

Innovation, Risk, Agility, and Learning, Viewed as Optimal Control & Estimation

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Abstract. This paper summarizes how a well-understood problem—optimal control and estimation in “noisy” environments—provides a framework to advance understanding of a well-known but less well-mastered problem—system innovation life cycles and management of decision risks and learning. The ISO15288 process framework and its exposition in the INCOSE SE Handbook describe system development and other life cycle processes. Concerns about improving the performance of processes in dynamic, uncertain, and changing environments are partly addressed by “agile” systems engineering approaches. Both are typically described in the procedural language of business processes, so it is not always clear whether the different approaches are fundamentally at odds, or just different sides of the same coin. Describing the target system, its environment, and the life cycle management processes using models of dynamical systems allows us to apply earlier technical tools, such as the theory of optimal control in noisy environments, to emerging innovation methods.

Introduction: Overview and Background

Problem Statement

Advancing understanding and performance of the system innovation life cycle is central to INCOSE. Current understanding is exemplified by the Systems Engineering Handbook, ISO15288, and Guide to the SE Body of Knowledge (Walden et al 2015) (ISO 15288 2015) (Pyster et al 2013), describing established principles and practices grown pragmatically out of decades of real-world experience. This is a different kind of foundation than STEM understanding of the phenomena of electrical, mechanical, or chemical systems as the basis for Electrical, Mechanical, and Chemical Engineering disciplines. Complex engineered systems and environments, systems of systems, compressed innovation cycles, and dynamically changing competitive markets and technologies challenge understanding and capabilities to perform system innovation effectively enough. The traditional principles might still apply, but how do we know whether we are performing the overall process as effectively as possible? We understand the possibilities and limits on efficiency of engines from thermodynamics, but how do we understand the possibilities and limits on innovation cycles? This paper suggests that certain existing STEM-based foundations are available, enabled by the transition to Model-Based Systems Engineering (MBSE), that can be exploited in pursuit of optimizing innovation cycles, and as a foundation for understanding currently emerging methods.

The Geometrization of Innovation Space

Converting physical and mathematical descriptions into “spatial” geometric terms, while seemingly abstract, has a long history of positive impacts in the history of science, technology, engineering, and mathematics (STEM). This paper introduces the same kind of thinking into how we understand the process of innovation in general as a system, and particularly in more challenging cases involving highly dynamic environments, continuous learning, and

uncertainties in our ability to fully observe or control what is occurring during the innovation process. Even where current practices may be seen in this approach, it provides a more general way to understand them, and therefore to perform and improve them in the future.

Before introducing this alternate perspective, this paper will briefly summarize some of the traditional as well as emerging perspectives across seemingly different domains. Then, the impact of shifting to more model-based representation of systems on our ability use the ideas of mathematical spaces will be described. Following that, the paper will describe the spaces of interest in this case, and how they are addressed by the existing theory of optimal control and estimation. An immediate application is noted in the world of agile, “continuous, and “fail fast and recover early” development, and other applications are briefly summarized, with additional application suggestions for future pursuit.

Innovation, Risk, and Agility: Traditional and Emerging Concerns

This section briefly summarizes some of the more prominent risk-connected aspects of traditional and emerging perspectives on system innovation and related life cycle management. For purposes of this discussion, we will consider innovation to mean the delivery of improved stakeholder value, through any aspects of the system life cycle management processes. This is an explicit formalism, because the approach explicitly models value across all stakeholders. (Kline et al 2017) (Simoni et al 2016)(Rogers 2003) It avoids a technology-centric view, without ducking the challenge of complexity. It also creates an explicit space for improved understanding of variation and selection.

Concerns of Traditional Approaches to Innovation. The traditional systems engineering view of these life cycle processes can be described by the ISO15288 standard (ISO 2015) or its further description in the INCOSE SE Handbook (Walden et al 2015). Within that perspective, a number of differently configured specific forms of the Development portion of these life cycles may apply, based on the metaphors of waterfall, spiral, waves, or otherwise. Additional portions of the traditional ISO15288 life cycle processes include Production, Distribution, Operation, Maintenance, Update, and Retirement, any of which may be subject to innovation delivering enhanced stakeholder value.

The Risk Management perspective in the traditional case would include concerns such as multiple types and sources of risk, among these limited knowledge of changing environment, stakeholder situations and needs, as well as technical and other risks to performance, costs, and schedule. Traditional risk management concerns include identifying risks, assessing them, and working to avoid, transfer, mitigate, and monitor those risks. (Walden et al 2015) More attention is recently paid to risks arising when systems of interest or their environments exhibit dynamical complexity. (Sheard et al 2016)

Concerns of Emerging Approaches to Innovation. New approaches to innovation are rapidly emerging, and are sometimes perceived (correctly or not) as at odds with systems engineering, at least as traditionally performed. In the agile and lean start up communities (for systems, software, products, business, etc.), risk is addressed by seeking early and continuing feedback through short or incremental “experiments” (whether called “sprints” or otherwise) that encourage discovery, exposure, or exploration of instances of risk early enough that they can be addressed while the cost of doing so is still relatively smaller, even if this causes change to what would otherwise have been fundamental assumptions. Examples can be seen in the methodologies of agile software and systems (Rigby et al 2016) (Dove and LaBarge 2014), lean start up, the Minimum Viable Product, pivoting (Ries 2011), and experimentation in general (Schrage 2014, Anderson et al 2011, Clarke 2016, Kohavi et al 2009, Manzi 2012, Teller 2016, Thomke 2003).

How System Models Can Shift Our Perspective on Innovation

INCOSE has recognized the importance of the continuing rise of model-based methods (Friedenthal et al 2015), and formalized an objective of supporting systems engineering becoming a model-based discipline. (Peterson et al 2017) We note that this emergence is still at a relatively early and progressing stage--what is currently referred to as a "system model" may not represent what is possible in the future. This larger shift can include moving from system engineering's traditionally process- and procedure-oriented emphasis to something closer to the system model emphasis of other STEM disciplines (Schindel 2016), without abandoning the discipline of process.

