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A HIGHLY-OPTIMIZED TOLERANCE (HOT)-INSPIRED MODEL OF THE LARGE SCALE SYSTEMS ENGINEERING PROCESS

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ABSTRACT

Large-scale systems engineering efforts involving multiple stakeholders often have been problematic, and there has been recent interest in understanding how to improve the systems engineering process. This paper presents an approach to modeling the systems engineering process, with possible extensions to systems investment and systems operations, inspired by the highly optimized tolerance (HOT) framework for understanding complexity in designed systems. HOT is complementary to agent-based modeling (ABM) in the sense that it emphasizes the centrally planned aspect of designed systems with tradeoffs and uncertainty, rather than distributed decision making based on local knowledge and goals. To begin the exploration of models of the systems engineering process, a temporal model is presented with stakeholder interactions modeled as random events. Following the HOT approach, planning behavior is framed as stochastic optimization, which is reduced to a open-loop control problem. The initial results suggest promise for the HOT-inspired framework in helping to understand how to improve the systems engineering process, but more exploratory work is needed, including work on relating actual systems engineering experience to the models.

INTRODUCTION

Many large-scale, complex systems engineering projects have been problematic. A few examples are listed below (Bar-Yam, 2003 and Cullen, 2004), and many others have been late, well over budget, or have failed:

- Hilton/Marriott/American Airlines system for hotel reservations and flights; 1988-1992; $125 million; “scrapped”
- Federal Aviation Administration Advanced Automation System; 1982-1994; $3+ billion; “scrapped”
- Internal Revenue Service tax system modernization; 1989-1987; $4 billion; “scrapped”
- Boston “Big Dig” highway infrastructure project; $14 billion; $10 billion over budget and late.

This paper focuses on software and technology-intensive systems engineering projects, like the first three examples above, but the methodology may be applicable to other types of large projects, like the Boston “Big Dig,” as well as other transportation and energy infrastructure projects.

Models of the systems engineering process may be useful to understanding how to improve it, for several reasons. First, a model can test and sharpen our understanding of potential improvements to systems engineering. If we really understand a concept for improving the process, then we should be able to construct a model of the improvement and show how benefits accrue in the model. If we cannot model an improvement, then it is legitimate to question whether we truly understand the improvement and its impact. Second, a model can be a basis for achieving understanding and consensus among different people with different perspectives. Modeling requires precise and explicit formulation of issues and tradeoffs, usually in quantitative terms, and the process of developing and using a model can help clarify different perspectives and make differences between these perspectives more explicit. Third, a model may produce otherwise overlooked or unexpected behavior, and thus serve as an “intuition pump” for deeper understanding of the systems engineering process.

In order to take advantage of the potential of modeling to help improve systems engineering, a model framework is needed that adequately represents the essential features of large-scale complex systems engineering. One possible modeling approach, which has been applied to complex adaptive systems in other domains, is agent-based modeling (ABM). An important strength of ABM is that it models decision making distributed across multiple decision makers with local outlooks and concerns, which is an important aspect of complex systems engineering. However, ABM is limited for modeling the systems engineering process because ABM by itself does not lend itself easily to modeling long-term planning, which is another important component of systems engineering. This led us to explore other methodologies for modeling the systems engineering process, which might eventually be combined with ABM to encompass all essential features of the systems engineering process.

TRADITIONAL AND NON-TRADITIONAL SYSTEMS ENGINEERING

The traditional approach to systems engineering is expressed well by the International Council on Systems Engineering (INCOSE, 2004):

"Systems Engineering is an interdisciplinary approach and means to enable the realization of successful systems. It focuses on defining customer needs and required functionality early in the development cycle, documenting requirements, then proceeding with design synthesis and system validation while considering the complete problem:

- *Operations*
- *Performance*
- *Test*
- *Manufacturing*
- *Cost & Schedule*
- *Training & Support*
- *Disposal*

Systems Engineering integrates all the disciplines and specialty groups into a team effort forming a structured development process that proceeds from concept to production to operation. Systems Engineering considers both the business and the technical needs of all customers with the goal of providing a quality product that meets the user needs."

