and 0.240 kg as 25%, see Figure 6.6(b). In figure 6.7 the uniform cumulative distribution of the satellite Components is shown.

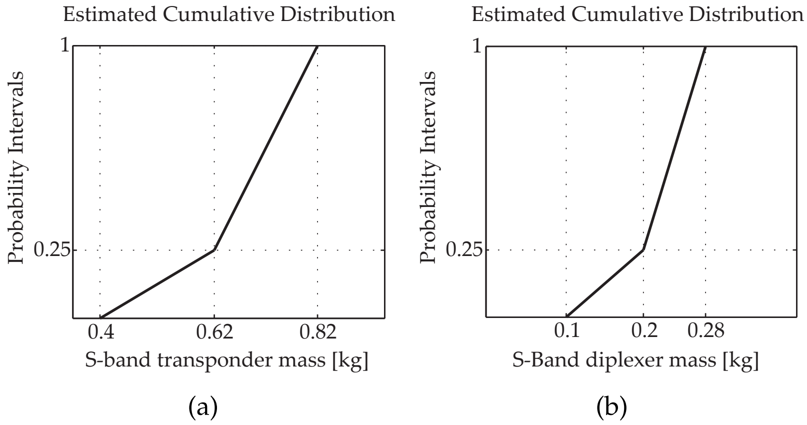


Figure 6.4 Mass cumulative distribution estimated by the subsystems engineers.

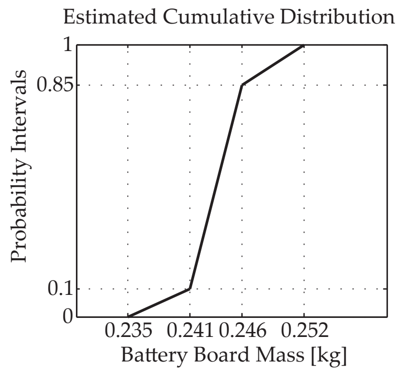


Figure 6.5 Battery-board mass cumulative distribution estimated by the subsystems engineers.

AOCS The mass of the AOCS is composed of the sum of the masses of the magnetometer, Sun sensors, GPS, magnetic torquers, reaction wheels, and PCB. In this case overall mass uncertainty estimation was provided by the subsystem expert, rather than estimation of the uncertainties of each single component. The uncertainty intervals are shown in Table 6.4, whereas in Figure 6.8 the estimated cumulative distribution is presented. The nominal value is estimated as being at the 50% of the probability distribution. It is also estimated that the AOCS mass will be between 0.34 kg and 0.38 kg with 60% probability.

Structure The estimated uncertainty distribution of the structure has been estimated by the structural expert as being between the nominal value of 0.55 kg and the value of 0.6 kg, with a uniform distribution.

Instruments The mass of the four cameras has been estimated as being between the nominal value of 0.092 kg (from the datasheet) and the value of 0.100 kg, with a uniform distribution.

Results

The mass of the cubesat is computed as the sum of the masses of all its subsystems. The methods presented in Chapter 3 are used to compute the uncertainty distribution of the whole satellite system given the uncertainties estimated by the experts at subsystem level. In Figure 6.9 the result is presented in the form of a probability density function of the mass of the

		Min	Nominal	Max	
GumStiX + SD card	kg	0.018	0.018	0.019	Uniform Distribution. Max: Nominal +5% margin (data sheet). 4 GumStiX and 4 SD cards.
ASIC+FPGA	kg	0.002	0.003	0.006	Max: Nominal + 100% margin
PCBs	kg	0.150	0.200	0.240	Max: Nominal + 20% margin
X-band Antenna	kg	0.100	0.100	0.105	Uniform Distribution (5% margin)
Components	kg	0.050	0.120	0.144	Uniform Distribution. Max: Nominal + 20% margin.
TOTAL	kg		0.340		

Table 6.3 Command and data handling subsystem mass uncertainty estimation

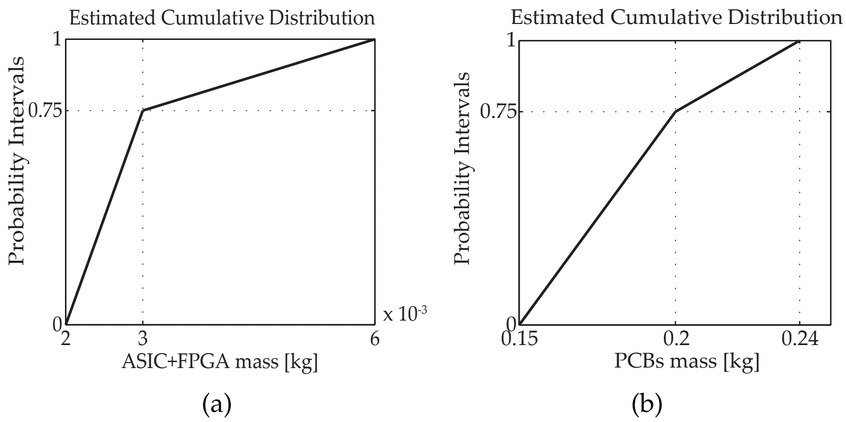


Figure 6.6 Mass cumulative distribution estimated by the subsystems engineers.

cubesat. In Table 6.5, the summary of the mass budget of the cubesat is presented. The mass considering the sum of the nominal values of the subsystems is 3.983 kg, while the mass of the cubesat considering also the subsystems margins is equal to 4.380 kg. According to the computed distribution, there is a probability of 99.96% for the mass being lower than 4.38 kg, see Figure 6.9. Therefore, we can conclude that the mass of the cubesat computed using the subsystems mass plus the margin, considering the probability distribution assigned by the experts, corresponds to a very low-probability event. It can be interpreted as the probability of (almost) all the subsystems being at their maximum value concerning the mass. Therefore, if one would apply a further 20% of system margin, the final mass value would be far from the worst-case scenario estimated by the probability density function: 4.380 + 20% = 5.250 kg.

Therefore, in this case, it was decided to take the mass corresponding to the 95^{th} percentile (95% probability of the mass being lower than that value) into account as the mass on top of which applying the 20% system margin, thus obtaining a final mass equal to 4.2 + 20% = 5 kg.

A sensitivity analysis, using RBSA, was performed to assess on the contribution of the

		Min	Nominal	Max	
AOCS	kg	0.250	0.360	0.410	Max: Nominal + 15% margin.
TOTAL	kg		0.360		

Table 6.4 AOCS subsystem mass uncertainty estimation.

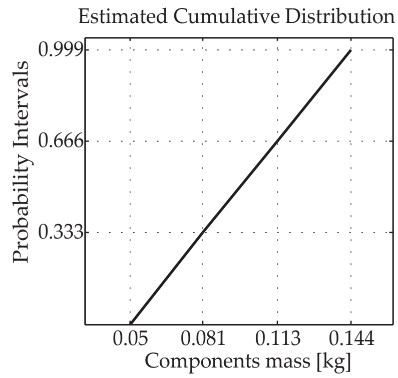


Figure 6.7 Components mass cumulative distribution estimated by the subsystems engineers.

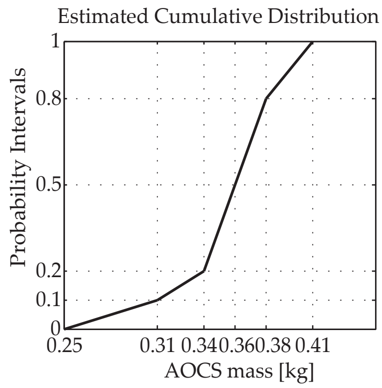


Figure 6.8 AOCS mass cumulative distribution estimated by the subsystems engineers.

various elements of Ops-Sat to the mass budget. The results are presented in Figure 6.10. The bars in the plot indicate the elements that mostly affect the uncertainty related to the mass of Ops-Sat at this stage of the design process. To reduce the estimate of the mass, one should try to reduce the uncertainty related to the elements that present a larger sensitivity index.

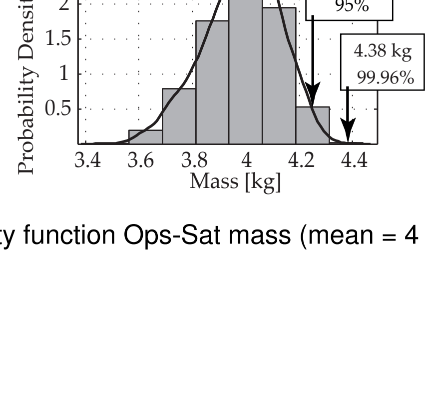


Figure 6.9 Probability density function Ops-Sat mass (mean = 4 kg, sigma = 0.140 kg).

