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Modeling the Effects of Dispersion of Design Teams on System Failure Risk

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Budget restrictions and advances in technology are making the use of geographically distributed teams in satellite systems more common than ever. However, the influence of dispersion of design teams, cost, performance, and reliability of the final system is not always clear. An outside source may provide benefits in terms of increased skill and experience or decreased costs but also may increase the probability of communications or interface errors. Evidence is presented that supports the argument that satellite anomaly rates increase when one company does not make an entire satellite. The probability of a technical failure in operations is focused on and a model is presented that attempts to quantify the risk, performance, and cost tradeoffs associated with the geographic dispersion of a major part of a satellite, for example, the payload. Our model is based on probabilistic risk analysis, expert opinion, influence diagrams, and the system–action–management framework that involves technical as well as human and organizational factors. We provide an illustrative example, combining actual data and expert opinion, that demonstrates and compares the evaluation of a hypothetical mission with and without team dispersion. The model allows analysis of the sensitivity of the results to the values of the inputs.

Nomenclature

A	=	performance of attitude control
D	=	amount of data acquired by the satellite mission, where is desired amount
L_D	=	launch delay, where 0 is no delay and 1 is maximum delay
L_V	=	performance of launch vehicle
P_L	=	performance of payload
P_P	=	performance of propulsion system
P_{TCR}	=	performance of telemetry, command, and ranging
P_W	=	performance of power system
S	=	performance of structure
S_{CP}	=	performance of processor
T	=	performance of the thermal system
U	=	users
U_{mission}	=	mission utility to the main decision maker, 0 to 100, inclusive

Introduction

WITH the advancement of computer and communications technology, the use of geographically distributed design and production teams in engineering projects is increasing rapidly.[1] Whether to employ such teams has become an important management decision in the development of complex systems. In general, distributed design teams allow a company to take advantage of external knowledge and skills to provide a component that may be more reliable, have a higher performance, and be less expensive than in-house production. The dispersion of production teams, however, may also increase the probability of communication errors between the separated working groups. For example, geographic dispersion of the operating team contributed to some extent to the loss of the Mars Climate Orbiter, which occurred because data were communicated in the British Imperial system and understood at the receiving end as if they were expressed in the metric system.

Direct, statistical quantification of the effects of team dispersion is made difficult by the absence of a sufficient data.[2] The issue of lack of data at the system level frequently arises in the case of a new design, or when the number of previous similar systems is small, making a quantitative analysis difficult.[3] However data often exist at the component level. In this paper, we use systems analysis, Bayesian probability, and expert opinion to create a framework to attempt to quantify these effects. We then present a model that compares the expected performance of the system with and without geographical distribution of the design team for a project subsystem.

Geosynchronous space satellites are the subject of our investigation and an illustration of the more general method because they are complex engineering systems that are increasingly designed by geographically distributed teams. In addition, they pose specific reliability problems because of their uniqueness and the dynamic nature of a constantly evolving technology. Therefore, statistical data are not generally available to analyze the failure risks at the global system level. Instead of a classical statistical analysis based on past frequencies, we use a Bayesian analysis based on available information and expert opinion throughout our illustration. As additional flight data become available, the model can be updated to incorporate that information. A valuable use of this model is, thus, to determine which parts of the system are most in need of further investigation, which is feasible when test data, or surrogate data from other spacecraft, can be used to characterize subsystems of the satellite of interest.

In this paper, which focuses on commercial geosynchronous satellites, the decision is whether or not to select, for the payload, a design and production team that is geographically separated from the rest of the production teams. By that, we mean that a given company is the main satellite provider and that the project manager has to choose between making the payload in-house or at a remote location, possibly in another firm. These two alternatives are evaluated for differing initial budget constraints for the entire project. The goal of this model is to compare the expected utilities of a mission in which the satellite could be produced with or without geographic distribution of the payload design team, for different initial resource constraints. After formulating the model, we provide evidence, albeit indirect, that suggests that distributing parts of the production can lead to an increased anomaly rate. We then present an illustrative, quantitative, example of the use of model and the effect of the probabilities on the final utilities.

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Background Information

Distributed Teams

The geographic distribution of work teams allows a project to take advantage of people and technology residing away from the main production/design group. However, geographically distributed teams present a new set of problems for systems' engineering. Readings on the advantages and the perils of distributed teams can be found in Ref. 4, in which Kiesler and Cummings summarize the literature on the implications of distance for working groups.[5] They conclude that close proximity is beneficial due to the "mere presence of others, face-to-face communication, shared social settings, and frequency of spontaneous communication." Furthermore, that "technological and organizational remedies for the absence of these factors... are popular but often problematic."[5] Distance collaborators can easily misunderstand each other or have different goals and agenda, which may lead to reliability problems. Cramton identifies five main problems pertinent to distributed teams[6]: 1) failure to communicate and retain information, 2) uneven distribution of information, 3) difficulties in communicating and understanding salience of information, 4) differences in speed of access to information, and 5) difficulty in the interpretation of the meaning of silence. To this list, we add possible differences in preferences and priorities among distributed teams.

Conflicts of various kinds can also arise among distributed teams: "Conflicts escalate strangely between distributed groups, resisting reason. Group members at sites separated by even a few kilometers begin to talk in the language of 'us and them.'"[7] Teams tend to think less of other groups, often falling prey to the fundamental attribution error[8] and assigning mistakes or delays to other teams' ability and character rather than situational factors. Such attributions can easily lead to a loss of confidence in the work of others to the detriment of the entire project.