Traditional systems engineering (TSE), (Norman, 2004) defines a step-by-step planned approach to systems engineering, which has proven effective across many systems engineering efforts. However, some systems engineering efforts defy the TSE process, due to various complexity-related factors along a set of dimensions which include (Hoffman, 2004):

- Enterprise scope
- Geographical scope
- Mission type
- Organization
- Acquisition strategy
- System and technology maturity
- Stakeholders

Complexity along any of these dimensions can potentially confound the TSE process and lead to severe cost and time overruns, or failure.

In some domains, TSE has been extended to incorporate such means as incremental development and experimentation as part of the systems engineering process. For example, following the Federal Aviation Administration's Advanced Automation System failure in the 1990s, much more emphasis was placed on a "build-a-little-test-a-little" approach, using trained operators and real system users, in the systems engineering process for air traffic management systems in the United States (U.S.). In the military operations domain, it has been suggested that more emphasis be placed on building infrastructure, onto which applications can be built that better meet mission needs (Norman, 2004).

A fundamental question remains, though, regarding what are the bounds of TSE, and when and how it should be extended. The degree of long-range planning implied by TSE may be inappropriate when complexity demands adaptation and fluidity, but some level of planning is still prudent, and government or other budget cycles may demand it.

THE CONTEXT FOR SYSTEMS ENGINEERING

Large-scale systems engineering typically happens in the context of systems operations and systems investment. For example, systems engineering with respect to civil air traffic management (ATM) is concurrent with daily air traffic control (ATC) and traffic flow management (TFM) operations. Here, ATC refers to the process of keeping aircraft safely separated and other tactical ATM functions, and TFM refers to the more strategic process of managing demand to respond to resource capacity changes, typically due to bad weather. In the U.S., ATM is a Federal Aviation Administration (FAA) function, and multiple organizations within the FAA are concerned with ATM systems engineering and operations. The FAA also generates a set of investments to maintain and improve ATM, and these investments interact with systems engineering and operations.

Stevens (2004) has emphasized the importance of pluralistic decision making among multiple stakeholders, each with their own local concerns, in systems engineering. To continue the FAA example, not only are multiple organizations within the FAA concerned with ATM investments, engineering and operations, each with its own local perspective, so are many other stakeholders. These include U.S. and foreign airlines, general aviation and military aviation organizations, airport authorities across many municipalities, the U.S. Congress, various lobbying groups, the air traffic controllers' and pilots' labor unions, other countries that interact with the ATM system, and a diverse "flying public." Each of these stakeholders may be involved in its own system investment and engineering processes, as well as participate in operations, and these interact to greater or lesser degrees with ATM investments, engineering and operations. Sometimes there is explicit collaboration between the stakeholders: for example, the

Operational Evolution Plan (OEP) is an extensive ten-year plan for improving the U.S. aviation system across many dimensions. The OEP is heavily funded by the federal government, but includes wide participation across many stakeholders. The whole system is made even more complex because of ongoing business and technology changes in aviation, as traditional airlines are supplanted by or forced to change in response to low-cost carriers, and as new technology such as low-cost jets becomes available for aviation operations. Stakeholder decision making may be driven by short-term needs, e.g., survival in the case of airlines in a highly competitive market system, rather than a long-term outlook.

A RELATIVELY SIMPLE MODEL IS NEEDED

The question of whether and how to extend TSE in the face of such complexity needs to be addressed in ways that help us not get lost in the trees of the complexity itself. In this paper, we present a modeling framework that attempts to capture the essential features of complexity in systems investment, engineering and operations, but is relatively simple and abstract. In this first modeling attempt, we do not emphasize solving the problem completely or even correctly in many respects, but try to suggest an approach which can be improved upon incrementally. Inspiration for this outlook came from the Santa Fe Institute (SFI) 2004 Complex Systems Summer School (CSSS) discussions of mathematical models of complex fluid flows and natural ecologies. These models are often not "correct," but they provide a means for making gradual progress towards understanding these complex systems. Similarly, we would like to provide a means for gradually developing a deeper understanding of how to deal with the complexity of systems investments, engineering and operations involving multiple stakeholders. We begin with a relatively simple modeling framework.