Mathematically-oriented models have a long history in design optimization, (Fisher 1971, Bellman 1957, Koch 1998, Pontryagin et al 1962, Smaling 2005, Box 2013), predating more recent use of system (MBSE) models for other purposes (Friedenthal et al 2015). However, the scope of such design optimization mathematical models was generally focused on key architectural or other specific, important, but limited scope decisions, not the overall system being innovated, and not a dynamical model of the overall process of innovation.

In contrast to but building on that history, our interest in this paper is the convergence of (1) the earlier design optimization models (cited above) with (2) wider-scope, system-level MBSE models having strengthened STEM foundations (cited above), (3) more powerful computational environments (Friedenthal et al 2015), (4) continuous incremental development methodologies (cited above), and (5) extension of the system models to include both the target system of interest and the development and other life cycle management environments as systems in their own right (Schindel and Dove 2016).

The traditional issues summarized in the earlier sections above are fundamental and not likely to disappear through technique or method. However, the rise of system models as tools for innovation can have similar effects to their historical emergence in the other scientific and engineering disciplines--increasingly powerful ways to understand and attack those traditional issues, with increased clarity, quantification, and qualitative understanding.

Where do systems come from? System life cycle trajectories in S*Space

SE Information versus SE Process

The systems engineering process is often conceptualized by systems engineers using the life cycle management process models of ISO 15288 and the INCOSE SE Handbook, exemplified by the "Systems Engineering Vee" model (Forsberg et al, 2000), in one form or another, such as illustrated by the upper portion of Figure 1.

As also illustrated in Figure 1, the systems engineering process consumes and produces information, along with other kinds of resources. The perspective of this paper assumes an INCOSE-visualized future of model-represented information, representing system configurations progressing over the system life cycle. Because this paper emphasizes the impact of system models, Figure 1 uses symbology from the S*Metamodel summary Framework (INCOSE Patterns Working Group 2015) to illustrate the iterative production and consumption of information within the systems engineering process. The S*Metamodel framework represents the smallest set of information sufficient for the purposes of science and engineering in model form including: a significant range of stakeholder value/fitness space and purpose, technical requirements, design architecture, quantitative couplings and sensitivities, and failure modes and impacts.

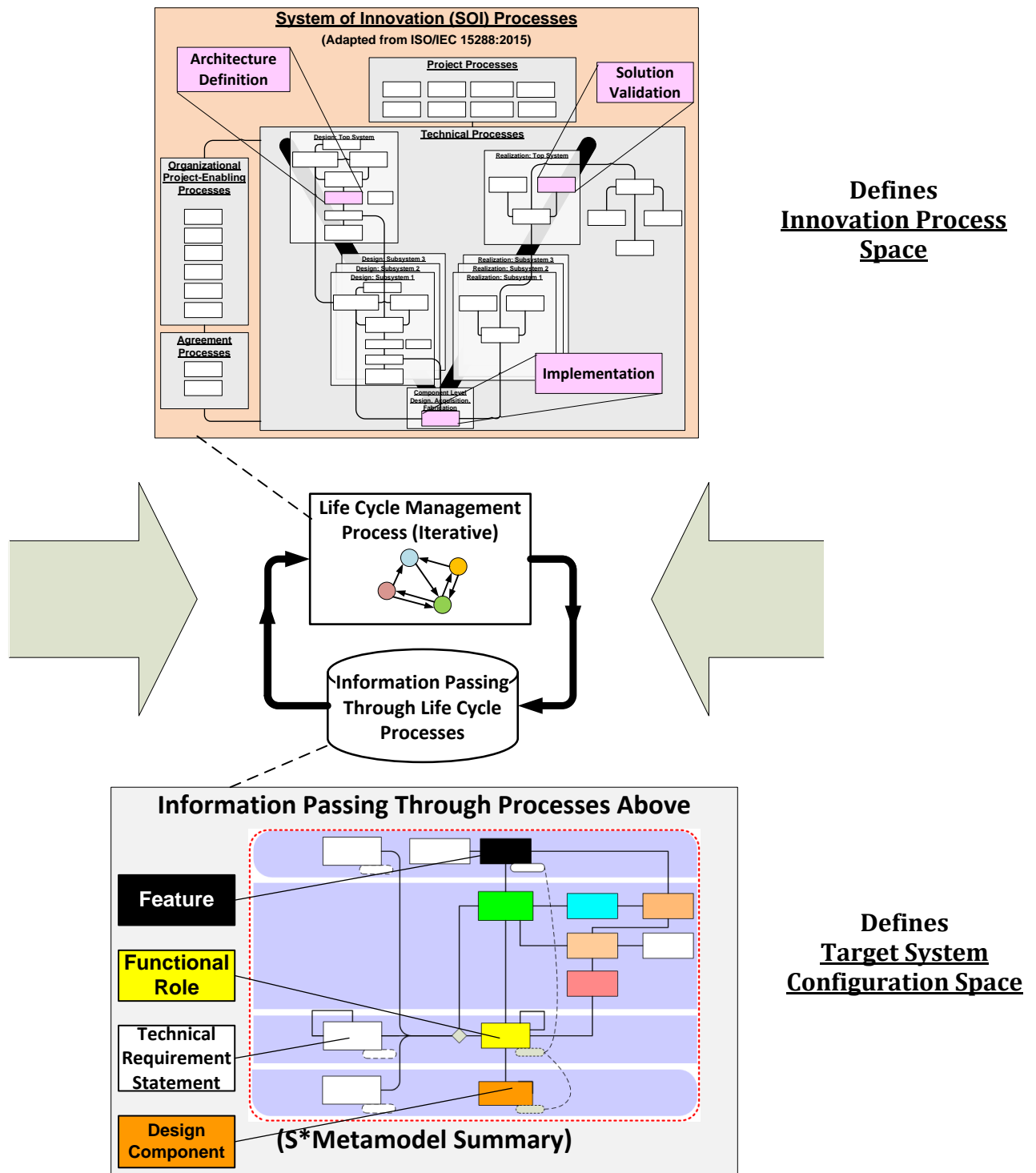


Figure 1: The SE Process Produces and Consumes Information

Traditional systems engineering has historically emphasized process and procedure over the information those processes consume and produce. As evidence (Walden et al 2015; Schindel 2015; INCOSE MBSE Patterns Working Group 2015) of this relative emphasis, one may refer to the amount of ink and paper spent to describe expected process and procedure versus to describe the expected information consumed and produced. The referenced industry and enterprise process standards certainly refer to both process as well as information, but the rise of model-based methods is shifting the relative balance of these two back in the direction of information models. It is informative to compare this to the history of physical science-based engineering disciplines (ME, CE, ChE, EE, etc.), in which there is relatively more emphasis on the models of underlying phenomena and system models, and relatively less

emphasis on the “procedure for performing electrical engineering”. As noted in (Schindel 2005, 2015, 2016), historical impacts of this situation have included:

1. Difficulty determining when we are “done” performing systems engineering, measuring where we are in Process and Procedure Space (top of Figure 1) instead of where things stand in modeled Target System Configuration Space (bottom of Figure 1).
2. In the same way, more subjectivity than would be desired in describing what comes next, by referring to procedural steps (Procedure Space) instead of modeled Target System Configuration Space progress.
3. Ambiguity in what the procedure-oriented approach says we should do with what we already know from past projects, versus what we are finding out for the first time. (Have we ever designed a switching power supply before?)
4. More subjectivity and interpretation are required in reviews than would be preferred.
5. Arguments about whether systems engineering has its foundation, like the other engineering disciplines, in underlying phenomena, physical laws, and first principles.

Geometrization of SE Model Information Space

By “geometrization”, we refer to the use of spatial coordinate system frameworks to represent state (in this case, the configuration of a modeled system), and with that transformation the availability of certain important formal mathematical tools coupled with intuitive spatial references. A familiar framework of this sort is a three-dimensional representation of space above a small region of the surface of the earth, used to represent the ballistic trajectory of a projectile fired from and returning to the earth. Other geometrized representations describe more abstract ideas in more familiar looking 3-space, or higher numbers of dimensions.

Two very famous geometrizations occurred in the history of mathematics, both having profound practical impacts on the day-to-day tools of modern engineering, noted in Figure 2:

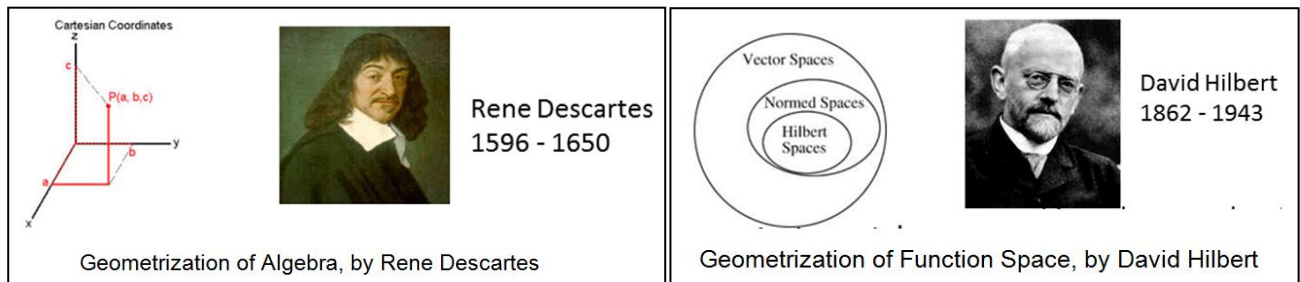


Figure 2: Two Geometrizations Had Enormous Impact: Descartes and Hilbert

1. The geometrization of algebra, by Rene Descartes, associated with graphs of conic sections or other shapes generated by algebraic formulae (Boyer 1959)
2. The geometrization of function spaces, by David Hilbert, associated with function inner products and distance metrics, correlations, angular direction, frequency domain transformations and projections, etc. (Simmons, 2003)

The practical effect of these become available when we begin to describe innovated systems using models, if the models are based on a strong enough metamodel foundation:

- A. Viewing the configuration of system information (whether about stakeholder value and system fitness, or technical requirements, or design architecture, or failure modes, or sensitivities and couplings, or otherwise) as a point in System Configuration Space.
- B. Visualizing “where we are” in an innovation process as a (moving) point in that System Configuration Space, representing the current understanding of the system of

interest--instead which step of a procedure we have completed. We begin to think in System Configuration Space instead of Process and Procedures Space. (See Figure 1.)

- C. Visualizing “where we are going” as points we want to reach in System Configuration Space, instead of steps in Process and Procedure Space.
- D. Taking advantage of the mathematical concepts and tools that go with such spaces, including distance metrics, velocities, inner products, projections, and other tools.
- E. Visualizing the progression of points in System Configuration Space as a Trajectory, along which we want to move during innovation in an optimal way toward a goal.
- F. Realizing that this has converted the problem of innovation into one of optimal dynamical travel along an (agile) trajectory, in the presence of uncertainty.

Nothing about the above should be interpreted as suggesting that innovation is a simple deterministic process (quite the opposite—many random processes are involved), or that we can predict its outcomes (also not so), fail to use the deep lessons learned by experienced leaders in traditional environments (rather, we want to share them more widely), or that we are not including serendipity or creativity (think about models of biological innovation or earthquakes). Rather, we are suggesting that, as with other applications of science and engineering, we are seeking STEM models of the world we occupy, to improve our ability to learn and succeed within it.

Trajectory Projections in S*Subspaces

The full S*Configuration Space set of information modeled across the engineering process and system life cycle has much higher dimension than three-space, and involves a mixture of dissimilar ideas, such as stakeholder value, material properties, laws of physics, etc. That may suggest putting all this into an integrated configuration space is too daunting a task.

However, a powerful aspect of geometrization is the idea of subspaces, in which some dimensions are temporarily ignored and a smaller number of current interest are visualized. This idea is illustrated by Figure 3, in which a trajectory in 3-space is projected onto three different sub-spaces, each of two dimensions.