The study of distributed teams is especially relevant to space systems operations. NASA's dispersion among centers has often been a cause of problems, and the relatively recent focus on faster–better–cheaper missions has led to more emphasis on small rather than large project teams. It has also played a role in the Mars Climate Orbiter failure (MCO) described earlier. However this was a management error as well. A former mission director at the Jet Propulsion Laboratory (JPL) wrote: "[MCO] was a problem of transition from the era of very large teams to when teams are very small."[9] Part of the blame lay in "inadequate communications between project elements,"[10] most likely exacerbated by their physical separation, as MCO experienced problems related to communications among project elements. The error was not picked up as soon as it should have been because the navigation team was understaffed and not sufficiently familiar with the spacecraft to understand and correct the observed orbit anomalies.[10] Separate navigation teams were used for the developmental and test phases and for operations and navigation. One organization was responsible for the design and when a different one took over operational control 30 days after the launch, their navigators were not sufficiently familiar with the operation of the spacecraft. Clearly, the management of the interface between the ground operations and the technology of the spacecraft, along with the lack of depth of knowledge due to the smaller sized teams, were causes of the MCO failure.

Typical Design Process for a Geosynchronous Satellite

The operations of a geosynchronous satellite involve four major components: payload, spacecraft, launch vehicle, and ground control operations.[11] The typical design process is as follows. A customer determines the resource constraints and the scope of a project. Once these are determined, a project integrator is chosen and is responsible for flight systems integration (payload and subsystems), launch vehicle procurement, and ground systems development. This paper focuses on the flight systems' integration (payload and platform) because this is where the supplier has the most autonomy. The two satellite-production design team structures that are compared in this paper are shown in Fig. 1.

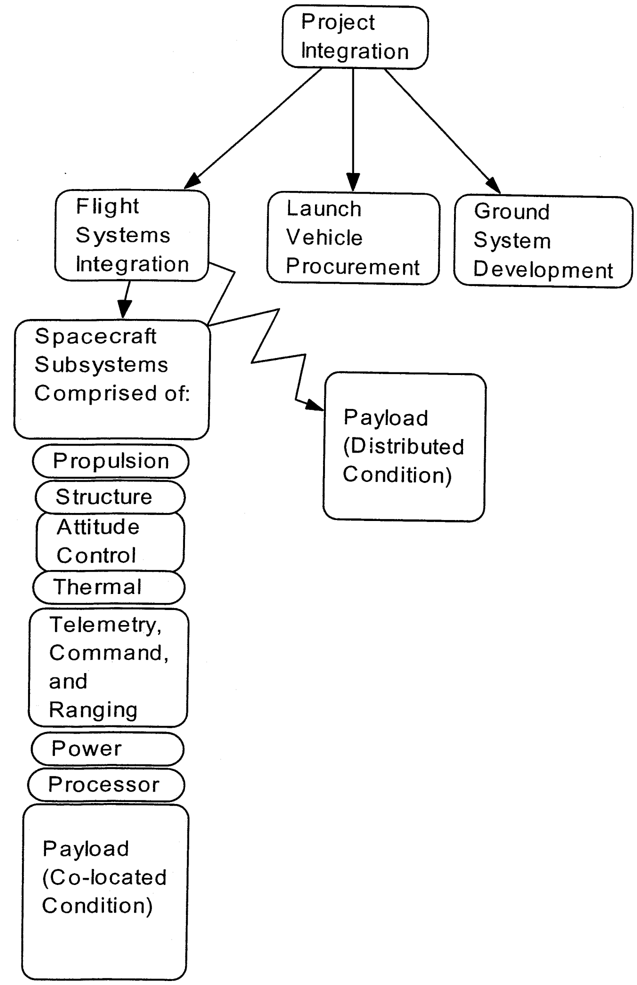

Fig. 1 Satellite design chart.

Interface Issues

One of the objectives of this paper is to examine the effects of some of the interfaces between the spacecraft and the payload on the reliability and the value of the mission. The interfaces of interest are those between the spacecraft computers and the payload and between the spacecraft computers and the ground operations. We do not consider the payload–ground operations interface because, on a geosynchronous commercial satellite, the interaction between the two is minimal inasmuch as the main computers are within the telemetry, command, and ranging subsystem. Our model seeks to determine the influences and effects of human decisions and actions on the performance at the interfaces, as well as the relation of these interfaces to the reliability and performance of the satellite. To model these interactions, we use the system–action–management (SAM) framework[12] as described further in this paper.

Modeling Approach

SAM Model

The objective of a probabilistic risk analysis (PRA) is to compute the failure probability of a system as a function of the performance of its components, accounting for the dependencies and failure modes that result from its design and operation. Management's decisions and actions play a large role in the reliability of a system because their choices regarding resource constraints, organizational structure, design, operation, and personnel have a direct link to what people do and, therefore, to the system's reliability. The SAM framework addresses these human and management causes of system failure by starting from a quantitative risk analysis model of the physical system and expanding the scope of the analysis by incorporating the human decisions, actions, and errors that affect the physical system. SAM then links upper management decisions to

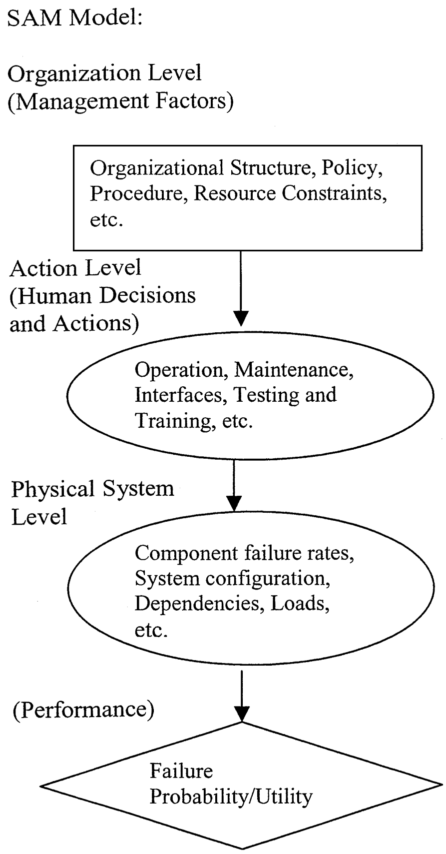

Fig. 2 Graphical representation of a generic SAM model (from Ref. 12), where the rectangle stands for management decisions, ovals represent probabilities from the viewpoint of upper management, the diamond represents the utility of the system as a whole, and arrows represent influences from one part of the system to another.

the midlevel decisions and actions, effectively relating upper management decisions to the performance of the physical system.[12] This probabilistic analysis takes advantage of the power of influence diagrams[13] to reflect dependencies between different elements of the system and its management. A generic version of the SAM framework is shown in Fig. 2.

