On Uncertainty, Ambiguity, and Complexity in Project Management

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This article develops a model of a project as a payoff function that depends on the state of the world and the choice of a sequence of actions. A causal mapping, which may be incompletely known by the project team, represents the impact of possible actions on the states of the world. An underlying probability space represents available information about the state of the world. Interactions among actions and states of the world determine the complexity of the payoff function. Activities are endogenous, in that they are the result of a policy that maximizes the expected project payoff.

A key concept is the *adequacy of the available information* about states of the world and action effects. We express uncertainty, ambiguity, and complexity in terms of information adequacy. We identify three fundamental project management strategies: instructionism, learning, and selectionism. We show that classic project management methods emphasize adequate information and instructionism, and demonstrate how modern methods fit into the three fundamental strategies. The appropriate strategy is contingent on the type of uncertainty present and the complexity of the project payoff function. Our model establishes a rigorous language that allows the project manager to judge the adequacy of the available project information at the outset, choose an appropriate combination of strategies, and set a supporting project infrastructure—that is, systems for planning, coordination and incentives, and monitoring.
(*Project Management; Uncertainty; Complexity; Instructionalism; Project Selection; Ambiguity*)

1. Introduction

An extensive literature on project planning has developed our understanding of project task scheduling (e.g., CPM, PERT, and GERT) and "risk management" (sequential decision making, dynamic programming), including work on contingency planning and the management of project buffers. This work has given project managers an intuitive feel for what to do in the presence of risk factors in the environment that are identified but whose outcome is uncertain.

There is also empirical work recommending an "iterative, experimental" project management approach when the environment is fast-changing or highly uncertain (e.g., Eisenhardt and Tabrizi 1995, Lynn et al. 1996). Other work proposes that multiple solutions should be pursued "in parallel," choosing the best once their outcomes are observable (e.g., Sobek et al. 1999).

These existing project management approaches advocate partially conflicting approaches to the project team, such as the need to execute planned tasks, trigger preplanned contingencies based on unfolding events, experiment and learn, or try out multiple solutions simultaneously. While all of these approaches encompass the idea of uncertainty, no conceptual model currently exists that enables project managers to understand why different approaches exist, which one to choose, and when. As a consequence, project failures are numerous in practice; for example, budget and schedule overruns, compromised performance, and missed opportunities, (see, e.g., Morris and Hugh 1987 pp. 7–12, Tatikonda and Rosenthal 2000).

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This paper makes two contributions. First, drawing on sequential decision theory, we conceptualize a project as a project payoff function that depends on states of the world and a chosen network of actions. Using this conceptual model (§3), we show that ambiguity and complexity are the factors that explain the coexistence of different approaches to project management. Task scheduling and risk management (contingent action) represent an *instructionist* approach, prespecifying and triggering actions based on signals. This is sufficient as long as information about the states of the world and the payoff effects of actions is *adequate*. Inadequacy of information is caused either by events or causality being unknown (ambiguity), or by an inability to evaluate the effects of actions because too many variables interact (complexity). We argue that information inadequacy requires a combination of *learning* (the capacity to conduct new and original planning in the middle of the project) and *selectionism* (the pursuit of multiple candidate solutions until the best can be identified).

To illustrate the completeness of this model we draw parallels with the survival problem in biology, as it involves a mathematically equivalent "project" of producing successful offspring in an ambiguous and complex environment. The empirical observation that nature has, over three billion years, developed survival strategies that correspond to instructionism, learning, and selectionism would seem to confirm that our model captures important principles (§5).

Second, in terms of its managerial implications (§6), our model provides the conceptual language to enable a project team to judge information adequacy at the outset. This allows fundamental decisions to be made early on concerning project management strategy and, in turn, project infrastructure in terms of systems for planning, coordination and incentives, and monitoring.

2. Literature Review

The study of task scheduling started with the development of activity network techniques (PERT, CPM) in the late 1950s, which allowed project managers to identify the "critical path" for projects—even those involving thousands of activities (Lockyer 1969). This was extended to include project risk analysis (e.g., Elsner 1962, Elmaghraby 1964). In 1966, Pritsker (1966) outlined the Graphical Evaluation and Review Technique (GERT), a graphical Monte Carlo simulation program that allowed probabilistic outcomes and looping of tasks (Clayton and Moore 1972). With tools such as GERT and its successor *Q*-GERT (Taylor and Moore 1980, Pritsker and Sigal 1983), the notion of identifying one critical path was replaced by a measure of task criticality (the likelihood that a task would find itself on the critical path). Extending this line of work further, Carracosa et al. (1998) used the design structure matrix framework of Steward (1981) to incorporate partially overlapping activities—and hence rework—into project schedule simulations.

The next step was to view tasks not as given but as decision outcomes, utilizing the tools of sequential decisionmaking (dynamic programming, decision trees, e.g., Marschak and Radner 1972, Brucker et al. 1999). For example, Ludwig et al. (1998) developed *dynamic policies* for project scheduling where activity times are revealed gradually over the course of a project. In project management practice, this approach is called *risk management*: the identification of possible (but uncertain) events and their impact on the project. It aims to reduce risk, defined as "probability times impact" (e.g., Conrow 2000), to establish as quickly as possible the likelihood that a critical event will actually occur, and develop contingent action to counter its impact (Cockerham 1979, Cooper and Chapman 1987, Chapman 1990, Kepner Tregoe 1992, Williams 1995, DSMC 1998). Similarly, scenario-planning techniques aim to identify risks and their drivers as broadly as possible using early warning indicators and response scenarios (e.g., Schwartz 1991).

Where levels of risk are considered low, project managers often deal with risk simply by including "slack" or time-and-cost buffers in their projects (Leach 1999). In order to prevent slack from becoming a self-fulfilling prophecy, it has also been proposed that the team be made collectively responsible for maintaining the buffers (e.g., Gutierrez and Kouvelis 1991, Goldratt 1997).

Another form of slack is *flexibility*—the use of technologies and processes that accommodate multiple possible outcomes of risk. For example, this can be done by deferring design choices or by designing a performance level into the product that is higher than initially thought necessary (e.g., Thomke and Reinertsen 1998, Bhattacharya et al. 1998).

In summary, operations research and decision theory literature has concentrated on complete probability spaces with (subjective) probabilities—that is, the project team knows the event is possible but they do not know whether it will happen. Existing work has implicitly viewed it as impossible to "manage events that cannot be foreseen" (Wideman 1992, Williams 1999).

However, the reality is that we live in an ambiguous and complex world. Empirical work has emphasized the need for iteration, or the repetition of problem solving and testing cycles, which are ubiquitous in engineering (e.g., Thomke 1998). Eisenhardt and Tabrizi (1995), and Iansiti and MacCormack (1997) found that such iterative cycles are very important in environments requiring fast time-to-market. Research in the marketing and strategy domain has indicated that iteration goes much further in "radical innovations" where both technology and market are new. Such projects seem to be characterized by a broad and flexible vision, a prototype construction that precedes assessment and analysis, and by a need to "probe and learn"—that is, to launch the project in the market, learn from failures, and modify for future attempts (Lynn et al. 1996, Veryzer 1998, O'Connor and Veryzer 2001).