		Nominal	Nominal + Subsystem margin
Structure	kg	0.550	0.590
Data Handling	kg	0.341	0.410
Power	kg	0.820	0.880
Comms.	kg	1.820	2.000
AOCS	kg	0.360	0.400
Instruments	kg	0.092	0.100
TOTAL	kg	3.983	4.380

Table 6.5 Cubesat mass-budget summary.

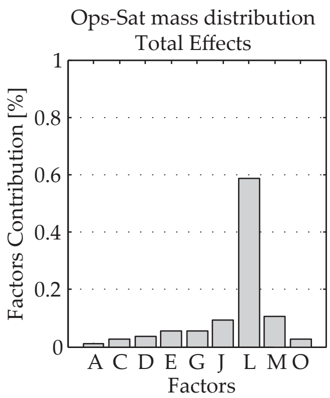


Figure 6.10 Sensitivity analysis, main contributors to the Ops-Sat mass, and mass uncertainty. A: Structure, B: DH PCBs, D: DH components, E: AOCS, G: Solar arrays, J: X-Band transmitter, L: S-band transmitter, M: S-band diplexer.

6.3 Support of the Concurrent Design Platform^{TM} at J-CDS

Based on an experience of more than 15 years in the aerospace industry, JAQAR-Concurrent Design Services B.V. (J-CDS) brings concurrent design services for supporting the engineering activities also to the non-space industry, (J-CDS, 2012; Fijneman and Matthysssen, 2010). During the course of the PhD, we had the opportunity to co-operate with J-CDS for supporting the concurrent engineering design activities and the implementation of some of the design methods presented in this thesis in the J-CDS Concurrent Design Platform (CDP^{TM}). In this section, we present two applicative examples, and the main results that were achieved.

6.3.1 Test case: new medical-product development

J-CDS was actively involved in the implementation of concurrent design within the development process of a medical electronics company (hereafter indicated as *the company*). The company applies concurrent design to gain a quick understanding of the overall cost of the project, time resources needed, and the final product price. In this subsection we take a specific business case, that J-CDS performed in cooperation with the experts of the company, into account. In particular, the study is focussed on the development of an integrated model for assessing the final price of a new product that may be placed on the market. The study involves groups of experts from sales, engineering and production, purchasing, quality assurance, research and development, and management. For each group, an Excel® workbook was developed to allow for the design at discipline-level. These workbooks were used by the discipline experts to determine the characteristics of the product through complicated mathematical models. Inter-discipline relationships are managed through the CDP^{TM}. In Figure

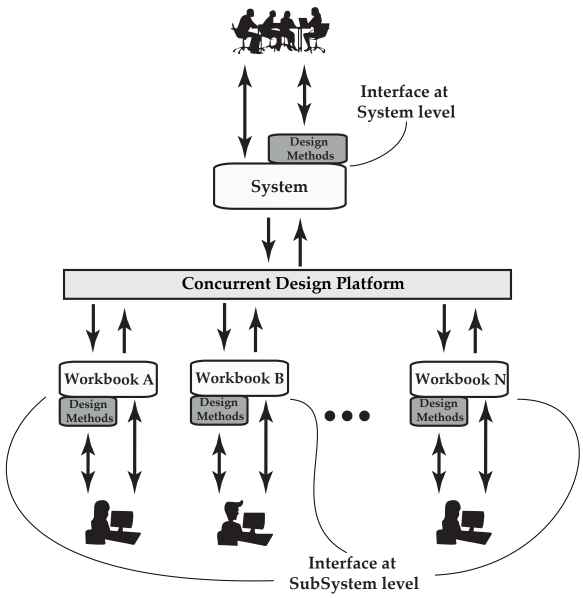


Figure 6.11 Interfaces between the Concurrent Design Platform^{TM} and the design methods.

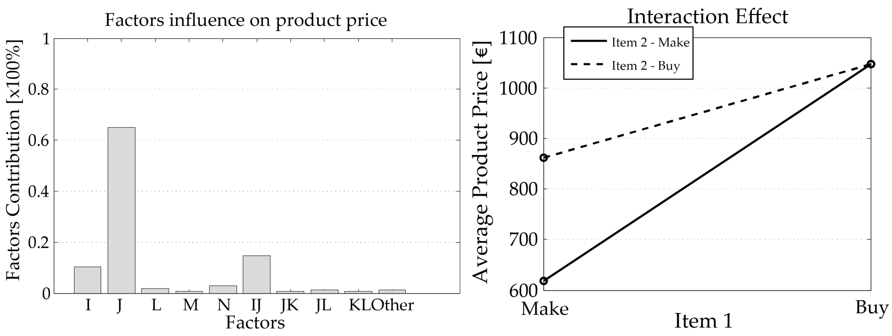
	Code		Min	Max
Production batch size	A	[-]	100	500
PCB Assy SMT operating and visual inspection time	B	[min]	2	10
PCB Assy HMT visual inspection time	C	[min]	10	20
PCB test	D	[min]	2	7
Assembly time	E	[min]	2	7
Testing and programming time	F	[min]	8	15
Packaging time	G	[min]	2	7
Number of elements for break-even	H	[-]	2000	6000
Make or Buy Item 1	I	[-]	Make	Buy
Make or Buy Item 2	J	[-]	Make	Buy
Make or Buy Item 3	K	[-]	Make	Buy
Make or Buy Item 4	L	[-]	Make	Buy
Make or Buy Item 5	M	[-]	Make	Buy
Make or Buy Item 6	N	[-]	Make	Buy

Table 6.6 Design variables medical-product development test case.

6.11 we show the interfaces of the CDP^{TM} with the discipline-domain workbooks and with the design methods that we implemented.

The study was conducted following four different stages, from the very preliminary to a more advanced one. We used the design methods at system level to fine-tune the design parameters and to determine what the best settings are that minimize the final product price. The design factors that were taken into account are described in Table 6.6. The numbers in Table 6.6 are not representative of actual data, but a scaled version of it so to keep representative relative quantities.

The parameters are mainly coming from the R&D workbook, Engineering and Production, and Sales. The Sales experts, through their workbook, collect all the data and determine the final product price made of recurring and non-recurring costs. The non-recurring costs are divided by the total number of elements of that product that the management team wants to produce to reach the break-even point. This influences the final product price. In Table 6.6 some variables that are expressed in time units are indicated. R&D associates a certain hourly cost to these activities, so that in the Sales workbook a global cost can be computed.



(a) (b)

Figure 6.12 (a) Sensitivity analysis. Factors' influence on the product price. (b)Factors' interactions. Support of *Make or Buy* decision in the case of two of the six items of which the product is made of.

In Figure 6.12(a) we present the results obtained from a screening analysis on the parameters under study for the determination of the final product price. The results clearly show that the final product cost is driven by the Make or Buy decisions, related to the items that are needed to build the product. In particular, the Make or Buy decision on Item1 and Item2 will drive the cost much more than Make or Buy decision on the other items. In Figure 6.12(b) we show the combined effect of these two factors. On average the product price will benefit if both the items are built by the company itself. The price gain in making *Item1* is enhanced when also *Item2* is made by the company instead of being outsourced. Concerning the other Items, their effect on the product price is shown in Figure 6.13. Given the estimation from Purchasing and R&D design groups, *Item3*, *Item4* and *Item6* are cheaper if purchased rather than internally produced, while *Item5* is cheaper if not outsourced. The linear graphs in Figures 6.12 and 6.13 indicate the average product price given that the factor of interest is *made* or *bought* with the other factors at all the levels between their minimum and maximum values indicated in Table 6.6.

At this point of the analysis, we decide to freeze *Item1*, *Item2*, and *Item5* at *make* level, and *Item3*, *Item4* and *Item6* at *buy* level, to explore what the contribution of the other factors is. The factors influence on the product price is computed again, considering only the factors from A to H, see Table 6.6. The results are presented in Figure 6.14(a). The product price is reduced if all the operations are completed quickly, but, the inspection time of *Assembly1* and the assemblage time of *Assembly2* play the most important role. The minimum product price that can be achieved under the settings in Table 6.6 is 548 Euro, see Figure 6.14(b). The production batch-size and the number of elements for break-even have a very limited effect on the product price, given the intervals used for the analysis, see Table 6.6. This is due to the reduced effect of the non-recursive costs estimated by the R&D group that amount to 1500 Euro only. Indeed, when amortization of this cost is considered on 2000 to 6000 elements to produce, it has an impact on the total cost that is lower than 1%.