Model Description

The model presented here is a framework designed to assess the performance (and subsequent mission utility) of the satellite system, with and without geographic and organizational separation of the team that designs and produces the payload. The SAM framework is used to model the probabilistic influences among management decisions, the subsequent intermediate decisions and actions, and the physical system's reliability. A utility node reflects the overall value of the system's performance to the main decision maker (the client) based on the amount (and the quality) of the data gathered during the mission, discounted for any possible time delays and cost overruns. The actual encoding of the probability distributions of each random variable is left to the model's user. Obviously, these data are specific to the designs considered. These distributions will be in part subjective when the subsystems involved have not been tested in previous flights because, in those cases, only test data and engineering models are available. In other instances, surrogate data from the use of the same subsystems in different missions might provide a good basis for estimation. As it is often the case, the decision maker needs to use expert opinion to update test and surrogate data when actual flight data are not available.[14]

As an application of the SAM model, the PRA completed by a study of the project review procedures allows a better assessment of the failure risk. A single incident seldom brings down a complex system; in addition, existing procedures are generally adequate to catch simple errors. Many failures of major projects, such as satellites, are caused by a conjunction of events (related or not), and conditional probability estimates are necessary to capture potential dependencies among those events. These estimations require data that explicitly account for couplings. In what follows, we describe the analysis from the bottom up.

Systems PRA

PRA uses the probability of different initiating events and the conditional probabilities of subsequent events or random variables to derive the probabilities of all outcome scenarios and a distribution of the final states of the system, for example, partial failures, failure, or success. The major components of a geosynchronous satellite in this PRA are launch vehicle, payload, and the spacecraft subsystems (besides payload) including propulsion, attitude control, power, telemetry, command, and ranging, (TC&R), thermal power, structure, and the spacecraft processor (Fig. 1). In addition, we consider elements, such as ground operations, that are not part of the physical system but do affect performance. Other such elements include the skills of the satellite's users, the mission's final orbit, and external events, for example, radiation or collisions with micrometeorites.

The PRA model is structured as follows (Fig. 3). The state of each system element is characterized by a probability distribution (performance level) that affects the state of the entire system at that time. Some probabilities are influenced by external events and others by the state of the rest of the system. For example, there is a probabilistic dependence between the states of the propulsion and attitude control subsystems. For simplicity, most of the nodes in the Fig. 3 representation of the performance of the physical system are characterized by three possible realizations: fully functional, partially functional, and not working. (The exceptions are external events and orbit mission.) In reality, each subsystem has many partial failure modes (anomalies) that we do not attempt to describe here. In Appendix A one partial failure mode per subsystem, as well as dependencies among subsystems' partial failures, is described.

The performance (data) node reflects the amount and quality of the data obtained from the mission given the state of all of the satellite parts that influence this metric. It is assumed that failure of any of the main parts of the system will cause complete mission failure. Therefore, the influences that require the most attention are those of partially functioning subsystems because they may or may not affect the mission reliability and value in terms of data gathering.

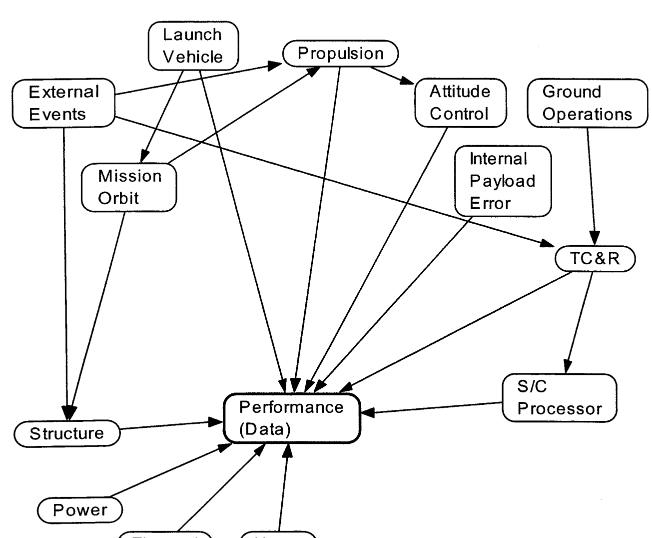

Fig. 3 Probabilistic risk analysis of the satellite system; all nodes indicate uncertainties except for the bounded rectangle, performance (data), which is a deterministic node.

Performance (Mission Data Acquisition)

The satellite's performance is measured by the amount and the quality of the mission data. The performances of the subsystems, as well as the ability of the users to interpret them, determine the value of the performance (data) node. Even in this simplified model, the 10 factors (and their realizations) that affect, in principle, the system's performance create too many combinations ($\sim 3^{10} = 59{,}049$) to permit elicitation of the conditional probabilities required. Therefore, to create a workable model, this node is simplified by estimating the value of the mission data as a deterministic function of the inputs to the performance (data) node. To do so, we use a deterministic equation that reflects the influence of each subsystem's performance on the amount and quality of the data received, D. All variables are evaluated on a scale ranging from values 0 to 1 (inclusive) where 1 represents a perfectly working system and 0 represents the state of a failed component. The intermediate states have been defined by experts and are discussed further.