In the strategy domain, Hamel and Prahalad (1994) observed that competition for the future takes place in unstructured arenas where the rules of competition have yet to be written. Hence, it is not enough to develop contingency plans around likely scenarios: One must be willing to speculate beyond "what could be" and develop capabilities rather than simply a plan of what to do (Hamel and Prahalad 1994 pp. 82–108).

Similarly, the venture capital (VC) literature advocates making small investments in a project vision and a competent team of entrepreneurs, and then to determine project continuation when "milestones" are met that eliminate important ambiguities or knowledge gaps (e.g., Bell 2000, Sahlmann 1994).

Drawing from cognitive science, artificial intelligence (AI) planning techniques have also distinguished planning from iteration (Russell and Norvig 1995). Used to drive the functioning of artificial agents (e.g., robots), AI planning techniques recognized early on that in dynamic, uncertain environments, agents must be able to effectively manage their plans during execution (Fikes et al. 1972). AI planning techniques differentiate between *conditional planning*—where actions may have unexpected effects but these can be enumerated and described as part of the action plan, and *execution monitoring*—where unexpected effects are too numerous to elaborate and therefore oblige the artificial agent to respond and replan as the plan is executed (Warren 1976, Olawsky and Gini 1990, Ambros-Ingerson and Steel 1988). Agents may need to learn, so as to improve the adequacy of information needed to evaluate hypothetical activity paths, and to plan, so as to reduce the number of uninformed—and thus inefficient—learning trails (Weiss 2000).

Some work has proposed that multiple solutions may have to be pursued in parallel, choosing the best only after their effectiveness has been observed (e.g., Sobek et al. 1999 call this "set-based engineering;" see also Project Management Institute Standards Committee 2000).

While existing work covers a diverse portfolio of project management approaches, it has not provided managers with a conceptual understanding of why so many exist and how to choose among them. McFarlan (1981) recognized this need in major IS projects back in the 1970s, suggesting that uncertainty required adapting management style to the project uncertainty profile as measured by the dimensions of project size, project structure, and experience with the technology. Shenhar and Dvir (1996) proposed an important project empirical classification scheme based on the degree of technical uncertainty and complexity of the project. Their constructs, however, do not hold up for projects across different industries (Dvir et al. 1998).

Schrader et al. (1993) emphasized the difference between uncertainty and "ambiguity" (defined as absence of knowledge about functional variables), but did not link them to project management approaches. While these characterizations have all made important contributions to project management, they coexist independently and offer partially conflicting prescriptions. No model exists that places them in a common context and explains which approach to use and when. In this paper, we develop a general model of projects that can provide such an explanation.

3. Planning and Execution Monitoring in Projects

A project is often seen as a collection of simultaneous and sequential activities which together produce an identifiable outcome of value (e.g., Morris and Hugh 1987, Meredith and Mantel 1995, Smith and Eppinger 1997). In its simplest form, project management consists of planning, executing, and monitoring these activities. In most operations research planning methods, such as activity network approaches, activities are taken as given: The only decision required is how best to schedule them. It is assumed that human planners, possibly using formalized risk management tools, will generate the "best" network of activities.[1] In artificial intelligence, the term "planning" is used for the process of determining the network of activities, while "scheduling" is used for the process of determining the timing and allocation of resources to these activities (Russell and Norvig 1995).

In this section, we propose a general model of projects that takes the network of activities (including the scheduling of these activities) as a decision variable. Activities are chosen to maximize the project payoff, represented by a preference function $\Pi = \Pi(\omega', A)$. It maps an ending state of the world, $\omega' \in \Omega$, and a network of activities, $A \in \mathscr{A}$, to a project payoff. The ending state, ω', is itself determined by a starting state, $\omega \in \Omega$, and by the network of activities executed. The mapping $\Omega \times \mathscr{A} \Rightarrow \Omega : M(\omega, A)$ denotes this causal relationship:

$$\omega' = M(\omega, A).$$

The state of the world ω contains all the factors that might influence the outcome of activities, and activities A influence the state of the world in terms of generating a new state of the world ω'. This new state of the world could then be seen as a new starting state, influencing a new network of activities A' and so on. States of the world or influence factors may include product feature requirements, resource costs, competitor intentions, market demographics, technological difficulty, regulatory changes, and a myriad of "small," uncontrollable, and unavoidable influences.

When a project team sets out to plan a project, it must have a consistent model of the project in terms of the possible states of the world and how they will evolve as activities are executed. If the project team knew for certain the complete set of influence factors, or starting state ω and the causal model M, and if M and Π were "tractable" in the sense that an optimal network A^* could be found, then the project team could *plan* and *execute* a network of activities, A^*, so as to optimize the project payoff for the known influence factors ω:

$$A^* = \arg\max_{A \in \mathscr{A}} \Pi(M(\omega, A), A). \tag{1}$$

Take, for example, the simple application of the Critical Path Method (CPM). The predetermined set of activities and their precedence relations that are used as input to the CPM constrain the set of all possible activity networks in $\mathscr{A}$. The preference function Π is simply to minimize project duration, and the causal model M and state of the world ω are deterministic. The CPM is designed to deal with project complexity: With the advent of the CPM, a broader set of projects becomes *tractable*—that is, the activity network A^* minimizing the project duration could be derived for projects with a large number of tasks and precedence relationships.

In reality, the complete set of influence factors ω may not be known with certainty, and the causal model M may be so complex that only an approximation $\widehat{M}$ is known to the project team. In this case, for a fixed activity network A, the ending state, and thus the project payoff, will be a random variable. The project team's possibly limited understanding of the *possible* states of the world can be represented by a probability space $(\Omega, \mathscr{F}, P)$. The sigma-field $\mathscr{F}$ represents the set of all events (or Ω-subsets), X, whose occurrence or nonoccurrence can be anticipated, hence planned for, by the project team. Drawing from the work of Marschak and Radner (1972), we say that $\mathscr{F}$ is *payoff adequate* with respect to Π and $\mathscr{A}$,

[1] We purposely use the term "network of activities" to emphasize that a project may have both simultaneous and sequential activities.

if for every basic event[2] $X \in \mathcal{F}$, every pair $\omega_1, \omega_2 \in X$, and every sequence of actions $A \in \mathcal{A}$,

$$\Pi(\omega_1, A) = \Pi(\omega_2, A). \qquad (2)$$

That is, for a given Π and $\mathcal{A}$, a payoff adequate sigma field $\mathcal{F}$ provides as much useful information as any finer partition of $\mathcal{F}$, thus a further refinement of $\mathcal{F}$ cannot yield any improvement in the project payoff.