6.3.2 Test case: a scientific instrument in the *eternal darkness* Moon's crater

As a test case, to teach the utilization of the Concurrent Design Platform^{TM}, a hypothetical scientific Moon-mission scenario was developed by J-CDS. The mission goal was to design an instrument that can perform scientific experiments in the eternal darkness crater on the Moon and transmit data to Earth, eventually via relay satellite. After the initial trade-off, the solution with a relay station at crater's edge with mechanical contact to the scientific instrument that is

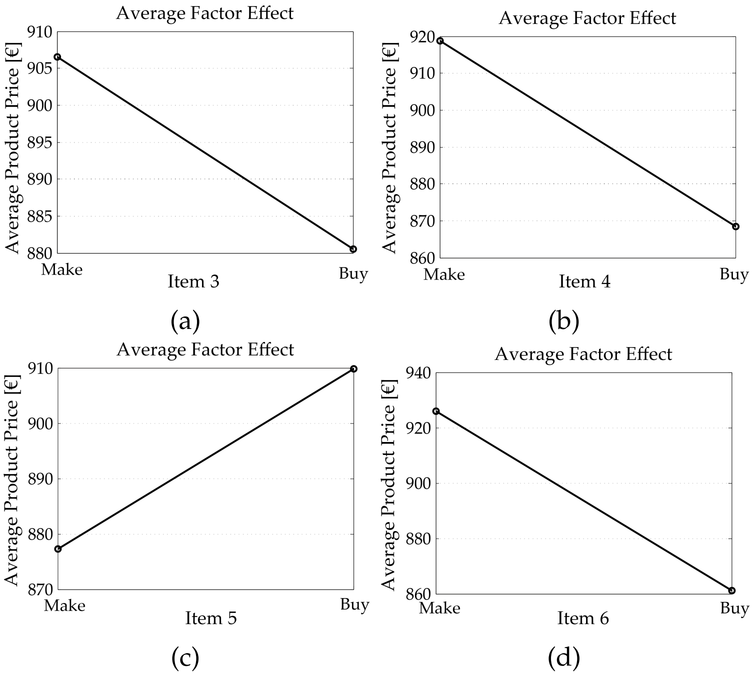


Figure 6.13 Factors main effects. Support *Make or Buy* decisions for the remaining items.

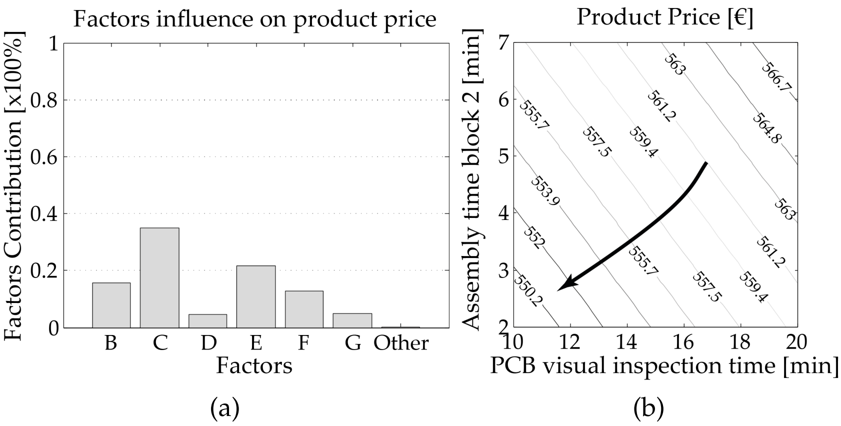


Figure 6.14 (a) Sensitivity analysis. Factors' influence on the product price. (b)Contour plot. Product price decreasing as inspection time (C) and assembly time (E) decrease.

placed at the base of the crater was selected. The relay station communicates with Earth, once per day. In this case, we want to demonstrate the possibility of supporting the design activities of the engineering team-members also at discipline level, besides system level as shown in the previous section. In particular two analyses are performed regarding the communication architecture and the power subsystem.

Supporting the design activities with *soft requirements*

Questioning the requirements is often a good way of understanding whether the design could be radically improved with a little sacrifice of some of the constraints. On the other hand, bargaining on the requirements, or bargaining on data coming from external sources, shall be supported by clear evidence on the impact that that requirement has on the design of the

	Code		Min	Max
Requirement: Data-volume per day	A	[kbit]	80,000	120,000
Data rate	B	[kbps]	30	70
Antenna diameter	C	[m]	0.10	0.40
Transmitter power output	D	[W]	1	5

Table 6.7 Design variables for the communication system of the Moon scientific mission.

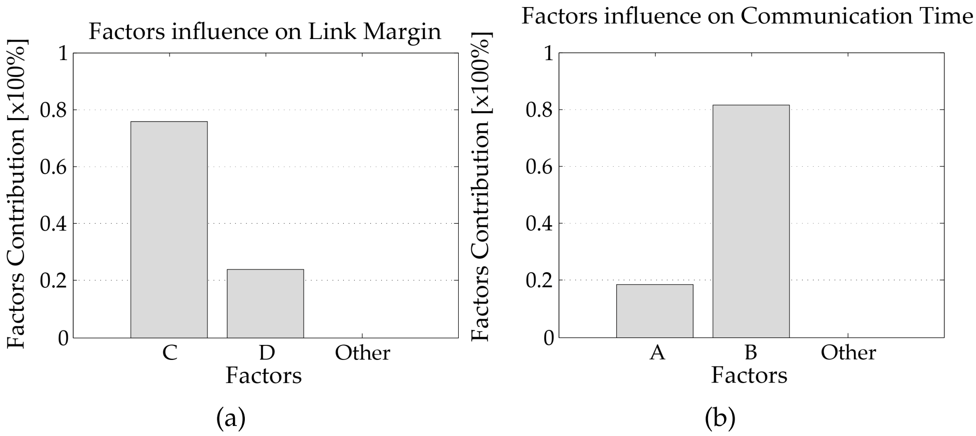


Figure 6.15 Sensitivity analysis. Factors' influence on (a) the Link Margin, (b) the communication time.

system. In the test case proposed here, we use the design methods developed in this thesis to support the design activity of the communication subsystem engineer while analyzing the effect of a *soft requirement* on the performance of the subsystem. The design variables are introduced in Table 6.7. The purpose is to determine the settings for having a good communication link between the relay station and the Earth at the minimum impact in terms of mass. This is translated into having two constraints: link margin that shall be larger than 3 dB, and communication time that shall be lower than 33 minutes (the daily time-window available to communicate with one location on Earth). The results of the analysis are presented in Figures 6.15, 6.16, and 6.17. In Figure 6.15 (a) and (b) we show the influence of the design factors on the *link margin* and the *communication time*, respectively. First, we notice that according to the model that was developed by the J-CDS customer, the *link margin* is not directly connected to the *communication data rate*.

This is evident by the fact that the sensitivity analysis does not show any effect of the factor *B* on the *link margin*, see Figure 6.15(a). This may be an intentional feature that the customer wanted, or not. The important aspect is that with a structured analysis method we were able to spot this uncommon behavior. The contour plots in Figures 6.16 (a) and (b) show that to make sure that the *link margin* is larger than 3 dB, the *antenna diameter* and the *transmitter output power* shall be on the high side of the intervals identified in Table 6.7, towards their maximum value. Bargaining on the required *data volume per day* means, in this case, bargaining on the compression algorithms and the amount of data to be actually sent to Earth. Given the 33-minutes constraint, the contour plot in Figure 6.16(b) shows iso-time curves for different settings of *data rate* and *data volume per day*. Graphs of this type may actually promote discussions, for instance, regarding the actual need of having 100,000 kbit as *data volume required per day*, in contrast of having a reduced data volume. A reduced data volume may be obtained, for instance, using compression algorithms, and this may lead to the

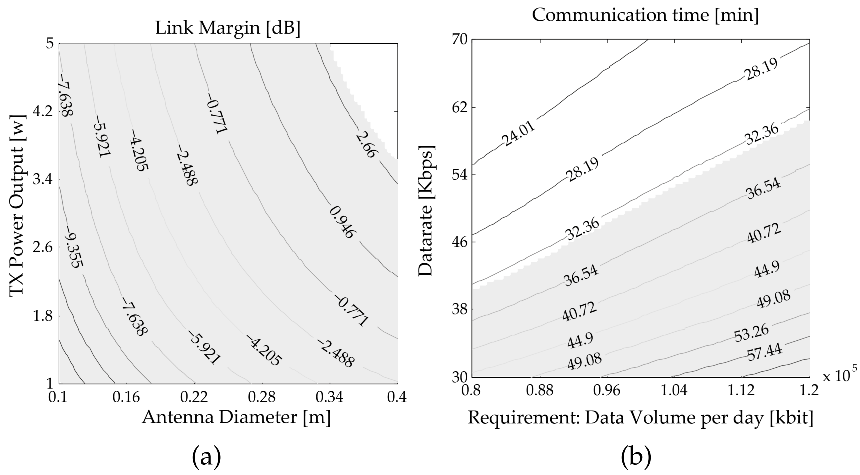


Figure 6.16 Contour plots with constraints analysis of (a) the Link Margin, (b) the communication time. The shaded areas represent the constraints.