This function meets the following requirements. First, if all influencing components are fully functional (have a value equal to 1), the performance of the system is set to 1 (maximum performance). Second, if any of the main influencing components has failed completely (have a value equal to 0), no data are received, and the performance of the system is 0. Third, the performance of the system reflects partial failures to the extent that they inhibit the satellite's performance. Each partial failure for each influencing subsystem is attributed a partial-failure coefficient (Appendix B), which represents the relative (decreased) performance of the system in each case given that all other parts are working properly. For example, we are using 0.75 as the partial-failure coefficient for a partial failure of the power subsystem. This means that, if all other influencing components are working, the partial failure of the power subsystem will lead to a value of the mission data equal to 0.75, compared to a maximum value of 1. Fourth, the effects of partial failures are considered independent except when dependencies between two subsystems could exacerbate the effects of their partial failures on the performance. We assume here that these dependencies further reduce the mission's value by an additional factor equal to the square of the product of the original performance coefficients. The synergistic failures considered here are those of the following subsystems: 1) attitude control and power, 2) attitude control and propulsion, 3) propulsion and launch vehicle, and 4) TC&R and users. If both components of any of these synergistic pairs do not experience simultaneous failures, the performance function is assumed to be the product of the performance factors of each of the components:

$$\text{Performance (data)} = D = L_V \times A \times P_W \times S_{\text{CP}} \times T \times S \times P_P \times P_{\text{TCR}} \times U \times P_L \tag{1}$$

An illustration of synergy effects is the following. Assume a partial failure both in the propulsion subsystem and in the launch vehicle. Such a partial failure could occur if the launch vehicle inserts the satellite into an incorrect orbit and there is a leakage in the propulsion system. (See Appendix B for a description of this partial-failure mode.) Individually, the partial-failure coefficients of propulsion and launch vehicle are 0.8 and 0.6. If all of the other subsystems are working perfectly, the performance of the mission will be reduced to a value equal to the squared product of 0.8 and 0.6, 0.23, significantly less than 0.48 if the synergy were not taken into account. Positive synergies, or examples where certain partial failures do not influence the system as much as if other partial failures had not occurred, are not taken into account here but could be included in a similar fashion (using, for example, the square roots of the factors involved). Fifth, if three or four of the synergistic elements described (A, P, P_P; and L_V) experience partial failures, we do not discount the final performance by more than the square of each partial failure. An important limitation of this model is that it does not include the timing of failures and anomalies, that is, the case where data have already been received before loss or degradation of the system.

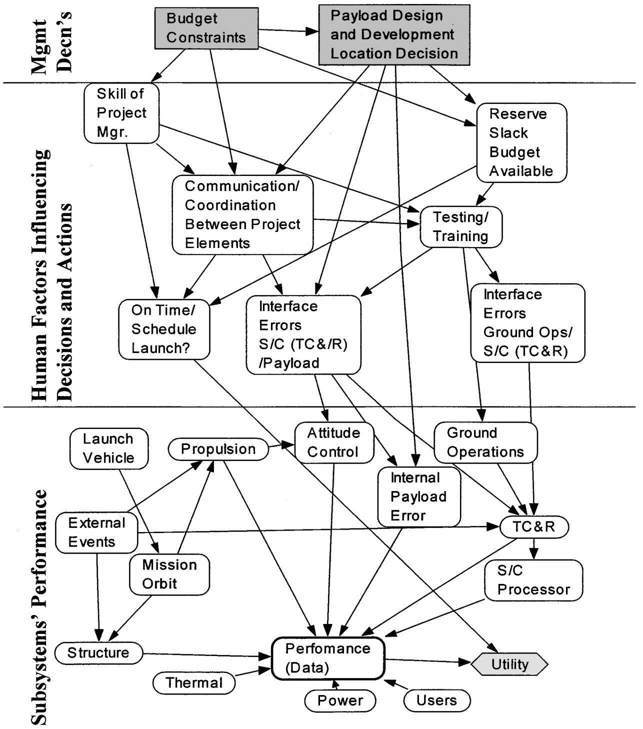

Fig. 4 Influence diagram representation of the SAM model for the analysis of the effects of payload design team distribution on the realiability of a satellite.

Global Risk Analysis of the Process in the SAM Framework

Global SAM Model

The entire probabilistic (SAM) model is shown in Fig. 4 where the rectangles represent management decisions, the ovals represent uncertainties, and the diamond is the value of mission data. The darkened hexagon is a deterministic node, and the arrows represent influences between nodes, that is, among the random events and variables that they represent.

Model Assumptions

The main assumptions of the model are the following. First, all subsystems besides the payload are produced in-house. Second, the original mission resources are all used, either in the system itself or to solve development problems, and no money is saved if less expensive choices are made. Third, we do not examine the effects of the choice of a launch vehicle. (See Guikema and Paté-Cornell[15] for an in-depth analysis of launch vehicle failure probabilities.) Fourth, the model does not consider the value of mission data received before a failure. Fifth, insurance compensation for lost missions is not accounted for. Finally, the utility node does not account for the amount of initial resources allocated to the project.

Decisions and Actions Nodes

Human factors in the middle level represent decisions, actions, and errors that, in turn, affect the robustness of the system and the elements of the PRA model. These actions are uncertain events influenced by management decisions that condition them. Although many of these intermediate nodes include operator decisions, from the point of view of upper management, they are uncertain and are, thus, represented as random events or variables.

Skill of Project Manager

The amount of resources dedicated to compensation, training, and experience enrichment influences the skill of the project manager. Furthermore, the resources available for a project does influence whether a good manager may be willing to head the mission. The skills of the project manager also affect the communication and coordination among the teams responsible for the different project subsystems, the nature of component testing and personnel training, and the critical launch decision. Therefore, it affects directly the behavior of the operators, engineers, and technicians who design and manufacture the system. The (simplified) realizations of the variable describing the managers' skills are as follows: 1) The manager has successfully managed previous missions, especially in the last five years (high). 2) The manager does not meet the preceding criterion (mediocre).

Available Budget Reserves

The budget reserves are the funds available to deal with unanticipated problems. The reserves affect how much testing and training can be performed and whether unexpected problems can be handled so that the project remains on schedule and within budget.[16] The reserves are modeled here as a deterministic node set by management decisions. The realizations of the budget reserves node that we consider here are 1) ample, that is, the slack budget is greater than 20% of the minimum budget; 2) large, that is 12–20% of the minimum budget; 3) medium, that is, 6–12 of original the minimum budget; and 4) little, that is, 0–6% of the minimum budget.