The $\mathcal{F}$-measurable probability measure P summarizes the project team's subjective probabilities for the different events $X \in \mathcal{F}$. The project team's causal model $\widehat{M}(X, A)$ will be based on what it knows about possible events, and thus will map events $X \in \mathcal{F}$ and actions $A \in \mathcal{A}$ to events $X' \in \mathcal{F}$. That is, it cannot generate "unknown" events that lie outside of $\mathcal{F}$; it simply moves probability mass from one event to another. We say that $\widehat{M}$ is *transition adequate* with respect to $M, \mathcal{F}$, and $\mathcal{A}$, if for every event $X \in \mathcal{F}, \omega \in X$, and every network of actions $A \in \mathcal{A}$,

$$M(\omega, A) \in \widehat{M}(X, A). \qquad (3)$$

To summarize, a payoff adequate $\mathcal{F}$ implies that the project team is aware of all possible events that might have a significant impact on the project payoff Π, while a transition-adequate $\widehat{M}$ implies that the project team's causal model is consistent with the true causal relationships in M. In this section, we argue that the classic project planning methods assume a *payoff adequate* $\mathcal{F}$ and a *transition adequate* $\widehat{M}$ (we will refer to this as *information adequacy*).

Consider the Program Evaluation and Review Technique (PERT), which is similar to CPM but allows for random activity durations. The set of possible activity networks is again constrained by the preselected set of activities and their precedence relations. For a given activity network A, the project duration is stochastic and the preference function is now to minimize the *expected* project duration. For more complicated projects, Monte Carlo simulation techniques can be used to translate the project team's model of the causal relationships in $\widehat{M}$ and the uncertainty in X into a payoff probability distribution for a proposed activity network A.

[2] An event $X \in \mathcal{F}$ is basic if it has no proper subset that is in $\mathcal{F}$.

Both of these approaches recognize uncertainty but still offer a fixed activity network. If the distribution around the expected project payoff is too great, the project team may choose to build *buffers* into the plan to increase the probability of achieving a promised or agreed-upon project target (e.g., Gutierrez and Kouvelis 1991, Goldratt 1997).

A more sophisticated approach to dealing with uncertainty allows for *contingent action* in response to execution monitoring. In this case, the project team monitors the project, gathering information about the state of the world as activities are executed so as to adjust the choice of activities as the project unfolds. The information available to the project team at any time t is a function of: (i) the true state of the world at time t: $\omega_t = M(\omega, A_t)$, where A_t is the network of activities executed up to time t; and (ii) the *information structure* η_t that transforms the true state of the world at time t into signals y_t (Marschak and Radner 1997, Lovejoy 1991). This is also similar to the concept of "accessibility" in AI planning (see Russell and Norvig 1995):

$$y_t = \eta_t(M(\omega, A_t)). \qquad (4)$$

Given their understanding of the types of signals that will become available over the life of the project, the project management team develops *policies* as opposed to a pre-specified set of actions. A policy α is a "contingency plan," a function assigning the available information and the history of past actions to current action (e.g., Heyman and Sobel 1984 pp. 109–111). A policy maps current information about the state of the world and previous activities to an updated activity network A^t:

$$A^t = \alpha(y_t, A_t).$$

Because activities are endogenous to the model—that is, they are strictly determined by the policy—the network of activities A is uniquely determined by the *policy* and the *information structure* as realized in $y = \{y_{\tau_1}, y_{\tau_2}, \ldots\}$. We write this as

$$A = \alpha(y). \qquad (5)$$

The policy identifies in advance a complete set of actions, and the realization of the signal 'triggers' the action when the team applies the policy to the signal.

The information structure $\eta_t(M(\omega, A_t))$ usually costs something to obtain, call it $C(\eta)$, but it also has *value* because the project team can, by implementing a policy instead of a fixed activity network, increase the expected project payoff. The value of the information structure can be defined as:

$$\max_{\alpha} E\big[\Pi(\widehat{M}(X, \alpha(y)), \alpha(y))\big] - \max_{A} E\big[\Pi(\widehat{M}(X, A), A)\big]. \tag{6}$$

Marschak and Radner (1972 p. 52) showed, *assuming* information adequacy, that the policy α is optimal if for every signal y, $\alpha(y)$ maximizes the conditional expected payoff given the signal. Thus, the optimal policy α^* is designed to maximize the expected project payoff:[3]

$$\alpha^* = \arg\max_{\alpha} E\big[\Pi(\widehat{M}(X, \alpha(y)), \alpha(y)) | y\big]. \tag{7}$$

In many real-world cases, derivation of the true optimal policy is extremely difficult. Thus, project teams often use heuristics or general rules-of-thumb to generate their policies. Consider a simple example of a decision tree (Clemen 1996), where a signal identifies a branch in the tree and the subsequent actions to be executed, followed by further signals and so forth. A combinatorial explosion of the many possible future signals may make planned contingencies too complex and time consuming to generate a priori. In this case, project teams might plan for major contingencies but may delay the development of less important contingencies until such time as specific signals are received. This is called *execution monitoring with replanning* in the AI planning literature (Ambros-Ingerson and Steel 1988).

Replanning, in this context, is based on the same model of the world as full contingency planning. The full contingency plan could have been developed in theory, but in order to avoid excessive calculation, the project team chose not to. Of course, with replanning there are risks associated with execution monitoring: The complete policy is never evaluated in total and early activities arising from an incomplete policy might negatively affect later activities arising from the replanned policy. However, because the project team has adequate project information, they can at least approximate what these risks might be. As we will see in the next section, no such approximation is possible in projects with inadequate information.

4. Learning and Selectionism in Projects

The previous section describes an *instructionalist* approach to project management: Policies are derived —either a priori or as the project is executed— that completely determine the activities executed in response to signals: $A = \alpha(y)$. The derivation of the optimal policy α^* relies on the project team's model of the project. But what happens when that model is not adequate—that is, if the partition $\mathcal{F}$ is not payoff adequate, or the mapping $\widehat{M}$ not transition adequate?

If $\mathcal{F}$ is payoff inadequate, then states of the world exist that are not represented in $\mathcal{F}$ but which have a significant influence on the project payoff. Engineers refer to these unknown influences as "unknown unknowns" or "unk-unks."[4] In contrast to the "known unknowns" discussed in §3, contingencies cannot be planned for unk-unks. Engineers feel uncomfortable about them—understandably so, as existing decision tools do not address them. Transition inadequacy of $\widehat{M}$ implies that transitions $\widehat{M}(X, A)$ that were thought to be impossible—that is, no probability mass is assigned to the outcome—are possible, or vice versa. Without an adequate transition model, one could not hope to generate an optimal policy and is likely to find signals that are inconsistent with what was planned for in the policy, leaving the team at a loss to know what to do next.

Information inadequacy can arise from both project ambiguity and project complexity. Ambiguity refers to a lack of awareness of the project team about certain states of the world or causal relationships (Schrader et al. 1993). Project complexity means that many different actions and states of the world parameters interact (in Π and M), so the effect of actions is difficult to assess (e.g., Simon 1969 p. 195, or Kauffman 1993 p. 42). In complex projects, an

[3] The policy α also determines the (possibly random) stopping time for the project.

[4] We thank Steve Eppinger and an anonymous referee for alerting us to the use of "unk-unks."

adequate representation of all the states that might have a significant influence on the project payoff, or of the causal relationships, may simply be beyond the capabilities of the project team.

In either case, information inadequacy implies that the chosen policy α^* might not maximize the real project payoff $\Pi(M(\omega, \alpha^*(y)), \alpha^*(y))$. But the project team cannot specifically plan for this—that is, no expectation or variance measure can be computed for events or causalities that lie beyond the team's understanding of the project. An important challenge for a project team that is not sufficiently addressed in the existing project management literature is dealing with inadequate project information. If the project team's model is inadequate for developing a near-optimal policy, they only have two choices: either to improve their model over time through *learning*, or avoid instructionism all together by adopting a *selectionist* strategy. We describe both of these approaches in the subsections below.