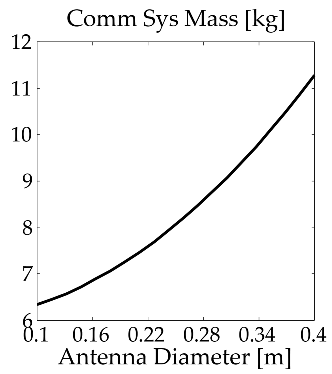


Figure 6.17 Communication subsystem mass-trend as a function of the antenna diameter.

same amount of information delivered on Earth. This in turn will reflect on savings in terms of mass of the subsystem, and cost, for subsequent phases of the design process.

Supporting discipline analysis with missing data

When designing in a team, in an environment with multiple stakeholders, it is often the case that at a certain point of the analysis some data that are actually required for the analysis may be missing. It can be the case, for instance, that a Prime contractor hides sensitive data to sub-contractors or competitors. Further, during a design session, it could be that some data from a certain discipline are required before those data are actually available. The CDP^{TM} has explicit mechanisms in place to prevent the team from interrupting the design activity given that data are not available yet, namely the manual value input. It allows to start working with one's own estimate of missing data. In this structured framework provided by the CDP^{TM} with our methods we allow for exploring ranges of manual values more easily and to compute parametric results based on assumptions on the missing or unknown data. In this test case we support the activity of the electrical power engineer. We facilitate the activity in establishing the performance of the subsystem and the cost estimate of the solar arrays given missing data from the payload, the thermal-control subsystem, and the communication-subsystem design experts. In Table 6.8 we show the factors that the electrical power engineer is missing to provide a cost estimate for the solar arrays of the relay station. The power to be produced is dependent on the

	Code		Min	Max	Uncertainties
Communication subsystem duty cycle	A	[%]	0.1	5	Normal with 0.1 and 5 representing the 0.01 and 99.9 percentile
Relay station heater peak power	B	[W]	4	7	Uniform
Sensor duty cycle	C	[%]	3	6	Normal with 3 and 6 representing the 0.01 and 99.9 percentile
Instrument heater peak power	D	[W]	4	7	Uniform

Table 6.8 Unknown design parameters for the power subsystem cost analysis.

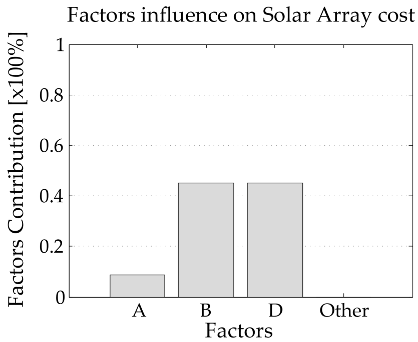


Figure 6.18 Sensitivity analysis for determining the missing-factors influence on the Solar Array cost.

power required by the payload and by the thermal-control subsystem, but it also depends on the energy required for communicating the scientific data back to Earth. These factors will in turn influence the required solar-array area, which will affect their final cost. In Figure 6.18, we show that the uncertainty on the *sensor duty cycle* does not affect the final *solar-array cost* much. This is due to the fact that the peak power consumption of the sensor is limited. This also means that the payload-subsystem engineer could be kept out of the loop in determining the solar-array cost, if his/her analysis is not yet ready. On the other hand, the uncertainties from the communication and the thermal subsystem are causing large variations in the solar-array area. With the proposed approach for concurrent design using structured analysis methods, the electrical-power engineer can now determine parametric values for the cost of the solar arrays based on educated assumptions for the other three missing design factors. In particular, in Figures 6.19(a) and (b) we show the solar-array cost as a function of the peak power of the heaters in the relay station and the instrument. The difference between Figures 6.19(a) and (b) is the value of the communication subsystem duty cycle, which is larger in Figure 6.19(b).

In addition to this, one may actually think of associating a certain probability level to each one of the unknown parameters to try to estimate a probability figure for the cost of the solar arrays. Doing so, the power-subsystem engineer may provide a certain value for the solar-array cost, given a certain confidence level, also helping the cost engineer to take precautionary margins on top of it, depending on the confidence level itself. For instance, in Table 6.8 in the last column we associate a hypothetical probability distribution to the unknown factors. In Figures 6.20(a) and (b) we present two of these probability distributions, in the form of cumulative distribution functions. The uncertainties are propagated in the mathematical model obtaining the probability distribution for the cost of the solar array as shown in Figure 6.21. This means, for instance, that given the uncertainty levels estimated for the unknown param-

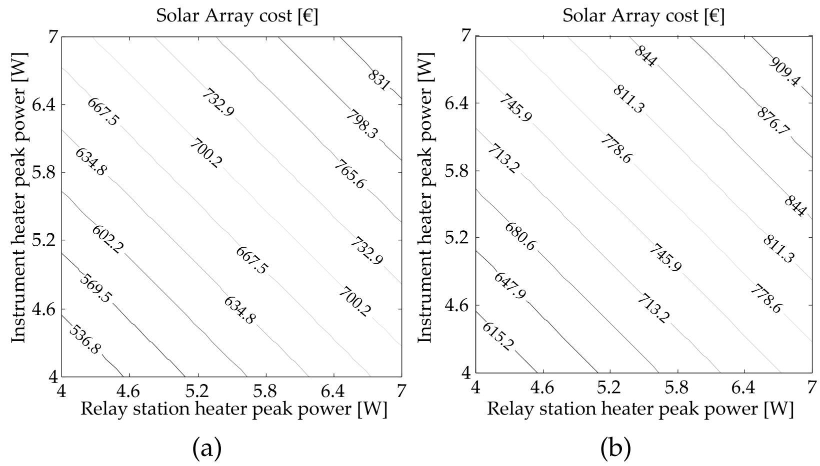


Figure 6.19 (a) Contour plot obtained with minimum communication subsystem duty cycle. (b) Contour plot obtained with maximum communication subsystem duty cycle.

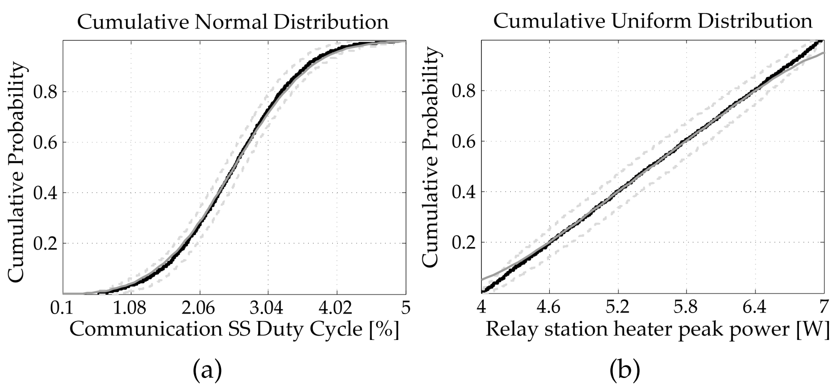


Figure 6.20 Uncertainty analysis. (a) Normal cumulative distribution for the communication subsystem duty cycle and (b) uniform cumulative distribution of the relay-station heater peak power.

eters, the cost of the solar array will be lower than 900 Euro with a probability of 99%. We may also conclude that the probability for the solar-array cost of exceeding 800 Euro is 20%.

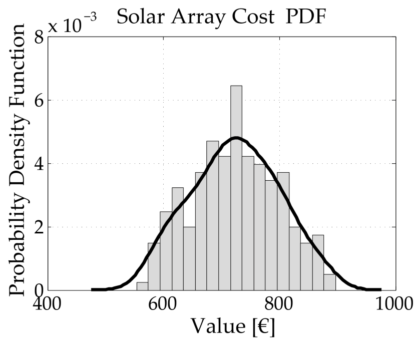


Figure 6.21 Probability distribution of the Solar Array cost as a function of the uncertainties assigned to the unknown parameters.

6.4 Summary

We envision an evolution of Concurrent Design, where concurrent design borne analysis tools are concurrently exploited and fully integrated in the infrastructures built to facilitate concurrent design. In the course of the research that lead to the production of this thesis we proposed the implementation of some of the design methods presented here to the ESA Concurrent Design Facility, and to J-CDS. The design methods presented in this thesis were used to facilitate two main interfaces of a concurrent environment, the human-model interface, and the human-human interface. Several test cases have been taken into account to demonstrate the advantages of the discipline-domain experts in using structured analysis techniques during concurrent design.