In the same way, subsets of the S*Configuration Space may be separately studied, for a system that has projections into many subspaces. Figure 4 shows three such subspaces of interest, each of which represents potential creative or discovered syntheses:

1. **Stakeholder Feature Subspace**: A discovered or learned synthesis of stakeholder types and their respective value or fitness space, against which systems will be judged. The place where the value of delivered innovation is ultimately realized and validated.
2. **Technical Behavior Subspace**: A discovered or learned concept of operations and its related black box technical specification. The place where a technical behavior appears as a potential way to deliver value in (item 1 just above), and where a candidate’s design performance is judged technically.
3. **Physical Architecture Subspace**: A discovered or learned design solution, including physical architecture, the technologies upon which it is constructed, and the means of delivering the technical performance called for in (item 2 just above).

This is not to suggest that projection onto subspaces is something new: Model views, reducing dimensions, applying Principal Component Analysis, and the like are familiar enough in engineering. Rather, what we are pointing out is that MBSE is nearing the point at which the whole system innovation problem—not just a part of it—can be cast in this framework. At this point, the “guidance system” discussed in the next section becomes a practicality, as follows.

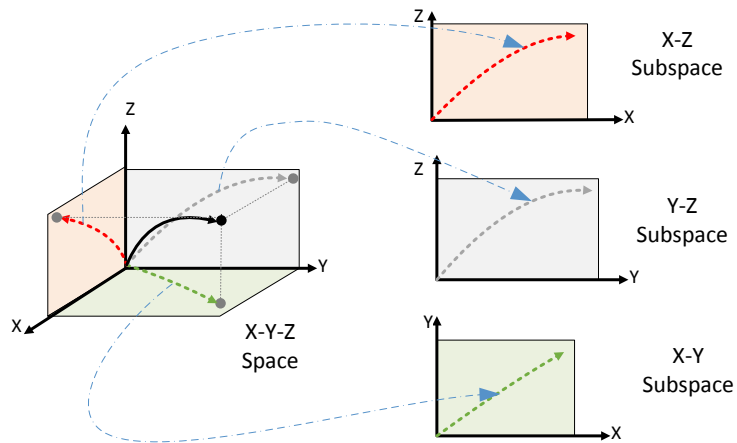


Figure 3: Projections onto Subspaces

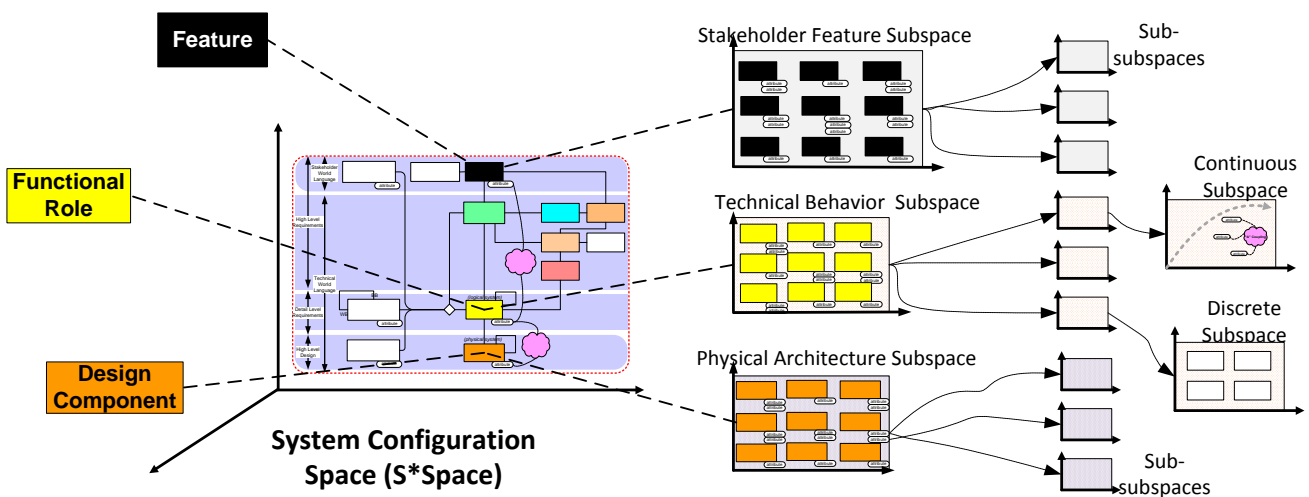


Figure 4: Stakeholder Feature Subspace; Technical Behavior Subspace; Design Subspace

A system's configurations, during the innovation cycle, can now be conceived as moving along a trajectory in each of those individual subspaces, representing projections onto each of them, from the combined trajectory in the total space. We can consider paths that are more or less desirable, think about velocity along the path, ideas of uncertainty about location, development response time, agility, and other important issues. The idea of optimality of trajectory now becomes more clearly related to innovation over life cycles. This optimality may have to do with minimizing transit time, response or recovery time, resources expended along the trajectory, and uncertainty as to position or other feedback.

The scope of S*Configuration Space thus includes not just issues of technical requirements and design, but also identity of stakeholders and models of stakeholder value. This means that innovation opportunity is a part of this space, and the innovation process includes discovery of opportunity and purpose, not just design. We are reminded that this trajectory includes discovery and learning about all three of the subspaces in Figure 4, and others, bearing on current interest in emergence or discovery of purpose, and "pivoting" (Reis 2011).

This nearly brings us to the point of having transformed the view of innovation to a view of optimal trajectory guidance in a noisy environment, but we still need to add the guidance system, as well as arrangements for learning.

The Guidance System: Including the System of Innovation In the Model

Based on the above, we now have the Target System, subject to innovation, represented by a model, having a configuration to be guided along an innovation trajectory path in System Configuration Space. The “guidance system” for that trajectory becomes the life cycle management systems of ISO15288, including systems engineering and other processes. We are still very interested in that ISO15288 process set, which has great community-learned reference value, but we can also view it in a new light, as follows.

The traditional “Vee diagram” view of the ISO15288 model (upper part of Figure 1) focuses on key interdependencies of the life cycle management processes, arising from the nature of developed systems, and with an emphasis on the management of those processes. What we will see below emphasizes different aspects of the same processes—the discovery, learning, and use of learning aspects, and how they relate to the very same ISO15288 processes. It is a different emphasis on the traditional processes—not an abandonment of them.