Learning

In our simple model of projects, learning comes from signals $y_t = \eta_t(M(\omega, A_t))$ that are incompatible with the project team's predictions. As project teams monitor their projects, they must recognize that observed signals are incompatible with their model of the world and be willing to change their representation of the world either by updating the partition $\mathcal{F}$ or the transition mapping $\widehat{M}$. We refer to this process as *learning*.

Of course, the project team does not know the true value of the improvement in the project payoff from learning. Learning, unlike contingent action, cannot be planned in advance. The project team may have a hypothetical model of how activities might yield signals suitable for learning. In the context of tools such as the design of experiments or Failure Mode and Effect Analysis (FMEA), actions are deliberately taken specifically to establish causal relationships between actions and outcomes. In this way a project team learns *incrementally*—that is, they calculate an estimate of the expected net gain from past learning and extrapolate this to the current situation. If the result is positive in terms of an improvement to the project payoff, then the team may refine further; if not, they stop. This approach assumes that benefits from further learning have predictable returns which may not in fact be true. Alternatively, learning can proceed *opportunistically*—that is, by paying attention to new information that may arrive from the environment and recognizing when this information implies a change of the project map.

Learning is time consuming, psychologically difficult, and often resisted (e.g., Staw and Ross 1987). The team must *actively incorporate* the new information, develop a new model, and then replan the project in terms of a new set of activities or new policy. This evidently requires that the team be flexible. Unlike in contingency planning, where "flexible" actions are predetermined and then either "triggered" by signals or "used up" as design slack (Thomke and Reinertsen 1998), here the exact changes required cannot, by definition, be anticipated. Thus, it involves a greater level of flexibility than that required by contingency planning.

Selectionism

Learning can be seen as an extension of the instructionist approach: The project team improves their project model in order to improve their policy. Thus, the team is still relying on their ability to identify an *optimal* policy, albeit modified over time as the project model evolves. Some projects, however, are not suitable for this approach.

For instance, the project payoff and transition model, while known in principle, may be so complex that they are intractable. Recent results from combinatorial optimization show that pure optimization does not work well for large, complex problems. Known sophisticated optimization algorithms, such as simulated annealing, tabu search, or general hill-climbing algorithms, are outperformed by "randomized local search"—that is, the repetitive or parallel execution of local searches around randomly chosen initial values (e.g., Ferreira and Zerovnik 1993; Fox 1993, 1994; Jacobson and Yücesan 1998).

Alternatively, the nature of the project may render learning ineffective. If the environment is inaccessible, signals perceived by the project management team will be too costly or not sufficiently rich to learn from. Or, the nature of unk-unks may be such that radical changes to the project are required every time the project team learns, which may be too costly or may not "converge" to a global optimum within a reasonable number of iterations.

In either case, the project team is left with a project black—or at best dark gray—box: Neither an instructionist nor learning approach can be expected to yield an optimal policy reasonably effectively. As the team cannot effectively *predict* the project payoff, nor are they likely to learn to predict it without unreasonable effort, they are left with having to *observe* the project payoff. Thus, the team puts forward a reasonable policy α, and then observes the outcome $\Pi(M(\omega, \alpha(y)), \alpha(y))$. We refer to this approach as *selectionism*.

The team may choose to "hedge," pursuing multiple approaches in the hope that one will work (as proposed by Abernathy and Rosenbloom 1968). Examples of selectionism—as opposed to optimization—abound in management. Multiple parallel product concepts are frequently pursued for consumer products (Srinivasan et al. 1997) and cars (Sobek et al. 1999). The process of introducing multiple new products into an unknown market and seeing which ones succeed has been referred to as "vicarious selection" in technology management (e.g., Leonard-Barton 1995, Veryzer 1998). Similarly, technological evolution at the level of an economy has never been successfully planned—history has often chosen one of several available candidates ex post (e.g., Mokyr 1990).

When projects are run sequentially, typically a target is set (e.g., derived from a minimum requirement or a known lower bound), and the first to surpass the target is taken as the global optimum (thus m is a stopping time). When m projects are run in parallel, the best of the actual project payoffs (observed only ex post) is retained and taken as the available approximation of the global optimum. Utilizing our notation, we can write the project payoff under a selectionist strategy as:

$$\operatorname*{Max}_{i=1}^{m} \Pi\big(M(\omega, \alpha^i(y^i)), \alpha^i(y^i)\big). \tag{8}$$

5. Model Completeness: Analogy with Biology

The question arises whether our model of learning and selectionism in response to unk-unks and complexity is complete and robust. We find evidence for completeness and robustness by comparing our results with another field of science: biology. Biological organisms have explored vast numbers of strategies for coping with complex and uncertain environments for over three billion years.[5]

The project management challenges of dealing with uncertainty have the same structure as the "uncertain futures problem" in biology (see Plotkin 1993 Chapter 5). In our terminology, the uncertain futures problem is framed as follows: The payoff function Π is the number of copies of an organism's genes that successfully propagate into the next generation. Genes provide an individual with phenotypical and behavioral instructions corresponding to a policy α. This policy is the result of the species' history and reflects successful actions for survival and propagation in the face of past events in the environment $\mathcal{F}$.

As the gene pool reflects experience from the past, the genes' policies account for stochastic environmental changes observed in the past, corresponding to $(-, \mathcal{F}, P)$. History, as reflected in the events $X \in \mathcal{F}$, may not reflect every important event in the organism's own lifetime that will significantly influence its ability to pass on its genes—that is, $\mathcal{F}$ may not be payoff adequate with respect to Π. In addition, the environment may be too complex to be adequately responded to by the genetic instructions (especially for simple animals)—the causal mapping $\widehat{M}$ encoded in the genes is inadequate. Analogously to the complexity results cited in §4, biologists have discovered that high complexity makes "the odds for effective rule-based operation vanishingly small" (Edelman and Tononi 2000 p. 136).

The biological world has developed a number of strategies to cope with this problem as listed in

[5] Evolution provides an unparalleled "database" of strategies to deal with ambiguity and complexity. Darwinian evolution has generated creative solutions in biology over three billion years (see e.g., Simonton 1999). If biology has produced the same fundamental strategies that we find, this is evidence that there are no other fundamental strategies.

Figure 1 Strategies for Coping with the Uncertain Futures Problem

	Optimization	Selectionism
Learning	**Learning Devices** Acquire "new" (unforeseen by the genetic instructions) responses to the environment. Examples: immune system remembers encounters with pathogens, intelligence remembers events in organism's history. - discover new discernible patterns (new causal map M) - respond to new events (e.g., new predator appears).	**Learning *and* selectionism in human culture** Cultural variation combined with learning in each culture increased human behavioral variability manyfold and enabled survival in different and more varied environments.
No Learning	**Instructionism** **Avoid Uncertainty** • Reduce rate of environmental change per generation: mature and propagate quickly (short life spans) • Live in uninhabited and stable niches: e.g., animals living at the north pole or in some areas of the deep sea avoid competition and the need for change. **Contingent Policies** • Continuous time regulation: e.g., automatic temperature regulation, "follow the light" rule, "grow fur in Winter" rule. • Genetic "triggers": e.g., gender determination by egg temperature in reptiles, plant phenotype triggered by environment.	**Selectionism** "R-strategist" animals produce many offspring with genetic variations. Mutations produce new maps$M$. • Variants selected by a complex environment (e.g., behavior of predators too complex for individuals to learn) • Variants selected after catastrophic unforeseeable events (e.g., volcano eruption).