Communication and Coordination Among the Teams Responsible for the Different Project Elements

This node reflects the amount of interaction among the teams in charge of the different elements of the satellite's development. Increased and better interaction decreases the probability of interface errors. The project's resource constraints, design team distribution, and the skill of the project manager all influence the amount and the quality of communication and coordination among the different design groups. The communication and coordination node influences the amount of testing and training, whether or not the launch will be on schedule, and the potential for interface error between the spacecraft and the payload.

The realizations of the communication and coordination node are as follows: 1) The different project subgroups meet often (at least once per week), work together in the production phase and interact on appropriate testing and personnel training (high). 2) The meetings are neither regular nor frequent, for example, biweekly or less, and there is only moderate discussion about interface issues and coordination of testing and training (medium). 3) There is little or no interaction between the subgroups, and testing and training is carried out by each team separately; groups are not necessarily trained to fully understand the other subsystems (low).

Testing and Training

This node reflects the amount of training of team members, both about their component and the other parts of the system, and of testing of the satellite (by components and at various levels of assembly) under many different possible operating conditions. Testing and training are a part of the project where corners can easily be cut when resources are low because it is difficult to determine appropriate measures. There are specific rules and procedures about what is appropriate, but they are sometimes subject to interpretation, and as the budget gets tighter, the rules can get looser.

Testing and training are influenced by the skills of the project manager, the communication and coordination of the different project elements' design teams, and the budget reserves. The robustness of the interfaces among the spacecraft, the payload, the launch vehicle, and the ground operations are all affected by the quality of testing and training. An ample amount of testing and training can increase system reliability by decreasing the probability of interface and operator errors and increasing the probability of early detection of defects. What constitutes proper amounts of training or testing, however, is often subjective, and again, liable to be cut when funding is tight. In the case of the MCO, for example, the operators may not have been provided sufficient training for this specific spacecraft, so that, when they took over operations 30 days after launch, they were not fully prepared for the job.[10]

The realizations of the testing and training node are as follows: 1) The ground users are well trained, for example, >100 h training, to operate the spacecraft after launch. The satellite is tested for a large spectrum of specified scenarios and has passed all standard testing procedures. The interactions among subsystems are tested as well. If all combinations cannot be examined, then orthogonal arrays can be used in the design of experimental testing to test interactive factors[17] (thorough). 2) All performance requirements as just described are not met. Corners have been cut in the training of key technicians and in system testing for all possible scenarios (incomplete).

Launch on Schedule

This node reflects whether the satellite is launched on time and on budget. It is influenced by the skills of the project director to manage the schedule, the funding, the communication and coordination between project elements, and the reserves. An example of a potential cause of delay and cost overrun is fairing fit problems causing difficulties in the attachment of the launch vehicle to the spacecraft. The launch decision directly affects the value (utility) of the mission because cost overruns and/or delays reduce mission utility. The realizations of the launch on schedule node are 1) on schedule, 2) on schedule with cost overruns, and 3) delayed and cost overruns.

Interface Errors

The most significant causes of interface errors are lack of communication and coordination among the different design and manufacturing groups and inadequate personnel training and system testing. In our model, we focus on the spacecraft/payload and spacecraft/ground operations interfaces, which affect the physical system as described next. Interfaces involving the launch vehicle have not been examined because they are outside the main scope of this paper. Interface errors influence the chance of total and partial failure for different spacecraft subsystems, which, in turn, influences the mission's value. The interface problems listed next provide illustrations of interface errors. This list is by no means complete.

Spacecraft—Payload

This interface influences the probability of a software error in the payload and the TC&R subsystem. Two common failure modes are 1) the payload software overwriting and dominating the spacecraft software by error and 2) a TC&R software error causing improper spaceship pointing resulting in loss of the payload functions. The realizations of the spacecraft-payload interface node are 1) software overwrite problems, 2) pointing problems, and 3) no errors.

Spacecraft—Ground Operations

Errors at this interface also involve software problems and influence the performances of the structure and the TC&R. The main failure mode involves faulty software changes made on the ground that cause pointing errors in the spacecraft. The realizations of the spacecraft–ground operations node are the following: 1) serious software errors that endanger the satellite's mission, for example, by causing a major shift in the attitude of the spacecraft, 2) minor software errors that only reduce the utility of the mission, and 3) no errors.

Upper Management Decisions

The upper part of the SAM model involves a description of themanagement decisions that affect the rest of the system, their nature, and the options considered. Our model is intended to support these decisions by quantifying their effect on the reliability. The question is which choice (payload designed in-house or elsewhere) will maximize the expected utility of the mission. To analyze the choice of a design team architecture, we must also consider the decision regarding the project's budget because the optimal payload design decision may be influenced by the need for budget reserves, the costs of testing and training, and the difference in cost between collocating and dispersing the design and production of the payload.

Budget Constraints

The choice of the budget is one of the first decisions to be made. As already mentioned, the budget affects the decision of a project manager to accept the job because the manager may take the size of the budget into account. Furthermore, and given the choice of a structure for the design team (whether to contract out the design and production of the payload), the overall budget determines the reserves available for training and testing, as well as for solving all development problems that may occur before launch. The realizations of the budget constraint are defined in terms of reserves available given that the development of the payload is contracted out (or not). 1) In this case, the budget reserves are always ample regardless of where the payload is developed (super). 2) There is a large reserve available when the payload design and development is distributed, and a medium reserve when the payload is produced in-house (ample). 3) There is only a medium reserve slack budget when the payload design and production is distributed, and there is little reserve if the payload is produced in-house (tight).

Payload Design and Development Location Decision

This is the major decision analyzed here. As mentioned already, the tradeoff here could be between lower probability of interface errors (in-house) and lower cost and greater experience (offsite). (Note that this is not always the case; for example, the offsite producer could also be more expensive and more reliable.) The money saved through subcontracting can then be used as part of the reserves. The realizations of the payload design and development location decision node are 1) payload team geographically distributed from the other teams and 2) collocation of all of the design teams. The question is then to assess the effects of this decision on the final mission utility through the influences from this decision on communication/coordination, reserve slack budget available, and internal payload error (Fig. 4).