The margins given during the design process of a space system in general come from a subjective estimation made by the experts, based on their previous experience or agency practice in general. In this case Ops-Sat was the first attempt to design a cubesat-mission in the CDF, thus such estimation would be solely subjective, not supported by previous experience or agency practice. Therefore, it was decided to tackle the mass-margins management problem with a probabilistic approach. The probabilistic approach to mass-margins allowed us to determine that the baseline mass provided by the classical approach represented the 99.96 percentile of the mass-uncertainty distribution. Applying the 20% mass margin on top of the 99.96 percentile seemed a too stringent assumption for Ops-Sat. Having a probability distribution of the mass of the system available, the systems engineers had the opportunity to select another baseline value, with a larger probability, on top of which to apply the system margin. The system 20% margin on top of the 95^{th} percentile seems a more adequate choice, also due to the fact that the schedule is very compressed for this cubesat programme. Using a structured analysis approach during the concurrent design of Ops-Sat it was also possible to compute the impact of the system's components on the total mass budget uncertainty, providing an effective graphical output for summarizing the results at system level and presenting them to the subsystems experts and the customer.

This demonstrates that using structured analysis methods (such as those presented in this thesis) in the concurrent design process allows for fostering the competitive advantage gained by using concurrent design. In this chapter, we also described the way we supported the concurrent design process of J-CDS for two different test cases. The first one is related to the business analysis of a new non-space product to be commercialized. The results clearly show the best policy in terms of make-buy of the various elements of the product and identify cost-reducing trends in the design parameters. As a second test-case, we supported the activity of the subsystems engineers in dealing with flexible requirements and enhancing the functionality of the CDP^{TM} in allowing the design also when data from other disciplines are missing. The results demonstrated that in both cases these analysis methods help in keeping project consistency by allowing parametric analysis of system performance and enhance the communication of the results through standardized graphical output.

Chapter 7
Conclusions and Recommendations

The research presented in this thesis was driven by the following problem definition:

How and to what extent can design techniques, usually implemented for advanced design phases, assist the engineering team during the conceptual design of complex systems? And in what way can these techniques contribute to obtain better, faster, and eventually cheaper design processes?

Through the chapters of this thesis we have approached the problem of designing space systems using a *helicopter view* on the design space, *i.e.,* from local analyses techniques to global ones. In this final chapter, the conclusions of the work will be discussed in Section 7.1. In Section 7.2 we provide some guidelines to the engineers designing their systems using integrated mathematical models. Recommendations for improvements of the proposed methods and for their actual implementation in practice for future design activities will be given in Section 7.3.

7.1 Conclusions

7.1.1 Local design methods

Efficient sampling is the key for the successful utilization of a mathematical model for system-design purposes. This activity is tightly coupled to the type of analysis of interest and the available resources. In this thesis we have shown that even with a limited utilization of computational resources the Augmented Mixed Hypercube (AMH) approach is able to support all the analysis techniques taken into account. The AMH can be adapted from case to case to support sampling of continuous design spaces, mixed continuous-discrete design spaces, and design spaces with stochastic or epistemic uncertain factors. The AMH was also used as sampling technique for sensitivity analysis.

Why sensitivity analysis for modelers? Would you go to an orthopedist who did not use X-ray?

This is a quote from Jean-Marie Furbringer trying to convey the message that sensitivity analysis is one of the most important aspects for modeling in general, thus also for engineering design and scientific research activities that make use of mathematical models. In this thesis we have demonstrated that we agree very much with Dr. Furbringer. Sensitivity analysis allows to check the validity of model assumptions and to prioritize amongst the design factors that are supposed to influence a certain performance. However, sensitivity analysis needs to be computed in a standardized way and shall provide a global picture on the entire design region of interest. Starting from the principle of computing sensitivity analysis based on the variance decomposition, in this thesis we introduce the Regression Based Sensitivity Analysis (RBSA) method. We demonstrate that under certain assumptions on the design region of interest, the RBSA outperforms other popular global sensitivity analysis methods in terms of computational cost. RBSA provides quantitative sensitivity analysis information in a shorter time. The utilization of the Sobol′ sequence as part of the AMH, enables the iterative RBSA to be successfully implemented, by allowing the efficient re-utilization of previously simulated points for subsequent analyses.

The final chapter of this thesis demonstrated how local design techniques can support the engineering activities for conceptual design in the concurrent design infrastructures. Graphical visualization and standardization of the results are of primary importance. Sensitivity, regression, and robustness analyses successfully supported make-or-buy decisions at system level, providing insight in the effects of design factors coming from different disciplines in the determination of the final product price. The same techniques demonstrated to allow the discipline-domain experts to easily answer some of the most common questions related to conceptual design. We refer to designing with flexible requirements and designing with data missing from other disciplines, for instance.

The AMH sampling approach, the RBSA, and the regression and robustness analysis arranged together as presented in this thesis improve the overall design process for conceptual design in concurrent environments. In case of low-complexity systems, when few variables are under analysis, and when previous experience on similar systems is present, these techniques could be used as a confirmation of the expected trends, or as a proof for the model-underlying assumptions. For more complex and new systems, the implementation of these techniques could reduce the engineering-team effort in exploring different solutions and architectures. In the cases where very experienced specialists are present within the engineering team (who would probably have already a clear picture of the priorities of the factors for the inherent problem), the standardized graphical approach could be a valid tool for them to explain and share thoughts and solutions. However, understanding performance trends in the presence of constraints and multiple objectives beforehand could be a non-trivial task also for them. On the other hand, the less-experienced team members could benefit from these techniques even with easy problems and expected behaviors, thus improving the overall design process, quality and effectiveness.

The success of conceptual design, especially when performed in a collaborative environment, is based on the people, *i.e.,* the engineering team. The methods presented as *local* shall be used with experience, they are not the solution to the problem of designing, they are instruments to reach the solution. Proper skills are needed from the engineering team members to set the analysis and interpret the results.

7.1.2 Global design methods

Optimization has demonstrated to be a powerful tool in the hand of the designers of engineering systems using mathematical models, in a way that it allows to effectively narrow down the search space to only those solutions that are considered optimal. In the *lunar space station mission design*, for instance, it allowed us to understand the best combinations of systems and deployment missions giving us the opportunity to only focus on two configurations, instead of ten.

Multi-objective optimization techniques alone can provide excellent results, however the integration with local techniques is the key to successfully reach global optimal solutions, and at the same time provide insight to the engineering team and additional information related to the robustness of the optimal solutions. Especially from the engineering point of view optimal solutions are not all equal to each other. As demonstrated in this thesis, robustness is an important aspect that will prevent design baselines to have extremely unsatisfactory performances when the level of the design factors are slightly modified, or in the presence of uncontrollable factors.

Using the Pareto-Robust Optimization Algorithm, the integrated approach with global and local analysis methods introduced in this thesis, allowed us to optimize the *satellite system for Earth observation* mission, going from initial requirements to a first baseline estimate, considering optimality and Pareto-robustness. Multi-objective optimization, coupled with a local search using AMH, provided excellent results in searching for robust-optimal solutions in the presence of uncertain design factors and environmental parameters. The optimal-robust configurations of the *atmospheric entry vehicle* make sure that these capsules will perform well also in the presence of a worst-case scenario in terms of environmental parameters, *i.e.,* non-controllable factors.

Even though we believe that MOO (especially when complemented by local analysis methods) can effectively support engineering decisions, it does not seem to be an appealing technique to be implemented for concurrent design at the conceptual phase. The comment that we often receive is that optimization is a technique that somehow limits the concurrency of the design process, by leaving the utilization of the model to a computer. Further, optimization is not considered a reliable source of solutions when it comes to preliminary models used during conceptual design. According to our experience, it all depends on the use that is made of the optimization techniques by the designers. Optimization used as a preliminary analysis, can effectively narrow down the options to be assessed by the engineers. Optimal, and eventually robust-optimal, solutions shall be considered indications to the engineering team. These solutions need to be explored in detail, possibly with the local-analysis techniques presented in this thesis. In this sense, optimization may be considered as a tool to be used during preparatory phases of the concurrent design process, giving the opportunity to focus the discussions on the best candidate solutions only, during the actual design sessions, thus leading to a more efficient design process. The Pareto fronts often presented and discussed in this thesis, allowed us to obtain the best solutions in terms of performance and constraints satisfaction from the models that we had developed. Irrespective of the quality of the model, optimization techniques, if properly implemented, can provide the best possible solutions obtainable with that model, thus saving time to the engineers that are only left with the interesting part of the job, that is the interpretation of the results.

The contribution of the human factor is fundamental for obtaining a final product with a high effectiveness/cost value. With the global MOO techniques presented in this thesis we do not mean to substitute the humans in the process of designing but, quite on the contrary, to better support their activities.

As mentioned several times, obtaining meaningful results with MOO means setting the proper objectives for the analysis, with the proper constraints and proper design factors and intervals. It is a fundamental activity that has to be done by users that have insight in the problem at hand, and it has to be tuned from case to case. Multi-objective optimization is far from being a *push-and-go* technique, if ever; it requires human intellect to be initiated, tuned, and to interpret the generated results.