Figure 1 (see Plotkin 1993 pp. 145–148). Each of these has a parallel with the project management strategies discussed in the previous sections.

Instructionism

One strategy is simply to avoid uncertainty by restricting oneself to ecological niches that are simple and change very slowly. In this case ω exhibits very little uncertainty and a good causal mapping $\widehat{M}$ can be genetically encoded over a reasonable number of generations. Here, a near-deterministic set of actions A^* suffices for success. Both in biology and in project management this typically means not only a slowly changing natural environment, but also an absence of competition, as competition tends to increase the speed of change. However, this strategy can be devastating if there are sudden changes to the environment.

A more flexible version of instructionism, with the ability to cope with foreseeable (in evolutionary time) uncertainty, takes the form of contingent policies α. For example, many species tolerate variations in their physical state (e.g., caloric intake, body temperature) up to a certain degree, and start taking action only when this variation exceeds a threshold (e.g., growing fur in winter). These preprogrammed "genetic triggers" adjust physiology or behavioral patterns in response to signals from the environment (e.g., a plant species whose appearance varies radically according to the climate in which the seed is sown). As long as history, as reflected in $\mathcal{F}$, adequately describes the significant events in the individual's lifetime, these policies will be effective in terms of Π.

Learning

We now move to the upper left box in Figure 1, where biological organisms have developed *learning*. Such organisms can modify their policies α in response to observed events in the environment or causal patterns that are unanticipated by the genetic instructions. This learning is a result of purposeful changes to representations of $\mathcal{F}$ and $\widehat{M}$ independently of the genetic code.

Animals that have the ability to learn can extend their behavior beyond pre-specified triggers by perceiving critical new features of their environment and by "replanning," modifying their behavior accordingly. It is important to note that such learning devices are metabolically costly. Thus, not all organisms exhibit learning behavior—biologists estimate that only about 5% of all species possess a learning capability (Plotkin and Odling-Smee 1979).

Selectionism

Certain species do not have the ability to learn, yet have a tremendous ability to adapt to new environments that lie outside their historical experience. These "r-strategists" respond to uncertainty and complexity by producing many offspring. As each individual offspring "dips" into the gene pool, coming up with *variants* of genetic instructions (e.g., Crow 2001), the resulting genetic variation increases the chance that some will survive.

Each genetic variant i corresponds to a different policy α^i, yielding a different realized payoff Π. These new policies are not the result of updates to $\mathcal{F}$ and $\widehat{M}$—that is, they are not the result of learning. However, as the number of variants increases, the probability that some policies reach a given survival threshold increases. For example, bacteria with fast propagation and high mutation rates have conquered niches that were until recently believed to be hostile to life forms (such as hot sulfur vents in the deep sea or cracks in Antarctic ice).

6. Discussion and Implications

We have argued that widely used project management approaches assume adequate information and represent an instructionist approach to project management. Figure 2 summarizes the preceding discussion, showing that learning and selectionism go beyond instructionism to cope with complexity and ambiguity. The question arises: "What does this imply for project managers?" Our model suggests that it is of fundamental importance to first take the time to map the project terrain. For example, if a project with inadequate information is managed with instructionism, it will have a high probability of failure. Two critical initial tasks for any project management team are: (i) to clarify at the outset the *adequacy* of what is known about states of the world and action effects; and (ii) to determine whether this is due to lack of awareness (ambiguity) or lack of understanding (complexity).

The project team should concentrate on getting a complete picture of the partition $\mathcal{F}$, even if some "regions" of $\mathcal{F}$—that is, events—are quite coarse and may need further refining as the project progresses.

Figure 2 Summary of Instructionism, Learning, and Selectionism

	Optimization	Selectionism
Learning	**Learning Strategies** *Learning*: scanning for unk-unks, then new, original problem solving • Learn about unforeseen uncertainty (new $\mathcal{F}$) • Learn about complex causal effects of actions on payoffs ($\hat{M}$)	**Learning and Selectionism** • A project may be stopped based on favorable progress of another candidate • Exchange information among candidates to increase learning: candidate projects become complements
No Learning	**Instructionist Strategy** Payoff adequate $\mathcal{F}$ and decision adequate causal mapping $\hat{M}$. • include buffers in plan • plan project *policy* • monitor project influence *signals* • trigger *contingent action*	**Selectionist Strategy** Launch multiple "candidate" project efforts and choose the one with best payoff *ex post* • Hedge against unanticipated events • Explore larger part of complex action space to find better solution

Including events of the type: "I really don't know where it could come from, but I have the feeling that the regulatory environment could have a significant impact on this project" gives an indication of possible project unk-unks. The project team should also take the time to understand the true complexity of transition mapping M and payoff Π. Too often project teams accept the validity of their simplified causal model without further examination, even though it may have been adopted simply to facilitate the generation of a project plan. It is important for the project team to clarify whether the payoff effects of actions can be analyzed with an acceptable effort, or whether there are so many interrelated influences that the expected performance of two alternative policies cannot be compared at the outset (as is sometimes the case for complex technical systems; see Sobek et al. 1999).

The project map then implies a combination of three very different project management strategies, which require different *project infrastructures* for planning, coordination and incentives, and monitoring—as summarized in Figure 3.

Known Project Terrains: Instructionist Strategies

Consider the construction of a cruise ship that we have observed in St. Nazaire. The project plan is

Figure 3 Fundamental Project Management Strategies and Project Infrastructure

	Planning Systems	Coordination and Incentives	Monitoring Systems
Instructionism	Critical Path Planning • Task scheduling • Buffers (e.g., budget or schedule "contingencies") • Simulation	Critical Path Planning • Target setting • Workstructure, responsibilities • Coordination in hierarchy	Critical Path Planning • Target achievement • Progress tracking (e.g., % complete)
	Risk Management • Risk lists • Preventive actions • Contingency plan (dynamic programming, decision tree)	Risk Management • Contingent targets and contracts • Mutual adjustment according to events	Risk Management • Contingent target achievement (per tree branch) • Monitor risk realization
Learning	• Overall vision • Detailed plan only for next tasks, then high level logic based on hypotheses • Plan learning actions • Provide capacity for re-planning	• Long-term relationships with stakeholders, • Flexible and lateral coord-ination in mutal interest • Upward incentives (no punishment for failure due to uncontrollable events) • Incentives for good *process*	• Scan for new events • Track assured achievements • Track quality of process used in addition to outcomes • Explicity evaluate what has been learned
Selectionism	• Plan multiple trial projects • Plan performance hurdle for the "winner"	• "Winner" shares upside with "Losers" (all contribute, as winner cannot be predicted)	• Sharing of intermediate results among projects (learning) • Performance of trial projects versus hurdle

well mastered and major risks can almost certainly be excluded. The complexity of coordinating hundreds of subcontractors working simultaneously and monitoring their work to prevent shortcomings in quality are by far the major concerns of the project manager. The challenges are (a) scheduling and coordinating thousands of actors and activities, and (b) managing variation in profits, schedules, and budgets. Simulation techniques can help to assess the probability of running against "control limits" requiring corrective action. Project buffers (cost, schedule) may need to be introduced to manage a project successfully. It does not pay to build an expensive information structure to plan and identify major contingencies, but close contact with the customer is necessary to prevent unexpected reconfigurations.