A reference model is shown in Figure 5, the Agile Systems Engineering Life Cycle Management (ASELCM) Pattern, in use by the INCOSE ASELCM Discovery Project (Schindel and Dove, 2016). It includes three major subsystems:

1. **System 1:** Target system of interest, to be engineered or improved. (The system modeled in the earlier sections above, whose configuration trajectory is to be guided.)
2. **System 2:** The environment of (interacting with) System 1, including not only its operational environment, but also all the life cycle management systems of System 1, *including learning about System 1 and its environment.*
3. **System 3:** The life cycle management systems for System 2, including learning about Systems 2 and its environment.

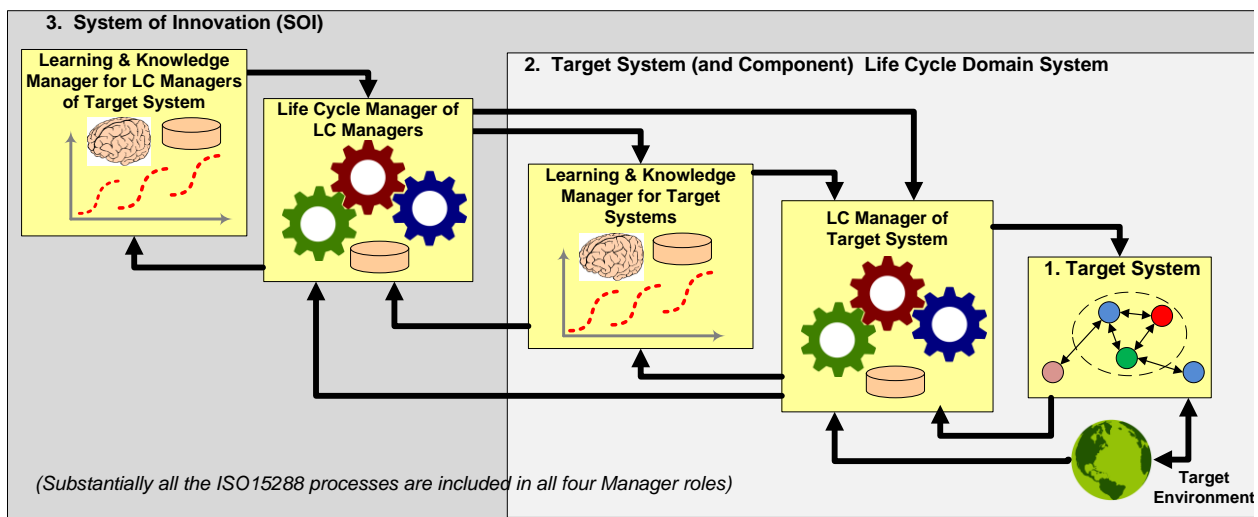


Figure 5: The ASELCM Pattern: Top Level Reference Boundaries

Note that System 2 is further divided into:

- A. **Learning and Knowledge Manager for Target System:** Discovers and accumulates new and existing knowledge about System 1 and its operating environment.
- B. **Life Cycle Manager for Target System:** Uses what has already been learned (in A above) about System 1, performing all the necessary life cycle management processes

The same sort of sub-division occurs for System 3, but concerned with discovery and learning about System 2 and its environment, and managing its life cycle. So, System 3 includes all process improvement for System 2.

The ASELCM Pattern of Figure 5 shows observation and feedback loops. This pattern models Innovation itself, not just the innovated thing—and is non-linear, iterated, and exploratory as to configuration space. It is a complex adaptive system reference model for system innovation, adaptation, operation/use/metabolism, sustainment, and retirement or replacement. It applies to 100% human-performed or automation-aided innovation, or hybrids thereof, whether performed with agility or not, ISO15288 oriented or informal, and whether performed well or poorly. It includes representation of pro-active, anticipatory systems. The rise of a number of newer innovation methods and emphases, in business and technical systems, supports the need for such a combined reference model:

1. Agile engineering of systems and software (Dove and Labarge 2014; Rigby et al 2016)
2. Product Line Engineering of composable, configurable systems (INCOSE PLE WG 2015)
3. Experiment-based Innovation (Schrage 2014; Anderson et al 2011; Manzi 2012)
4. Fail Fast and Recover Early (Dove et al 2016)
5. Lean Business Start Up, the Minimum Viable Product, and Pivoting (Ries 2011)

Effective Learning: More than “Lessons Learned” Reports

The emerging innovation methods cited above particularly emphasize learning, whether it is discoveries about stakeholders and their value space, the evolving environment, competitive alternatives, system concept of operations and technical requirements, designs and technological characterization, or failure modes and design limits. As methodologies couched in agility, experiment, pivot, or fail fast and recover early, the hallmark of these methods is admission that a changing or uncertain world creates risks and opportunities in the form of incomplete knowledge. Of course, this has always been true, at least to some degree, in the world of innovation, traditional or otherwise—but the newer methods particularly emphasize means of accelerating the related discovery and learning process, managing related risks.

Accordingly, strategies for learning are of particular importance (Christensen et al 2011; Schindel et al 2011). This learning amounts to filling in more knowledge in the models of the configuration spaces described above. Because these spaces are usually very large, with many degrees of freedom and parametric ranges, and because exploration, experimentation, and learning require expending time and other resources, the strategy for picking what to learn about, what to invest experiment and learning resources in, becomes important. The concept of configuration space and trajectories through it can help us see this exploration as “flying through” the space in designated “search patterns”. Interest in optimal strategies (i.e., trajectories, routes) for exploration of this space becomes a natural extension of the theory of Design of Experiments (Fisher 1971), and has become the subject of a significant literature on experiment, in its own right (Schrage 2014, Anderson et al 2011, Clarke 2016, Kohavi et al 2009, Manzi 2012, Teller 2016, Thomke 2003).