Mission Value (Utility) Node

The mission value determined by the amount and quality of data collected varies with system performance and is expressed by a utility function. The expected utility of this function over the range of possible scenarios is the ultimate value of an option. To model the value of different amounts of information provided by the mission, we use an illustrative logarithmic curve minus a penalty factor for delays and/or cost overruns. Therefore, the relation between the amount and quality of the data received and the utility of the mission is a strictly concave, increasing function that reflects a decreasing marginal value of additional data. The mission utility is then adjusted downward to reflect the costs of potential delays or budget overruns. Let D be the amount of data received from the satellite and L_D the monetary losses associated with a delayed launch or the extra costs to ensure a timely launch. Both have a range of 0–1. The illustrative utility function that we have chosen is

$$U_{\text{mission}} = 10 + 299 \times [\log(D+1)] - (10 \times L_D) \tag{2}$$

Equation (2) is scaled so that the mission's utility equals 100 when the satellite is fully functional with no delay or cost overrun and 0 for a failed mission with maximum cost overrun. Figure 5 shows the utility as a function of the payload performance for $L_D = 0$.

Evidence from the Data

To get some base failure rates of particular subsystems, we investigated 116 geosynchronous satellite launches from 1984 to 2001. The marketing department of a major satellite-producing firm collected these data. The original sources are all in the public domain and consist of Internet sites, newspaper accounts, space journals, and corporate releases, for example, the Associated Press, satellite encyclopedia, *Space News*, etc. Because satellite production firms do not reveal their design methods, there was no way to tell which satellites had employed distributed teams and which had not. We were able, however, to determine which satellites were built, at least partially, by a different company than the parent organization. This was in the case of companies that underwent acquisition or merger at the time the satellite was built. Therefore, two companies were involved, generally geographically separated. The evidence from these 116 launches shows that those built in the merger/acquisition condition had a significantly greater anomaly rate than others. An anomaly is defined as any mishap leading to any degradation of performance, including (total) failure. Whereas a merger/acquisition is more complex and potentially more chaotic to an engineering project than simply building a component offsite, one can argue that mergers or acquisitions do provide an example that shares some similarities with that of distributed design teams because the parent company is not directly in charge of all of the project's elements at the time of design and production. Although the act of a merger/acquisition is certainly a confounding factor, the evidence does suggest that distributing part of the process leads to increased anomaly and failure rates.

Table 1 Statistical analysis of difference in failure probability between satellites built under merger or acquisition conditions vs those built by a single supplier

Merger/acquisition condition (%)	Base condition (%)	Significance (Z score), %
Anomalies		
20 of 33 (61)	33 of 74 (45)	94
Failures only		
6 of 33 (18)	5 of 74 (7)	96

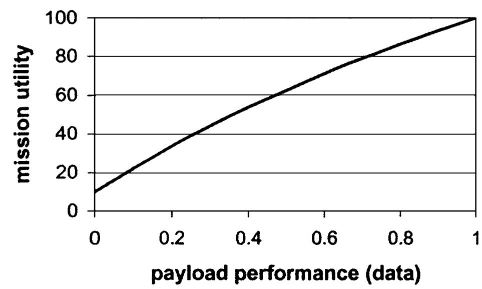

Fig. 5 Mission utility vs payload performance (excluding delays and cost overruns).

Analyzing the aforementioned 116 missions shows that 36 (31%) had an original manufacturer that was not the final spacecraft supplier. The data also show that the satellites produced under the merger/acquisition condition show an increase of occurrence in anomalies that is statistically significant. The results are summarized in Table 1. Nine launch failures have been removed from the data because they are usually attributed to specific launch vehicles, independent of satellite integration.

Of these 107 missions, there were at least (some may not have been reported) 53 anomalies (19 were failures), leading to an overall anomaly rate of 53%. When these missions are partitioned among satellites that were produced by companies that had gone through a merger or acquisition and those that were not, the latter show significantly greater system reliability. With no merger or acquisition, there were 33 anomalies of 80 missions (45%), as compared to 20 of 33 (61%) for the merger/acquisition condition. The same pattern emerges when only failures are accounted for. We identified 5 failures of 74 missions (7%) when no merger occurred vs 6 of 33 (18%) in the merger/acquisition condition. This difference is significant at the 96.1% confidence level.

Model Illustration

This section illustrates how a decision maker could use the model. Consider a satellite producer deciding whether to subcontract the

Table 2 Anomaly rates for 116 space satellite missions[a]

Total missions	Problem area	No. of anomalies	% Anomalies
116	All anomalies	62 (19)	53.4 (17)[b]
107	Attitude control	11 (5)	10.3 (5)
116	Launch failure	10 (9)	8.6 (8)
107	Payload	15 (0)	14.0 (0)
107	Power	10 (1)	9.3 (1)
107	Propulsion	8 (2)	7.5 (2)
107	Processor	2 (1)	1.9 (1)
107	Spacecraft structure	0	0.0 (0)
107	TCR	3 (1)	2.8 (1)
107	Thermal	1 (0)	0.9 (0)
107	Other/unknown	2 (0)	1.9 (0)

[a]All components other than launch vehicle have only 107 possible missions because the 9 launch failures have been omitted.
[b]Numbers in parentheses indicate failures and failure rates.

Table 3 Propulsion subsystem conditional failure probabilities

Mission orbit	External event	No failure	Partial failure	Total failure
On course	Yes	0.85	0.11	0.04
On course	No	0.93	0.05	0.02
Off course	Yes	0.7	0.24	0.06
Off course	No	0.75	0.22	0.03

design and production of the payload to a company that has an excellent record of making payloads, whereas the satellite producer does not have the expertise to produce in-house a payload of the same reliability without incurring high expenses. Distributing the payload will, thus, allow more resources to be available for communication/coordination and the slack budget but will result in an increased probability of interface error between the spacecraft (TC&R) and the payload. For the conditional probabilities needed in our model (Fig. 4) and for the hypothetical example considered here, we used the data of the 116 satellite missions as base probabilities and expert judgment to adjust the conditional probabilities, as necessary.