Now consider a construction company with which we have worked. The Ladera Ranch team moves millions of cubic yards of dirt to provide independent builders in Southern California with house pads, streets, water runoff, landscaping, and utilities. Their major objective is to plan the cuts and fills in a way that moves dirt the shortest possible distance. Although geological studies exist, the moisture level and exact soil type are uncertain, which is problematic because moist earth requires more excavation. Also, moist earth takes longer to settle before it can be built on, so the project team might opt to dry the dirt rather than delay selling lots. Some types of soils may require different gradients for stability. A gentler slope means that it is more difficult to provide the same amount of flat area for houses and streets.

The team could, in theory, handle the uncertainty as a series of foreseen uncertainties, building a contingency plan for each scenario ("If soil is moist and type x at location y, do Plan A. If it is dry and soil type z, do Plan B" and so on). However, in practice this rapidly becomes unfeasible because of the interdependent nature of cuts and fills across locations. The number of scenarios proliferates with the number of locations considered.

Instead, the project management team applies execution monitoring and replanning, using principles the project leader experienced first-hand in the U.S. Marine Corps: "Every play we run," he says, "is an option play. I want my people to be able to make decisions in the field without having to report back to me every time something comes up." The team meets weekly to discuss whether or not the project path or target will change and, if so, how. As an added benefit, the meetings also ensure that team members don't pass off their mistakes as "unforeseen uncertainty." Thus, the management style is adapted to contingencies in the planning, monitoring, and coordination approaches.

Learning Strategies

In addition to "normal" soil variations, the Ladera team sometimes encounters unk-unks, or truly unforeseen events—such as the discovery of prehistoric Indian ruins or a rare animal or plant species—which completely alter their operation.

In these cases, risk management techniques like execution monitoring and replanning, are insufficient. The challenge is to recognize these events quickly and develop an appropriate response. Quickly "recognizing an unk-unk when I see one" requires continuous scanning of the environment and comparing the signal with the current influence factor map. Moreover, the team must have the will and the capacity to learn and replan rather than just trigger preplanned contingency responses. The benefits of redefining the course of action (the policy α) or even the project objectives (payoffs Π) may outweigh the cost.

When significant unk-unks arise, a lot of time and effort must go into managing relationships with stakeholders and getting them to accept unplanned changes. Stakeholders often resist change, so much of the manager's job is to anticipate and soften resistance by creating flexible contracts and keeping stakeholders well informed. Top management support, negotiation techniques, team-building exercises, and the project manager's charisma can help overcome conflicts of interest.

The project management team at Ladera Ranch has worked hard to share the risk with their subcontractors, recognizing that taking advantage of a supplier today will limit their flexibility tomorrow. The relationship is characterized by trust, relieving both the management team and the subcontractors of having to anticipate every little event and activity. Without such trust no subcontractor would take action until the project team had drawn up a formal contract, making it virtually impossible to respond flexibly to unforeseen events. This degree of flexibility is difficult to obtain and is often unenthusiastically received. Such resistance is understandable, given that most top managers are more concerned with hitting established targets than doing the best overall job possible. However, flexibility is key to evolving projects out of the vague assumptions characteristic of unforeseen uncertainty.

Providing this level of project management flexibility is a major managerial decision that is often resisted. A team must be evaluated not only on targets (which may become obsolete), but on the quality of their problem solving and their ability to pursue new opportunities that arise during the project.

Putting in place such flexibility is costly in terms of management attention and systems. A team needs a tracking mechanism, the capacity and the authority to work out responses to unexpected events or causal patterns. A steering committee or oversight process must be put in place with the organizational authority to change the policy (the plan), or the target (the payoff). Such costly systems must be established at the outset, and only when the initial project terrain mapping suggests that unforeseen events are potentially significant. Creating this infrastructure after carefully judging the quality of the available project information is a major management responsibility.

Selectionist Strategies

When complexity prevents an evaluation of the causal mapping, it is impossible to choose a best policy. The project team may adopt a selectionist approach to project management if it believes there is a benefit to being able to select the best project from the pool of trials. The pool may be produced by pursuing several candidates in parallel, or by producing candidates sequentially until the result is satisfactory. As a consequence, a subteam working on one alternative cannot be judged on its candidate solution being the winner (since that is not under the subteam's control): To foster information sharing and motivation, the team should be rewarded for the *overall* success.

In an R&D environment this means several project teams pursuing different solutions for the same problem and retaining the one with the best outcome. Typically, selectionism and learning are combined: Parallel projects should share information, and once it becomes clear that one project cannot match the result of another, it should be discontinued.

NASA employed this strategy in the 1960s for the development of the lunar module. Likewise, today's automobile companies tend to develop several concepts for a new car model—all the way to complete prototypes—to explore the complex design space more fully before choosing the best prototype for industrialization (e.g., Sobek et al. 1999). Sometimes one needs to go all the way to market introduction to be able to select the best alternative. For example, in the first half of the 1990s Japanese consumer electronics companies developed and launched multiple products to see which would succeed in the complex consumer market—a strategy known as "product churning" (see Stalk and Webber 1993). This approach is consistent with recent empirical findings that projects with a high degree of uncertainty perform best if they explore the solution space and iterate quickly (e.g., Iansiti and MacCormack 1997, Lynn et al. 1998, Veryzer 1998).

Framing the Project

It is important to remember that a project's uncertainty and complexity can, to some extent, be influenced by how the project is framed (c.f., Schrader et al. 1993). The initial project definition determines the causality of actions, as defined in §3, which in turn determines the project complexity and the payoff adequacy of any initial partition $\mathcal{F}$ of the states of the world Ω. For example, the use of a new—as opposed to a proven—technology makes unforeseen events relevant in the payoff function (i.e., renders the existing partition associated with the proven technology payoff inadequate). Similarly, an ambitious system scope (e.g., in the form of the number of features included) increases project complexity. If the project terrain implies challenges that the organization cannot master (e.g., because the necessary structures are nonexistent), management may have to change the project's definition. Evidently the organization's stock of experience and problem-solving capacity will determine the levels of uncertainty, ambiguity, and complexity that the team faces.

The right *combination* of instructionism, learning, and selectionism depends on the urgency of the project, the amount of learning that can be achieved—either about $\mathcal{F}$ or about $\widehat{M}$ (see a simplified model in Loch et al. 2001), the cost of multiple candidate projects in a selectionist strategy, and the nature of the ambiguity and complexity of the project. Precise rules of when to use which approach are currently unknown and we are pursuing this line of inquiry in further work.