The essential features we wish to capture in the modeling framework are:

- Stakeholder interactions, including different look-ahead times for decision making
- External sources of uncertainty, e.g., macroeconomic, political, or technological
- Tradeoffs that are inherent in system investments, engineering and operations
- A planning process that may look years into the future

There is a tension among this set of essential features, because a planning process looking years into the future demands predictability, whereas stakeholders with a short-term outlook and other external sources of uncertainty imply unpredictability. It is precisely this tension that underlies the fundamental TSE versus non-TSE issue, and that we seek to model explicitly.

Although the model developed here focused on systems engineering, it is expected that such models could also be applied, at least at a high level, to systems investment and operations as well. Perhaps such models could be extended to apply to the entire ecology of investment, engineering and operations across multiple stakeholders. The model described below is only a starting point; further research is needed to extend the approach to a broader domain.

A HIGHLY OPTIMIZED TOLERANCE (HOT) MODEL

Highly optimized tolerance (HOT) is a framework for understanding certain aspects of complexity in designed or engineered systems. Carlson and Doyle (1999) originally developed the HOT concept and applied it to forest fire management. They showed how power laws in event size emerge from minimization of expected cost in the face of design tradeoffs. Since then, HOT has been associated with tradeoff analyses in such systems as internet architecture (Alderson, et al., 2004). HOT is identified with power laws, but in this paper we apply the HOT methodology without necessarily finding power laws as a result; for that reason, it may be more correct to call this a HOT-inspired model, rather than a HOT model.

The HOT-inspired approach we take here is to create a model of the system tradeoffs taking into account uncertainty, then to assume the system is optimized on average, and finally to examine the consequences of the optimization. In the case of modeling the systems engineering process with stakeholder interactions, a game theoretic framework might be appropriate to capture the effects of different goals, information, and look-ahead times for decision making. Appendix A shows one example of such a game representing stakeholder interactions in a specific systems engineering context. However, we take a different approach here in order to generalize to all types of stakeholder interactions in an approximate way.

Figure 1 shows a timeline for the systems engineering process, including a period for base system development starting at time 0, and a subsequent period for system operations, until the system is retired at time T_F. An optional parameter, T_0, is a cut-off time for base system development, i.e., it is the time after which there is no more development of the base system. In the simple model presented here, stakeholder interactions are modeled as random events that affect the cost incurred by the system throughout its lifetime. Thus, some interactions may affect cost during the base development time and others during the period of system operations. Similarly, all external sources of uncertainty are rolled up into random events during the lifetime of the system.

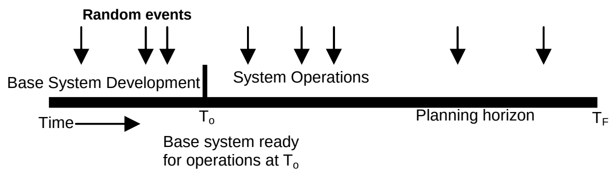

Figure 1. Timeline for the Systems Engineering Process

Tradeoffs among economic, political, technical and other factors are represented with a cost function over the lifetime of the system. The planning aspect of systems engineering is represented by optimization of the cost function over the system lifetime, with respect to a control function corresponding to a plan for building the base system. For simplicity, the plan is represented by a single function of time, r(t), which is the instantaneous rate at which the system is built. We define the control function s(t) to be a measure of how much of the system is completed at time t:

$$s(t) = \int_0^t r(t^*)dt^*$$

And, s(t) is assumed to start at zero at time zero, and to be bounded by 1; i.e., the base system is completed when s(t) = 1. Finally, s(t) is assumed to never decrease. Therefore, the constraints on s(t) and the first derivative s'(t) are:

$$s(0) = 0$$

$$0 \le s(t) \le 1$$

$$s(t) = s(T_0) \text{ for } T_0 \le t \le T_F$$

$$s'(t) \ge 0$$

The cost density function is given by:

$$c(t) = A(1 - s(t))(1 - e^{-t/\tau}) + Bs(t)\delta_p(t) + D(s'(t))^2$$

In this cost density function, A, B, D and τ are constants, and random variable $\delta_p(t)$ is a delta function with probability density p. The parameter p is assumed to be a constant. The first term of the equation for c(t) models the pressure to finish the base system, whether from actual system needs or other sources like political pressure. The second term represents the cost incurred from random events that change how the system will be used relative to the base system capabilities. This term incorporates stakeholder interactions as well as other external events. The second term is proportional to s(t), which represents greater impact on a system that is closer to completion. The cost of actually building the system is modeled by the third term, which is non-linear in s'(t). The non-linearity models the relative difficulty of building the system in a short time compared to a longer time.

Then, the expected cost over the lifetime of the system is:

$$\langle c_{tot} \rangle = \int_0^{T_F} < c(t) > dt$$
$$= \int_0^{T_0} L(s'(t), s(t), t)dt + \phi(s(T_0), T_0),$$

where:

$$L(s'(t), s(t), t) = A(1 - s(t))(1 - e^{-t/\tau}) + Bps(t) + D(s'(t))^2$$

$$\phi(s(t), t) = \int_t^{T_F} \{A(1 - s(t))(1 - e^{-t^*/\tau}) + Bps(t)\}dt^*$$

Substituting into the equation for expected cost, adding Lagrange multiplier terms for the inequality constraints, then taking differentials and integrating by parts (see Bryson and Ho, 1975), a necessary condition for minimization of expected cost is:

$$0 = \left[\left(\frac{\partial L}{\partial s'}\right)_{T_0} + \left(\frac{\partial \phi}{\partial s}\right)_{T_0} + (\lambda_3)_{T_0}\right](\delta s)_{T_0} - \left(\frac{\partial L}{\partial s'}\right)_0 (\delta s)_0$$
$$+ \int_0^{T_0}\left[-\frac{d}{dt}\left(\frac{\partial L}{\partial s'}\right) + \frac{\partial L}{\partial s} + \lambda_1(t) + \lambda_2(t) - \frac{d}{dt}(\lambda_3(t))\right]\delta s(t)dt$$

….. (1)

In equation (1), the Lagrange multipliers $\lambda_1(t)$ and $\lambda_2(t)$ correspond to the upper and lower bounds on s(t) and the Lagrange multiplier $\lambda_3(t)$ corresponds to the lower bound on s'(t).[1] And, since s(0) = 0, $(\delta s)_0$ = 0.

[1] The lower bound on s(t) is actually redundant, since s(0) = 0 and s'(t) is never negative.

RESULTS

In general, equation (1) must be solved numerically by piecing together solutions across regimes where either no constraints apply or one or more constraints apply. Where the constraints are slack, Lagrange's equation holds:

$$0 = \frac{d}{dt}\left(\frac{\partial L}{\partial s'}\right) - \frac{\partial L}{\partial s} \ ,$$

which yields a second-order differential equation in s(t) that can be integrated to obtain:

$$s(t) = s_0 + (s'_0 + \frac{A\tau}{2D})t + \frac{(Bp - A)}{4D}t^2 - \frac{A\tau^2}{2D}(1 - e^{-t/\tau})$$

where s_0 and s'_0 are constants corresponding to s(0) and s'(0) if the function s(t) were evaluated at the origin. (Of course, this solution may not apply at the origin because of constraints on s(t) and s'(t).) In the results shown below, these constants were found by piecing together the slack solution with solutions meeting the constraints, and numerically minimizing the expected value of total cost by varying the values of the constants.