For the systems engineering process, there are a number of learning-related implications:

1. **How is Continuous, Incremental Learning Represented?** In the approach described above, what is already known about System 1 is represented by the smallest model sufficient for purposes of engineering or science. It follows that what is learned in the future about System 1 would be represented as (incremental) changes to that model.
2. **Learning Must be Compressed and Placed “In the Way” of Future Performance:** For learning to be effective, it must impact future behavior. Just “storing” what is learned is not the objective, which is improved future performance about what was learned. So, what was learned must be effectively incorporated in future performance. While the internal means of this are somewhat masked by biology for individual humans, when it comes to teams and enterprises we must ask how learning is to

improve future performance of the group. We suggest that it is not effective to accumulate ever-growing sets of “lessons learned reports”, even if searchable as databases. The INCOSE MBSE Patterns Working Group describes S*Patterns as the configurable, re-usable models of whole target systems (INCOSE Patterns Working Group 2015). These are subsequently configured as the starting point of future performance, so that whatever has flowed into the Patterns becomes a (configurable, as needed) part of future performance. Think of “muscle memory” in humans.

3. **Learning in Each ISO15288 Process:** Figure 6 shows that the ISO15288 life cycle management processes appear twice in System 2 and twice in System 3. Two of those appearances are learning processes—they are the learning aspect of each of the (already defined) ISO15288 processes. They are about learning new things about the subject of those processes—whether they are about stakeholder or technical needs, designs, verifications, or otherwise. Every ISO15288 process potentially has a learning aspect. But each of them also has a “non-learning” execution only aspect, in which what has already been learned is applied. It is not the case that engineering a system requires learning. In the case of Product Line Engineering (PLE) for configurable platforms, there are rapid-execution versions of each of the ISO15288 processes that essentially “configure” what is already defined in the platform pattern, for a specific case. The platform and its supporting patterns represent what was learned in the past—what we already know.

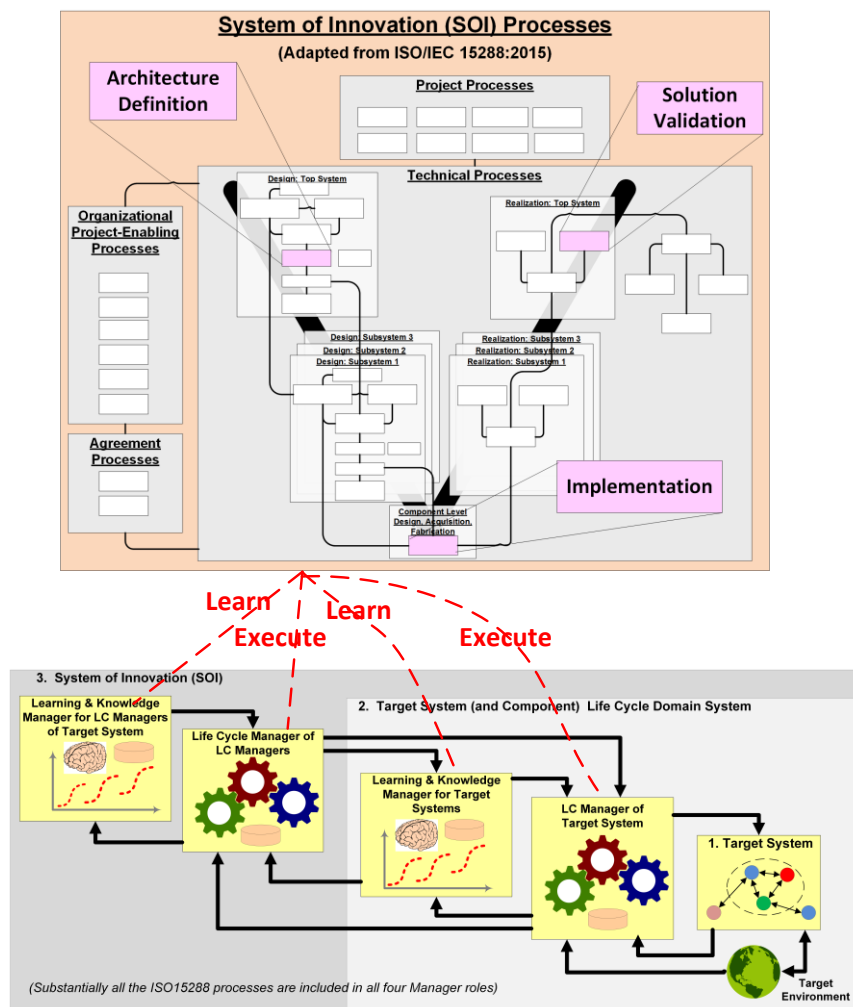


Figure 6: The Systems Engineering “Vee” Appears Four Times In the ASELCM Pattern

4. **What About What We Already Know?** The traditional description of the systems engineering process actually describes all the things we would do if we knew nothing in advance about a system or its domain. But what about what we already know, which is usually quite a lot? Very little of the traditional life cycle process description addresses that question, nor how it would be blended with new learning processes. So, splitting up processes into the learning - execution pairs of Figure 5 has the further advantage of explicating this important aspect, essential to agility.
5. **Learning about System 2:** These same points, concerning System 2's learning about System 1, will also apply to System 3's learning about System 2.

What Optimal Control and Estimation Theory Can Tell Us

It is hard to overstate the transformative successes and spread, during the last fifty years, of the theory of optimal estimation, with related technologies for extracting signals from noisy environments, and the theory of optimal control, with applications of feedback control systems. Among the key modern contributors to these underpinnings have been Norbert Wiener (time series, fire control systems, feedback control, cybernetics), Rudolph Kalman (filtering theory, optimal Bayesian estimation), Lev Pontryagin (optimal control, maximum principle), and Richard Bellman (dynamic programming). Applications spread from defense fire control systems, through multi-sensor navigation systems, to control strategies implemented in manufacturing, transportation, energy, communication, medical, entertainment, scientific instrumentation, and other domains. Without these accomplishments, much of modern life would disappear or shift to much less favorable human experience of a century or more earlier (Wiener 1949; Kalman 1960; Pontryagin et al 1962; Bellman 1957, 1959; Bryson 1967; Bryson and Ho 1975).