If independent approaches are expensive or the urgency of getting a result is low, it may be preferable to pursue one single approach, adapting and learning over time. If, in contrast, learning is costly or difficult and urgency high, one may prefer to pursue multiple independent attempts, picking the best ex post. If learning and more independent candidates exhibit decreasing returns, one may choose to pursue several candidates and learn in each as it progresses.

Finally, instructionism, learning, and selectionism may be staggered in the context of a stage gate process, as uncertainty is reduced over the course of an R&D program (e.g., Cooper 1994, Verganti 1999).

7. Conclusion

In this article, we have conceptualized a project as a payoff function that depends on the state of the world and the action sequence chosen. Actions arise endogenously as the result of decisions and influence the states of the world through a transition function (causal model of the world). We characterize the information available in the project as *inadequate* if too little is known about the states of the world or the causal effects of actions on the payoff (ambiguity) or if the effect of actions on the payoff cannot be analyzed because too many parameters interact in the transition or payoff function (complexity).

Our model makes two contributions. On the theoretical side, it allows us to identify what classic project-planning approaches have in common. The critical path method (CPM), stochastic networks (GERT), and decision trees (risk management and contingent action) assume an adequate information structure where all possible events can be anticipated (although their occurrence may be stochastic). Which of these approaches is best will depend on the cost of information. All of them are a variant of instructionism—the ex ante determination of actions or policies in which preplanned actions are triggered by signals.

Moreover, our model allows us to put a wide variety of recent project management approaches in the context of two fundamental strategies that become necessary when the project information is inadequate: *Learning*—that is, scanning to identify unk-unks and problem solving to modify policies; and *selectionism*—pursuing multiple approaches and choosing the best one ex post.

In terms of its second contribution, we believe that our model is directly relevant to project managers in practice. The model is as parsimonious as possible, while still allowing managers to distinguish among the three fundamental project management strategies and characterizing the reasons for choosing them. Although the ideal types of information adequacy are never clearly satisfied in practice, the terminology established in the model helps managers to characterize information adequacy at the outset and choose a strategy and a project infrastructure accordingly, including systems for planning, coordinating, and monitoring.

The current study should be extended both on the theoretical and the application fronts. First, more research is needed to refine the suggested management approaches and determine when to use which approach—a direction we are already pursuing. Some work has been done in organizational theory about learning from "unusual events" that should be taken as signals when operating under threatened conditions. Sufficient resources are necessary to be watchful, and to ensure that rare events should be experienced "richly" (from multiple angles) (March et al. 1991, Marcus and Nichols 1999). Combining these perspectives with project management approaches may yield fruitful insights.

Second, the theory developed in this study needs to be tested empirically. We have begun to discuss our insights with managers to develop robust decision rules (see De Meyer et al. 2002). Notwithstanding, a theoretically solid concept of project information adequacy should contribute to a better use of the existing set of tools in practice.

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References

Abernathy, W. J., R. S. Rosenbloom. 1968. Parallel and sequential R&D strategies: Application of a simple model. *IEEE Trans. Engrg. Management* **EM-15**(1) 2–10.

Ambros-Ingerson, J., S. Steel. 1988. Integrating planning, execution and monitoring. *Proc. Seventh National Conf. Artificial Intelligence* **AAAI-88** 735–740.

Bell, J. 2000. Beauty is in the eye of the beholder: Establishing a fair and equitable value for embryonic high-tech enterprises. *Venture Capital J.* **40**(12) 33–34.

Bhattacharya, S., V. Krishnan, V. Mahajan. 1998. Managing new product definition in highly dynamic environments. *Management Sci.* **44** S50–S64.

Brucker, P., A. Drexl, R. H. Moehring, K. Neumann, E. Pesch. 1999. Resource-constrained project scheduling: Notation, classification, models and methods. *Eur. J. Oper. Res.* **112**(1) 3–41.

Carracosa, M., S. D. Eppinger, D. E. Whitney. 1998. Using the design structure matrix to estimate product development time. *Proc. DETC'98, 1998 ASME Design Engrg. Tech. Conf.* Atlanta, GA.

Chapman, C. B. 1990. A risk engineering approach to project risk management. *Internat. J. Project Management* **8** 5–16.

Clayton, E. R., L. J. Moore. 1972. PERT vs. GERT. *J. Systems Management.* (February) 11–19.

Clemen, R. 1996. *Making Hard Decisions*. 2nd ed. Duxbury Press, Belmont, MA.

Cockerham, J. M. 1979. Army RTDE funding, planning and management: Total risk assessing cost estimate (TRACE) concept. *Army Res. Development and Acquisition Magazine*. (July) 24–26.

Conrow, E. H. 2000. *Effective Risk Management: Some Keys to Success*. American Institute of Aeronautics and Astronautics, Reston, VA.

Cooper, D. F., C. B. Chapman. 1987. *Risk Analysis for Large Projects: Models, Methods and Cases*. John Wiley & Sons, New York.

Cooper, R. G. 1994. Third-generation new product processes. *J. Product Innovation Management* **11** 3–14.

Crow, J. F. 2001. The beanbag lives on. *Nature* **409**(15) 771.

De Meyer, A., C. H. Loch, M. T. Pich. 2002. Managing project uncertainty. *Sloan Management Rev.* **43**(2) 60–68.

DSMC. 1998. *Risk Management Guide for DoD Acquisitions*. Defense Systems Management College Press, Fort Belvoir, VA.

Dvir, D., S. Lipovetsky, A. Shenhar, A. Tishler. 1998. In search of project classification: A non-universal approach to project success factors. *Res. Policy* **27** 915–935.

Edelman, G. M., G. Tononi. 2000. *A Universe of Consciousness*. Basic Books, New York.

Eisenhardt, K. M., B. N. Tabrizi. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Admin. Sci. Quart.* **40** 84–110.

Elmaghraby, S. E. 1964. An algebra for the analysis of generalized activity networks. *Management Sci.* **10** 494–514.

Elsner, H. 1962. A generalized network approach to the planning and scheduling of a research program. *Oper. Res.* **10** 115–125.

Ferreira, A. G., J. Zerovnik. 1993. Bounding the probability of success of stochastic methods for global optimization. *Comput. Math. Appl.* **25** 1–8.

Fikes, R. E., P. E. Hart, N. J. Nilsson. 1972. Learning and executing generalized robot plans. *Artificial Intelligence* **3**(4) 251–288.

Fox, B. L. 1993. Random restarting versus simulated annealing. *Comput. Math. Appl*. **27** 33–35.

——. 1994. Integrating and accelerating tabu search. *Ann. Oper. Res.* **41** 47–67.

Goldratt, E. M. 1997. *Critical Chain*. North River Press, New York.

Gutierrez, G. J., P. Kouvelis. 1991. Parkinson's Law and its implications for project management. *Management Sci.* **37** 990–1001.

Hamel, G., C. K. Prahalad. 1994. *Competing for the Future*. Harvard Business School Press, Boston, MA.

Heyman, D. P., M. J. Sobel. 1984. *Stochastic Models in Operations Research.* Vol. II, McGraw Hill, New York.