For the special case where the inequality constraints are slack for all t from 0 to T_F, (i.e., the Lagrange multipliers are zero everywhere), the optimal s(t) can be expressed analytically:

$$s(t) = \frac{(A - Bp)}{2D}(T_F t - t^2/2) + \frac{A\tau^2}{2D}(e^{-T_F/\tau} t/\tau - 1 + e^{-t/\tau})$$
$$\text{for } 0 \le t \le T_0$$

$$s(t) = s(T_0) \ \text{ for } \ T_0 \le t \le T_F \, .$$

For some parameter values, this analytic solution s(t) can be less than 1 at time T_F, i.e., the base system is never completed.

Figure 2 shows numerical solutions for a range of values of the constant product, Bp, which is a measure of the impact of uncertainty on the system. The other parameters have the following values:

A = 1
τ = 10
D = 10
T_0 = 100
T_F = 100.

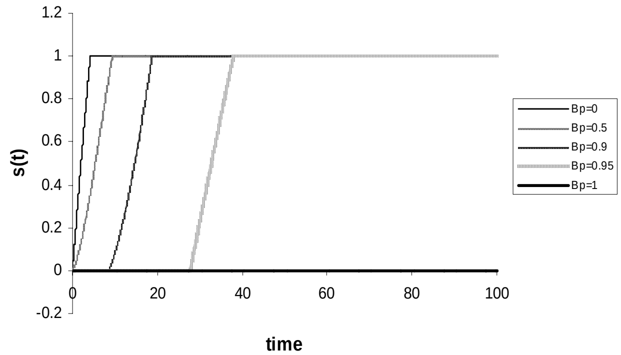

Figure 2. Optimum s(t) with D = 10

For small values of the expected impact of stochastic events (Bp) compared to pressure to complete the base system (A), the best course of action is to build up the system rapidly; this can be termed the "TSE limit." When Bp is at least as large as A, the best course is to not build the base system at all and respond to stochastic events as they occur; this can be called the "reactive limit." And, the optimum s(t) shows increasing sensitivity to Bp, as Bp approaches A. This is a kind of "critical regime" where small changes in the estimate of Bp can radically change the optimum plan for completing the base system. Note also that, as Bp approaches A, the optimum s(t) shows a lag before beginning any work on the base system. The lag corresponds to a kind of "strategic pause" to resolve some of the uncertainty before beginning to build the system.

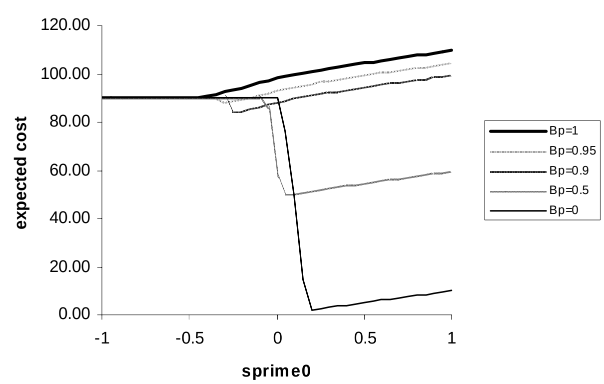

Figure 3. Expected Cost Sensitivity with D = 10

Figure 3 shows how expected cost changes with the parameter of variation, s'_0. In this example, the value of s_0 at optimum was approximately zero in all cases. Changing the value of s'_0 from -1 to 1 generates considerable change in the function s(t) from 0 to T_F. Note that as Bp approaches A, cost is relatively insensitive to s'_0. Hence, in the critical regime, it may appear that, in terms of expected cost, it doesn't matter much what is done, from building up the system quickly to doing nothing at all on the base system. And this may suggest a conservative approach to minimize risk of large costs, which would be not building the base system at all.