There are, however, some points of attention that we would like to summarize. Heuristic MOO techniques have demonstrated to provide excellent results also in the presence of mixed continuous/discrete search spaces. However, it cannot be mathematically proven that the solutions they provide will be the global optima. The quality of the solutions increases with the number of simulations performed, and so does the computational time. In engineering, sometimes, *better is the enemy of good-enough*, therefore appropriate termination criteria shall be selected from case to case. The computational load increases also proportionally with the number of design factors. Long-running mathematical models, coupled with a large number of factors to be taken into account may quickly lead to non-feasible implementation of such methods. To mitigate this problem, smarter sampling methods can be used as indicated in this thesis by introducing the Double-Repository Archive Maintenance Scheme. But the best approach that we envision is to follow an ancient Roman political strategy, *divide et impera*, meaning divide and conquer. Using the mathematical model in a non-monolithic way will consent to perform optimizations at subsystems level, then only working on interface-variables to balance the results at system level. In this sense, a concurrent-design infrastructure is amongst the best candidates to implement optimization for conceptual design.

Screening techniques on the design factors prior to start any optimization process are always a good practice, and therefore we strongly advice their utilization. This will allow to focus only on the most relevant factors, and in turn this will allow to save computational time.

7.2 Guidelines for conceptual design using integrated mathematical models

The design of a successful system begins with a thorough understanding of the customer's needs, and continues with translating these needs into proper requirements. A mathematical model of the system under study will evolve with the design cycle of the system itself. In all phases of the design cycle this representation of the system is a powerful tool to be used by the engineering team. In addition to that, the analysis methods with which the model is used are at least as important as the model itself. In this thesis we focus on such methods, for supporting the design activity of the engineering team during the conceptual design phase. In this respect, in this section of the final chapter, we would like to provide some guidelines for designers using integrated mathematical models for conceptual design of engineering systems in general, based on the lessons we learned in this endeavor.

Development of the mathematical model

In Chapter 2 we quoted Dr. Sobieszczanski-Sobieski saying: *if you cannot model it, you cannot optimize it.* This is true not only for optimization purposes. When a decision has to be made, at all levels, a model of the phenomenon of interest is a fundamental tool. A model is needed to understand the effects of the decisions on the object of the study. Also when simply analyzing pros and cons of a certain decision, one subconsciously is using a model for forecasting the consequences of this decision. *What if* scenarios are the main purpose of the utilization of a model. In this thesis we have used mathematical models for understanding the effect of design choices on the performance of the system under analysis. In all cases, the outcome of the model is not better than the information that is already encapsulated in the model. When a certain behavior is to be studied it has to be modeled first. There is no analysis method, not even these presented in this thesis, that is able to create knowledge. The great advantage of the analysis methods presented here is that they are able to aggregate knowledge in a customizable way, allowing for complex relationships to be explained and visualized.

In addition to that, one should not forget that a model is only a representation of reality, and therefore it must not be confounded with reality itself. It would be like going to a restaurant and eating the menu in place of the tasty meal you ordered.

Sensitivity analysis

The difference between developing a model and using it is substantial. A model developer is an expert in the field, encapsulating his/her technical knowledge in equations and logical relationships. The developer of a mathematical model will most likely know all the implications that certain inputs of the model have on certain outputs. This is not necessarily true for somebody using a mathematical model, not having developed it. The user of a model may not know all the details and only be interested in the cause-effect relationships of input and output. This is true especially when the objective of the analysis is to perform higher-level analyses by linking together several mathematical models.

In all these cases sensitivity analysis is a fundamental tool that supports model developers and users in better performing engineering analyses. Sensitivity analysis helps model developers in validating models' assumptions, and it helps model users in determining the importance of selected inputs on selected outputs. In this thesis we have discussed several sensitivity analysis methods, including RBSA that was developed by us. For engineers using sensitivity analysis, we advise the following:

- when the purpose of the analysis is to quickly determine a qualitative ranking of the influence of the factors, used as inputs to the mathematical model, to the determination of the outputs, we advice the utilization of the method of Morris. This method is very effective in ranking the design factors, allowing the designers to perform an initial screening, and for selecting only the most influential factors for subsequent analyses.
- when the purpose of the analysis is to have a quantitative estimate of the factors' importance, including interaction terms, then RBSA is the method to use. With limited dimensions of the design space, RBSA can provide accurate results with a very limited computational effort.
- for analyses in which the design space is particularly large, or when the behavior is highly non-linear or quasi-chaotic, the method of Sobol' or FAST shall be used instead.

Optimization

Optimization is often considered an analysis method for fine-tuning certain design choices. This is not true in general, it depends, amongst others, on the dimensions of the design space that are taken into account. In the course of this thesis optimization has been used from a different perspective. We used optimization as a preliminary analysis to identify the most promising regions of the design space, to be studied in more details in later stages. Computers are better and faster than humans in executing repetitive tasks. Whenever possible, we advise the designers to use automatic techniques, such as optimization, to perform the non-creative part of the analysis, *i.e.*, execution of sets of simulations.

Optimization is not the *panacea* of systems design. Important pre-processing effort is needed to set the proper objectives, constraints, design factors, and their intervals. These settings have to be carefully assessed on the basis of the requirements that drive the design. This is the creative part of the job, and it is best done by the engineering team.

Design, robust design, and uncertainty propagation

We also want to give some suggestions that concern the utilization of the Mixed Hypercube and the Augmented Mixed Hypercube approach, in different design situations:

- when the purpose of the analysis is to study the best settings of the controllable design variables to optimize the performance while meeting the constraints, the mixed hypercube approach in conjunction with RBSA, response surfaces and linear and interaction graphs, provides a way to answer many of the most common design questions.
- when the purpose of the analysis is to obtain a robust design, thus studying the settings of the controllable design factors that optimize the performances while keeping the system insensitive (to a pre-defined extent) to uncertain factors, then the Augmented Mixed Hypercube approach shall be used, see Fig. 3.37(a). For every combination of the levels of the

controllable design variables, an uncertainty analysis can be executed using the Unified Sampling Method to obtain the performance of the system, and the relative statistics, due to uncertain factors.

- when, instead, the effect of the modification of the controllable design variables in later stages of the design process is under investigation, the general case presented in Fig. 3.37(b) can be implemented. The variables used to determine the baseline can be studied in perspective of their uncertain future variation. The continuous variables are more likely to be modified, since the discrete ones commonly represent different architectures of the system (whose change usually brings more radical modifications of the design, thus most likely high costs). However, in general a figure of robustness can be computed for each combination of discrete-factor levels. Propagation of the uncertainty into the model can also be tackled by using the Augmented Mixed Hypercube in Fig. 3.37(b).

Concurrent design process

Concurrent design processes in general are iterative, also when applied to conceptual design. Spirally, the design converges starting from a mission definition and few preliminary requirements, iterating for refining the design baseline. Concurrent design infrastructures are exceptional facilities that make the concurrent design possible, enhancing the capabilities of each single engineering team-member, providing the best environment for new systems and missions to be conceived. As discussed in Chapter 6 we had the opportunity to work with concurrent design infrastructures, and according to our experience we can conclude that the analysis methods proposed in this thesis may be applicable:

- during preparatory phases, when the models are developed, and the interfaces are determined, to check the models' adequacy to customer expectations (models validation). In the space industry, for instance, everybody would expect that if more power is needed for a spacecraft to function, the solar array area must be increased. But if the solar array area increases, the mass increases and the cost follows as a consequence. However, understanding if this chain of relationships was correctly implemented and understanding to what extent the power influences the cost is not trivial, especially if structured design methods are not available.
- during preparatory phases the design methods can also help in selecting already the most important parameters for a given performance of interest, thus contributing in reducing the delivery time to the customer.
- during the design sessions at discipline-domain level to support the experts in exploring options, and performing trade-offs.
- during the design sessions at system level to enhance the capabilities of the integrated model in checking for design consistency, and to identify and evaluate possible design baselines.
- during the design activities within sessions but also during off-line work in-between sessions.

Design sequence

In general we can conclude that one large set of designed experiments is almost never the best approach to answer the key design questions. An iterative approach, using several smaller-size sets of experiments is a more efficient strategy. Indeed, when one decides to study a complex system using its mathematical representation, we suggest the following steps to be taken subsequently:

1. Carefully select the performance to study, the constraints, the factors that represent the degrees of freedom of the analysis, and their ranges of variation in the design space.
2. Perform a preliminary screening analysis.
3. Fix the non-important design factors to a convenient value.
4. Perform a global (eventually multi-objective) optimization to obtain the Pareto front of the model of the system.
   (a) In case of uncertainties, perform robust optimization instead.
5. Perform a local analysis of the performance of the solutions on the Pareto front.
6. Select some design baselines, amongst these on the Pareto front, and compute the sensitivity analysis (possibly using RBSA).
7. Compute contour plots and linear graphs (if applicable), using the most influential factors.
8. Select the best design baseline based on the results from the local analysis.
   (a) Eventually perform again an optimization, restricted to the design region pertaining to the selected baseline.
   (b) Eventually select another solution from the Pareto front coming from this new optimization procedure.