Data Input

Because the necessary probabilities are conditional in nature, and we may be considering new technologies, we cannot gather statistical data for all possible combinations of events and contingencies. We will, thus, use expert opinion to update the prior probability distributions of their failure modes based on situational factors. Table 2 displays the problem (anomaly and failure) rates that are used as priors.

For example, the data set shows that the propulsion subsystem has had an anomaly rate of 7.5% (partial equal to 5.5% and failure equal to 2%). We used these percentages as the base rates and then updated the conditional probabilities. Figure 4 shows that the mission orbit and external events nodes are the only influences on the propulsion system. Thus, when the orbit is in an on-course state, and there is no external event, the probability of partial failure has been set to 5.5% and failure to 2%. Our experts, given the state of the influencing variables, then adjust the conditional probabilities. Table 3 shows the model inputs for the propulsion node.

Model Snapshot

Figure 6 represents as an influence diagram a snapshot of our model (with some of the probabilities included) in the case where the management adopts the option of an offsite payload design team under tight budget constraints. The input shown in Fig. 6 leads to an expected utility of 65.25 (maximum equal to 100). As already noted, the budget reserve available is medium because the resource constraints are tight and the payload design team is separated from the other subsystems. Note that with medium budget reserves, there is a 0.661 probability that testing and training will be incomplete. This outcome is also influenced by the probabilities in the skill of

Table 4 Utility values for all combinations of resource constraints and payload distributions

Resource constraints	Payload distribution	Utility 0–100
Super	Colocated	75.37
Super	Distributed	72.90
		Delta[a] = 2.47
Ample	Colocated	71.14
Ample	Distributed	70.60
		Delta[a] = 0.54
Tight	Colocated	67.60
Tight	Distributed	65.25
		Delta[a] = 2.35

[a]Difference in utility between colocated payload design and a geographically distributed one.

the project manager and of the communication and coordination nodes.

Figure 6 also shows the probability of a launch delay, as well as the distribution of the amount of data received by the users. The performance (data) node shows that, given our illustrative input, the probability of obtaining the maximum data is 0.266 and that the probability of a fatal error causing total loss of data is 0.224. In reality, this last number may be too high because some data may have been already received before a failure.

Results Discussion

Using the SAM framework described earlier, we model the effects of the different combinations of management options for the two decisions considered. The comparative results based on illustrative probabilities and values for the nodes of the SAM model, are given in Table 4. (The modeling was done using Netica™.)

As could be expected under our assumptions, the results show that the highest expected utility values are achieved when the resource constraints are least restrictive and when the payload design is colocated with the other subsystems. This is not surprising because there is no tradeoff between the increased probabilities of interface errors due to geographic separation and the amount of reserves. Under the other conditions considered here (ample and tight resource constraints), this tradeoff exists and is reflected by the decrease of the mission's expected utility with respect to optimal conditions. This tradeoff can be measured, for example, by the difference between expected mission utilities under the tight and ample resource constraint conditions and under the super condition. There is also a tradeoff between utility and initial budget constraints because our model calculates the mission utility independently from the budget constraints. We leave to the user the decision of whether the increase in utility is worth the added expenditures given the utility function.

Although this model is dependent on expert opinion and the decision maker's preferences, it also provides valuable insights into the organizational design and failure modes of a geosynchronous satellite. The process of constructing this model leads one to think about contingencies that may not have been previously considered, and it can be easily updated to consider additional realizations for each node and other possible organizational designs.

In our illustrative study, collocated design teams (payload and systems) dominate geographically distributed ones. This is based on the expert opinions that we received as to how the budget reserves, the testing and the training, and the communication and coordination among teams affect the chances of interface errors and their subsequent effects on the space system and ground operations. This general result also comes from our assumption, in this particular illustration, that the payload distribution decision does not directly affect the probability of a design error in the payload (internal payload error). If this is not the case, for example, if the payload contractor is significantly more experienced in that domain, our model can easily handle this contingency through the arrow from the payload design and development location decision node to the internal payload error node. Note, that the relationships implied by the input values are very case specific. For example, company A could have excellent