Iansiti, M., A. MacCormack. 1997. Developing products on Internet time. *Harvard Bus. Rev.* **75**(5) 108–117.

Jacobson, S. H., E. Yücesan. 1998. Performance results for generalized hill-climbing algorithms. Working paper, INSEAD, France.

Kauffman, S. A. 1993. *The Origins of Order*. Oxford University Press, Oxford, U.K.

Kepner Tregoe. 1992. *Analysis of Potential Problems*. Company brochure (in German).

Leach, L. 1999. Critical chain project management improves project performance. *Project Management J.* **30**(4) 39–51.

Leonard-Barton, D. 1995. *Wellsprings of Knowledge*. Harvard Business School Press, Boston, MA.

Loch, C. H., C. Terwiesch, S. Thomke. 2001. Parallel and sequential testing of design alternatives. *Management Sci.* **47**(5) 663–678.

Lockyer, K. G. 1969. *An Introduction to Critical Path Analysis.* Pitman and Sons, London, U.K.

Lovejoy, W. S. 1991. A survey of algorithmic methods for partially observed Markov decision processes. *Ann. Oper. Res.* **28**(1–4) 47–66.

Ludwig, A., R. H. Möhring, F. Stork. 1998. A computational study on bounding the makespan distribution in stochastic project networks. Technical Report 609-1998, Technical University, Berlin, Germany.

Lynn, G. S., J. G. Morone, A. S. Paulson. 1996. Marketing and discontinuous innovation: The probe-and-learn process. *California Management Rev.* **38**(3) 8–36.

——, M. Mazzuca, J. G. Morone, A. S. Paulson. 1998. Learning is the critical success factor in developing truly new products. *Res. Tech. Management* **41**(3) 45–51.

March, J. G., L. S. Sproull, M. Tamuz. 1991. Learning from samples of one or fewer. *Organ. Sci.* **2** 1–13.

Marcus, A. A., M. L. Nichols. 1999. On the edge: Heeding the warnings of unusual events. *Organ. Sci.* **10** 482–499.

Marschak, J., R. Radner. 1972. *Economic Theory of Teams*. Yale University Press, New Haven, CT.

McFarlan, F. W. 1981. Portfolio approach to information systems. *Harvard Bus. Rev.* **59**(5) 146.

Meredith, J. R., S. J. Mantel. 1995. *Project Management—A Managerial Approach*, 3rd ed. John Wiley and Sons, New York.

Mokyr, J. 1990. *The Lever of Riches.* Oxford University Press, Oxford, U.K.

Morris, P. W. G., G. H. Hugh. 1987. *The Anatomy of Major Projects*. Wiley, Chichester, U.K.

O'Connor, G. C., R. W. Veryzer. 2001. The nature of market visioning for technology-based radical innovation. *J. Product Innovation Management* **18** 231–246.

Olawsky, D., M. Gini. 1990. Deferred planning and sensor use. K. P. Sycara, ed. *Proceedings, DARPA Workshop on Innovative Approaches to Planning, Scheduling, and Control*, Defense Advanced Research Projects Agency, San Diego, CA.

Plotkin, H. C., F. J. Odling-Smee. 1979. Learning, change and evolution: An enquiry into the teleonomy of learning. *Adv. Stud. Behavior* **10** 1–41.

——. 1993. *Darwin Machines and the Nature of Knowledge*. Harvard University Press, Cambridge, MA.

Pritsker, A. A. B. 1966. GERT: Graphical evaluation and review technique. Memorandum RM-4973-NASA, The Rand Corporation, Santa Monica.

——, C. E. Sigal. 1983. *Management Decision Making: A Network Simulation Approach*. Prentice Hall, Inc, Englewood Cliffs, NJ.

Project Management Institute Standards Committee. 2000. *A Guide to the Project Management Body of Knowledge (PMBOK™ Guide)*. Project Management Institute, Upper Darby, PA.

Russell, S., P. Norvig. 1995. *Artificial Intelligence: A Modern Approach*. Prentice Hall, Englewood Cliffs, NJ.

Sahlmann, W. A. 1994. Insights from the venture capital model of project governance. *Bus. Econom.* **29**(3) 35–41.

Schrader, S., W. M. Riggs, R. P. Smith. 1993. Choice over uncertainty and ambiguity in technical problem solving. *J. Engrg. Tech. Management* **10** 73–99.

Schwartz, P. 1991. *The Art of the Long View*. Doubleday, New York.

Shenhar, A. J., D. Dvir. 1996. Toward a typological theory of project management. *Res. Policy* **25** 607–632.

Simon, H. 1969. *The Science of the Artificial*, 2nd ed. MIT Press, Boston, MA.

Simonton, D. K. 1999. *Origins of Genius: Darwinian Perspectives on Creativity*. Oxford University Press, Oxford, U.K.

Smith, R. P., S. D. Eppinger. 1997. A predictive model of sequential iteration in engineering design. *Management Sci.* **43**(8) 1104–1120.

Sobek, D. K., A. C. Ward, J. K. Liker. 1999. Toyota's principles of set-based concurrent engineering. *Sloan Management Rev.* **40** 67–83.

Srinivasan, V., W. S. Lovejoy, D. Beach. 1997. Integrated product design for marketability and manufacturing. *J. Marketing Res.* **34** 154–163.

Stalk, G., A. M. Webber. 1993. Japan's dark side of time. *Harvard Bus. Rev.* **71**(4) 93–102.

Staw, B. M., J. Ross. 1987. Behavior in escalation situations: Antecedents, prototypes, and solutions. *Res. Organ. Behavior* **9** 39–78.

Steward, D. 1981. The design structure matrix: A method for managing the design of complex systems. *IEEE Trans. Engrg. Management* **EM-28**(3).

Tatikonda, M. V., S. R. Rosenthal. 2000. Technology novelty, project complexity, and product development execution success. *IEEE Trans. Engrg. Management* **47** 74–87.

Taylor, B. W., L. J. Moore. 1980. R&D project planning with Q-GERT network modeling and simulation. *Management Sci.* **15** 44–59.

Thomke, S. H. 1998. Managing experimentation in the design of new products. *Management Sci.* **44**(6) 743–762.

——, D. Reinertsen. 1998. Agile product development: Managing development flexibility in uncertain environments. *California Management Rev.* **41** 8–30.

Verganti, R. 1999. Planned flexibility: Linking anticipation and reaction product development projects. *J. Product Innovation Management* **16** 363–376.

Veryzer, R. W. 1998. Discontinuous innovation and the new product development process. *J. Product Innovation Management* **15** 304–321.

Warren, D. H. 1976. Generating conditional plans and programs. *Proc. AISB Summer Conf.* 344–354.

Weiss, G. 2000. Planning and learning together. *Proc. Internat. Conf. Autonomous Agents*, Barcelona, Spain, 102–103.

Wideman, R. M. 1992. *Project & Program Risk Management*. Project Management Institute, Newton Square, PA.

Williams, T. M. 1999. The need for new paradigms for complex projects. *Internat. J. Project Management* **17**(5) 269–273.

——. 1995. A classified bibliography of recent research relating to project risk management. *Eur. J. Oper. Res.* **85** 18–38.

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