By following all, or part in some cases, of the steps presented here, one can conclude to have exploited the mathematical model at its best, serving the purpose of actually supporting the decision process in an effective way.

7.3 Recommendations

The analytical approaches to complex-systems design presented here of course do not consider all the possibilities offered by the operations research discipline. More and different types of analysis methods may be used to help the engineering team in taking objective decisions. Below we provide some recommendations for further research, related to each specific research field that was approached in the thesis.

Sampling and sensitivity analysis

- correlated inputs to the mathematical models are often required for a proper analysis to be executed. Iman and Conover (1982) proposed an elegant and efficient method for producing correlated sample matrices. The possibility to deal with correlated inputs should be available to the engineering team.
- when the design factors are correlated, the output variance cannot be decomposed with the methods presented in this thesis, see Eq. 3.1. Sensitivity indices, as computed with the methods presented in this thesis, will give an indication of the factors' importance but will not accurately take the correlation into account. For implementing variance-based methods in the presence of correlated input data, we advise the reader to take Saltelli *et al.* (2004) experience into account.
- variance-based sensitivity analysis is not the only approach that can be used. Oakley and O'Hagan (2004) present a probabilistic approach to sensitivity analysis. Their approach can be a valid alternative when the problem at hand does not present discontinuities and when a certain knowledge on the behavior of the model can be assessed a-priori.

Uncertainty and robustness analysis

- the approach proposed by Oakley and O'Hagan (2004) can also be adapted for propagating uncertainty in a complex model using a non-sampling-based approach.
- also in the case of uncertainty propagation and robustness analysis, correlation plays an important role. The engineering team should be able to deal with correlated inputs also in these cases.
- robustness is a central issue in many fields of engineering. In particular, in system and control theory it has become the fulcrum of a specific research branch. There are many parallels between the approach we had on robustness and the approach to robustness implemented by practitioners of robust control. Robust identification of uncertain (or noisy) models is tackled by using several techniques. A very promising one is the H_∞ set membership identification (Milanese and Taragna, 2005). We believe that the adaptation of the techniques used by control engineers to system analysis can be an interesting challenge to try to reduce the computational effort required by sampling-based approaches, as discussed in this thesis, even further.

Optimization

- the optimization methods presented in this thesis demonstrated to be flexible, model-independent and easy to implement. One of the weak points, often raised, is that they do not exploit all the information that is available iteration after iteration. The sample points are *just* used as a means to select the improvement direction. The double-repository archive maintenance scheme presented in this thesis is only a partial contribution to the field and a small step forward, specifically for the case of robust optimization. The incorporation of machine-learning techniques into multi-objective heuristic algorithms is seen by many as viable, possibly more efficient, strategy. Pelikan *et al.* (2006) describe several approaches to incorporate probabilistic modeling in heuristic research of optimal solutions. It would be interesting to understand the behavior of such optimization algorithms in the presence of discrete mathematical models for conceptual systems design.
- optimization using multi-fidelity models is often used when engineering models of different level of detail are available (Rajnarayan *et al.*, 2008). It would be interesting to understand how these algorithms would behave in a collaborative environment having mathematical models of the system belonging to different design phases, *e.g.*, a *Phase 0* and a *Phase A* model.

Facilitation of the design process in collaborative environments

The efficient management and utilization of mathematical models for conceptual design is not the only challenge, as hinted several times along this thesis. Management of people, and their knowledge and experience that cannot be encapsulated in a mathematical model is a big challenge as well. Engineering team-members are *knowledge-owners*. A capable team leader and systems engineer are valuable assets for capturing the required knowledge, putting it in the right place when needed. However, there are also more structured approaches that could be used to deal with *soft* knowledge, to support their activity. These methods fall under the umbrella of methods for decision-making aid, *e.g.*, ELECTRE methods (Mousseau and Slowinski, 1998), multi-attribute utility theory (Ross, 2003), Delphi method (Linstone and Turoff, 1975), *etc.* We have not investigated such decision-making methods here, but it would be an interesting research cue to understand if they could be used in synergy with the analysis methods presented in this thesis.

For a large part of the techniques presented in this thesis, it was also demonstrated that they bring benefits and added value to engineering facilities for concurrent design. Some of the methods mentioned as possible extension of the research presented in this thesis are currently used by researchers in different fields. However, their utility for conceptual design and collaborative environments has yet to be demonstrated, and this would be the main challenge for future research activities.

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Appendix A
Communication and Power Subsystems

In this section we describe the mathematical models for the *communication and power subsystem*, and the settings of the design variables that are used for the analysis presented in this thesis. The model presented here is intentionally focussed on the interactions existing between the communication and the power subsystem of a satellite. In particular, the model of the communication subsystem is used to estimate the uplink and the downlink budget between the satellite and the ground station, and its mass and power consumption. The model of the power subsystem, instead, is used to estimate the mass and power consumption of the power subsystem. Most of the equations presented in this section are adapted from Wertz and Larson (1999b) and also presented elsewhere (Ridolfi *et al.*, 2009, 2010). This Appendix is organized as follows. In Sections A.1 and A.2 all relationships and the design variables used for the design of the communication subsystem and the power subsystem, respectively, are described. The settings of the design variables for these two subsystems and the mission characteristics of the satellite to which they belong are discussed in Section A.3.

A.1 Communication subsystem

A.1.1 Link-budget design

The Bit Error Rate (BER) can be considered as a measure of the communication quality in case of digital communications. It is a measure of the likelihood that a received bit is not correct. This performance parameter can be derived from the carrier-to-noise density ratio, C/N, or from the bit-energy-to-incremental-noise ratio, E_b/N_0. The relationship between the BER and E_b/N_0 depends on the type of modulation chosen for the communication link, see Figure A.1. With a certain required BER, and once the frequency-modulation technique is chosen, the required value for the E_b/N_0 can be obtained. This parameter is the most common Figure of Merit for the link budget, in case of a digital communication link. From an estimated output power of the transmitter, provided as first guess, thanks to the environmental losses and antenna performances (transmitting and receiving antenna), the E_b/N_0 and the margin relative to the required E_b/N_0 can be computed. The following relationships are sequentially computed. From the transmitter output power expressed in W, we obtain the value in dB as follows:

$$P_{dB} = 10 \log_{10} (P) \tag{A.1}$$

The transmitter-to-antenna power loss, often called *line loss* L_l [dB], represents another input parameter for the design of the communication subsystem. It is the loss that occurs from the transmitter to the antenna. The transmitting antenna diameter D_t [m], or the half-power beamwidth θ_t [deg], must be given as input as well; those two parameters can be derived from each other thanks to the following empirical relationship:

$$D_t = \frac{21}{f_{GHz}\theta_t} \tag{A.2}$$

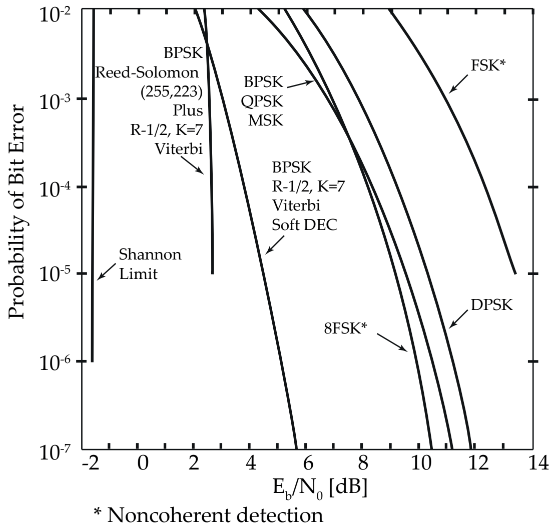

Figure A.1 Bit error probability as a function of E_b/N_0 and the type of modulation. Figure adapted from Wertz and Larson (1999b).