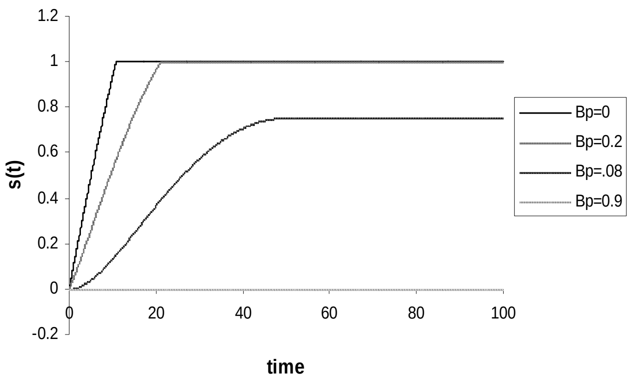

Figure 4. Optimum s(t) with D = 100

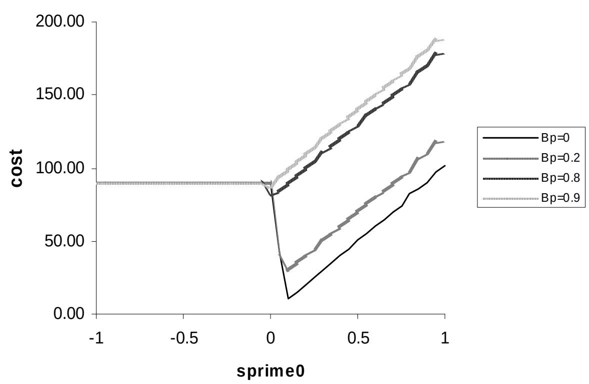

Figure 5. Expected Cost Sensitivity with D = 100

Figure 4 shows another set of optimal s(t) curves, with parameters A, τ , T_0, and T_F the same as before, but D = 100 instead of 10. A larger value of D means that the system is more costly to build quickly, which is likely to be the case if the development is more complicated. These curves are qualitatively different from the curves with D = 10; note that the behavior of s(t) tends towards an incomplete system rather than a lagged start. Also, the position of the critical regime, where s(t) is sensitive to the value of Bp, shifts to smaller values of Bp and appears to be broader with respect to Bp. (More work is needed for this case; the optimum curves are very sensitive to the parameters of variation and the sensitivity has not been thoroughly explored.)

Figure 5 shows the sensitivity of expected cost to the parameter of variation, s'_0. As before, the value of s_0 is near 0 at the optimum across all cases in Figure 4. As Bp approaches 90% of the value of A, there is insensitivity to the value of s'_0 to the left (i.e., in the direction of not building the system at all), but strong sensitivity to the right. Even more so than when D = 10, it may appear best to avoid risk and not build at all.

CONCLUSIONS

The model illustrates a TSE limit, for which the pressure to build a system greatly exceeds the ambient uncertainty (A>> Bp), as well as a reactive limit (A<<Bp), for which there is incentive to not build the base system at all and simply respond to stochastic events as they occur. In the TSE limit, cost and time over-runs can arise from stochastic events such as stakeholder interactions. The model suggests that there is a critical regime in which the optimum course of action is very sensitive to perceived conditions but the expected cost is relatively insensitive to these conditions, at least over a range. In the critical regime it may appear that, in terms of expected total cost, it does not matter much what is done. A direction for future research is to understand the characteristics of the regime between the TSE and reactive limits for less simplistic models of systems engineering, and to understand if this regime is where "complexity" arises in systems engineering.

Behavior in the critical regime, as it manifests in this simple model, is similar to an effect observed in aviation traffic flow management (TFM) *operations* (rather than systems engineering), for which a Bayesian network analysis of experience in past events revealed no correlation between actions taken and the result (Pepper, Mills, Wojcik, 2003). TFM is characterized by considerable uncertainty and decision-making interactions across multiple airlines and FAA organizations. More work is needed to explore this possible relationship of the model to operational experience, and to attempt to determine if such relationships exist in systems engineering and investments.