These successes have been powered by mathematical models of the related (engineered) systems of interest and their environments. These include their equations of motion (state) and model elements representing measurement, control, uncertainty, risk, and feedback. The accumulation of progress in the capabilities of related models and technologies stands in contrast to the progress of the less formal theories and practice of human organizations, business and management, including the process and procedure of Systems Engineering in particular, or human-performed innovation in general. While these latter human activities have clearly progressed in very important ways, they have been supported by less formal descriptions, subjective judgement, and human intuition—all of these powerful but something different than the above-referenced theory and applications of optimal control and estimation. A reasonable and expected first reaction would be that they simply do not apply in a concrete way, because it has simply not been clear how to practically apply those tools to complex problems such as the management of development processes. So, the latter have been described by informal prose, including prominent examples such as the INCOSE SE Handbook and the ISO 15288 Life Cycle Management Standard.

Is It Plausible To Apply Optimal Control to the Innovation Process?

As the underlying approaches to model-based representations of systems are progressing, we may ask whether this progress is yet sufficient to help us to apply the more powerful mathematical frameworks to the domain of innovation itself. Is it plausible that optimal control and estimation might have practical application to the innovation process itself? And, if it is, why has this not occurred on a widespread basis already?

We first review the nature of these technical frameworks, as they have succeeded in their contemporary application domains, then ask whether and how they apply to innovation itself.

Optimal estimation theory is based on models of estimation, from noisy (corrupted) observations or measurements, of the current state of an (also modeled) system, which may itself also be driven by random processes. This framework addresses the question of how to optimize those estimates, as to their uncertainty. Optimal control theory begins with models of a system's equations of motion, including the model of its environment and drivers, adds models of control inputs, and asks how to optimize those control inputs so as to optimize various objective functions, such as trajectory, elapsed response time, frequency response, expenditure of fuel, energy, or other resources, proximity to moving targets or set points, or other more complex objective functions. The deterministic theory is then extended by adding random processes to both system environmental drivers as well as noise-corrupted observation processes. Optimal control objectives are then extended to include uncertainty.

So, how well does the innovation process itself sound like it might fit what the theory of optimal control and estimation addresses? Table 1 compares the application of the theory, applied to a guidance system, to the same theory, applied to a system of innovation. How are the seemingly different concepts of Table 1's middle and right columns in fact similar? The answer is that they play the common roles listed in Table 1's left column. This is similar to the idea that a control system embedded in an automobile and embedded in a manufacturing system still depend upon the same theoretical foundations from controls theory.

Table 1: Informal Comparison of Two Domains, As a Plausibility Test

Aspect of Common Theoretical Framework	Application to a Vehicle Guidance System	Application to a System of Innovation
Overall domain system	Propelled airborne vehicle guidance to moving airborne target	Development of new system configuration for a system of interest
The controlled system	Airborne Pursuit Vehicle	The development process
Control system	Flight control system and pilot sometimes	Development management & decision-making process
Other actors	Target, atmosphere	Stakeholders, operating environment of system of interest, suppliers
State space in which controlled performance occurs	Vehicle position in 3-D geometric space	Configuration space of system of interest, including its features, technical requirements, and physical architecture
Driving processes	Target dynamics, pursuit thrust, flight control surface movements	Stakeholder interest, supply chain
Random aspects of driving processes	Buffeting winds	Stakeholder preferences, competition, technologies
Observation process model	Radar tracking of moving target, sensor characterization	Status reporting, market feedback, development status report process
Random disturbances of observation processes	Sensor errors	Inaccuracies or unknowables in development status; sampling errors
Environmental Conditions	Target maneuvers; atmospheric effects	Market or other environmental conditions;
Control input	Flight control surface orientation	Management direction; resources
Objective function to optimize	Time to target	Time to market; Competitive Response Time; Innovated System Performance; Innovation Risk vs. Reward
Dynamical model	Ballistic Flight, Atmospheric Effects, Thrust	Coupled development processes
Outcome risk	Risk of missing airborne target	Risk of innovation outcomes across stakeholders

The inspiration of vehicle trajectory control as a trajectory metaphor for travel through innovation state space is further supported by the vehicle work of (King et al 2016) and (Martinovich 1988). The typical formulation of the Table 1 left column concepts, independent of domain, is in the next section.

Risk-Optimal Control and Estimation: Typical Problem Frameworks

Mathematical frameworks of optimal estimation, prediction, and control problems, including deterministic and stochastic, linear and non-linear, continuous and discrete time, as well as combinatorial, have been the subject of extensive attention for decades, resulting in many feedback-based applications in estimation and control. While not every class of problem is covered by these advances, their range of successes is formidable.

For comparison to Table 1, a typical time continuous problem statement framework (discrete forms also available) is as follows (Levi 2014, Bryson and Ho, 1967):

System defined by: $\dot{\mathbf{X}} = \mathbf{f}(\mathbf{X}, \mathbf{U}) + \mathbf{W}$, having system state $\mathbf{X}(t) \in \mathbb{R}_n$, with control $\mathbf{U}(t)$, driven by random process $\mathbf{W}(t)$; allowing observations $\mathbf{Y} = \mathbf{h}(\mathbf{X}) + \mathbf{V}$, $\mathbf{Y} \in \mathbb{R}_n$, having observation corruption by random process $\mathbf{V}(t)$.

Find an optimal control $\mathbf{U}(t)$ minimizing expected objective functional: $\int_0^T \mathbf{g}(\mathbf{X}(t), \mathbf{U}(t)) dt$, and describe the means of quantifying uncertainty based on model and observation.

In linear, or linearized, cases and for discrete time cases, Figure 7 illustrates the form of a representative feedback system, adapted from (Bryson and Ho 1967), where the coefficients shown are generated from system specifications or learning about the random processes from observation (Schindel, 1972); other aspects quantify how uncertainty propagates.