where f_{GHz} is the frequency of the link in GHz. The antenna transmits half of the power within a certain angle, through the main lobe. This angle is called the half-power beamwidth; it is a direct indication of the gain that the antenna can provide. The larger the beamwidth, the lower the gain. The receiver antenna may not be located at the center of the transmitter-antenna's main lobe so that some gain losses occur. The antenna pointing offset e_t [deg] is a parameter that indicates the offset of the antenna's mechanical mounting (or directional control) with respect to the desired direction. Based on the antenna pointing offset the transmit-antenna pointing loss can be computed,L_{pt} [dB]:

$$L_{pt} = -12 \left(\frac{e_t}{\theta_t}\right)^2 \tag{A.3}$$

The peak transmit-antenna gain, G_{pt} [dB], is the ratio of the effective aperture area of the antenna and an hypothetical antenna considered to be isotropic $\lambda^2/4\pi$:

$$G_{pt} = 10\log_{10}\left[\left(\frac{\pi D_t^2 \eta}{4}\right)\left(\frac{4\pi}{\lambda^2}\right)\right] = 10\log_{10}\left(\frac{\pi^2 D_t^2 \eta}{\lambda^2}\right) \tag{A.4}$$

The parameter η is the efficiency of the antenna, ranging from 0 to 1. It is intended to encompass the feed losses, the aperture blockage and the manufacturing imperfections that causes a deviation from the design. The wavelength λ [m] is calculated from the frequency and the speed of light, $c \approx 3 \times 10^6$ km/s:

$$\lambda = \frac{c}{f} \tag{A.5}$$

The gain computed as in Eq. (A.4) is referred to an aperture antenna, or parabolic reflector. This type of antenna usually provides high gains with relatively large mass, volume and cost. Other antenna types can be implemented for satellite systems, for instance helix, horn, and omni-directional antennae. These antennae provide lower gains if compared to aperture antennae, with reduced mass, complexity and cost. In Figure A.2 a schematic representation of a helix and horn antenna is shown. The peak gain, as a function of the parameters shown in Figure A.2, can be computed as shown in Eq. (A.6) and Eq. (A.7). The peak gain of an omni-directional antenna can be considered to be equal to 0 [dB] instead. The *type of antenna* variable that we introduced at this point in the discussion, is a typical example of a categorical variable.

$$G_{pt-Helix} = 10.3 + 10\log\left(\frac{C^2 L}{\lambda^3}\right)$$
$$0.8 \le C/\lambda \le 1.2 \tag{A.6}$$

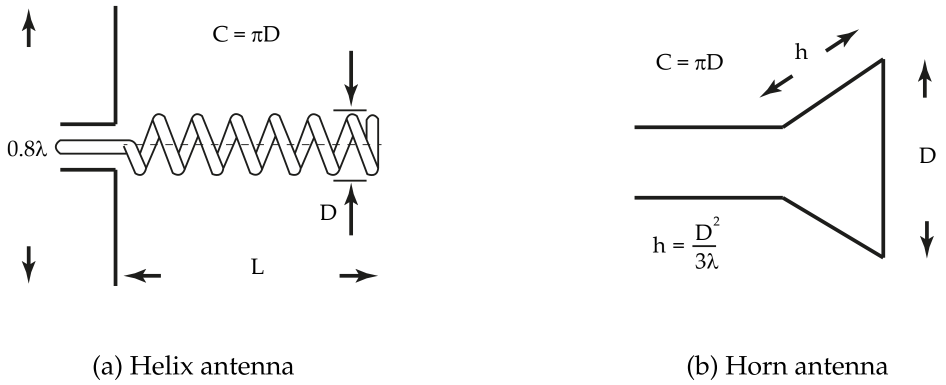

Figure A.2 Schematic representation of two types of satellite antennae.

$$G_{pt-Horn} = 20 \log \left(\frac{C}{\lambda} \right) - 2.8 \tag{A.7}$$

The net transmit antenna gain, G_t [dB], is obtained subtracting the pointing losses from the peak transmit-antenna gain:

$$G_t = G_{pt} - L_{pt} \tag{A.8}$$

The Effective Isotropic Radiated Power, $EIRP$ [dB], of the transmitting antenna can now be computed as follows:

$$EIRP = P_{dB} - L_l + G_t \tag{A.9}$$

The $EIRP$ usually represents the Figure of Merit for transmission systems. From the propagation path length (*i.e.,* the relative distance between the transmitting and the receiving point), D [m], the space-loss can be computed:

$$L_s = 10 \log_{10} \left(\frac{\lambda}{4\pi D} \right)^2 \tag{A.10}$$

The space loss is the free-space attenuation between the antennae. This represents the main source of noise, but there are more noise sources that may be taken into account: atmosphere attenuation, polarization loss, attenuation by rain. Those loss sources depend on the frequency used for the communication and usually represent only a small percentage of the total loss, if compared to the space loss. The atmospheric loss, L_a, can be divided into two main categories: one that takes place in the ionosphere and another one in the troposphere. The ionosphere effects are predominant for low frequencies, but negligible for frequencies of the order of MHz and onwards. The tropospheric effects can be considered predominant, and among them, the attenuation is the one that can cause most of the problems in the communication link.

In Figure A.3, we observe the attenuation due to the atmosphere at zenith, as a function of the frequency. The model has been derived from Wertz and Larson (1999b). The attenuation due to the rain is a function of the frequency as well. The attenuation prediction is usually based on semi-empirical statistical models that take the rainfall statistics into account and transform those into rain attenuation. Those models developed by the International Telecommunication Unit, ITU, provide the rain attenuation as a function of the frequency, probability of rain occurrence, ground station location and satellite elevation angle. In Figure A.4, we observe the rain attenuation predicted with the Crane model, for the northern part of the U.S. This model shows that the rain attenuation is significant for frequencies above 8 GHz; in the worst case, the rain attenuation is around 40 dB. This value is around 15% of the usual space loss. The loss for polarization mismatch for large ground antennas may be estimated as $0.3 - 0.6$ dB, ITU (2002).

The same approach used to estimate the $EIRP$ of the satellite communication subsystem should be used on the receiving system on the ground, *i.e.,* the ground station, to complete the link budget

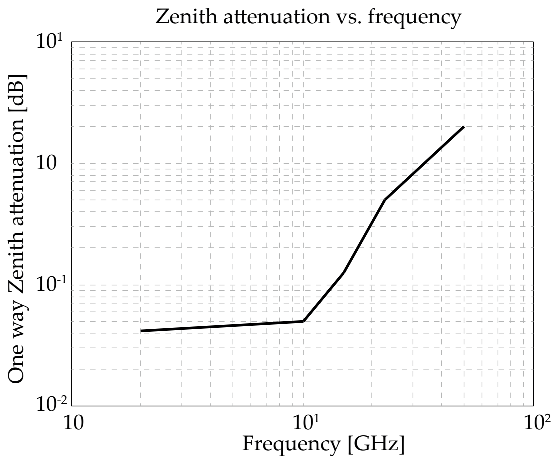

Figure A.3 One way zenith attenuation vs. frequency. Figure adapted from Wertz and Larson (1999b).

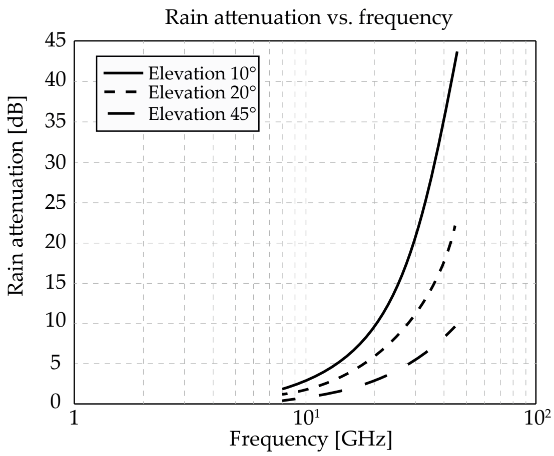

Figure A.4 Rain attenuation vs. frequency, function of the elevation angle. Crane model for a rain climate typical for the northern U.S. Figure adapted from Wertz and Larson (1999b).

and compute the communication margins. For the receiver system, the receiving-antenna diameter, the half-power beamwidth and the pointing offset are required. The antenna diameter and the half power beamwidth are linked to each other thanks to the same empirical equation mentioned before, Eq. (A.2). The antenna peak gain, G_{pr} [dB], pointing loss, L_{pr} [dB], and net gain, G_r [dB], of the receiver antenna, can be calculated with the same equations as used before: namely equations A.3, A.4 (or alternatively equations (A.6), or (A.7)), and (A.8), respectively. In addition, for the receiver system, some noise sources must also be taken into account; the antenna noise and the receiver noise give rise to the so-called system noise temperature. The higher the temperature, the higher the noise the system will experience. In literature, some values for the system-noise temperature may be found, as a function of the frequency range, see also Table A.1.

The system-noise-temperature increase due to the presence of the rain is proportional to the rain

		Downlink			Uplink	
Frequency range	$[GHz]$	0.2	2-12	20	0.2-20	40
System Noise Temperature	$[K]$	221	135	424	614	763

Table A.1 Typical system-noise temperature in satellite communication links, in clean weather. Data from Wertz and Larson (1999b).