The systems engineering model presented here shows some level of qualitatively different behavior when the level of uncertainty (Bp) is changed by an order of magnitude, but more exploration of this effect is needed.

In addition to calculating optimal functions s(t) and sensitivity to integration constants, another type of analysis that could be done is to simulate the randomly produced stakeholder interactions and other effects to generate a probability distribution for cost. This follows the basic HOT methodology of Carlson and Doyle

(1999). For the model presented here, in the limit as T_F is large compared to system development time, this distribution is Poisson, and the variance due to stochastic events equals the mean. Thus, we would not expect power laws to emerge in cost, but variance can be fairly wide nevertheless.

Next steps should also include relating the model to actual systems engineering experience. Possible case studies for comparison might include the FAA Advanced Automation System program in the aviation domain, or a well-documented case like the Space Shuttle safety program. It may be possible to interpret such programs in light of modeling of the type suggested in this paper. There is a precedent for relating theory to experience in complex systems involving human decision-making interactions, and potentially much to draw upon from the field of organizational science (e.g., Simon, 1976).

Further model development could be in the direction of extending the model to encompass systems investment and operations more explicitly. A hybrid of HOT and agent-based modeling might be appropriate for this. Another area for modeling exploration is attitude towards risk on the part of planners; as they become more risk averse or risk seeking, their plans are expected to shift accordingly (Raiffa, 1976).

APPENDIX A: A SIMPLE GAME OF STAKEHOLDER INTERACTIONS

To cite an example of stakeholder interactions in the systems engineering process, we take the example of air-to-ground data link communication for civil aviation. After decades of research and development, the controller-pilot data link communications (CPDLC) system came into daily operational use at one Federal Aviation Administration (FAA) en-route air traffic control center in late 2002 (Federal Aviation Administration, 2003) but the FAA decided to slow down further development of the system because of reluctance of many airlines to equip with avionics to take advantage of CPDLC infrastructure and applications (Steenblick and Wiley, 2003). In Europe, where similar issues exist, the data link program approach includes subsidies for airlines to equip with data link avionics (Eurocontrol, 2003). A reasonable explanation for why many airlines may not readily equip without incentives such as subsidies is that, in an extremely competitive industry with low or no profits for many airlines, airlines do not want to take on expenditures in equipment that promise long-term net benefit but short-term net cost.

However, even if airlines take a longer term view, they still may not wish to invest in avionics for CPDLC, because the decision must be weighed against other possible investments including, for example, investment in additional aircraft to increase their long-term competitiveness against other airlines (Morser, 2004). Table 1 shows a simple game matrix for a hypothetical symmetric game in which each of two airlines chooses between investing in avionics and investing in aircraft. Airline 1's choices are along the vertical axis and airline 2's choices are along the horizontal axis. Long-term payoffs to airlines 1 and 2 are in parentheses for each pair of choices by the two airlines. The game payoffs are expressed in terms of these parameters:

E = benefit from one airline's investing in avionics,
F = synergistic benefit from both airlines investing in avionics,
G = benefit of increased competitiveness if one airline invests in aircraft,
H = negative benefit of mutual competitiveness

Table 1. Game Matrix for Two Airlines

	Invest in avionics (airline 2)	Invest in aircraft (airline 2)
Invest in avionics (airline 1)	(E+F,E+F)	(E-G,G)
Invest in aircraft (airline 1)	(G,E-G)	(-H,-H)

Depending on the values of these parameters, the game can be a Prisoner's Dilemma (PD) (Luce and Raiffa, 1957). One set of parameters giving rise to a PD is E = 2, F = 1, G = 6, H = 2. In a PD, the equilibrium for a single play of the game is where both players invest in aircraft, even though both would do better if they both invested in avionics. Thus, each airline among a set of pairwise-competitive rational airlines may decide not to invest in avionics, even though it is better for each one if they all did. With incentives, payoffs for investing in avionics increase and if large enough, they can shift the equilibrium to where each airline finds the long-term benefit of investing in data link avionics greater than investing in aircraft.

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