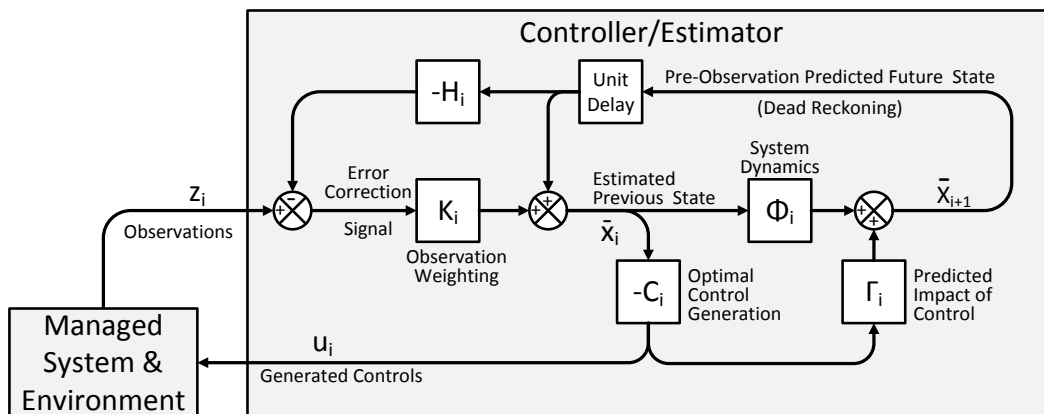


Figure 7: Form of typical optimal stochastic estimator/controller, in linearized discrete time form
(adapted from (Bryson and Ho 1967) and (Schindel 1972))

The framework and Figure 7 are suggestive, not meant to establish the specific form for the innovation problem summarized in Table 1. However, the annotations added to Figure 7 are practical reminders, even in the most non-linear, manual human-performed control, of more fundamental aspects of management and estimation in uncertain environments, concerning:

1. Use of knowledge of managed system dynamics to predict future state (“dead reckoning” based on beliefs about prior state and system behavior)
2. Use of observational data to correct what was otherwise believed
3. Relative weighting of (1) versus (2)
4. Steering to desired trajectory goals based on current estimated state, goal, and beliefs about system response dynamics
5. Exploration to improve knowledge/beliefs of system structure, dynamics, stochastics

Just as these ideas are important in any manually human-managed innovation, so they can also be important in applying optimal estimation and control to innovation.

Agility as Risk-Optimized Control of Trajectory in S*Space

Learning Trajectories versus Mission Trajectories. In a dynamic and uncertain environment, the above can help us understand how to plan trajectories that are optimal with respect to two different goals:

1. **Mission Response to Environment**: Adjusting course (system configuration) in a responsive way, to perform the base mission, or to improve ability to perform the mission. This form of agility exploits what is already known (expressed in the model), based on basic mission and the current or projected operational environment.
2. **Exploration for Learning**: This goal is concerned with exploring to capture additional information to improve understanding about (the model of) the system of interest or its environment, and possibly in the presence of random process corruption of observations as well as random processes driving the systems.

(Simkins et al 2008) illustrates optimal control in a mixed Exploitation-Exploration approach.

Support for Experiment Selection in “Fail Fast and Recover Early” Risk Strategy. When dealing with “moon shot” or less familiar areas (e.g., early stage technologies, early stage market concepts), concerns of later stage “too late” discovery of infeasibility, financial, or stakeholder issues is significant. The literature on “Fail Fast and Recover Early” innovation suggests the strategy of addressing the apparent highest risk issues earliest, to eliminate as soon as possible what turn out to be infeasible choices. (Teller 2016) This is a much different strategy than the WSJF (Weighted Shortest Job First) strategy sometimes applied in agile systems engineering to pick next increments (Reinertsen 2009).

Gradient-Based Versus Exploratory Direction. Given a current location in S*Space, the Principle of Optimality (Pontryagin et al 1962) describes the direction of the optimal trajectory from that point, assuming reachability from that point. If reachability is not assured, then “fail fast” experiments such as in the above approach are suggested.

Intermediate Gain Delivery Trajectories. Even in the case of starting toward a known reachable point, though, agile principles suggest that the trajectory needs to deliver intermediate progress along its route to a destination. That is, intermediate points along the trajectory need to be sought out as intermediate “agile” deliverable configurations that offer incremental improvement in their own right, if the objectives require.

Innovation in Populations: Markets, Segments, Ecosystems

This approach can also be extended beyond trajectories of a single system, by considering populations of systems. In market or ecological frameworks, systems of different configurations of multiply instantiated (populated) instances interact with other systems in roles acting as predators, prey, commercial or military competitors, customers, suppliers, infrastructure, or others.

The global configuration of the entire ecosystem is a point in a higher-dimension configuration state space, and the entire ecosystem is moving along an evolutionary / innovation trajectory. This problem is important to understanding markets and ecosystems, and includes not only issues of development of new system types, but also rates of production and distribution across global supply networks, as a part of the overall innovation model. The diffusion of system types (species, product types, technologies) across the population may be studied in this way. The population perspective has been studied at length in diffusion of technology (Rogers 2003) and proliferation and limits of biological species populations (MacArthur and Wilson 1967).

Conclusions and Future Steps

1. Theories of optimal control and optimal estimation are based in state space, and become more applicable to innovation strategy when explicit system models are used to express system configuration.
2. Geometrization of formal spaces, already a source of major insights in the history of STEM, when applied to the innovation domain brings insight and understanding to planning and executing system innovation.
3. Heuristic practices for innovation strategy, agility, risk management, and learning may be enhanced by the use of mathematical system models of life cycle trajectories over innovation cycles.
4. For learning to be effective, the products of learning must be built into the roles that will perform future tasks to be informed by that learning—"lessons learned" filed in reports or searchable databases are not really learned in an effective sense.
5. Use of models does not replace human judgment, but enhances it in much the same way that STEM has advanced other human-managed activities, adding science and math-based foundations to previously intuitive practices.
6. Quantitative understanding of agile, fail-fast and recover early, lean, and experiment-based innovation methods is enhanced by viewing these through the lens of trajectory in configuration space.

Implications for future pursuit include:

7. How automated engineering tooling can be enabled to assist innovation teams by improving their decision-making around selection of activities;
8. Further exploitation of the historical work of (Pontryagin et al 1962), (Bellman 1957, 1959), and (Kalman 1960);
9. Extension of the mathematical theory by moving to populations, applicable to markets and other ecologies;
10. Incorporation of model verification, validation, and uncertainty quantification (VVUQ), and related application of learned system patterns (PBSE);
11. Enhanced visualization of product life cycle trajectories;
12. Simulation of innovation as a dynamical system.

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Biography



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