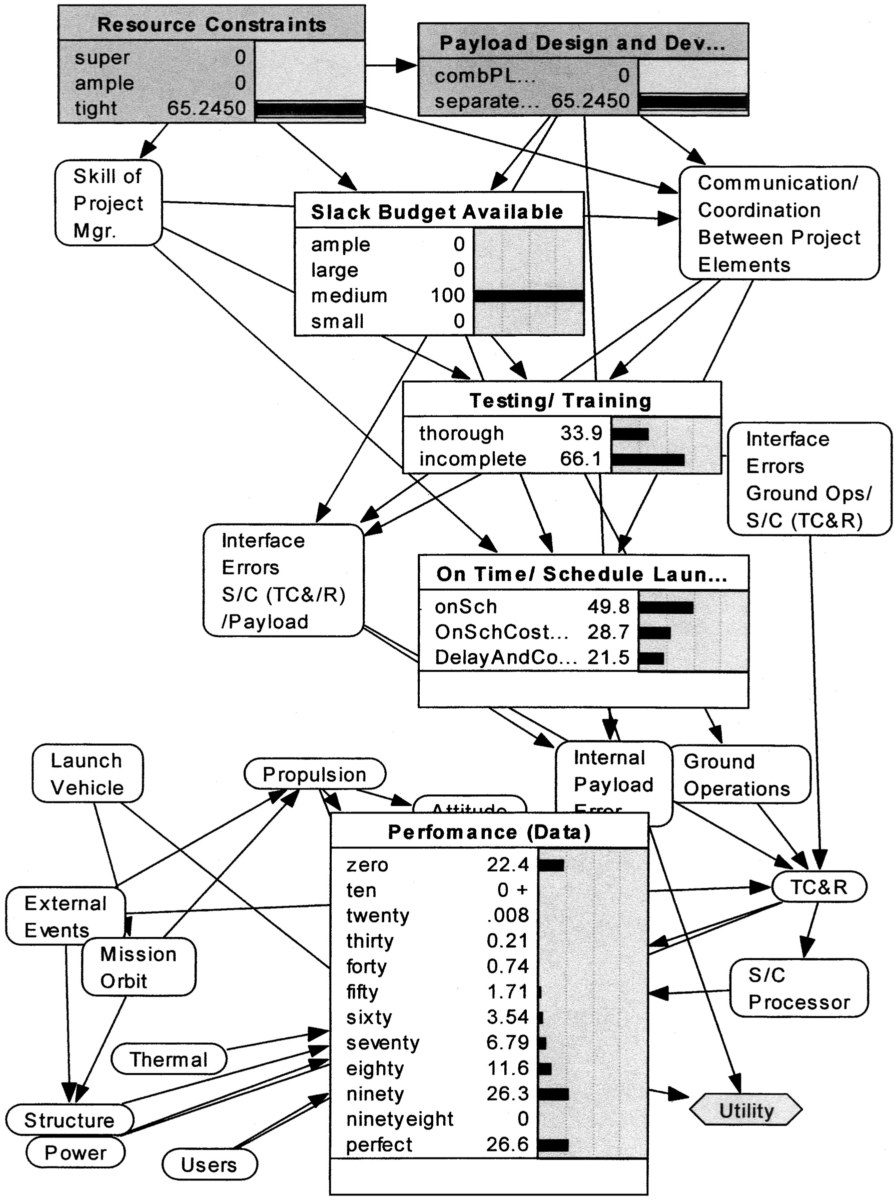

Fig. 6 Influence diagram of the SAM model including probabilities and decisions, where bars and numbers represent the probabilities of each realization. For performance data node, the numbers on the left represent the amount of data on a scale from 0 to 100, discretized for readability.

interactions with company B (and, thus, less chance of interface error) and poor relations with company C (greater interface issues). The particular level of coordination, as well as the expected reliability of the payload, will determine whether geographic distribution of the design teams is the optimal choice.

Sensitivity Analysis

Sensitivity analysis can also be performed to determine which variables are most important to management decisions. The decision maker can then determine which parts of the process should be further investigated to gain more accurate probability assessments. A good example of application of our model would be to examine the effect of geographic separation of the design teams on the probability of an error internal to the payload (which is one of the dependencies highlighted in Fig. 4). In the preceding illustration, we inputted the same reliability for the payload whether or not it was built in-house or at another location. What if this is not true? We can vary the reliability of the payload produced in-house in the internal payload error node. At a decrease in reliability of 18.5% (broken down into 5.25% greater chance of total failure and 13.25% greater chance of partial failure) for the in-house payload (relative to the subcontracted payload), there is no difference between the two choices because both have a utility of approximately 65.3 (for the tight resource constraint). If, in the tight budget condition, the decision maker believes the loss in reliability of making the payload in-house is greater than the given amount, then making the payload off site is now the optimal choice. A similar analysis can be performed for any of the variables in our model.

Conclusions

Upper management decisions are essential to the success of any complex system. In this paper, SAM provides a method for thinking about the entire satellite development process and its effect on the mission's utility and reliability. Quantification of management alternatives was made possible by the use of expert opinions (where needed) in addition to existing component data. The best alternative was identified in a field where statistical data are not always readily available at the system level. If and when such data become available, it will not only facilitate the use of our model but also permit updating of the Bayesian framework presented here. Through sensitivity analysis, our model also facilitates recognition of which decisions or components of the system are most relevant to the final

Table A1 Partial failure examples

Subsystem	Sample partial failure	Partial-failure coefficient
Launch vehicle	Satellite launched into incorrect upper stage orbit	0.60
Attitude control	Sensor failure inhibiting earth/sun energy transfer	0.90
Power	Premature degradation of solar array	0.75
Thermal	Detachment of heaters from surface due to thermal cycling	0.75
Spacecraft processor	Dendritic growth causing a shorting out of the processors	0.50
Structure	Antenna deployment failures	0.75
Propulsion	Leakage or stuck valves causing operation to enter the safe mode	0.80
TC&R	Local oscillator out of specifications	0.80
Payload	Electronic circuitry failure	0.90
Users	Lack of knowledge in using/receiving the data	0.80

utility of the mission, allowing the managers to decide where to focus their search for additional reliability/performance data.

This paper examined the potential positive and negative aspects associated with the use of distributed teams working on complex systems. Clearly, the input from social scientists that study the effects of team distribution would be important if they could effectively observe the design and development process. The value of this paper is in the analytical framework that it provides to satellite suppliers for the analysis of the make or buy decision regarding the payload subsystem under different resource constraint values.

Appendix A: Examples of Partial Subsystem Failures and Their Effect on Satellite Performance

The partial-failure coefficient is the relative efficacy of the mission given the particular sample partial failure. For example, a subsystem experiencing a partial failure with a performance coefficient of 0.6 would yield by definition 60% of the amount of data that would be provided by a perfectly operating satellite. Examples are given in Table A1.

Appendix B: Dependencies Among Partial Failures

The partial failures of the following pairs of spacecraft systems are dependent, which leads to an increase of the level of degradation of the satellite operation when both are experiencing a partial failure.

The first pairing is of propulsion and launch vehicle: If the launch vehicle has not inserted the satellite in the desired orbit, it is necessary for the propulsion system to help bring it back into the appropriate orbit. If there is a leakage in the propulsion system, it will be much more difficult to provide the necessary incremental velocity for the orbital correction. If that is the case, a lack of propellant in the future can cause a shortening of the mission's life.

The second pairing is of propulsion and attitude control, which is similar to the first case described. An attitude control partial failure can be corrected through increased propulsion effort, and a partial propulsion failure will inhibit this process.

The third pairing is of attitude control and power: Power is also necessary to bring an errant attitude control system under control and to set the spacecraft at the correct angle. The combination of partial failures of both attitude control and power can, therefore, compound the problem.

The fourth pairing is of users and TC&R: If the users' knowledge is limited, they will have particular difficulties in reading and understanding signals that may contain some errors.

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